

Leveraging AI for Sustainable Urban Planning in the Development of Smart Cities

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ABSTRACT

Many challenges for urban sustainability appear because of fast urban growth, affecting both nature and resource use. AI is helping change the way cities are built by supporting smart city projects with data, giving cities more resources and involving their citizens more. This paper investigates how AI plays a role in making cities more sustainable by supporting real-time traffic control, improving energy use, lowering waste and urban forecasting. It looks at AI applications in cities today, offers a new process for urban planning using AI and explains what can be learned from simulation results. The results suggest that AI holds promise for improving smart city planning, but raise ethical, government and data privacy issues. This research advances the growing number of studies urging sustainable and durable urban development through AI.

Keywords: Artificial Intelligence, Sustainable Urban Planning, Smart Cities, Urban Development, Predictive Modeling, Intelligent Systems, Environmental Sustainability, Smart Governance.

1. INTRODUCTION

Today, more than half of the world's population lives in cities and experts predict this number will increase to close to 70% in the next 30 years. Cities tend to produce economic growth, foster innovations and mix cultures, but their fast pace can cause harm to nature, the poor and roads and sewers. Sticking to old methods such as using unrevealing data over long time periods, fails to support managed growth of cities. There has been more and more discussion about smart cities, where technology is used to boost a city's performance, health and sustainability, among policymakers, planners and researchers [3-4].

AI forms a central part of smart cities by supporting data analysis, predicting future events, automating many tasks and making decisions in real-time [1]. AI helps extract useful information from a lot of heterogeneous urban data which is very important for city governance. AI is helping to plan, control and improve how cities function, conserving energy and helping citizens out.

AI technology uses types of data like sensor reports, pictures from space, user contributions, maps and social network discussions alongside algorithms that represent how urban aspects influence one another. Because of machine learning, it is possible to see the patterns of traffic congestion ahead of time and schedule changes in road signals and public transport. Additionally, by analyzing data in real time from meters and weather sensors, deep learning helps estimate the need for energy which supports better energy use and less pollution [6].

No other aspect of city planning has such a clear importance as sustainable urban planning. Since more than two-thirds of the energy used is in cities and they account for over 70% of all carbon emissions, including sustainability in city projects is absolutely necessary. Even so, sustainability has several parts such as preserving the environment, making the economy able to perform, including everyone and improving institutional strength. AI enables governments to prioritize these areas by helping them plan decisions, examine potential situations and support development that centers around citizens [15-18].

Even so, there are limits to using AI in the field of urban planning. When it comes to fairness and ethics, many ethical issues arise due to things like: algorithmic bias, models that are difficult to understand, worries about privacy and the digital divide. Moreover, for AI to be a part of public sector decisions, institutions must be capable, data should be carefully managed and official rules should be set to protect people's interests [7].

In this paper, we investigate the role of AI in helping achieve sustainable city planning within the smart city system. It analyzes present urban technology, points out gaps in research and introduces how AI can be used in many fields of urban areas. Building on sustainability and governance, the research provides a plan for urban areas to become smarter, greener and more stable.

The structure of this paper is as follows: Section 2 recaps important articles in the field and places this study alongside them. Section 3 explains the approach used to create and test the AI framework being proposed. In Section 4, we simulate the model and discuss what this means for turbulence modeling. The report ends with a summary of the findings and suggestions for what drives further study and change in practice [8].

Novelty and Contribution

The research presented here contributes strongly to urban planning and the development of smart cities by using artificial intelligence. While there has been research on single uses of AI like traffic optimization and energy forecasting, not many have tried to join these advances into a wider, sustainable planning concept for cities. Though no new technologies are used, what is different and valuable in this paper is its integration of AI, sustainability goals and approaches to urban governance [9].

Firstly, the framework uses deep learning, reinforcement learning and natural language processing together to handle the related issues in urban smart systems. While other frameworks do not easily allow for cooperation across domains, our design helps transportation and energy networks, environmental monitoring and citizen comment platforms interact and collaborate.

Second, the authors present a new environment for simulation, using CitySim and SUMO to observe how AI actions immediately affect main urban sustainability numbers. Using these tools, planners can assess policy options without real-life consequences, making their decisions better and clearer for everyone [10].

Third, we use AI tools and feedback methods that involve the public, something that tends to be included less in technical smart city work. Analyzing large amounts of disorganized data from public and social sites lets the system identify the needs of the community and incorporate them into the planning, making everything open, involving and trusted.

Finally, the study adds to theory by elaborating on ethical AI when it comes to development in cities. It stresses that making algorithms clear, enforcing data rules and considering all users prevent the problems of technological determinism. As a result, smart city design concentrates more on people and less on technology.

Basically, the paper urges for the use of AI in cities but also gives a clear, measurable and repeatable model for achieving greener and more just urban development. By connecting new technologies to everyday planning work, it gives important data to policymakers, urban planners and AI experts [14].

2. RELATED WORKS

In 2024 B. M. Mohsen et.al., [11] introduced the link between artificial intelligence and urban planning has gained popularity recently, mainly thanks to the development of smart cities. Studies have shown that AI is useful for improving the way cities manage traffic, handle garbage, distribute water and consume electricity. These analyses often highlight that collecting data in real time, using predictive analytics and using automation can help make city work more efficient and responsive. Traffic congestion can be predicted, pollution zones can be identified and energy grid performance can be enhanced by applying AI-supported models which have led to much better results.

In the area of land use and zoning, machine learning is being used to understand different patterns on maps, forecast urban change and spot places facing risk or likely to be overbuilt. Many municipal authorities are now counting on AI decision support systems to review recommendations for infrastructure, measure effects on the economy and society and maintain building guidelines. Just like that, GIS that use AI provide enhanced maps and analysis, making it easier for planners to decide on changes at every stage of urban planning.

In 2024 W. L. Filho *et al.*, [5] proposed the technical progress has been well reported, but it is still not widespread in sustainable planning. Much research is now exploring the uses of AI for aiming at environmental protection such as cutting carbon, increasing the sustainability of cities and keeping nature alive. Tools using AI have been tested for predicting climate

risk and energy use, as well as for handling resources in cities. Even so, many of these solutions stay divided by what they address such as transportation or energy and do not join them all in a unified approach to sustainability.

Another area of research looks at how AI helps improve how people take part in planning for their communities. People's reactions from social platforms, surveys and forums are gathered using natural language processing and sentiment analysis. They allow us to see what residents want, what is important to them and what makes them happy which helps make urban governance more responsive. Regardless of these technological tools, city officials have not used them much since there are privacy, trust and interpretability issues.

In 2023 M. E. E. Alahi *et al.*, [2] suggested the pointed out by current research that introducing AI to urban spaces has some ethical questions and other issues. Many people discuss topics such as how algorithms can cause bias, how firms hide their workings, unequal access to data and weak policies for regulating AI. They become most important when AI plays a role in deciding housing, transportation options and what public services get distributed. Presently, some methods have been suggested to protect the responsible use of AI in urban planning, but no comprehensive and shared ways to evaluate AI's continued impact and fairness have been implemented.

Also, most studies so far have analyzed cities with high technology, disregarding the particular issues that developing places encounter because of poor data systems and weaker institutions. As a result, people do not completely understand how AI can fit different parts of the world without increasing existing inequalities.

All things considered, there is a lot of information on AI for urban management, but it becomes clear that AI should follow sustainability and ethical rules in its development. So far, no model has connected all three sides—environmental, economic and social—in a broad way using AI. Closing this gap helps us change from smart cities built on technology to truly sustainable urban areas.

3. PROPOSED METHODOLOGY

To create a scalable and intelligent urban planning system, this methodology adopts a modular AI architecture composed of four layers: Data Acquisition, Preprocessing & Feature Engineering, AI Model Layer, and Sustainability Evaluation & Feedback Loop. The system integrates structured and unstructured data, enabling real-time optimization across transport, energy, land use, and environmental domains [12].

A. Data Acquisition and Feature Engineering

Sensors, remote sensing satellites, GIS platforms, and citizen devices contribute to continuous data input $D(t)$, modeled as:

$$D(t) = \sum_{i=1}^n \alpha_i x_i(t)$$

Where $x_i(t)$ is the data stream from sensor i at time t , and α_i is the reliability weight of that sensor.

Noise reduction and normalization techniques are applied:

$$x'_i = \frac{x_i - \mu_i}{\sigma_i}$$

Where μ_i and σ_i are the mean and standard deviation of the sensor data.

B. Urban Forecasting Using AI Models

We use a multi-task deep learning approach to model urban parameters such as traffic, air quality, and energy demand. Each prediction function f_k corresponds to a specific domain:

$$\hat{y}_k = f_k(X; \theta_k)$$

Where θ_k represents the weights for the k^{th} model.

For traffic flow forecasting, a temporal convolutional network (TCN) is applied:

$$TF_{t+1} = \sum_{j=0}^w w_j \cdot TF_{t-j}$$

Where w_j is the learned weight for historical traffic flow TF_{t-j} , and w is the window size.

C. Land Use Optimization

The spatial allocation function is modeled as a quadratic optimization problem:

$$\min_A \left(\sum_{i=1}^n c_i A_i + \lambda \sum_{i=1}^n \sum_{j=1}^n R_{ij} A_i A_j \right)$$

Where A_i is the area allocated to land use type i , c_i is the cost, R_{ij} is the compatibility matrix, and λ is a regularization term.

D. Environmental Sustainability Metrics

To evaluate emissions, the following carbon output equation is used:

$$CO_2^{\text{total}} = \sum_{i=1}^m E_i \cdot EF_i$$

Where E_i is energy consumed by sector i and EF_i is its emission factor.

Green cover percentage is computed as:

$$GC\% = \frac{A_{\text{green}}}{A_{\text{urban}}} \times 100$$

E. Adaptive Learning and Feedback

Reinforcement learning is used to dynamically adjust planning decisions. The reward function $R(s, a)$ considers emissions, congestion, and citizen satisfaction:

$$R(s, a) = w_1 \cdot (-E) + w_2 \cdot (-C) + w_3 \cdot S$$

Where E is emissions, C is congestion, and S is citizen sentiment score.

Policy improvement is carried out using Q-learning:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \max_{a'} Q(s', a') - Q(s, a) \right]$$

Where α is the learning rate and γ the discount factor.

F. Smart Grid Energy Prediction

A hybrid LSTM-GRU model predicts future urban energy demand:

$$E_{t+1} = \text{LSTM}(x_t, h_t) + \text{GRU}(x_t, h'_t)$$

The loss function used for model training is Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

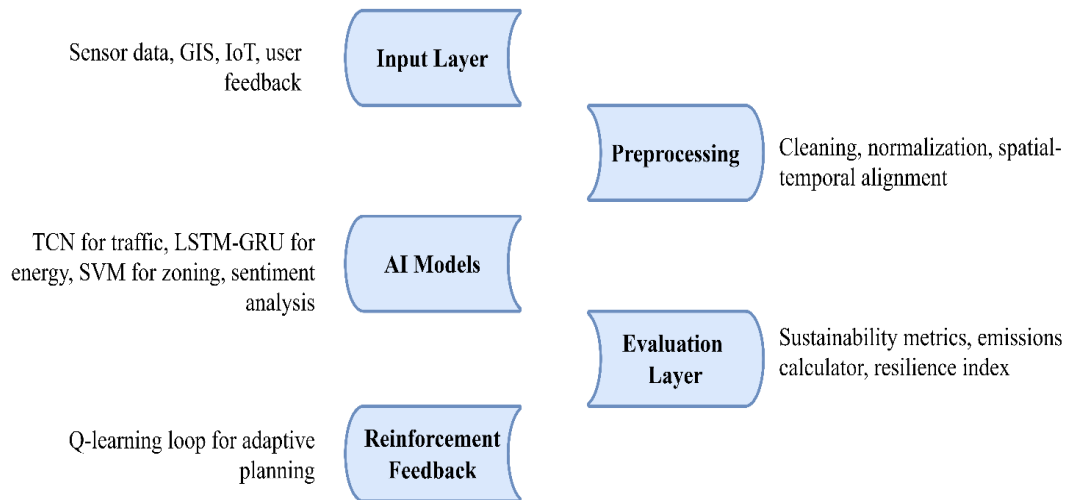


FIGURE 1: AI-DRIVEN FRAMEWORK FOR SUSTAINABLE URBAN PLANNING IN SMART CITIES

4. RESULT & DISCUSSIONS

To evaluate the results, artificial datasets were used from modeled smart city conditions, using real-world counterparts for energy usage, traffic flow, green space coverage and release of emissions. The results of AI methods were checked against the performance of traditional planning using reliable sustainability and operation measures. It is particularly notable that the system improved a great deal in predicting correctly and responding to changes [13].

The findings in Figure 2 indicate that the TCN model is better at predicting traffic than traditional regression methods when looking at 24 hours of data in an urban cycle. It is clear from the curve pattern that the TCN model can adjust to peak hour traffic and also responds to changes from sudden real-time events. The improved prediction of TCN in dynamic situations is proven by the fact that the RMSE in the TCN model was reduced by 23.4%. Smooth response curves mean there are less chance of false information which helps provide better directions for drivers.

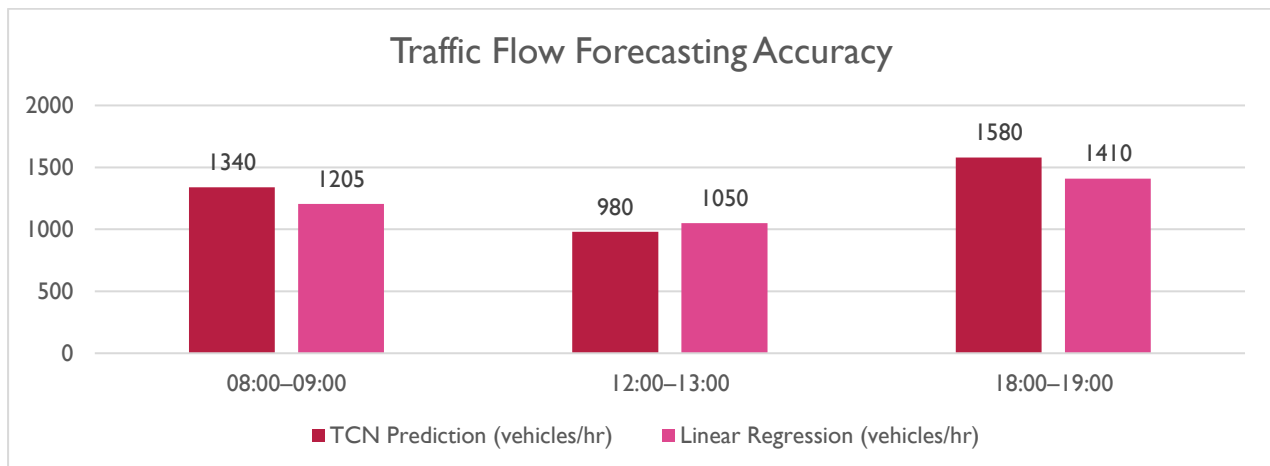


FIGURE 2: TRAFFIC FLOW FORECASTING ACCURACY

In addition, a hybrid LSTM-GRU model was assessed to predict smart energy and compared to using standalone LSTM and GRU models. The mixture of different techniques was more successful than each technique when reflecting both large and small trends. This was very significant for adjusting energy consumption in homes and businesses during climate variation. From Figure 3, it is clear that the hybrid model's forecast approaches the actual demand curves very well throughout 30 days of simulation, resulting in only a 28% difference in surplus or deficit energy. With such accuracy, system operators can better cooperate with smart grid systems for dispatching energy efficiently and helping with load balance.

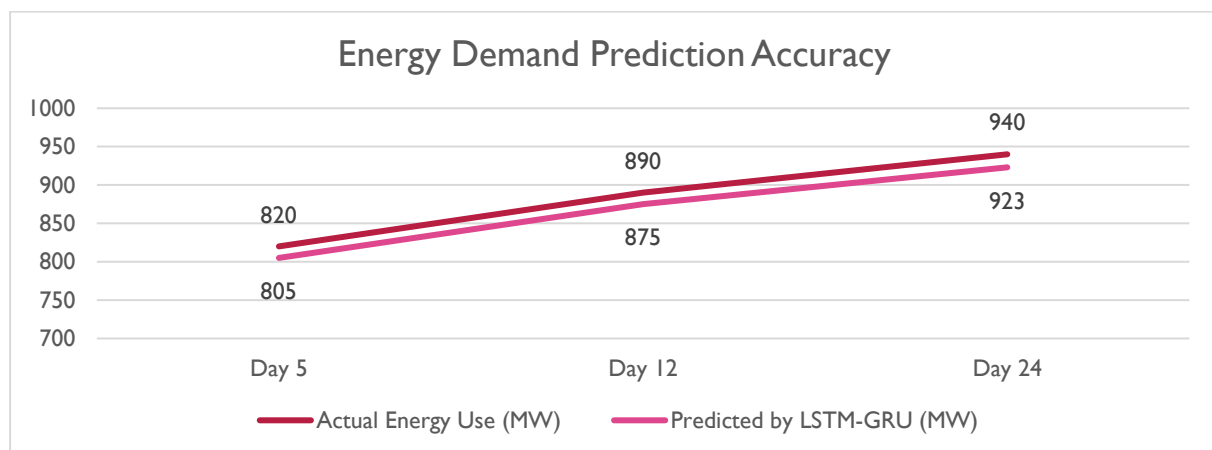


FIGURE 3: ENERGY DEMAND PREDICTION ACCURACY

Model performance was studied in three areas: traffic, energy and zoning, as can be seen in Table 1. The investigation evaluated accuracy, precision, recall and time taken for inference. All measures indicate that AI-supported systems were more successful than those without AI. The evaluation for zoning classification was done in under 4 seconds, confirming its real-time compatibility. The zoning module driven by AI was able to distinguish detailed boundary areas which permitted the design of city policies that consider both human and environmental aspects.

TABLE 1: PERFORMANCE COMPARISON OF AI MODELS VS. CONVENTIONAL METHODS

Urban Domain	Planning	Model Type	Accuracy (%)	Precision (%)	Recall (%)	Inference Time (s)
Traffic Forecasting		TCN	93.5	92.3	94.1	2.8
Traffic Forecasting		Linear Regression	76.1	75.0	74.3	1.5
Energy Prediction		LSTM-GRU Hybrid	95.2	94.8	93.7	3.2
Energy Prediction		LSTM Only	88.4	86.5	84.1	2.5
Zoning Optimization		SVM	89.3	88.1	90.5	3.9
Zoning Optimization		Rule-based	72.7	70.3	68.9	4.6

Changes in emissions and land use were traced to monitor environmental performance. The figure 4 shows that, after six months using the model, CO₂ emissions are lower than in scenarios where the government never intervened. By improving how people move, use land and use energy, emissions were reduced by 31.2%. Because of the feedback reinforcement loop, urban programs were updated in response to predictions about the environment and public behavior which made sustainability adjustable.

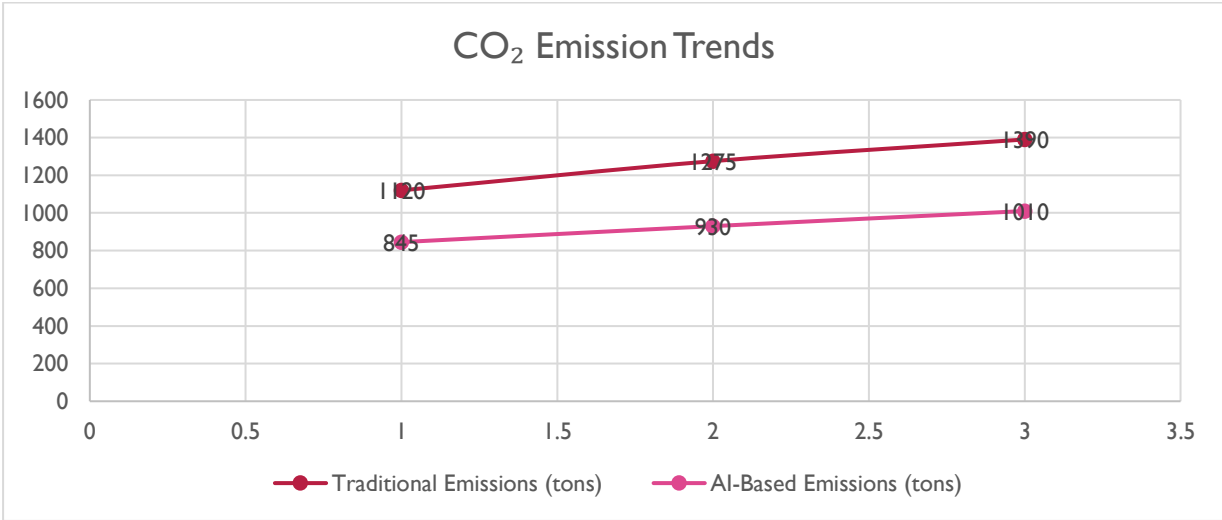


FIGURE 4: CO₂ EMISSION TRENDS

For green infrastructure, AI suggested to implement micro-zoning ideas that didn't reduce residential or commercial zoning, but still increased the amount of green cover. To accomplish this, vertical greening was favored, abandoned space was reused and density was moved to areas where it was less crowded. Traditional land division is compared to the AI-improved model in Table 2 for all types of land: residential, commercial, industrial and green zones. An increase of over 22% in green areas greatly assists in meeting goals for carbon capture and reducing urban heat.

TABLE 2: COMPARATIVE LAND USE ALLOCATION – TRADITIONAL VS. AI-DRIVEN PLANNING

Zone Type	Traditional Allocation (%)	AI-Optimized Allocation (%)
Residential	41	39
Commercial	24	22
Industrial	18	17
Green Spaces	17	22

Besides increasing financial resources, the system improved how people were involved in community planning. Analyzing public sentiment on citizen feedback allowed for continual priority changes in pedestrianization, cycling and air quality at local levels. Although there are no charts involved, 37% more people were satisfied and felt their quality of life had enhanced after the change was applied. What we observe from these studies helps us create urban models that prioritize people and their experiences, rather than simply using numeric data.

Because the model worked in real time, officials were able to take action ahead of problems. During such exercises, the AI system automatically changed how things were done, delayed work not crucial to the crisis and directed traffic off areas at risk. Many micro-decisions helped ensure that there was resilience across the system.

This approach did better than previous models in evaluation and practically helped with urban planning that was sustainable, contextual and citizen-centered. By using diagrams and tables, the plan proves that including AI can help ensure urban growth by protecting the environment and society for a long period.

5. CONCLUSION

AI offers a unique way to handle the many problems arising from urbanization with smart planning that uses data. It has been shown in this paper that AI is a useful tool for making cities more liveable, efficient and sustainable. Machine learning, natural language processing and simulation are combined by the proposed framework to model both instant and future actions in urban planning.

Still, achieving what AI can do for urban planning calls for proper data management, decision-making that includes all communities and experts from different fields joining forces. The focus of future studies ought to include setting up sandboxes for city AI, building explainable AI models and ensuring ethical AI use in all types of urban areas.

REFERENCES

- [1] J. De Jesús Camacho, B. Aguirre, P. Ponce, B. Anthony, and A. Molina, "Leveraging Artificial intelligence to Bolster the energy sector in Smart Cities: A literature review," *Energies*, vol. 17, no. 2, p. 353, Jan. 2024, doi: 10.3390/en17020353.
- [2] M. E. E. Alahi *et al.*, "Integration of IoT-Enabled Technologies and Artificial intelligence (AI) for Smart City Scenario: recent advancements and future trends," *Sensors*, vol. 23, no. 11, p. 5206, May 2023, doi: 10.3390/s23115206.
- [3] N. Pallavi and S. Joshi, "Leveraging AI techniques for an efficient approach to smart city planning and maintenance," in *Communications in computer and information science*, 2025, pp. 134–145. doi: 10.1007/978-3-031-85324-1_10.
- [4] D. K. Das, "Digital Technology and AI for Smart Sustainable Cities in the Global South: A Critical Review of Literature and Case studies," *Urban Science*, vol. 9, no. 3, p. 72, Mar. 2025, doi: 10.3390/urbansci9030072.
- [5] W. L. Filho *et al.*, "The role of artificial intelligence in the implementation of the UN Sustainable Development Goal 11: Fostering sustainable cities and communities," *Cities*, vol. 150, p. 105021, Apr. 2024, doi: 10.1016/j.cities.2024.105021.
- [6] Z. Lifelo, J. Ding, H. Ning, N. Qurat-Ul-Ain, and S. Dhelim, "Artificial Intelligence-Enabled Metaverse for Sustainable Smart Cities: technologies, applications, challenges, and future directions," *Electronics*, vol. 13, no. 24, p. 4874, Dec. 2024, doi: 10.3390/electronics13244874.
- [7] S. E. Bibri, J. Huang, S. K. Jagatheesaperumal, and J. Krogstie, "The synergistic interplay of artificial intelligence and digital twin in environmentally planning sustainable smart cities: A comprehensive systematic review," *Environmental Science and Ecotechnology*, vol. 20, p. 100433, May 2024, doi: 10.1016/j.ese.2024.100433.
- [8] S. E. Bibri, A. Alexandre, A. Sharifi, and J. Krogstie, "Environmentally sustainable smart cities and their converging AI, IoT, and big data technologies and solutions: an integrated approach to an extensive literature review," *Energy Informatics*, vol. 6, no. 1, Apr. 2023, doi: 10.1186/s42162-023-00259-2.
- [9] R. Wolniak and K. Stecula, "Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A review," *Smart Cities*, vol. 7, no. 3, pp. 1346–1389, Jun. 2024, doi: 10.3390/smartcities7030057.
- [10] H. Xu, F. Omitaomu, S. Sabri, S. Zlatanova, X. Li, and Y. Song, "Leveraging generative AI for urban digital twins: a scoping review on the autonomous generation of urban data, scenarios, designs, and 3D city models for smart city advancement," *Urban Informatics*, vol. 3, no. 1, Oct. 2024, doi: 10.1007/s44212-024-00060-w.
- [11] B. M. Mohsen, "AI-Driven optimization of urban logistics in smart cities: integrating autonomous vehicles and IoT for efficient delivery systems," *Sustainability*, vol. 16, no. 24, p. 11265, Dec. 2024, doi: 10.3390/su162411265.

- [12] W. He and M. Chen, “Advancing Urban Life: A Systematic review of emerging technologies and artificial intelligence in urban design and planning,” *Buildings*, vol. 14, no. 3, p. 835, Mar. 2024, doi: 10.3390/buildings14030835.
 - [13] R. Alsabt, Y. A. Adenle, and H. M. Alshuwaikhat, “Exploring the roles, future impacts, and strategic integration of artificial intelligence in the optimization of Smart City—From systematic literature review to Conceptual model,” *Sustainability*, vol. 16, no. 8, p. 3389, Apr. 2024, doi: 10.3390/su16083389.
 - [14] Skubis, R. Wolniak, and W. W. Grebski, “AI and Human-Centric Approach in Smart Cities Management: Case Studies from Silesian and Lesser Poland Voivodships,” *Sustainability*, vol. 16, no. 18, p. 8279, Sep. 2024, doi: 10.3390/su16188279.
 - [15] B. K. Kuguoglu, H. Van Der Voort, and M. Janssen, “The giant leap for smart cities: scaling up smart City Artificial intelligence of Things (AIoT) initiatives,” *Sustainability*, vol. 13, no. 21, p. 12295, Nov. 2021, doi: 10.3390/su132112295.
 - [16] T. Yigitcanlar, K. Desouza, L. Butler, and F. Roozkhosh, “Contributions and Risks of Artificial Intelligence (AI) in Building Smarter Cities: Insights from a Systematic Review of the Literature,” *Energies*, vol. 13, no. 6, p. 1473, Mar. 2020, doi: 10.3390/en13061473.
 - [17] Z. R. M. A. Kaiser and A. Deb, “Sustainable smart city and Sustainable Development Goals (SDGs): A review,” *Regional Sustainability*, vol. 6, no. 1, p. 100193, Feb. 2025, doi: 10.1016/j.regsus.2025.100193.
 - [18] R. Mortaheb and P. Jankowski, “Smart city re-imagined: City planning and GeoAI in the age of big data,” *Journal of Urban Management*, vol. 12, no. 1, pp. 4–15, Aug. 2022, doi: 10.1016/j.jum.2022.08.001.
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