

# A Proposed Methodology for Intelligent Decision-Making in Smart Cities and Urban Planning

**Desmond Lartey**

International School for Social and Business Studies, Celje, Slovenia

Urban Cycling Institute, Amsterdam, Netherlands

[larteydesmond3@gmail.com](mailto:larteydesmond3@gmail.com)

**Kris M.Y. Law**

Institute for Intelligent Systems and Research Innovation, Deakin University, Australia

[kris.law@deakin.edu.au](mailto:kris.law@deakin.edu.au)

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## Abstract

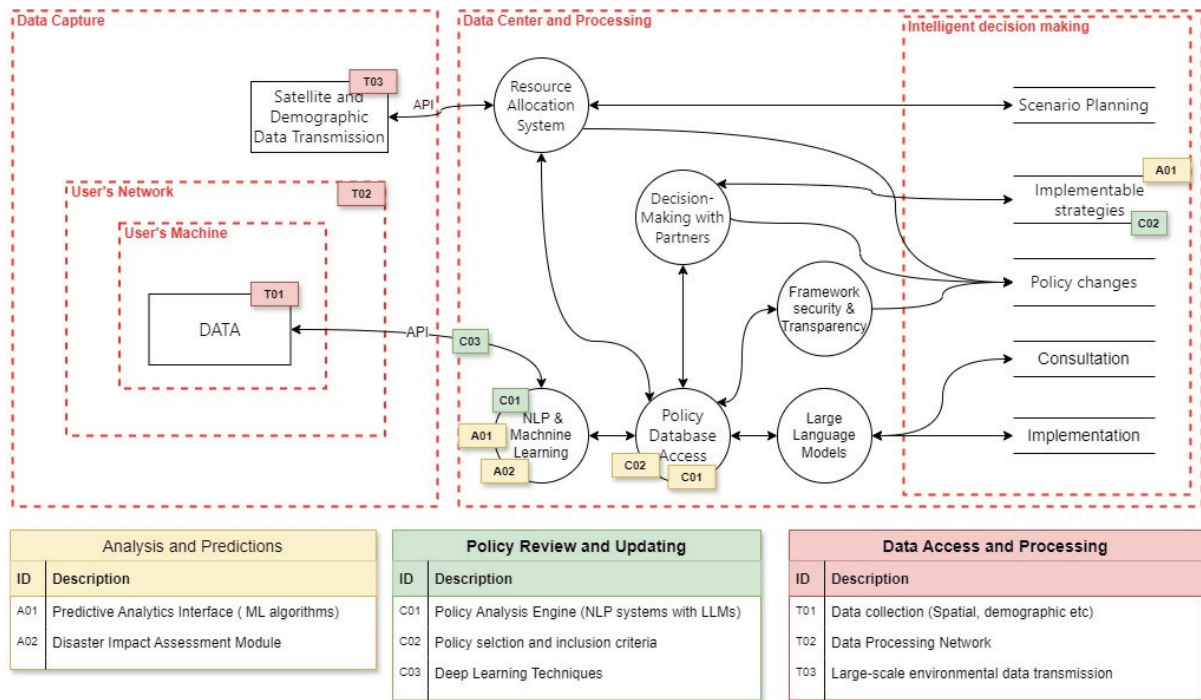
*Urbanization and climate change present unprecedented challenges to cities, necessitating innovative approaches to ensure urban resilience and sustainability. Currently, traditional approaches to urban management, policy development, and implementation are inadequate. Some evidence suggests that the integration of Artificial Intelligence (AI) into urban planning and policymaking processes is crucial for addressing these multifaceted issues. However, there is no methodological framework for intelligent decision-making to navigate the complexities of urban systems, policy formulation, and implementation thereof.*

*We conducted a literature review to understand the role of AI in urban planning and policymaking to evaluate how machine learning, deep learning, and natural language processing techniques can be adopted to address spatial phenomena and policy challenges.*

*An intelligent decision-making framework that aims to integrate and manage the knowledge management cycle of urban and environmental policymaking and implementation was proposed. It addresses the potential of leveraging both quantitative and qualitative techniques, including geospatial and policy analysis, through advanced machine learning and deep learning techniques with Large Language Models (LLMs).*

*It is anticipated that the proposed framework will streamline the policy development and updating process and enhance the overall stability of the implementation.*

**Keywords:** smart cities, urban planning, artificial intelligence, policy-making, decision-making



Graphical Abstract

## 1. INTRODUCTION

In the field of urban planning, which is continually advancing, the use of Artificial Intelligence (AI) represents a new era of innovation and effectiveness (Koutra & Ioakimidis, 2022; Ye et al., 2023). AI, with its exceptional analytical and predictive capabilities, has emerged as a promising tool for addressing the complexities of contemporary urban environments and the policies that guide them, especially given the growing challenges of urbanization and climate change, which necessitate more intelligent, data-driven decision-making processes (Allam & Dhunny, 2019; D'Amico et al., 2020). The urban planning and smart city sector is currently at a critical juncture, facing the dual challenges of rapid urbanization (Marzouk & Othman, 2020) and the intensifying consequences of climate change (Costello et al., 2009; Prein & Pendergrass, 2019).

Several studies have provided essential insights into the integration and impact of AI in this field. For example, Urban et al. (2021) examined the application of AI in urban planning and governance, highlighting its significant role in participatory urban design. There have been significant advances in AI's ability to effectively analyze and synthesize large datasets, which is crucial for optimizing decision-making in urban planning. Zhou et al., (2023) also investigated the use of AI in urban design and governance, with a focus on community regeneration. Their work illustrates how AI can facilitate equitable public participation and empowerment, which are vital elements in urban development.

Furthermore, Ye et al. (2023) significantly enhanced our understanding of Urban Artificial Intelligence (UAI) and its potential applications in various urban settings, such as energy management, environmental monitoring, and transportation. Their work highlights the transition towards a data-rich urban environment, where big data and computational algorithms are seamlessly integrated into the urban fabric, thereby improving the decision-making process in urban planning. In the context of disaster management, Abid et al. (2021) emphasized the critical role of AI in enhancing the efficiency and effectiveness of disaster responses. Recent discussions on AI applications in areas such as geospatial

analysis, remote sensing, and machine learning underscore the importance of AI in hazard and disaster research, enabling faster and more equipped responses in disaster management.

Also, Cici et al. (2016) provided valuable insights into the application of AI in the analysis of urban communication patterns. Their approach to predicting future interactions based on past activities demonstrates AI's potential to inform urban planning and policy decisions, which is crucial for understanding and managing urban dynamics. More recently, Yigitcanlar and Cugurullo (2020) examined the sustainability of AI in the context of smart and sustainable cities. Their findings raise important questions about the long-term sustainability of AI applications in urban services and advocate for a balanced approach to AI adoption that takes into account both technological advancements and urban sustainability.

These growing discussions emphasize the importance of AI applications in urban planning and governance, but they also highlight a significant gap. Thus, traditional decision-making processes in urban planning are inadequate to effectively address these multifaceted issues. However, the field lacks a comprehensive methodological framework that delineates the systematic integration of AI into urban planning, smart cities, and policymaking processes. Thus, there is currently no systematic methodology that outlines how to integrate AI into decision-making and policy-making processes, ensuring their resilience and relevance in the face of ever-changing urban climates and their subsequent challenges.

To steer this path towards a more empirically supported and intricate comprehension of AI's function in smart cities, urban planning, and policymaking, a new methodological framework is required. This paper aims to address this gap by (a) proposing an intelligent decision-making framework that leverages AI's analytical and predictive capabilities of AI (b) while aligning them with the iterative stages of policy formulation, implementation, and update. By incorporating AI into the cyclical dynamics of urban governance, our framework aims to surpass the existing narrative and promote a model of urban development that is responsive to contemporary challenges and is proactive in anticipating future spatial challenges.

## **2. THEORETICAL BACKGROUND**

Urban landscapes today are under significant strain from the rapid pace of urbanization, impacts of climate change, and escalating infrastructure needs (Kisvarga et al., 2023). Conventional urban planning techniques and policies are failing to keep up with these modern-day challenges (Elhanafy, 2023), making the use of AI to understand, analyse, predict, and assist smart decision making a promising alternative.

Despite these growing environmental challenges, policies and regulatory frameworks in place often fail to reflect or effectively manage these evolving challenges. The necessity for innovative management strategies to sustain high-quality urban life is undeniable, prompting a shift towards sustainable and habitable urban development approaches (Peng et al., 2023). Also, the implications of climate change require urgent attention in urban infrastructure planning. Cities on the front lines of climate impacts, such as severe weather events (Butsch et al., 2023), rising temperatures (Islam et al., 2023), and increasing pollution levels (Monoson et al., 2023), require policies that are both forward-looking and adaptable. Policymakers must assess the relevance of existing policies, contemplate necessary updates, and consider how these policies can remain effective in the face of current challenges and future projections. This requires a thorough understanding of existing policies, their efficacy, and the need for updates to ensure that they are equipped to manage such impacts (Jha et al. 2021).

Moreso, many urban areas are burdened by aging and overburdened infrastructure, which is ill-suited to meet the demands of growing populations (Chaillou et al., 2017). There is a pressing need to adopt intelligent decision-making frameworks and development strategies that can sustainably support urban expansion and modernization (Yigitcanlar et al., 2020). Resource management is another element that

presents a significant hurdle for urban centers, especially concerning water, energy, and waste management. Today, the sustainability and health of cities depend on the establishment of effective policies and adoption of sustainable practices to manage these vital resources judiciously (Wang et al., 2023). Consequently, the complexity of urban systems creates a challenging environment for those tasked with policy formulation and planning. The interconnected nature of these systems necessitates a more sophisticated, data-driven approach to decision making, which can enhance the policy development cycle and ensure more informed and effective solutions for present and future challenges.

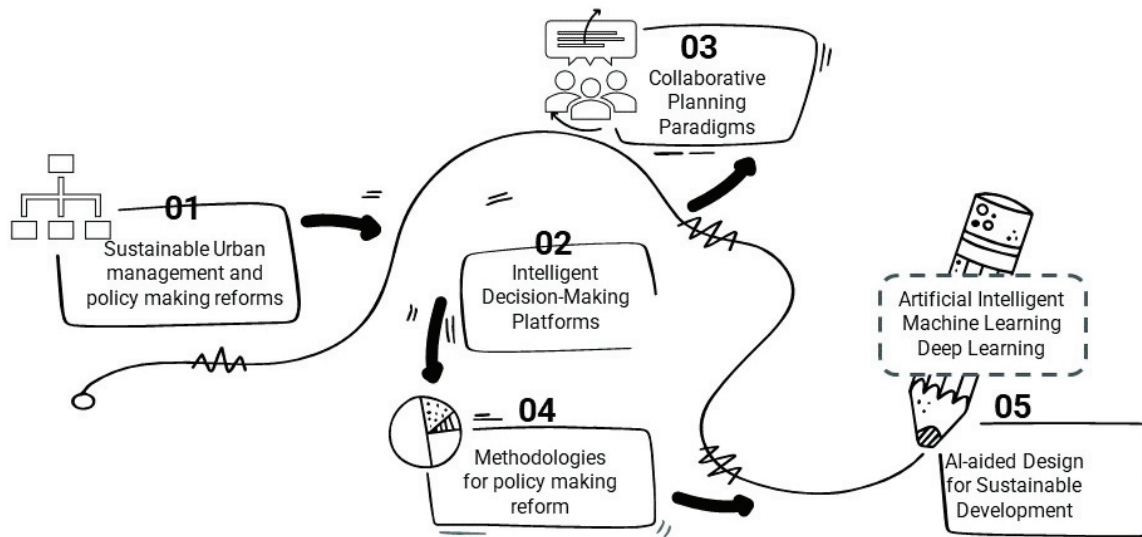


Figure 1: A summary of key highlights from literature

## 2.1 Research gap

Urban planning and development in the context of smart cities are increasingly confronted with complex challenges such as rapid urbanization (Paes et al., 2023), climate change (Kaur et al., 2023), and the need for sustainable infrastructure and policies. First, despite the rapid advancement of AI technologies, there still remains a significant disconnect in how these tools can be integrated into the decision-making processes of urban planning and policy development. The complexities of urban growth, climate adaptation, disaster risk management, and demographic shifts demand a sophisticated embedded understanding that is not fully addressed in existing methodologies (Alahi et al., 2023; Peng et al., 2023; Srivastava & Maity, 2023). The proposed methodological framework seeks to fill this gap by developing a decision-making framework tailored to the intricacies of urban environments and policies. Second, the proposed framework identifies and leverages the key data inputs necessary for effective planning and policy updates, which are often overlooked in both academic studies and industry practices. This will enhance the precision and relevance of AI in urban planning contexts and the implementation and formulation of their policies thereof.

Third, there is a lack of practical implementation of intelligent decision-making frameworks in real-world urban planning scenarios, which leaves a gap in knowledge about the effectiveness and scalability of these technologies. Systematically evaluating Decision-making frameworks in diverse urban settings provide valuable insights into their applicability and impact, guiding future policy development and implementation strategies. Finally, while the potential of AI to contribute to sustainable and equitable urban development is recognized, there is a lack of comprehensive strategies to implement these

principles in a way that aligns with broader urban sustainable development goals. The proposed framework addressed these gaps.

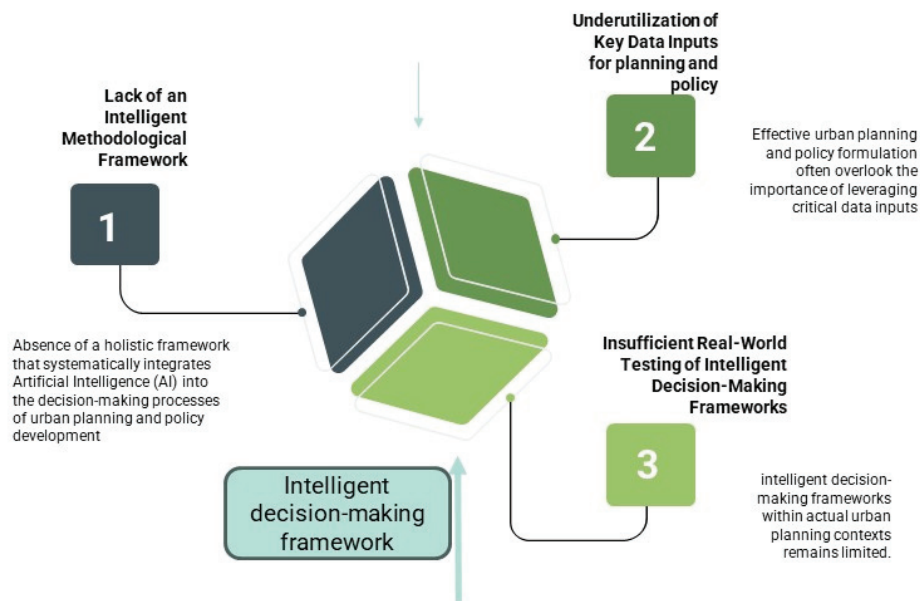


Figure 2: Research gap and proposed concept identified in the literature.

## 2.2 Research questions

We explored the role of Artificial Intelligence (AI) in improving the decision-making process in urban planning, specifically in addressing urban growth, climate adaptation, disaster risk management, and demographic changes through sophisticated decision-making frameworks. First, we identify the essential data inputs and analytical methods necessary to understand the spatial phenomenon and update the urban planning policies. Our objective is to develop an AI-supported decision-making framework that will be evaluated and refined using real-world scenarios to confirm its practicality, usefulness, and accuracy. Finally, we emphasize AI's substantial contributions to the sustainable and urban development goals, highlighting the consequences for policymaking and knowledge management in urban planning.

Table 1: Key research questions and objectives

Research Question	Objective
<b>How can AI improve decision-making in urban planning?</b>	To explore how AI can enhance decision-making by examining policy frameworks.
<b>What are the key data inputs for urban planning policy formulation?</b>	To identify specific data types and analytical methods needed for effective decision-making tools in urban planning.
<b>What are the frameworks to test and refine a decision-making model in real-world scenarios?</b>	To determine methodologies for testing the framework's practicality, effectiveness, and accuracy in urban planning scenarios.
<b>What is AI's contribution to sustainable urban development?</b>	To assess AI's impact on policymaking and setting new standards in urban planning for sustainable and equitable development.



### 3. CONCEPTUAL FRAMEWORK

Recent studies indicate a growing integration of AI technologies to address complex urban challenges (Bartolozzi et al., 2015; Allam & Dhunny, 2019). AI, machine learning (ML), and deep reinforcement learning (DRL) are being utilized to manage urbanization (Aatmaj 2023; Wang & Fu, 2023), energy consumption, and improve the economic and living standards of citizens. These technologies are pivotal in designing optimal policies for intelligent transportation systems (ITSs), cybersecurity, smart grids (SGs), unmanned aerial vehicles (UAVs), and smart healthcare systems within smart cities (Ullah, Al-Turjman, Mostarda, & Gagliardi, 2020). AI's contributions to smart cities are categorized under economy (Alahi et al., 2023), society, environment, and governance (Fabregue, 2023). Also, there are limited research on the risks of AI utilization and the need for further examination of AI's potential disruptions in urban contexts (Yigitcanlar, Desouza, Butler, & Roozkhosh, 2020).

Accordingly, the sustainability of AI from an urbanistic viewpoint is also being explored, with AI applications becoming integral to urban services (Zheng et al., 2014). This viewpoint discusses the potential symbiosis between AI and smart and sustainable urbanism, emphasizing the need for the sustainable adoption of AI in urban policymaking and planning (Yigitcanlar & Cugurullo, 2020). AI-aided design is another area of focus, with the development of a Smart Design framework that integrates AI search techniques, urban-scale performance simulations, and participation to inform decision making for sustainable city development (Quan et al., 2019).

Our review also includes various AI and Internet of Things (IoT) applications for urban planning that contribute to the development of smart and sustainable cities. This highlights the significance of decision-making frameworks that employ geographic artificial intelligence (GeoAI) for comprehensive urban analysis and policy formulation (Huang & Rust, 2018). Our proposed framework aims to boost the livability of urban spaces while promoting economic growth, aligning with participatory planning frameworks that prioritize city-specific requirements and sustainability objectives (Nikitas et al., 2020; Stratigea et al., 2015). Specifically, the integration of AI in decision making provides a strategic edge in policy formulation and urban management.

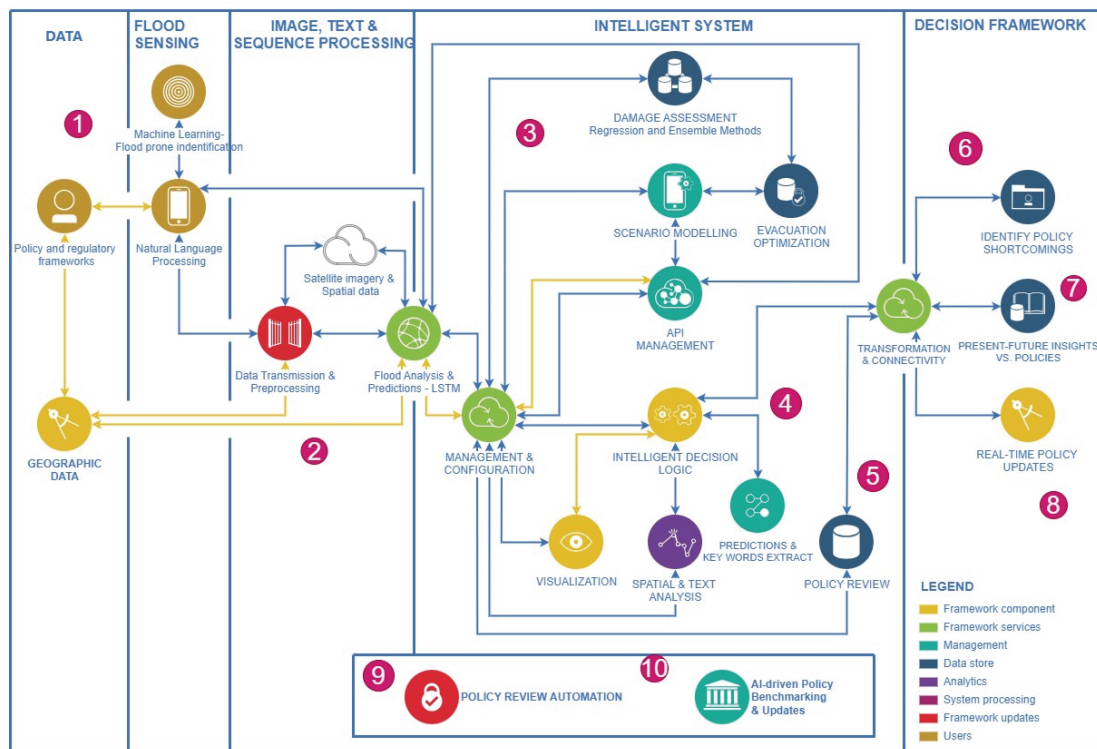


Figure 3: Proposed methodological framework for intelligent decision-making.

## 4. PROPOSED FRAMEWORK

The proposed decision-making framework operates as a closed-loop system that continually iterates and improves with each cycle of data, analysis, and policy review. This dynamic approach to urban planning and environmental management provides flexibility and adaptability for various spatial phenomena. The novelty of this framework lies in its ability to integrate a range of AI techniques, from machine learning and deep learning to NLP, to offer a comprehensive solution for urban planning and flood management challenges. The iterative nature of the framework enables continuous assessment, prediction, and policy evaluation to ensure that policies remain effective against the backdrop of evolving spatial phenomena. The following are descriptions of the key elements of the framework.

**1. Data Collection and Initial Processing:** Geographic and spatial techniques are used to capture large-scale environmental data, thus, for our use case, flood management. Machine learning algorithms, such as support vector machines (SVMs) or decision trees, are then employed to analyze these images and determine areas susceptible to flooding. These methods have been recognized for their ability to handle the complex spatial patterns associated with flood risks (Mosavi et al., 2018). The primary objective of this stage is to employ geographical and spatial techniques to systematically gather and prepare environmental data. This phase is not just about collecting data, but it lays the groundwork for the entire framework operations. By identifying high-risk flood areas, we set a stage for subsequent predictive analytics. The performance of this stage is streamlined using machine-learning algorithms, which are useful for recognizing intricate spatial patterns inherent to flood risks. This focused design approach guarantees that the model fulfills its intended function, thus offering a solid foundation for well-informed, data-driven urban planning decisions.

**2. Predictive Analytics:** Long Short-Term Memory (LSTM) networks and other deep learning models are utilized to analyze and predict flood events based on a range of environmental parameters. These deep learning approaches, particularly LSTM, have shown efficacy in capturing the temporal dependencies and spatial distributions necessary for accurate flood forecasting (Nearing et al., 2023; Hu et al., 2019). The objective of the Predictive Analytics stage in the framework is to forecast future flood events using LSTM networks. This stage transforms the raw data into actionable insights that allow urban planners to proactively develop response strategies.

**3. Damage Assessment:** Linear regression and other statistical methods are employed to analyze the current and future damages caused by flooding. This damage assessment is crucial for understanding the immediate and long-term impacts of flood events (Syeed et al., 2022). The main objective of a Damage Assessment is to measure the consequences of flooding by evaluating both immediate and potential future effects. This information is critical for determining the necessary interventions and guiding economic planning for disaster management, recovery, and building long-term resilience. The accuracy of this assessment is essential, as it directly affects the strategic planning that will follow in later stages.

**4. Evacuation and Safety Planning:** The model incorporates locational data to propose evacuation points and safe areas during flooding events. This process involves inundation analysis that takes into account the time required for floodwaters to reach different elevations, ensuring efficient evacuation strategies (Graovac et al., 2017). At this stage, the focus of the framework is to apply the insights gained from the analyzed data to practical applications. Specifically, the aim is to utilize location analytics to determine evacuation routes and safe zones. This is a crucial step in the development of the framework as it ensures that the predictive analytics carried out earlier are translated into concrete safety measures that can safeguard communities during real-time flood events.

**5. Interpretation of Assessment Results:** AI algorithms then take on the task of assisting the interpretation of flood assessment results, ensuring that the breadth and depth of the impact are fully understood in dialogue with relevant stakeholders. In addition, the interpretation of the assessment

results is a crucial aspect of the framework that highlights its integrative design by combining technical analysis with effective communication among stakeholders. The primary objective of this step is to simplify the complex data and make it easily comprehensible and actionable for all stakeholders involved. By providing a clear understanding of the impacts, this stage of the framework ensures that subsequent recommendations are well-informed and collaborative, thereby facilitating a comprehensive and effective decision-making process.

**6. Recommendation of Solution Scenarios:** Upon interpreting the data and predictions, the model will assist decision makers in recommending possible solution scenarios to address and mitigate the effects of flooding. These recommendations are based on the analysis and prediction models used earlier in the process. At this stage, the framework aims to foster innovative problem-solving approaches. The primary objective is to employ the analyzed and synthesized information to propose possible mitigation strategies. This stage also serves as the crossroads for decision making, where theoretical concepts and data converge to form actionable, feasible plans.

**7. Policy Review Using NLP:** Natural Language Processing techniques with Large Language Models (LLMs) are used to analyze and review existing policies and regulatory frameworks (Yalla & Sharma, 2015) related to flood management and to extract key insights from textual data (Bayat & Tavakkoli, 2022). The use of NLP with LLMs plays a crucial role in critically assessing current policy documents and ensuring that contemporary flood management strategies are consistent with the latest best practices and scientific knowledge.

**8. Benchmarking and Policy Shortcomings Identification:** The framework benchmarks AI-assisted recommendations against reviews of policy documents and highlights any shortcomings or areas for improvement in current flood management policies. The purpose of this stage in the model design is to act as a quality assurance measure within the framework. It is purposefully designed to contrast AI-assisted suggestions with existing policies used to manage spatial phenomena, thereby identifying areas that need improvement. This step guarantees that policies are not only grounded in scientific research but are also able to incorporate new knowledge.

**9. Policy Update Recommendations:** Based on the benchmarking process and identified shortcomings, the model then recommends how the ideal scenario or possible solutions can be applied to update and improve policies. The purpose of this stage is to serve as a catalyst for policy evolution. It provides a clear pathway for transforming insights and identifying gaps in concrete policy improvements, acting as a bridge between scientific insights and policy frameworks.

**10. Policy Document Updates:** The final step involves updating the key areas of policy documents to suit the existing and predicted spatial phenomena, ensuring that policies remain relevant and effective in the face of current and future challenges. The objective of this stage is to translate the analytical work that precedes it into concrete policy changes. This was the ultimate goal of the proposed intelligent decision-making framework. Rather than merely suggesting adjustments, this stage is designed to implement changes that ensure that policies remain effective, adaptable, and resilient in the face of evolving urban challenges.

The proposed framework is built on systems thinking and decision science (Maani & Maharaj, 2004), which offers an integrative approach to understanding complex urban systems and their multifaceted problems. The framework's logical progression from data acquisition to policy implementation reflects the cyclical nature of adaptive management and continuous improvement. The framework also refers to the theory of Complex Adaptive Systems (Baynes, 2009), which states that urban environments exhibit self-organization, scalability, and interconnectivity. More so, the framework's elements are structured to capture these dynamics, allowing for an iterative process that can adapt to new information and changing conditions. It also draws from data-driven decision-making methodologies, which emphasize the importance of empirical evidence (Bohner, 2006) in formulating strategies and policies.



The framework's initial stages will prioritize data collection and analysis to inform subsequent decisions. The application of Predictive Analytics and Prescriptive Analytics further supports the decision-making process, combining forecasts about future conditions with recommendations for action (Khediri et al., 2021). These analytical stages are also deeply connected to Operational Research (Davidson & Venning, 2011), a discipline that uses advanced analytical methods to help make better decisions. Additionally, the principles of Participatory Design and Human-Centered Design influence the framework's emphasis on stakeholder engagement and policy formulation (Perdicoúlis, 2010). The framework's latter stages integrate the components of the Policy Cycle theory (Tobey et al., 2019), including problem identification, policy analysis, policy instrument development, implementation, and evaluation. Our proposed framework emphasizes the importance of continuous policy review and adaptation as part of a responsive urban governance model.

Also, the interactive component of the proposed framework highlights the importance of the knowledge cycle and management, providing a flexible tool that can be adapted to various spatial issues beyond flooding, such as wildfires, urban growth, conservation efforts, and transportation challenges. This approach enhances the decision-making process in urban planning and policymaking, while ensuring that solutions are grounded in data-driven insights and adaptable to future changes.

## **5. SIGNIFICANT KEY FEATURES OF THE FRAMEWORK**

The integration of Geographic Information Systems (GIS) and Artificial Intelligence (AI) into urban planning and policy processes signifies a significant paradigm shift towards more informed and responsive urban management techniques. Stratigea et al. (2015) stressed the importance of Information and Communication Technology (ICT) assisted participatory planning frameworks, advocating application-centric approaches to effectively address urban sustainability objectives. Additionally, the creation and implementation of Integrated City Management Platforms (ICMPs) unlock the potential of Big Data, fostering a more unified approach to decision making across diverse urban sectors (Westraadt and Calitz 2020).

In addition, the constantly evolving nature of urban settings necessitates a versatile approach for policy development and updating. The predictive capabilities of AI can significantly aid in evaluating the efficiency of current policies and anticipating future urban challenges. This anticipatory strategy enables policymakers to refine and modify policies to align with changing urban landscapes. Quan et al. (2019) exemplified the potential of AI-assisted design in urban planning, demonstrating how AI can facilitate sustainable city growth through participatory decision-making processes. We propose that harnessing these intelligent systems will enable policymakers to not only gain a deeper understanding of the current environmental and societal conditions, but also forecast future scenarios and promote a proactive stance in urban planning and policy updates. We outlined six (6) possible implementations of the proposed framework.

### **5.1 AI as a Catalyst in Urban Planning**

The incorporation of AI into urban planning is not just a step forward, it represents a paradigm shift. AI's ability to analyze extensive amounts of data, conduct predictive analytics, and utilize machine learning capabilities is crucial for tackling the diverse challenges faced by contemporary urban areas (Chaillou et al. 2017). Research in this field has provided numerous examples of AI's transformative impacts of AI. For example, AI-driven models play a key role in traffic management, reducing congestion and improving urban mobility (Zheng et al. 2014). Additionally, AI predictive maintenance algorithms have been demonstrated to enhance the resilience and safety of urban facilities in infrastructure management.

AI-assisted design emphasizes the potential of technology to foster sustainable city development by enabling participatory decision-making and facilitating the exploration of extensive design spaces

(Quan et al., 2019). Concurrently, Integrated City Management Platforms (ICMPs) have made a significant shift towards data-informed, integrated decision-making, illustrating the critical role of AI in identifying synergies across urban sectors (Westraadt & Calitz, 2020). Additionally, strategic frameworks that integrate AI into urban planning have highlighted its capacity to resolve conflicting objectives, thereby enhancing the effectiveness of urban development projects (Sarnataro & Greco, 2021). Consequently, a comparative analysis of AI with other decision-support technologies in urban planning reveals its unique ability to grasp the dynamics of land change, supporting superior decision-making (Wagner & De Vries, 2019). The proposed framework promotes collaborative planning paradigms, demonstrating its capacity to align diverse stakeholder interests (Graovac et al., 2017).

## 5.2 Smart Cities and AI-Driven Decision Making

The idea of a smart city, in which technology is used to enhance urban services, is fundamentally connected to artificial intelligence (Alaeddini & Reaidy 2023). In these cities, AI acts as the foundation, enabling more efficient energy usage, better public services, and overall improvement in urban living. A key aspect of the proposed methodology for smart cities and urban planning is its capacity to support intelligent decision-making and understanding. Accordingly, intricate urban data can be examined to provide valuable insights that contribute to policy and planning decisions (Chaillou et al. 2017).

## 5.3 Addressing Urbanization and Climate Challenges

Growing urbanization poses a variety of challenges, including overcrowding and resource management. AI can help improve our understanding of how these issues can be addressed more effectively by examining urban trends and foreseeing future scenarios, thereby empowering planners to make well-informed decisions that preempt and ameliorate potential problems (Reckien et al., 2018). In the context of climate change, the proposed framework is vital for developing robust urban decision-making strategies. These models can predict climate-related risks such as flooding and heatwaves, enabling proactive urban planning and policy implementation.

## 5.4 Application of the proposed framework

Our framework would initially employ AI-driven predictive analytics to anticipate potential flood events more accurately than conventional methods. By analyzing historical weather patterns and real-time environmental data, the framework will provide urban planners with advance notice of probable flood zones. Additionally, the decision-making component of our framework would enable planners to evaluate various response strategies, such as emergency resource allocation or evacuation route optimization. With the integration of AI's comprehensive damage assessments, decision-makers can prioritize areas for immediate intervention and efficiently distribute relief resources. Finally, the iterative policy review capability of our framework, with advanced NLP techniques, ensures that policies are continuously updated based on the latest data and predictive models. This means that urban planning regulations and infrastructure projects can be adapted to account for changing flood patterns, leading to more resilient urban development over time.

## 5.5 The Need for Interdisciplinary Approaches

Urban planning in the age of AI advances requires an interdisciplinary approach at multi-governance level (Lartey & Glaser, 2024) that incorporates intelligent methodological insights into urban dynamics and sustainable solutions (Zheng et al., 2014). The combination of these fields has led to the development of innovative urban-planning strategies. Although AI offers numerous advantages in urban planning, it also presents ethical and privacy concerns. Consequently, it is important to pay significant attention to the responsible use of AI in urban environments and the need for transparent and ethical data handling practices across different stakeholders.

## 5.6 Keeping the questions open

The idea of artificial intelligence replacing human intelligence and decision-making in managing urban complexities has generated mixed feelings, eliciting both excitement and concerns. This duality emphasizes the need for a thorough and ongoing investigation into AI's potential benefits and drawbacks in contributing to intelligent decision-making processes in urban environments. In line with the belief that policy should not dictate scientific exploration, it is important to promote a paradigm in which AI's development in urban planning is guided by well-founded evidence-based research (Peng et al., 2023). Such an approach guarantees that AI's advancements are grounded in genuine needs (Ning & Silva, 2010) and challenges of urban development (Wagner & de Vries, 2019), rather than speculative or trend-driven interests. By maintaining an open and continuous discussion of AI's progress, the scientific and industrial sectors can better navigate the intricate terrain of urban planning management, where the strategic integration of AI with human expertise can cultivate cumulative innovation and sustainable solutions (Yigitcanlar et al., 2021).

## 6. ACTION PLAN AND CONCLUSIONS

This study proposes (a) an intelligent decision-making framework that harnesses the capabilities of Artificial Intelligence (AI), such as machine learning algorithms and Natural Language Processing (NLP), with existing Large Language Models (LLMs) to directly address these challenges. This framework is (b) capable of analyzing and forecasting spatial phenomena, such as flooding, and (c) adept at reviewing and updating policy frameworks to ensure their continued relevance in the face of current and future challenges.

By incorporating advanced AI techniques to systematically analyze data and predict future spatial phenomena, our framework offers predictive insights into spatial issues that threaten urban sustainability. The use of deep learning models, such as Long Short-Term Memory (LSTM) networks, for prediction and regression analyses for damage assessment represents a significant advancement in urban planning methodology. Additionally, the innovative application of NLP with LLMs to evaluate and benchmark existing policies with current spatial phenomena facilitates a dynamic policymaking process, ensuring that urban policies are informed by current issues and adaptable to future scenarios.

Traditional methods often fail to address the intricate aspects of modern urban environments and fail to keep pace with technological advancements. Our proposed framework presents a vital contribution to the field by offering an adaptive approach to urban planning and policy formulation. The innovation and importance of the proposed intelligent decision-making framework lies in its ability to transform urban planning and policymaking into a more proactive, data-driven, and adaptive process. By fusing the capabilities of AI, proper framing and characterisation of the problem (Stoof et al., 2024) with the complexities of urban management and governance, we contribute to the development of smart cities that are not only equipped to face current challenges but are also prepared for the future.

Future research adopting this proposed methodological framework can include enhancing the precision and productivity of the analytical and predictive parts of the model through the integration of more diverse data sources and more sophisticated AI techniques. Another potential future research area is the expansion of our framework to address a broader range of spatial phenomena. This includes, but is not limited to, urban expansion, traffic congestion, environmental conservation, as well as how these issues intersect and interact. Recognizing the interconnectedness of spatial challenges is crucial because our current framework, while robust, may inadvertently suggest isolation of these complex spatial phenomena.

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