Ai-Driven Smart Street Lighting and Urban Sustainability: The Dortmund Case

Aya.M. Abd El Salam[1], Mohga E. Embaby [2], Olfat A.S. Helwa[3]

[1] PhD Candidate -Teaching Assistant, Department of Architecture, Fayoum University- Nahda University (NUB). Email: Aya.mamdouh@rocketmail.com.
[2] Professor of Architecture, Department of Architecture, Fayoum University . Email: Mohgae@gmail.com.
[3] Associate Professor, Department of Architecture, Mataria– Helwan University. Email: Olfat_Helwa@m-eng.helwan.edu.eg.

Abstract
This study examines the contribution of AI-driven smart street lighting to sustainable urban development by focusing on its role in improving energy efficiency, reducing carbon emissions, minimizing unnecessary illumination, and strengthening data-driven urban management. The study evaluates the environmental, functional, and technological performance of Dortmund's smart street-lighting system in Germany. It applies a Litmap-based literature review and an analytical case-study model structured around three indicators: carbon-emission reduction, urban-use efficiency, and intelligent data-processing capability. The findings show that replacing conventional street lighting with smart wireless LED technology reduced annual electricity consumption by approximately 47%, equivalent to nearly 9.15 million kWh, and prevented an estimated 3,700–4,200 tons of CO_2-equivalent emissions each year. The system also achieved advanced data-processing performance through centralized monitoring, individual luminaire control, energy-consumption analysis, adaptive lighting schedules, and automated fault detection. In contrast, the average congestion level increased from 31.9% in 2024 to 33.3% in 2025, suggesting that the project did not produce a measurable improvement in citywide urban-use efficiency. The analytical model generated an overall score of 56.25 out of 100, reflecting a moderate urban impact. The results confirm that AI-enabled smart street lighting can contribute to sustainable urban development when supported by real-time monitoring, adaptive control, wireless communication, and predictive maintenance. Nevertheless, more direct project-level indicators are needed to assess its effects on pedestrian mobility, cycling activity, nighttime safety, and public-space use with greater accuracy.

Keywords: AI street lighting, urban development, carbon emissions, light pollution, sustainable infrastructure.

1. Introduction

Lighting systems represent a central part of urban infrastructure because they support road safety, pedestrian movement, night-time activity, and public security. However, conventional street lighting systems often operate according to fixed schedules and constant brightness levels, regardless of actual pedestrian presence, traffic movement, environmental conditions, or spatial demand. This rigid operation increases energy consumption, maintenance costs, carbon emissions, and light pollution [1], [2].

The significance of the research problem stems from the substantial environmental burden of lighting systems, which account for approximately 15% of global electricity consumption and contribute nearly 5% of greenhouse-gas emissions worldwide [3].

In addition, outdoor air pollution caused about 4.2 million premature deaths in 2019 [4], while more than 80% of the world's population lives under light-polluted skies and night-sky brightness is increasing by 7-10% annually [5], [6].

Recent urban research has increasingly integrated artificial intelligence, Internet of Things technologies, and real-time data into city and infrastructure management [7]. However, most studies focus on digital urban models, simulation, and decision support rather than smart street lighting. AI- and IoT-enabled lighting systems address this gap by using real-time data to detect movement, monitor performance, identify faults, and adjust illumination according to actual demand. Such adaptive strategies can reduce energy consumption by 40% to more than 80%, depending on system design and implementation scale [8], [9], [10].

In this context, Dortmund provides an important applied case. The city has developed a wireless smart lighting system based on LED luminaires, RF Mesh communication, central monitoring, individual luminaire control, and energy-consumption analysis. This makes Dortmund a useful case for evaluating the environmental, functional, and technical impact of AI- driven smart lighting systems.

2. Research Context Based on the Litmap

The Litmap analysis, presented in Figure. 1, reveals the thematic structure of light-pollution research and classifies the literature into five principal clusters: global monitoring and measurement, ecological impacts, human health and cultural effects, technological developments, and policy and management approaches. Earlier studies concentrated primarily on biodiversity loss, ecosystem disruption, and the economic consequences of inefficient lighting [11], [12].

The first cluster concerns global monitoring and measurement. Falchi *et al.* (2016) mapped the global distribution of artificial night-sky brightness, while Kyba *et al.* (2017) demonstrated that artificially illuminated areas were

increasing in both radiance and spatial extent. Citizen-science observations later indicated an annual increase of approximately 7–10% in night-sky brightness between 2011 and 2022 [13].
The second cluster examines ecological impacts. Artificial light at night can disrupt biological rhythms, alter species behaviour, and modify ecological interactions across terrestrial, urban, marine, and coastal ecosystems [14], [15], [16], [17].

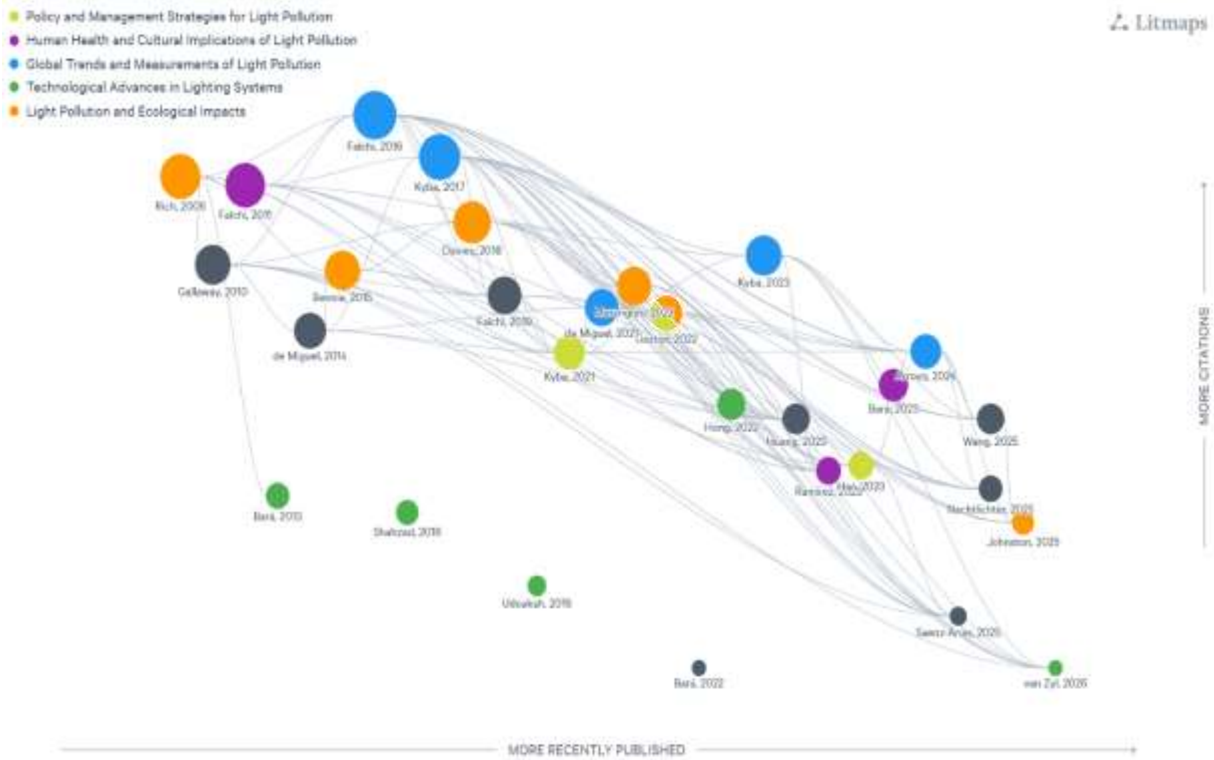

Figure 1. Research Trends and Gaps in Light Pollution, Urban Lighting Systems, and Environmental Impacts [Author].

The third cluster addresses human health and cultural effects. Night-time light exposure can disturb circadian rhythms, suppress melatonin production, and reduce sleep quality. It also limits the visibility of stars and weakens cultural and social connections with naturally dark skies [18], [19].
The fourth cluster focuses on technological developments in lighting systems, particularly energy efficiency and carbon emissions. Bara (2013) argued that reducing the carbon footprint of lighting is insufficient if its spectral, spatial, and ecological impacts remain unaddressed [20]. Conventional fixed-control systems can also generate high electricity consumption, operating costs, and carbon emissions, whereas adaptive lighting can regulate illumination according to actual demand [9], [21], [22].
The fifth cluster concerns policy and management approaches. Effective mitigation requires limiting unnecessary illumination, controlling upward light emissions, selecting suitable intensity and spectral characteristics, and integrating measurable light-pollution standards into urban policies [23], [24], [25], [26].
Together, these clusters provide a clear basis for evaluating AI- driven smart street-lighting systems. By integrating sensors, real-time data processing, and adaptive control, such systems can match illumination to spatial and temporal demand, reduce excessive brightness and energy consumption, and support evidence-based urban-lighting management [9], [21].

3. Research Gap

A critical gap in the current literature is the lack of a holistic and multidimensional framework capable of evaluating AI-drive smart street-lighting systems beyond their conventional role in energy conservation. Existing studies rarely capture the dynamic interactions between environmental performance, urban functionality, and technological intelligence within a single assessment model. Consequently, there remains no comprehensive approach that systematically examines how AI-enabled lighting can simultaneously reduce carbon emissions, optimize urban-use efficiency, and leverage real-time data-processing capabilities to support adaptive decision-making.
Bridging this gap is particularly important as cities transition toward smart and sustainable urban environments. In this context, lighting infrastructure is expected not only to minimize energy consumption but also to mitigate light pollution, enhance operational efficiency, enable predictive maintenance, and generate actionable insights that strengthen the resilience and sustainability of urban systems.

4. Methodology

4.1. Research Design

This study adopts an analytical case-study methodology to evaluate the urban impact of AI- driven smart applications. The proposed model translates qualitative and quantitative evidence into comparable scores across three interrelated dimensions: environmental performance, functional efficiency, and technological intelligence.

This approach is consistent with smart and sustainable city frameworks that emphasize measurable indicators and comparison across urban applications [27], [28].

The model can be applied to smart street lighting, intelligent traffic management, shared mobility, walkability systems, and data-driven public transport. However, it complements rather than replaces the contextual analysis of each case, since evaluation outcomes remain influenced by local infrastructure, data availability, implementation scale, and project objectives.

4.2. Evaluation Indicators and Weights

The model comprises three indicators:

1.Carbon-emission reduction, representing environmental performance

2.Improvement in urban-use efficiency, representing functional performance

3.Intelligent data-processing capability, representing technological performance

Each indicator is scored from 0 to 4. Carbon-emission reduction and urban-use efficiency are each assigned 35 points, while intelligent data-processing capability is assigned 30 points. The total score is therefore 100 points.

The weighting structure gives equal importance to direct environmental and functional outcomes, while technological capability is treated as an enabling factor that supports these outcomes. The weights are literature-informed but were defined by the researcher for comparative analysis.

4.3. Calculation of Indicator Scores

The weighted score for each indicator is calculated as follows:

Weighted indicator score = (Indicator score ÷ 4) × Indicator weight

The final score is obtained by summing the weighted scores:

Final score = Carbon-emission score + Urban-use efficiency score + Intelligent data-processing score

4.3.1. Carbon-Emission Reduction

This indicator compares emissions before and after implementation. The calculation follows established urban greenhouse-gas accounting principles based on activity data and relevant emission factors [29].

Reduction percentage = [(Emissions before implementation − Emissions after implementation) ÷ Emissions before implementation] × 100

Table 1 presents the scoring scale used to convert the calculated carbon-emission reduction percentage into a score ranging from 0 to 4.

Table 1. Scoring scale for carbon-emission reduction .

Reduction achieved	Score
No measurable reduction or less than 5%	0
5% to less than 10%	1
10% to less than 25%	2
25% to less than 50%	3
50% or more	4

Project-level electricity or fuel data should be prioritized. City and national databases may be used as contextual or proxy sources when direct data are unavailable.

4.3.2. Urban-Use Efficiency Improvement

This indicator measures improvements in travel time, waiting time, accessibility, congestion, service regularity, number of trips, or infrastructure use. The selected variable must remain consistent before and after implementation. These measures are commonly used in sustainable urban-mobility assessment [30].

Table 2. Scoring scale for urban-use efficiency improvement.

Improvement achieved	Score
No measurable improvement	0
Less than 5%	1
5% to less than 15%	2
15% to less than 30%	3
30% or more	4

For indicators in which a decrease represents improvement:

Improvement percentage = [(Value before implementation − Value after implementation) ÷ Value before implementation] × 100

For indicators in which an increase represents improvement:

Improvement percentage = [(Value after implementation − Value before implementation) ÷ Value before implementation] × 100

Table 2 shows the scoring scale used to assess the percentage improvement in urban-use efficiency.

4.3.3. Intelligent Data-Processing Capability

This indicator assesses how the system collects, analyses, and uses data rather than merely confirming the presence of digital technology. Smart-city systems increasingly depend on IoT sensing, real-time analytics, prediction, and automated decision-making to convert urban data into operational knowledge [31].

In smart-lighting systems, these functions may include real-time monitoring, movement detection, adaptive dimming, fault identification, predictive maintenance, and automated control [9], [21],

As shown in Table 3, the scoring scale progresses from the absence of systematic data collection to predictive analysis and automated performance optimization.

Table 3. Scoring scale for intelligent data-processing capability.

Data-processing capability	Score
No systematic data collection	0
Data collection without analysis	1
Retrospective data analysis	2
Near-real-time analysis and decision support	3
Predictive analysis and automated optimization	4

4.4. Final Classification

The final score is classified to support comparison among the selected cases. As shown in Table 4, presents the five evaluation levels adopted in the analytical model.

Table 4. Classification of the final evaluation score.

Final score	Evaluation level
Less than 50	Unsatisfactory
50 to less than 65	Moderate
65 to less than 80	Satisfactory
80 to less than 90	Strong
90 to 100	Outstanding

These categories represent a researcher-developed analytical scale rather than internationally standardized thresholds. They provide a structured interpretation of the environmental, functional, and technological performance of each case.

5. AI- driven smart street Lighting Infrastructure

Smart AI- driven street lighting refers to network-connected lighting infrastructure equipped with outdoor luminaire controllers, IoT devices, sensors, and centralized management systems. As illustrated in Figure . 2, these components operate as an integrated system that regulates illumination levels according to sunrise and sunset times, predefined schedules, pedestrian presence, traffic movement, and weather conditions. The system also transmits operational data to a central management platform, enabling operators to monitor individual luminaires, detect faults, analyses energy consumption, and optimize lighting performance [32], [33], [34], [35], [36].

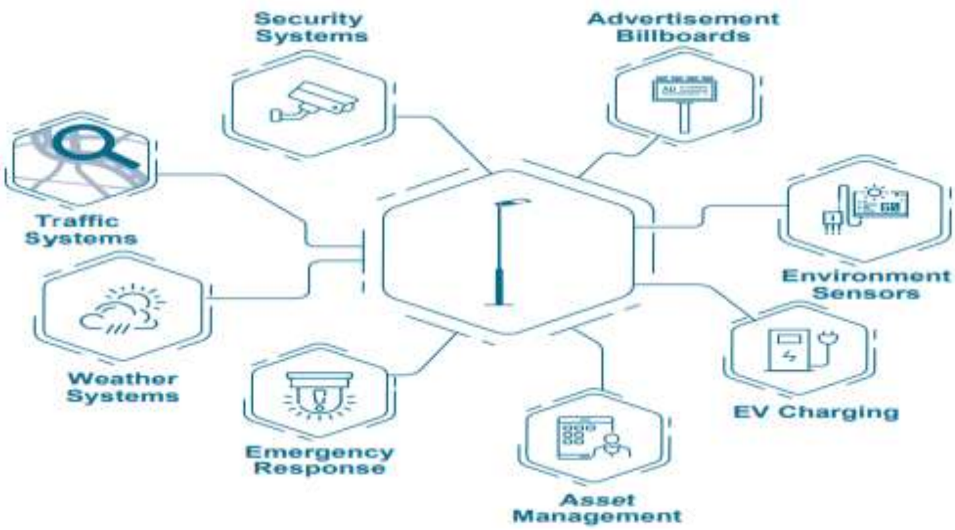

Figure 2. AI- driven smart street lighting pole as an integrated platform for smart-city services [36].

Smart lighting infrastructure can include motion sensors, ambient-light sensors, acoustic sensors, accelerometers, parking sensors, current sensors, wireless controllers, and IoT communication modules. These components make the lighting network capable of real-time control, fault detection, energy monitoring, and integration with wider smart-city systems [32], [36].

Communication technologies are central to system performance. RF Mesh networks are commonly used for smart lighting based on motion sensors because they support self-forming and self-healing wireless communication.

Cellular IoT, including NB-IoT and LTE CAT-M1, is increasingly used for large citywide deployments because it allows outdoor luminaire controllers to connect directly to local cellular towers without physical gateways. Other communication methods, such as LoRaWAN, UNB, and PLC, have different limitations related to bandwidth, security, standardization, or ageing infrastructure [36], [37].

These systems create value beyond energy saving. They provide full control over lighting infrastructure, shift maintenance from reactive to predictive, reduce unnecessary site inspections, improve perceived safety, and reduce light pollution through dimming outside peak hours or motion-based lighting. They can also serve as a platform for smart-city applications such as environmental sensing, security cameras, traffic monitoring, emergency alerts, and electric-vehicle charging [5], [8], [36], [38], [39].

6. Case Study: Dortmund AI- driven smart street Lighting System

Dortmund is located within the Ruhr urban region, one of the dense urban-industrial regions in Germany. Before the modernization of its lighting infrastructure, the city experienced high levels of artificial night brightness, especially in central urban areas. Light-pollution maps for 2016, Figure . 3, show that the city center was located within a relatively high brightness zone, reflecting the cumulative impact of roads, residential areas, industrial zones, commercial activity, and transport infrastructure [5], [40].

Figure 3. Spatial distribution of light pollution levels in Dortmund and its surrounding areas in 2016 [40].

This context made lighting modernization an environmental and operational necessity. Replacing conventional lamps with LED technology was not sufficient on its own. The city needed an integrated lighting management system able to control intensity, reduce unnecessary light spills, monitor performance, and respond to actual urban demand.

The Dortmund project involved the conversion of most street-lighting units into LED luminaires supported by wireless smart control. The project was implemented through cooperation between public and private actors. TRILUX supplied LED luminaires, DEW21 managed the project, SPIE SAG contributed to operation and installation, and Tvilight provided the smart lighting management system [36].

By August 2025, about 45,000 smart luminaires had been installed and operated in Dortmund. The system achieved energy savings of more than 70% and avoided more than 2,080 tons of CO2 emissions within six months. These Figure uses indicate that the project was not only a technical upgrade, but also an urban sustainability intervention that combined energy efficiency, emission reduction, public safety, and operational management.

7. Technical Structure of the Dortmund System

The Dortmund system depends on individual luminaire control, RF Mesh communication, central monitoring, energy measurement, and fault alerts Figure . 4. The system allows each lighting unit to be monitored and controlled separately. This provides a higher level of flexibility than conventional lighting systems, where large groups of lights are often operated together.

The RF Mesh network supports wireless communication between lighting controllers and gateways. This self-forming and self-healing network improve reliability and enables real-time communication between devices. It also supports lighting-on-demand applications, where light intensity increases when pedestrians or vehicles are detected and decreases during low-use periods [36].

Figure 4. Technical Structure of the Dortmund [36].

The system also depends on smart controllers such as Figure . 5 explain SkyLite-Prime, which support advanced system-status analytics, energy measurement, and asset-management functions. Through a central management system, operators can monitor the status of each luminaire, receive automatic fault notifications, analyze energy use, and adjust lighting profiles online. This structure changes the nature of street lighting. It becomes a digital urban platform rather than a fixed infrastructure service.

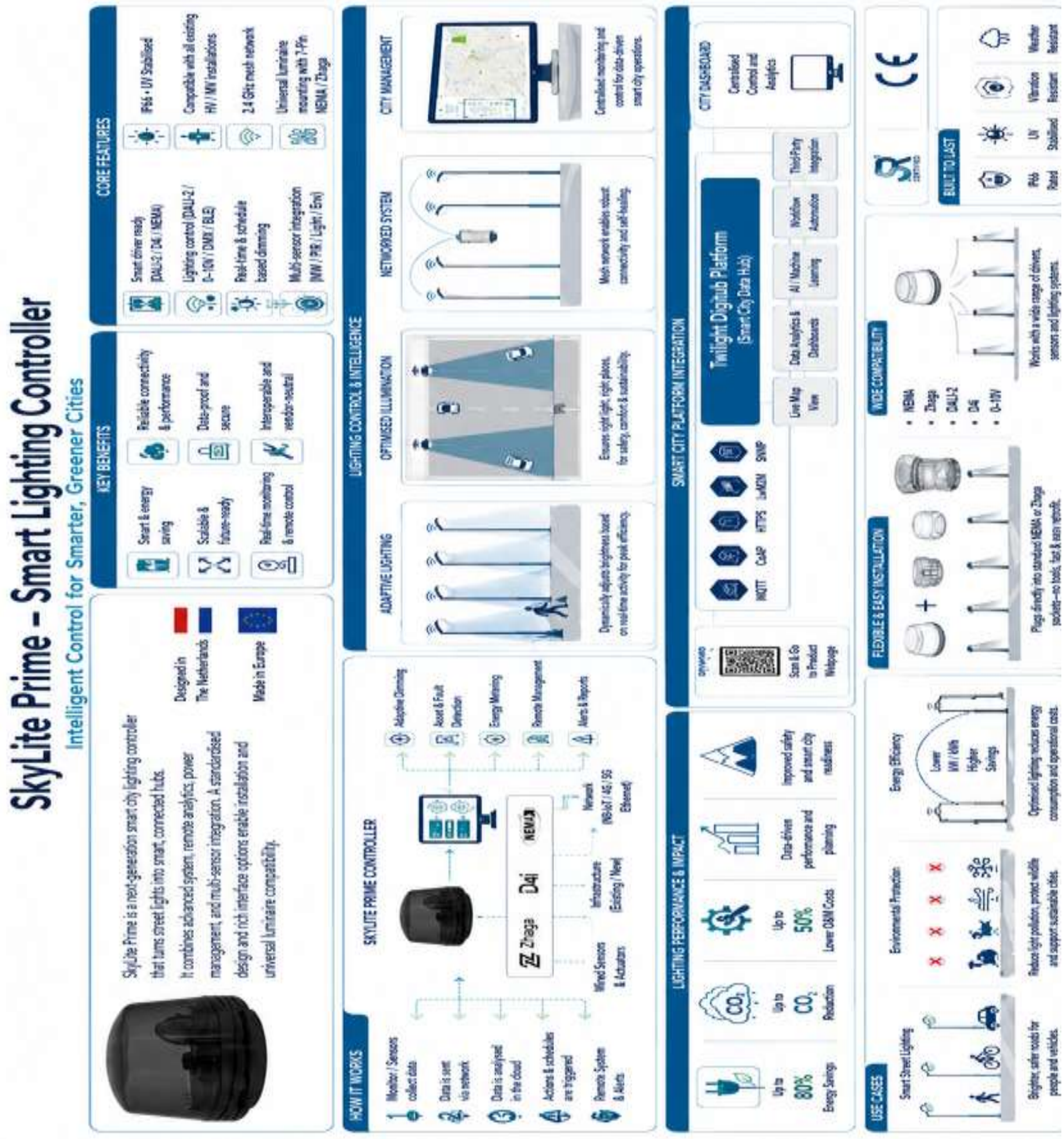

Figure 5. SkyLite Prime of the Dortmund System [Author].

Results and Discussion

The Dortmund experience in modernizing street lighting through a wireless smart-control system was analysed using the proposed analytical model for evaluating the impact of artificial intelligence on urban applications. The evaluation covers the period from 2024 to 2025 and is based on three main indicators: carbon-emission reduction, improvement in urban-use efficiency, and the system's intelligent data-processing capability.

8.1. Evaluation of the Carbon-Emission Reduction Indicator

The carbon-emission reduction indicator was evaluated using the documented decrease in annual street-lighting energy consumption as a direct operational proxy for the reduction in electricity-related carbon emissions. This indicator is more appropriate than a general urban CO_2 index because it directly reflects the environmental performance of Dortmund's street-lighting modernization programme. Previous studies have confirmed that replacing conventional luminaires with LED technologies and integrating adaptive control systems can substantially reduce electricity consumption and the associated operational carbon emissions [8], [9], [41].

By 2024, Dortmund had replaced approximately 42,000 conventional luminaires, increasing the share of smart LED streetlights to 86%. The modernization programme achieved annual electricity savings of approximately 9.15 million kWh, representing a 47% reduction in street-lighting energy consumption compared with the pre-modernization level [42]. This result is consistent with findings from previous smart-lighting applications, which demonstrated that LED conversion, adaptive dimming, centralized control, and real-time monitoring can produce substantial reductions in municipal lighting energy demand [9], [43].

Based on the documented annual saving of 9.15 million kWh and the reported reduction rate of 47%, the approximate annual electricity consumption before modernization calculations was based on City of Dortmund (2025), supported by Ożadowicz and Grela (2017), Bachanek et al. (2021), Pasolini *et al.* (2024), and Sankhwar (2025) as follows:

Annual electricity consumption before modernization:

9.15 million kWh ÷ 0.47 = approximately 19.47 million kWh/year

Annual electricity consumption after modernization:

19.47 − 9.15 = approximately 10.32 million kWh/year

The reduction rate is therefore calculated as follows:

((19.47 − 10.32) ÷ 19.47) × 100 = approximately 47%

The City of Dortmund estimated that these savings corresponded to approximately 3,700–4,200 tonnes of avoided CO_2-equivalent emissions annually [42]. This conversion method is consistent with established approaches that estimate avoided emissions from electricity savings using grid-emission factors [8], [44].

As shown in Table 5, the documented reduction of 47% falls within the evaluation range of 25% to less than 50% as shown Table 1. Therefore, the Dortmund case receives three out of four points. The weighted score is 26.25%

Table 5. Evaluation of Carbon-Emission Reduction in the Dortmund Case, 2024–2025.

Evaluation item	Result
Indicator used	Annual street-lighting energy-consumption reduction
Conventional luminaires replaced	Approximately 42,000 luminaires
Reduction-rate calculation	((19.47 − 10.32) ÷ 19.47) × 100 = 47%
Estimated annual CO_2e reduction	Approximately 3,700–4,200 t CO_2e/year
Evaluation criterion	Reduction from 25% to less than 50%
Score out of 4	3
Relative indicator weight	35 points
Weighted-score calculation	(3 ÷ 4) × 35 = 26.25
Weighted indicator score	26.25 %
Analytical interpretation	A substantial reduction was achieved in energy consumption and associated carbon emissions

8.2. Evaluation of the Urban-Use Efficiency Indicator

Urban-use efficiency in Dortmund was evaluated using the average congestion level reported by the TomTom Traffic Index. A lower congestion level indicates better traffic flow and more efficient use of the urban road network [45].

The congestion level increased from 31.9% in 2024 to 33.3% in 2025. Because congestion is a negative indicator, the calculated improvement rate was −4.39%, indicating a slight decline in urban mobility efficiency during the assessment period [45] .

Other indicators support this result. The average distance travelled within 15 minutes declined from about 7.5 km to 7.3 km, while the travel time for a 10 km journey increased by 29 seconds. Drivers also lost approximately 53 hours in rush-hour traffic during 2025 [45] .

Table 6. Evaluation of Urban-Use Efficiency in the Dortmund Case, 2024–2025.

Evaluation item	Result
Indicator used	Average congestion level
Indicator value before implementation	31.9%
Indicator value after implementation	33.3%
Improvement-rate calculation	((31.9 − 33.3) ÷ 31.9) × 100 = −4.39%
Evaluation criterion	No improvement
Score out of 4	0
Relative indicator weight	35 points
Weighted-score calculation	(0 ÷ 4) × 35 = 0
Weighted indicator score	0
Analytical interpretation	Urban mobility efficiency declined slightly

Although Dortmund's adaptive lighting system supports better lighting management, visibility, and nighttime safety, these benefits do not provide direct evidence of improved citywide traffic performance [8], [42], [43].

As shown in Table 6, the negative improvement rate places the case in the lowest evaluation category. Therefore, the indicator receives zero out of four points and a weighted score of zero out of 35.

8.3. Evaluation of the System's Intelligent Data-Processing Capability.

Dortmund's smart-lighting system enables individual luminaire control, centralized monitoring, energy-consumption measurement, fault detection, and remote adjustment of lighting profiles.

The system combines digitally controlled luminaires, wireless communication, motion sensors, radio-control technologies, and a centralized management platform. These components allow lighting levels to respond to user presence and local operational needs [42].

Table 7. Evaluation of Intelligent Data-Processing Capability in the Dortmund Case, 2024–2025.	
Evaluation item	**Result**
Types of data	Luminaire operation, faults, energy consumption, lighting intensity, and network status
Technologies used	Wireless lighting, RF Mesh, digital radio control, centralized management, and energy monitoring
Processing mechanism	Centralized monitoring, individual control, fault alerts, energy analysis, and lighting-profile management
Analytical output	Improved lighting operation, energy efficiency, and maintenance
Processing level	Intelligent monitoring, automated control, and continuous performance improvement
Evaluation criterion	Intelligent analysis supporting decision-making and performance improvement
Score out of 4	4
Relative indicator weight	30 points
Weighted-score calculation	$(4 \div 4) \times 30 = 30$
Weighted indicator score	30
Analytical interpretation	High intelligent data-processing capability

The platform collects operational and energy data, monitors individual luminaires, sends automatic fault alerts, and supports remote lighting control. RF Mesh communication also provides self-forming and self-healing connections between lighting controllers and the central system [36].

These capabilities demonstrate intelligent data processing through continuous monitoring, automated control, fault detection, and operational decision-making. Previous studies confirm that networked smart-lighting systems improve energy efficiency and lighting-network management through sensing, communication, and adaptive dimming [8], [43].

As summarized in Table 6, the system integrates data collection, analysis, automated control, and continuous performance improvement. Therefore, the Dortmund case receives four out of four points and the full weighted score of 30 points.

8.4. Final Evaluation of the Dortmund Case, 2024–2025

The final score of 56.25 out of 100 indicates that Dortmund's smart street-lighting experience achieved a moderate impact according to the proposed analytical model.

The case demonstrated a substantial reduction in street-lighting energy consumption and a high level of intelligent data-processing capability. However, the citywide urban-use efficiency indicator did not improve because the average congestion level increased during the assessment period.

Table 8. Final Evaluation of the Dortmund Case, 2024–2025			
Indicator	**Score out of 4**	**Relative weight**	**Weighted indicator score**
Carbon-emission reduction	3	35	26.25
Improvement in urban-use efficiency	0	35	0
Intelligent data-processing capability	4	30	30
Total	—	**100**	**56.25**

The result shows that the Dortmund case achieved different performance levels across the three analytical indicators.

The carbon-emission reduction indicator received a weighted score of 26.25 out of 35 points. This result reflects the documented 47% reduction in street-lighting energy consumption following the replacement of conventional luminaires with smart LED technologies. The annual electricity savings were estimated at approximately 9.15 million kWh, corresponding to around 3,700–4,200 tonnes of avoided CO_2-equivalent emissions annually [42].

The urban-use efficiency indicator received zero out of 35 points. The average congestion level increased from 31.9% in 2024 to 33.3% in 2025, producing an improvement rate of −4.39%. The travel distance achievable within 15 minutes also declined, while journey times and hours lost in rush-hour traffic increased [45].

This result does not necessarily indicate that smart lighting had a negative effect on urban mobility. Instead, it shows that the available citywide traffic data do not

provide measurable evidence that the lighting system improved Dortmund's general traffic performance. Smart lighting may still improve visibility, pedestrian safety, public-space operation, and the reduction of unnecessary illumination, but these benefits require direct local measurements.

The intelligent data-processing indicator received the full weighted score of 30 points. This result reflects the system's ability to collect and process operational data through wireless control, centralized monitoring, individual luminaire management, energy-consumption analysis, adjustable lighting profiles, and automatic fault notification [36], [42].

These functions allow operators to identify faults, monitor energy performance, and adjust lighting conditions remotely. The system therefore supports a shift from reactive maintenance toward continuous and proactive infrastructure management.

The overall result indicates that Dortmund represents a technically advanced and environmentally effective smart-lighting case. Its main strengths lie in energy reduction, digital control, automated monitoring, and intelligent infrastructure management. However, the lack of measurable improvement in citywide mobility reduced the overall score.

Future evaluations should use direct Dortmund-specific indicators, including pedestrian activity, cyclist movement, nighttime accident rates, perceived safety, maintenance records, electricity consumption, and verified carbon-emission reductions.

Conclusion

This study evaluated the contribution of AI-driven smart street lighting to sustainable urban development through the case of Dortmund, Germany. The proposed analytical model combined three dimensions: carbon-emission reduction, urban-use efficiency, and intelligent data-processing capability.

The findings show that Dortmund achieved substantial environmental and technical improvements. The modernization programmed reduced annual street-lighting energy consumption by approximately 47%, saving about 9.15 million kWh per year and avoiding an estimated 3,700–4,200 tons of CO_2-equivalent emissions annually. The system also demonstrated a high level of intelligent data processing through centralized monitoring, individual luminaire control, energy analysis, adaptive lighting profiles, and automatic fault detection.

However, the available citywide traffic data did not indicate an improvement in urban-use efficiency. Dortmund's congestion level increased from 31.9% in 2024 to 33.3% in 2025, resulting in an improvement rate of −4.39%. This finding does not prove that smart lighting negatively affected mobility. It indicates that general traffic indicators are not sufficient to measure the direct functional effects of street lighting on public-space use, pedestrian movement, cyclist activity, or nighttime safety.

The Dortmund case achieved a final score of 56.25 out of 100. According to the proposed classification scale, this represents a moderate overall impact. The project performed strongly in environmental efficiency and technological capability, while the lack of measurable improvement in citywide mobility reduced its final score.

The study concludes that AI-driven smart street lighting can support sustainable urban development when LED technologies, sensors, wireless communication, adaptive control, and centralized management operate as an integrated system. Its value extends beyond energy saving by supporting proactive maintenance, operational monitoring, flexible lighting management, and data-based infrastructure decisions.

Future studies should apply direct project-level indicators, including pedestrian and cyclist activity, nighttime accident rates, perceived safety, maintenance costs, lighting-operation records, and verified emissions avoided. These measurements would provide a more accurate assessment of the environmental, functional, and social impacts of smart street-lighting systems.

References

1- Kostic, M. and Djokic, L. (2009) 'Recommendations for energy efficient and visually acceptable street lighting', *Energy*, 34(10), pp. 1565–1572. doi:10.1016/j.energy.2009.06.056.

2- Yoomak, S. and Ngaopitakkul, A. (2018) 'Optimisation of lighting quality and energy efficiency of LED luminaires in roadway lighting systems on different road surfaces', *Sustainable Cities and Society*, 38, pp. 333–347. doi:10.1016/j.scs.2018.01.005.

3- Arun, M. and Gopan, G. (2025) 'Effects of natural light on improving the lighting and energy efficiency of buildings: Toward low energy consumption and CO_2 emission', *International Journal of Low-Carbon Technologies*, 20, pp. 1047–1056. doi:10.1093/ijlct/ctaf057.

4- World Health Organization (2024) *Ambient outdoor air pollution*. Available at: https://www.who.int/news-room/fact-sheets/detail/ambient-%28outdoor%29-air-quality-and-health (Accessed: 4 July 2026).

5- Falchi, F., Cinzano, P., Duriscoe, D., Kyba, C.C.M., Elvidge, C.D., Baugh, K., Portnov, B.A., Rybnikova, N.A. and Furgoni, R. (2016) 'The new world atlas of artificial night sky brightness', *Science Advances*, 2(6), p. e1600377. doi:10.1126/sciadv.1600377.

6- Kyba, C.C.M., Altıntaş, Y.Ö., Walker, C.E. and Newhouse, M. (2023) 'Citizen scientists report global rapid reductions in the visibility of stars from 2011 to 2022', *Science*, 379(6629), pp. 265–268. doi:10.1126/science.abq7781.

7- Marin, G.-G. (2024) 'Digital twin: An emerging tool for urban planning and design', *Urbanism. Architecture. Constructions*, 15(1), pp. 5–26. Available at: https://uac.incd.ro/Art/v15n1a1.pdf (Accessed: 4 July 2026).

8- Bachanek, K.H., Tundys, B., Wiśniewski, T., Puzio, E. and Maroušková, A. (2021) 'Intelligent street lighting in a smart city concepts: A direction to energy saving in cities—An overview and case study', *Energies*, 14(11), p. 3018. doi:10.3390/en14113018.

9- Pasolini, G., Toppan, P., Toppan, A., Bandiera, R., Mirabella, M., Zabini, F., Bonata, D. and Andrisano, O. (2024) 'Comprehensive assessment of context-adaptive street lighting: Technical aspects, economic insights, and measurements from large-scale, long-term implementations', *Sensors*, 24(18), p. 5942. doi:10.3390/s24185942.

10- Khalil, O.K., Ateeq, K. and Mouti, S. (2026) 'An AI-driven smart street lighting with object recognition for energy optimization', *Engineering, Technology & Applied Science Research*, 16(2), pp. 33123–33130. doi:10.48084/etasr.16934.

11- Rich, C. and Longcore, T. (eds.) (2006) *Ecological Consequences of Artificial Night Lighting*. Washington, DC: Island Press.

12- Gallaway, T., Olsen, R.N. and Mitchell, D.M. (2010) 'The economics of global light pollution', *Ecological Economics*, 69(3), pp. 658–665. doi:10.1016/j.ecolecon.2009.10.003.

13- Kyba, C.C.M., Kuester, T., Sánchez de Miguel, A., Baugh, K., Jechow, A., Hölker, F., Bennie, J., Elvidge, C.D., Gaston, K.J. and Guanter, L. (2017) 'Artificially lit surface of Earth at night increasing in radiance and extent', *Science Advances*, 3(11), p. e1701528. doi:10.1126/sciadv.1701528.

14- Bennie, J., Davies, T.W., Cruse, D., Inger, R. and Gaston, K.J. (2015) 'Cascading effects of artificial light at night: Resource-mediated control of herbivores in a grassland ecosystem', *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370(1667), p. 20140131. doi:10.1098/rstb.2014.0131.

15- Davies, T.W. and Smyth, T. (2018) 'Why artificial light at night should be a focus for global change research in the 21st century', *Global Change Biology*, 24(3), pp. 872–882. doi:10.1111/gcb.13927.

16- Gaston, K.J. and Sánchez de Miguel, A. (2022) 'Environmental impacts of artificial light at night', *Annual Review of Environment and Resources*, 47, pp. 373–398. doi:10.1146/annurev-environ-112420-014438.

17- Marangoni, L.F.B., Davies, T.W., Smyth, T., Rodríguez, A., Hamann, M., Duarte, C., Pendoley, K., Berge, J., Maggi, E. and Levy, O. (2022) 'Impacts of artificial light at night in marine ecosystems: A review', *Global Change Biology*, 28(18), pp. 5346–5367. doi:10.1111/gcb.16264.

18- Cho, Y.M., Ryu, S.H., Lee, B.R., Kim, K.H., Lee, E. and Choi, J. (2015) 'Effects of artificial light at night on human health: A literature review of observational and experimental studies applied to exposure assessment', *Chronobiology International*, 32(9), pp. 1294–1310. doi:10.3109/07420528.2015.1073158.

19- Tähkämö, L., Partonen, T. and Pesonen, A.-K. (2019) 'Systematic review of light exposure impact on human circadian rhythm', *Chronobiology International*, 36(2), pp. 151–170. doi:10.1080/07420528.2018.1527773.

20- Bará, S. (2013) 'Light pollution and solid-state lighting: Reducing the carbon dioxide footprint is not enough', in *Proceedings of SPIE*, 8785, p. 87852G. doi:10.1117/12.2025344.

21- Shahzad, G., Yang, H., Ahmad, A.W. and Lee, C. (2016) 'Energy-efficient intelligent street lighting system using traffic-adaptive control', *IEEE Sensors Journal*, 16(13), pp. 5397–5405. doi:10.1109/JSEN.2016.2557345.

22- Udoakah, Y.-O., Mudaheranwa, E. and Cipcigan, L. (2019) 'Municipal street lighting systems energy cost and carbon footprint estimation in Uyo, Nigeria', in *Proceedings of the 2019 IEEE PES/IAS PowerAfrica*, pp. 476–481. doi:10.1109/PowerAfrica.2019.8928661.

23- Falchi, F., Cinzano, P., Elvidge, C.D., Keith, D.M. and Haim, A. (2011) 'Limiting the impact of light pollution on human health, environment and stellar visibility', *Journal of Environmental Management*, 92(10), pp. 2714–2722. doi:10.1016/j.jenvman.2011.06.029.

24- Gaston, K.J., Davies, T.W., Bennie, J. and Hopkins, J. (2012) 'Reducing the ecological consequences of night-time light pollution: Options and developments', *Journal of Applied Ecology*, 49(6), pp. 1256–1266. doi:10.1111/j.1365-2664.2012.02212.x.

25- Bará, S., Falchi, F., Lima, R.C. and Pawley, M. (2021) 'Keeping light pollution at bay: A red-lines, target values, top-down approach', *Environmental Challenges*, 5, p. 100212. doi:10.1016/j.envc.2021.100212.

26- Linares Arroyo, H., Abascal, A., Degen, T., Aubé, M., Espey, B.R., Gyuk, G., Hölker, F., Jechow, A., Kuffer, M., Sánchez de Miguel, A., Simoneau, A., Walczak, K. and Kyba, C.C.M. (2024) 'Monitoring, trends and impacts of light pollution', *Nature Reviews Earth & Environment*, 5(6), pp. 417–430. doi:10.1038/s43017-024-00555-9.

27- Ahvenniemi, H., Huovila, A., Pinto-Seppä, I. and Airaksinen, M. (2017) 'What are the differences between sustainable and smart cities?', *Cities*, 60, pp. 234–245. doi:10.1016/j.cities.2016.09.009.

28- Huovila, A., Bosch, P. and Airaksinen, M. (2019) 'Comparative analysis of standardized indicators for smart sustainable cities: What indicators and standards to use and when?', *Cities*, 89, pp. 141–153. doi:10.1016/j.cities.2019.01.029.

29- Kennedy, C., Steinberger, J., Gasson, B., Hansen, Y., Hillman, T., Havránek, M., Pataki, D., Phdungsilp, A., Ramaswami, A. and Mendez, G.V. (2010) 'Methodology for inventorying greenhouse gas emissions from global cities', *Energy Policy*, 38(9), pp. 4828–4837. doi:10.1016/j.enpol.2009.08.050.

30- Gillis, D., Semanjski, I. and Lauwers, D. (2016) 'How to monitor sustainable mobility in cities? Literature review in the frame of creating a set of sustainable mobility indicators', *Sustainability*, 8(1), p. 29. doi:10.3390/su8010029.

31- [31] Hashem, I.A.T., Chang, V., Anuar, N.B., Adewole, K., Yaqoob, I., Gani, A., Ahmed, E. and Chiroma, H. (2016) 'The role of big data in smart city', *International Journal of Information Management*, 36(5), pp. 748–758. doi:10.1016/j.ijinfomgt.2016.05.002.

32- Achar, T.E., Rekha, C. and Shreyas, J. (2024) 'Smart automated highway lighting system using IoT: A survey', *Energy Informatics*, 7, p. 76. doi:10.1186/s42162-024-00375-7.

33- Fotios, S. and Gibbons, R. (2018) 'Road lighting research for drivers and pedestrians: The basis of luminance and illuminance recommendations', *Lighting Research & Technology*, 50(1), pp. 154–186. doi:10.1177/1477153517739055.

34- Leccese, F. (2013) 'Remote-control system of high efficiency and intelligent street lighting using a ZigBee network of devices and sensors', *IEEE Transactions on Power Delivery*, 28(1), pp. 21–28. doi:10.1109/TPWRD.2012.2212215.

35- Mohandas, P., Dhanaraj, J.S.A. and Gao, X.-Z. (2019) 'Artificial neural network based smart and energy efficient street lighting system: A case study for residential area in Hosur', *Sustainable Cities and Society*, 48, p. 101499. doi:10.1016/j.scs.2019.101499.

36- Tvilight (2025) *Smart City Dortmund: 45,000 smart street lights*. Available at: https://tvilight.com/case-study/smart-city-street-lighting-dortmund-germany/ (Accessed: 4 July 2026).

37- Raza, U., Kulkarni, P. and Sooriyabandara, M. (2017) 'Low power wide area networks: An overview', *IEEE Communications Surveys & Tutorials*, 19(2), pp. 855–873. doi:10.1109/COMST.2017.2652320.

38- Yang, Y.-S., Lee, S.-H., Chen, G.-S., Yang, C.-S., Huang, Y.-M. and Hou, T.-W. (2020) 'An implementation of high efficient smart street light management system for smart city', *IEEE Access*, 8, pp. 38568–38585. doi:10.1109/ACCESS.2020.2975708.

39- Barentine, J.C., Kundracik, F., Kocifaj, M., Sanders, J.C., Esquerdo, G.A., Dalton, A.M., Foott, B., Grauer, A., Tucker, S. and Kyba, C.C.M. (2020) 'Recovering the city street lighting fraction from skyglow measurements in a large-scale municipal dimming experiment', *Journal of Quantitative Spectroscopy and Radiative Transfer*, 253, p. 107120. doi:10.1016/j.jqsrt.2020.107120.
40- Lorenz, D. (n.d.) *Light Pollution Atlas*. Available at: https://djlorenz.github.io/astronomy/lp/overlay/dark.html (Accessed: 4 July 2026).
41- Ożadowicz, A. and Grela, J. (2017) 'Energy saving in the street lighting control system: A new approach based on the EN-15232 standard', *Energy Efficiency*, 10(3), pp. 563–576. doi:10.1007/s12053-016-9476-1.
42- City of Dortmund (2025) *2030 Climate Neutrality Action Plan*. Dortmund: City of Dortmund.
43- Dizon, E. and Pranggono, B. (2022) 'Smart streetlights in smart city: A case study of Sheffield', *Journal of Ambient Intelligence and Humanized Computing*, 13(4), pp. 2045–2060. doi:10.1007/s12652-021-02970-y.
44- Sankhwar, P. (2025) 'Conversion of streetlights to light-emitting diode type', *Journal of Electrical Systems and Information Technology*, 12, p. 3. doi:10.1186/s43067-025-00192-2.
45- TomTom (2026) *Dortmund traffic report: TomTom Traffic Index 2025*. Available at: https://www.tomtom.com/traffic-index/city/dortmund (Accessed: 4 July 2026).