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Implementation of Artificial Intelligence Technology to Improve Energy Efficiency in Street Lighting Systems

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Abstract

Public street lighting (PSL) systems are a major component of urban infrastructure and often account for 20–40% of a city's electricity expenditure. This paper examines how artificial intelligence (AI) has been implemented to improve the energy efficiency of street lighting through a systematic literature review reported in accordance with PRISMA 2020. Peer-reviewed studies published from January 2020 to December 2025 were retrieved from IEEE Xplore, ScienceDirect, MDPI, and Google Scholar; because the final search was completed in March 2026, all records dated 2025 had already been published at the time of retrieval. Seven studies met the eligibility criteria and their individual findings were extracted before synthesis, while one large-scale study of non-AI adaptive control was retained as a benchmark. The reviewed approaches include adaptive control based on real-time object detection with Convolutional Neural Networks (YOLOv5), forecasting of solar energy availability with Long Short-Term Memory (LSTM) networks, machine-learning prediction of illuminance, and AI-assisted optimization of solar-powered luminaires. The included studies reported energy reductions of about 31% for AI-based adaptive dimming relative to full-power LED operation, about 66% when this control was combined with the replacement of sodium lamps, and 54–65% lower grid energy for an AI-optimized solar luminaire, whereas rule-based full-adaptive control achieved about 22–56%. The incremental value of AI therefore lies less in raw savings than in forecasting for off-grid systems, reuse of existing cameras, and context-aware control. An illustrative estimate for five localities in West Papua and Southwest Papua, kept separate from the systematic synthesis, indicates potential savings of about 22 MWh per year for 255 luminaires.

Keywords: artificial intelligence, energy efficiency, smart street lighting, smart city, deep learning, systematic literature review

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1. Introduction

Global energy consumption continues to increase, with the lighting sector accounting for approximately 15–19% of total worldwide electricity consumption and contributing 5–6% of global greenhouse gas emissions (Bachanek et al., 2021). In urban environments, public street lighting (PSL) systems represent one of the largest sources of municipal energy expenditure, accounting for 20–40% of a city's total electricity budget (Khemakhem & Krichen, 2024). The continued reliance on non-renewable fossil energy sources, together with the inefficiency of conventional street lighting systems that operate at full intensity throughout the night regardless of actual environmental conditions, has created an urgent need for more energy-efficient and sustainable solutions.

Figures 1 and 2 illustrate examples of modern street lighting systems that integrate advanced technologies, specifically solar-powered LED street lights (300 W, IP67) equipped with photovoltaic panels as independent energy sources. Such systems provide the physical foundation for the implementation of intelligent street lighting, which is the primary focus of this paper.

The rapid development of the smart city concept has created new opportunities to transform urban infrastructure, including public street lighting (PSL) systems, into more intelligent and adaptive systems. One of the key technologies driving this transformation is Artificial Intelligence (AI). By integrating AI with the Internet of Things (IoT), conventional street lighting systems can be transformed into smart street lighting systems capable of dynamically responding to changing environmental conditions(Bachanek et al., 2021; Deepaisarn et al., 2023; Jiyal et

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al., 2022). Such systems function not only as lighting infrastructure but also as multifunctional platforms that improve energy efficiency, public safety, and the overall quality of urban life.

The implementation of AI enables street lighting systems to make autonomous decisions based on data collected from multiple sensors. For example, lighting intensity can be automatically dimmed when no vehicles or pedestrians are detected and restored to full brightness once movement is identified. Furthermore, AI can be employed to forecast energy demand, optimize the utilization of renewable energy sources such as solar power, and support predictive maintenance to reduce operational costs. Previous studies have demonstrated that the global transition to energy-efficient LED technology combined with intelligent lighting control can save more than EUR 18.8 billion while preventing the construction of 221 new power plants (Bachanek et al., 2021).

Fig 1. Control Unit of a Solar-Powered Smart Street Lighting System

Fig 2. 300 W Solar LED Street Lighting System

Several reviews have already mapped this field. (Bachanek et al., 2021) examined LED modernization and remote management within the smart city concept, (Agramelal et al., 2023) classified street light control methods ranging from time-based schemes to computer vision and deep learning, and (Khemakhem & Krichen, 2024) surveyed IoT-based architectures, communication protocols, and city deployments. Industry sources likewise argue that connected lighting can help AI make cities greener (Signify, 2025). However, these works mainly catalogue technologies; they rarely report a reproducible selection process, extract the individual quantitative outcomes of each study, or ask how much of the reported savings can be attributed to AI rather than to LED retrofitting or to simpler, non-AI adaptive control. This question matters for municipalities with limited budgets, and particularly for remote regions such as Papua, where many luminaires are solar-powered and operate independently of the grid.

This paper aims to provide a systematic review of the implementation of artificial intelligence technologies for improving energy efficiency in public street lighting systems, guided by three research questions: (RQ1) Which AI approaches have been applied to street lighting control, and for what functions? (RQ2) What energy reductions do individual studies report, and how do these compare with advanced non-AI adaptive control? (RQ3) What challenges constrain wider adoption? The contribution of this review is threefold: (i) a transparent, PRISMA-based selection with study-level data extraction; (ii) an explicit benchmark of AI-based control against non-AI adaptive strategies to isolate the incremental value of AI; and (iii) a discussion of transferability to resource-constrained, off-grid contexts, supported by an illustrative local estimate that is kept separate from the systematic synthesis.

2. Literature Review

The existing literature indicates that research on smart street lighting has advanced rapidly, with a primary focus on integrating LED technology, the Internet of Things (IoT), and Artificial Intelligence (AI) to achieve optimal energy efficiency. The fundamental concept of these systems is the transition from conventional static operation to dynamic and adaptive lighting control.

(Bachanek et al., 2021) presented a comprehensive review highlighting that the modernization of public street lighting through LED luminaires integrated with remote management systems forms a fundamental component of smart city development. These systems enable programmable lighting scenarios in which illumination levels can be adjusted according to weather conditions, seasonal variations, and traffic density. Their case studies demonstrated that, although the required investment is substantial, such modernization provides significant benefits for all stakeholders through reduced operational costs and lower light pollution. On a global scale, replacing conventional outdoor lighting with modern LED technology has the potential to save EUR 18.8 billion in energy costs, eliminate the need for 221 new power plants, and avoid approximately 245 million tons of CO_2 emissions (Bachanek et al., 2021).

From a technical perspective, the application of deep learning algorithms has become one of the major research directions. (Asif et al., 2022) proposed an adaptive lighting control framework based on YOLOv5, a Convolutional Neural Network (CNN) object detection model capable of identifying vehicles and pedestrians in real time. Implemented on the NVIDIA Jetson Nano embedded platform, the system dynamically adjusted lighting intensity according to the presence and movement of detected objects, resulting in substantial energy savings, particularly during periods of low traffic. The system was evaluated at two locations in Karachi, Pakistan, where the adaptive scheme reduced the annual consumption of a 140 W LED luminaire from 613 kWh to 449 kWh, a 31.25% reduction relative to full-power LED operation (Asif et al., 2022)

For fully autonomous street lighting systems operating independently of conventional power grids, the integration of renewable energy sources is essential. (Tukymbekov et al., 2021) proposed an autonomous public street lighting system powered entirely by photovoltaic panels(Bhayo et al., 2019; Daut et al., 2011; Wazed et al., 2017). A major challenge in such systems is energy management, particularly under adverse weather conditions that reduce solar power generation. To address this issue, the authors employed a Long Short-Term Memory (LSTM) network to predict solar energy production using weather forecast data. Based on these predictions, the system proactively adjusted lighting intensity to prevent the battery from reaching critical charge levels, achieving a failure probability not exceeding 0.10% during a 1,000-day simulation (Tukymbekov et al., 2021).

A comprehensive survey conducted by (Khemakhem & Krichen, 2024) provided a broad overview of IoT-based smart street lighting architectures. Their review discussed key system components, including sensor technologies (motion, light, and sound sensors), wireless communication protocols (such as ZigBee, LoRaWAN, and 5G), and intelligent control algorithms. Case studies from cities including Barcelona, San Diego, and Los Angeles demonstrated the practical impact of these technologies. Barcelona achieved energy savings of approximately 30%, while Los Angeles reduced energy consumption by up to 60% following the replacement of conventional lighting with LED luminaires integrated into intelligent control systems (Khemakhem & Krichen, 2024).

Advanced street lighting control does not necessarily require AI. (Asif et al., 2022) summarize earlier evidence that line control with astronomical clocks and power regulators yields savings of up to about 15%, whereas remote point-to-point control achieves up to about 30%, although both rely on static settings. More recently, (Pasolini et al., 2024) reported long-term measurements from large deployments in Italy operating under the UNI 11248 and EN 13201 framework, in which light levels are adapted using traffic, road luminance, and weather sensors without machine learning. (Agramelal et al., 2023) similarly classified control schemes from simple time-based switching to computer vision and deep learning and assessed the energy consumption associated with each approach. Such rule-based adaptive installations define the baseline against which the incremental value of AI should be judged, and they are therefore used as a comparator in this review. Table 1 summarizes the studies included in this review together with the key quantitative finding extracted from each of them.

Table 1. Studies Included in the Systematic Review and Their Extracted Findings (2020–2025)

No.	Authors & Year	Journal / Publisher	AI Method	Research Focus [Evidence Type]	Key Extracted Finding
1	(Bachanek et al., 2021)	Energies (MDPI)	Intelligent control system (LED + remote management)	Overview and municipal case study of LED modernization with remote management in the smart city framework [review / case study]	40–70% (range reported in the original synthesis)
2	(Asif et al., 2022)	Energies (MDPI)	CNN / YOLOv5	Real-time vehicle and pedestrian detection on Jetson Nano controlling LED	31.25% vs. full-power LED (613 → 449 kWh/year per luminaire);

No.	Authors & Year	Journal / Publisher	AI Method	Research Focus [Evidence Type]	Key Extracted Finding
				intensity; two sites in Karachi, Pakistan [field experiment]	≈66% vs. 300 W sodium lamp; precision 0.987
3	(Tukymbekov et al., 2021)	Energy (Elsevier)	LSTM / RNN	LSTM forecast of PV generation from weather data to set nightly brightness of autonomous solar luminaires; Almaty, Kazakhstan [simulation]	Critical-battery probability ≤0.10% over 1,000 simulated days; savings not reported as a single percentage
4	(Khemakhem & Krichen, 2024)	Franklin Open (Elsevier)	IoT + machine learning	Survey of IoT-based smart street lighting architectures, protocols, and city deployments [review]	City examples: ≈30% (Barcelona) to ≈60% (Los Angeles)
5	(Deepaisarn et al., 2023)	Sensors (MDPI)	ML regression (XGBoost, best of four models)	AI-assisted analytics platform predicting illuminance and setting dimming every 20 min; Thammasat University campus, Thailand [field implementation]	Illuminance prediction r = 0.922; energy saving not reported as a headline percentage
6	(Agramelal et al., 2023)	Energies (MDPI)	Review (rule-based to deep learning)	Classification of street light control methods and light schemes, including computer vision and deep learning [review]	Qualitative synthesis; energy consumption assessed for each control approach
7	(Belloni et al., 2024)	IEEE Access	AI-based optimization and consumption forecasting	PV-integrated LED street lamp monitored for several months in central Italy; optimization and techno-economic analysis [field monitoring + modelling]	Grid energy 35–46% of a conventional lamp (54–65% reduction); payback depends on tariff and lamp cost
C	(Pasolini et al., 2024)	Sensors (MDPI)	None (non-AI comparator)	Long-term measurements of traffic-, luminance- and weather-adaptive LED lighting in Italian municipalities [field, large scale]	Full-adaptive: 22.5–56.2% vs. astronomical clock (24.6% across 2,957 luminaires in Meda); motion sensing 2.7–24.5%

3. Methods

This study employs a Systematic Literature Review (SLR)(Bharadiya, 2023; González-Pérez & Ramírez-Montoya, 2022; Pati & Lorusso, 2018), reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Donici & Dumitras, 2024) statement (Page et al., 2021), to identify, evaluate, and synthesize studies on the implementation of artificial intelligence (AI) for improving energy efficiency in street lighting systems. The eligibility window covered publications dated from 1 January 2020 to 31 December 2025. Because the final search was completed in March 2026, the 2025 publication year was already closed at the time of retrieval; records dated 2025 were therefore eligible only if they had already been published in final form or as online-first (early access) versions with an assigned DOI. No projected, forecasted, or forthcoming publications were considered. In practice, none of the finally included studies was published in 2025, and the most recent included studies date from 2024. This approach ensures that the analysis is based on published, verifiable evidence and current technological developments in the field.

The methodological procedure consisted of four main stages. First, the research question was formulated as follows: "How can artificial intelligence technologies be implemented to improve energy efficiency in street lighting systems, and what are their main approaches, benefits, and challenges?", which was operationalized as RQ1–RQ3 in the Introduction. Second, a literature search was conducted using the IEEE Xplore, ScienceDirect, MDPI, and Google Scholar databases. The search used the Boolean string ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR LSTM OR YOLO) AND ("street lighting" OR streetlight OR "road lighting") AND ("energy efficiency" OR "energy saving" OR dimming), adapted to the syntax of each database, with the publication period limited to 2020–2025. Third, the retrieved studies were screened according to the following inclusion criteria: (a) peer-reviewed journal articles or conference proceedings; (b) studies explicitly addressing the application of AI in street lighting systems; (c) studies reporting energy-related outcomes; and (d) publications within the specified time frame. Records were excluded if they (e) addressed indoor or building lighting only, (f) were not written in English, (g) lacked accessible full text, or (h) were duplicates. Grey literature, such as industry reports, was used only for context and not in the synthesis. Fourth, the individual findings of each included study were extracted using the criteria in Table 2 and are reported study by study in Table 1 before being synthesized.

Screening was carried out in two stages, title/abstract and full text, by two authors independently, with disagreements resolved through discussion with the third author. The number of records at each stage and the reasons for exclusion are reported in the PRISMA flow diagram in Figure 4. Seven studies met all eligibility criteria. In addition, one large-scale study of non-AI adaptive control (Pasolini et al., 2024) identified during full-text screening was retained as a comparator for benchmarking, although it does not satisfy criterion (b). Each study was classified by evidence type (field experiment, field monitoring, simulation, or review), which is reported in Table 1 and was considered when interpreting the magnitude of the reported savings. Because the included studies used different baselines (sodium lamps, full-power LEDs, astronomical-clock operation, or grid-only supply) and different evidence types, a meta-analysis was not appropriate; the synthesis is therefore narrative and reports each value together with its baseline. The figures in the Results section are derived exclusively from the values in Table 1, except for the illustrative local estimate in Section 4.E, which is explicitly identified as the authors' calculation.

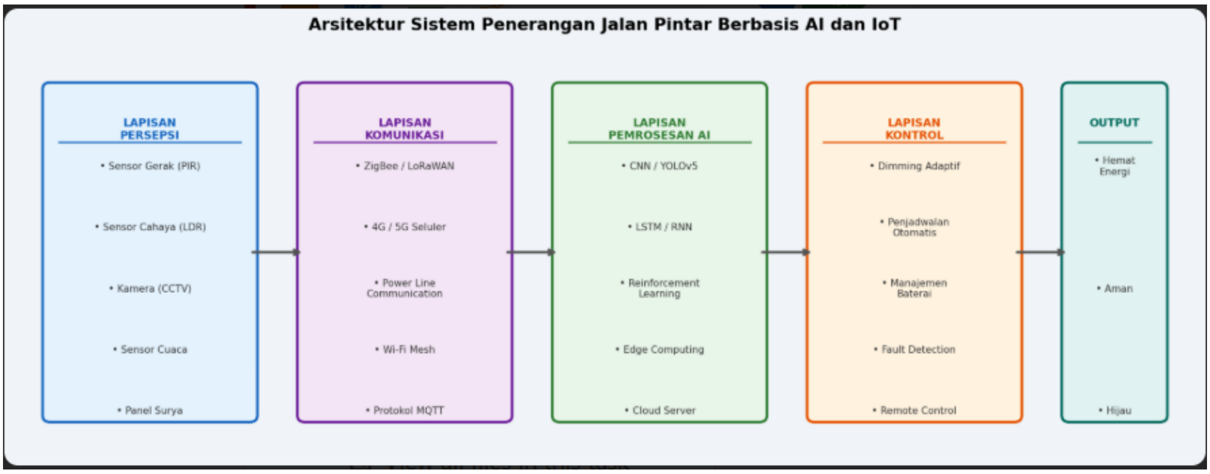

Fig 3. Architecture of an AI- and IoT-Based Smart Street Lighting System (in Indonesia)

The Table 2 presents the data extraction criteria used in the literature synthesis process.

Table 2. Data Extraction and Synthesis Criteria for the Systematic Literature Review

Category	Description of Extracted Information	Example Data
System Architecture	Hardware components (sensors, microcontrollers, actuators), network topology, and energy sources	PIR sensor, NVIDIA Jetson Nano, photovoltaic (solar) panel
AI Algorithms	Types of algorithms, application objectives, and implementation platforms (cloud or edge computing)	YOLOv5 (object detection), LSTM (prediction), Q-learning (optimization)
Performance Metrics	Energy savings, detection/prediction accuracy, latency, and cost–benefit analysis	31.25% energy saving vs. full-power LED; detection precision >90%
Case Studies	Implementation locations, deployment scale, and quantitative field results	Karachi (Pakistan), Almaty (Kazakhstan), Los Angeles (USA)
Challenges	Technical, economic, and social challenges identified in the studies	Initial investment cost, cybersecurity, data privacy

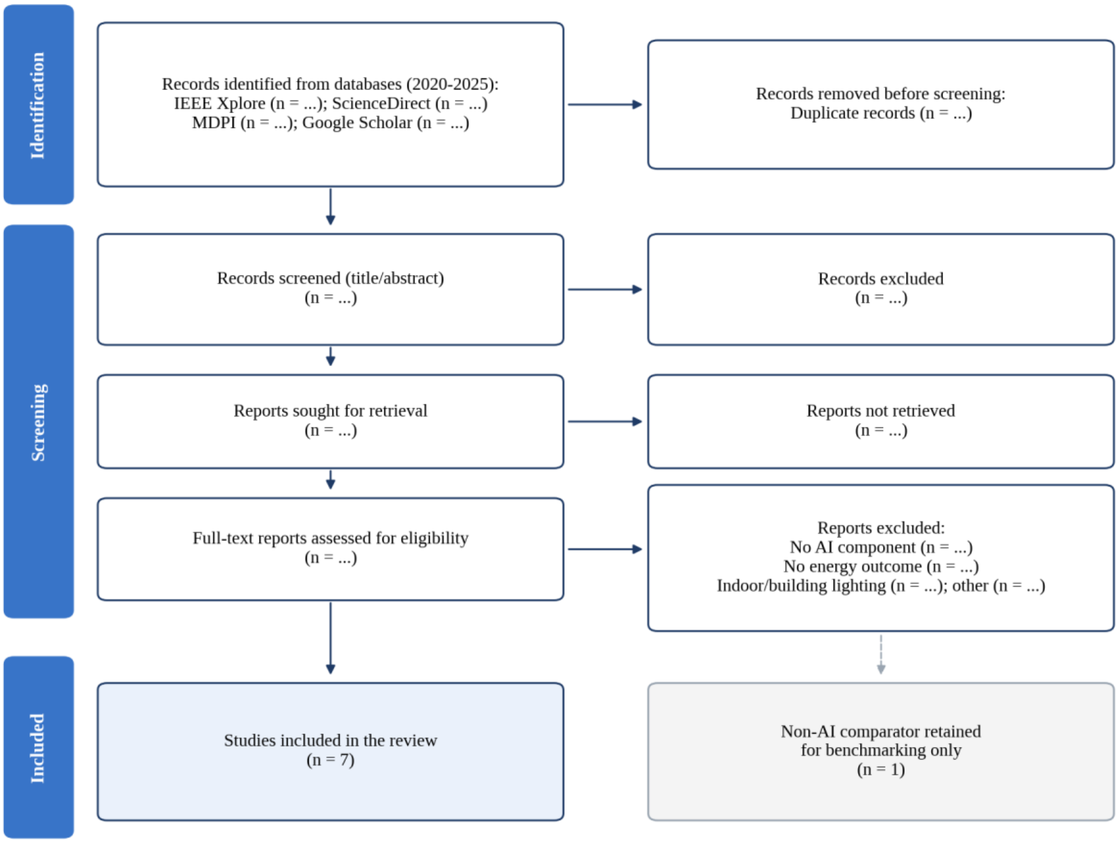

Fig 4. PRISMA 2020 Flow Diagram of the Study Selection Process

4. Result and Discussion

Analysis of the recent literature reveals the convergence of several key technologies that form the architecture of modern smart street lighting systems. In general, this architecture consists of four main layers: the perception layer (sensors), the communication layer (IoT network), the AI processing layer, and the control layer. The following subsections first benchmark the reported energy reductions against non-AI control (RQ2), then describe the AI functions identified in the included studies (RQ1), and finally discuss implementation challenges (RQ3).

4.1. Benchmarking AI-Based and Non-AI Control Strategies

One of the key indicators of successful AI implementation in public street lighting systems is the measurable reduction in energy consumption. Figure 5 compares the reductions reported by the individual included studies with those achieved by non-AI control strategies. Each bar or marker corresponds to a value or range reported in a specific study; the values are not pooled because the baselines differ.

Three observations from Figure 5. First, the largest reductions are obtained when AI-based control is combined with a change of light source or energy supply. (Asif et al., 2022) reported that YOLOv5-based adaptive dimming reduced the annual consumption of a 140 W LED luminaire from 613 kWh to 449 kWh (31.25%), which corresponds to approximately 66% when compared with a conventional 300 W sodium lamp (1,314 kWh per year), while (Belloni et al., 2024) found that an AI-optimized photovoltaic luminaire drew only 35–46% of the grid energy of a conventional lamp. Much of the headline saving is therefore attributable to LED retrofitting or solar supply rather than to AI alone. Second, when the light source is held constant, the AI-attributable saving of about 31% lies within the range achieved by advanced non-AI adaptive control: the full-adaptive installations measured by (Pasolini et al., 2024) reduced consumption by 22.5–56.2% relative to astronomical-clock operation (24.6% across 2,957 luminaires in Meda), whereas simpler virtual-midnight profiles and motion sensing achieved 11.6–18.6% and 2.7–24.5%, respectively. Third, AI therefore does not guarantee larger savings than well-configured rule-based control. Its distinctive advantages lie in (i) the reuse of existing traffic cameras without installing additional sensors (Asif et al., 2022), (ii) object classification that distinguishes vehicles from pedestrians, (iii) forecasting that allows off-grid luminaires to plan their energy use under uncertain weather (Tukymbekov et al., 2021), and (iv) data-driven adjustment of dimming levels to changing ambient conditions (Deepaisarn et al., 2023). These functions are most valuable where simpler automation is insufficient, for example in solar-powered systems exposed to consecutive cloudy days or on roads with mixed and irregular traffic.

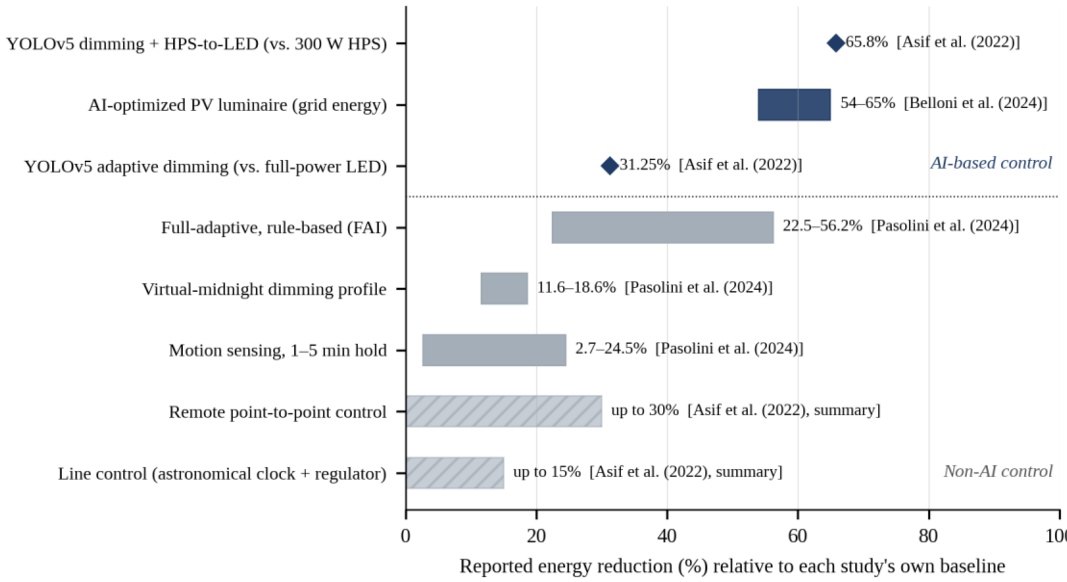

Fig 5. Energy Reductions Reported by Individual Studies for Non-AI and AI-Based Control Strategies (Relative to Each Study's Own Baseline)

4.2. Temporal Distribution of the Included Evidence (2020–2025)

Figure 6 maps the included studies by publication year and by the function performed by AI. The figure contains no projected or modelled values; each marker corresponds to one published study. The evidence base is small and spread across the period, with field-validated AI deployments (Asif et al., 2022; Belloni et al., 2024; Deepaisarn et al., 2023) complemented by one simulation study (Tukymbekov et al., 2021) and three reviews. No included study was published in 2025, which suggests that the most recent developments may first appear as conference papers or grey literature and should be captured in future updates of this review.

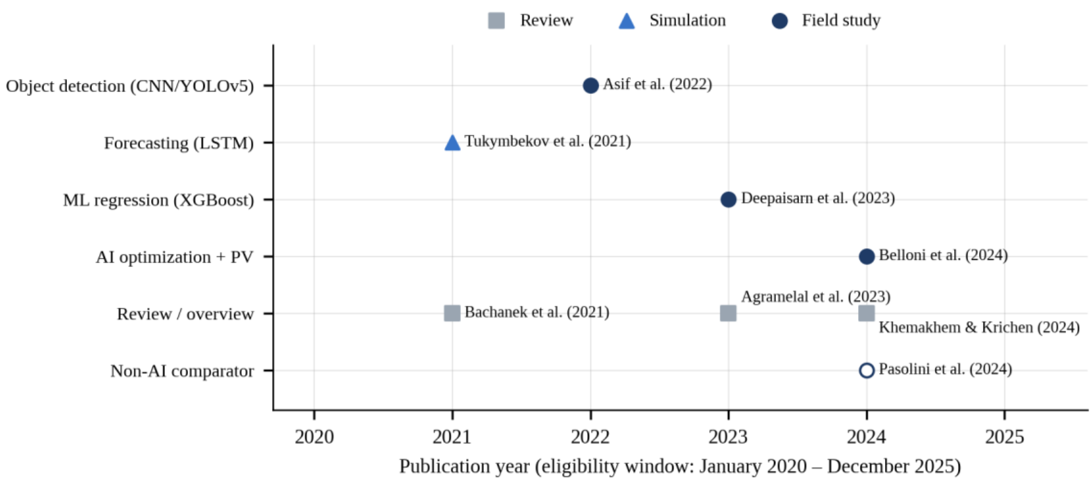

Fig 6. Evidence Map of the Included Studies by Publication Year and AI Function (2020–2025)

4.3. Implementation of Artificial Intelligence Algorithms

At the AI processing layer, data collected from sensors are analyzed by intelligent algorithms to generate lighting control decisions. The included studies identify two established approaches and one emerging approach.

1) Adaptive Control Based on Object Detection

Object detection-based adaptive control is the most extensively documented AI function among the included field studies. As demonstrated by (Asif et al., 2022), deep learning models such as YOLOv5 enable real-time detection and tracking of vehicles and pedestrians; their model achieved a precision of 0.987 and a recall of 0.98 on the local dataset. Based on the detected traffic conditions, the control algorithm dynamically adjusts the lighting intensity; in the Karachi deployment, luminaires operated at full power during the evening peak and were dimmed stepwise to 70%, 60%, and 50% of rated power after midnight as traffic declined (Asif et al., 2022). This adaptive dimming strategy is effective in reducing unnecessary energy consumption during periods of low traffic, although dimming levels must respect the minimum lighting classes required by road lighting standards.

2) Predictive Energy Management

For street lighting systems powered by intermittent renewable energy sources such as solar power, accurate forecasting of energy generation and consumption is essential. (Tukymbekov et al., 2021) used LSTM networks to predict photovoltaic output from weather and solar radiation forecasts and derived the brightness level for the coming night, keeping the probability of reaching a critical battery level at or below 0.10% in a 1,000-day simulation for Almaty. (Belloni et al., 2024) used monitoring data from a photovoltaic luminaire in Italy to develop an optimization and consumption-forecasting algorithm combined with a techno-economic analysis. These predictions enable the system to proactively schedule energy consumption and optimize battery utilization over multiple days, a function that rule-based controllers cannot perform without a forecast.

3) Network Optimization Using Reinforcement Learning

In large-scale deployments involving thousands of interconnected streetlights, network optimization becomes considerably more complex. Reinforcement learning (RL) is frequently proposed as a solution because each lighting unit, or group of units, can learn control policies through interaction with its environment. However, none of the included studies reported a field-validated RL deployment for street lighting; RL should therefore be regarded as an emerging direction whose energy benefits, training costs, and safety implications still require empirical verification.

4.4. Distribution of AI Methods Among the Included Studies

Figure 7 summarizes the composition of the included studies. Each of the four primary studies applied a different AI function: object detection with CNN/YOLOv5 (Asif et al., 2022), time-series forecasting with LSTM (Tukymbekov et al., 2021), machine-learning regression for illuminance prediction (Deepaisarn et al., 2023), and AI-assisted optimization of a solar luminaire (Belloni et al., 2024). The remaining three studies were reviews or overviews (Agramelal et al., 2023; Bachanek et al., 2021; Khemakhem & Krichen, 2024). No included study applied reinforcement learning or fuzzy logic as its primary method. Given the small number of primary studies, these counts describe the reviewed evidence rather than the prevalence of each method in the wider literature.

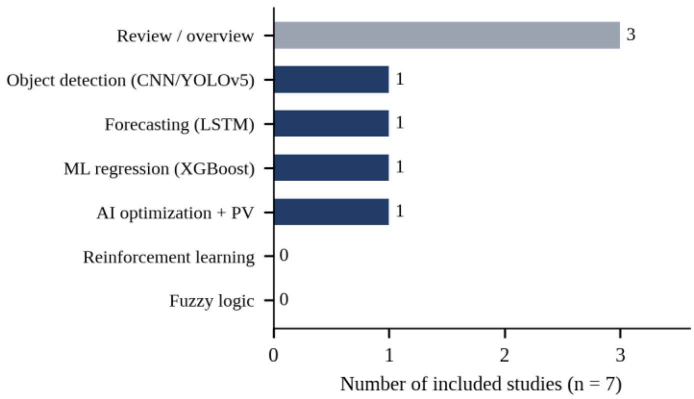

Fig 7. Composition of the Included Studies by Study Type and AI Approach (n = 7; Comparator Excluded)

Table 3. Comparative Analysis of AI and Non-AI Approaches for Smart Street Lighting Systems

Approach	Advantages	Limitations	Reported Energy Reduction	Evidence Source
CNN / YOLOv5 (Object Detection)	Real-time detection and classification of road users; can reuse existing traffic cameras; enhanced public safety	Requires GPU/edge computing hardware; camera privacy concerns; depends on local training data	31.25% vs. full-power LED; ≈66% incl. sodium-to-LED retrofit	(Asif et al., 2022); Karachi, Pakistan (field)
LSTM / RNN (Energy Forecasting)	Supports long-term energy planning; highly effective for solar-powered systems	Dependent on weather data quality; less responsive to sudden changes	Reliability-oriented: critical-battery probability ≤0.10%	(Tukymbekov et al., 2021); Almaty, Kazakhstan (simulation)
Reinforcement Learning (Optimization)	Handles large-scale network complexity; adapts to changing traffic patterns	Long training phase; complex implementation; limited field evidence	Not established	No field-validated study among the included studies
Fuzzy Logic / Rule-Based	Easy to implement; transparent and interpretable; standard-compliant	Limited flexibility; unable to learn from new data	Rule-based full-adaptive: 22.5–56.2% vs. astronomical clock	(Pasolini et al., 2024); Italy (field, non-AI comparator)
Hybrid AI (Combined Approaches)	Combines forecasting, optimization, and renewable supply	Higher computational complexity and development cost	54–65% lower grid energy (AI-optimized PV luminaire)	(Belloni et al., 2024); central Italy (field monitoring)

4.5. Illustrative Local Estimate for Selected Cities and Regencies in West Papua and Southwest Papua

To discuss transferability to resource-constrained regions (RQ3), Figure 8 and Table 4 present an illustrative estimate for five localities in the Bird's Head region of Papua, which now belong to the West Papua and Southwest Papua provinces. These values were calculated by the authors and are not part of the systematic synthesis: they do not originate from the reviewed studies and are not measured outcomes. The estimate assumes an average reduction of 45 W per luminaire during 6 hours of dimmed operation per night over 320 operating days per year (≈86.4 kWh per luminaire per year) and an electricity tariff of IDR 1,500/kWh. The assumed 45 W reduction is consistent with the magnitude observed in the Karachi field test, where adaptive dimming lowered average late-night power by 42–70 W relative to the 140 W rated load (Asif et al., 2022). Under these assumptions, the 255 luminaires considered would save about 22.0 MWh and IDR 33.05 million per year, with Sorong City accounting for the largest share because of its larger number of units.

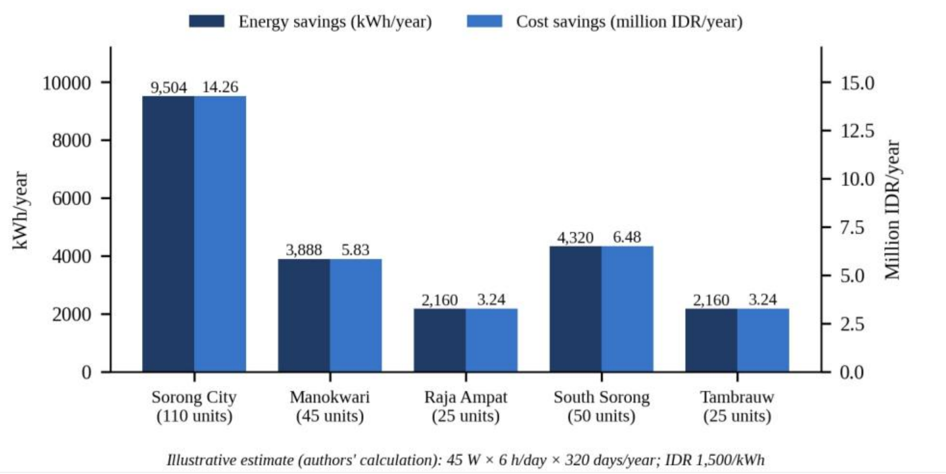

Fig 8. Illustrative Estimate of Annual Energy and Cost Savings for Selected Cities and Regencies in West Papua and Southwest Papua (Authors' Calculation; Not Part of the Systematic Synthesis)

Table 4. Illustrative Estimate of Annual Savings for Selected Cities and Regencies in West Papua and Southwest Papua

City/Regency	Number of Units	Estimated Energy Savings (kWh/year)	Estimated Cost Savings (Million IDR/year)	Regional Characteristics
Sorong City	110	9,504	14.26	Economic and trade center
Manokwari Regency	45	3,888	5.83	Provincial administrative center
Raja Ampat Regency	25	2,160	3.24	Tourism destination
South Sorong Regency	50	4,320	6.48	Rural and agricultural area
Tambrauw Regency	25	2,160	3.24	Remote, conservation-designated regency
Total	**255**	**22,032**	**33.05**	–

Note: Authors' calculation, not derived from the reviewed studies. Assumptions: 45 W average reduction per luminaire, 6 h/day of dimmed operation, 320 operating days/year, and IDR 1,500/kWh.

The estimate has limited generalizability. The five localities differ in traffic density, grid availability, and solar resources, and the savings scale linearly with the assumed number of luminaires, dimming hours, and tariff, so a change in any of these assumptions changes the result proportionally. Where the luminaires are solar-powered, as in the system shown in Figures 1 and 2, the principal benefit of AI is not a reduction in purchased electricity but greater lighting reliability through forecast-based battery management, as shown by (Tukymbekov et al., 2021). Field measurements in these localities are therefore required before the estimate can be treated as empirical evidence.

4.6. Implementation Challenges

Despite their significant potential benefits, the adoption of AI-based smart public street lighting (PSL) systems faces several challenges that must be addressed systematically. The initial capital investment required to replace conventional luminaires, install sensors, and deploy communication infrastructure can be a major barrier, particularly for cities in developing countries. Nevertheless, the investment can be recovered through lower energy and maintenance costs, although the payback time depends strongly on local electricity prices and on the initial cost of the equipment (Belloni et al., 2024).

Table 5. Identified Challenges and Proposed Solutions for the Implementation of AI-Based Smart Public Street Lighting Systems

Challenge	Criticality Level	Impact	Proposed Solution
Initial Investment Cost	High	Limits adoption in small cities and developing countries	ESCO financing schemes, government subsidies, and public–private partnerships (PPPs)
Cybersecurity	High	Risk of large-scale lighting outages and system manipulation	End-to-end encryption, multi-factor authentication, and regular security audits
Data Privacy	Medium	Potential violations of citizens' privacy rights	Transparent data governance policies, data anonymization, and clear regulatory frameworks
Interoperability	Medium	System fragmentation and high integration costs	Adoption of open standards (e.g., TALQ and DALI-2) and integrated management platforms
Technical Maintenance	Low–Medium	System performance degradation over time	AI-based predictive maintenance and technical workforce training

Cybersecurity represents another critical concern, as internet-connected street lighting networks are vulnerable to cyberattacks that could result in large-scale lighting failures or unauthorized system manipulation. Data privacy is also an important issue, particularly when cameras are used for traffic and pedestrian detection, requiring clear policies governing data collection, storage, and usage. Furthermore, interoperability among devices supplied by different vendors remains a technical challenge, limiting the development of fully integrated, scalable, and vendor-independent smart street lighting systems.

4.7. Limitations of This Review

This review has several limitations. The number of included primary studies is small, the studies used different baselines and evidence types, and several did not report energy savings as a single percentage, which precluded a meta-analysis. The search was limited to four databases and English-language publications, so relevant work published in other languages or indexed elsewhere may have been missed, and publication bias toward positive results cannot be excluded. Future updates should extend the search to additional databases, include studies published from 2026 onward, and prioritize field trials that report energy use against both a full-power and a rule-based adaptive baseline.

5. Conclusion

This systematic review, reported according to PRISMA 2020, examined the implementation of Artificial Intelligence (AI) in public street lighting systems using seven studies published between 2020 and 2025 and one non-AI comparator study. The included studies reported energy reductions of approximately 31% for YOLOv5-based adaptive dimming relative to full-power LED operation, about 66% when this control was combined with the replacement of sodium lamps, and 54–65% lower grid energy for an AI-optimized solar luminaire. Two established AI functions emerged from the evidence: real-time adaptive control through deep learning-based object detection (CNN/YOLOv5) and proactive energy management using forecasting models (LSTM and other machine-learning models), whereas reinforcement learning remains an emerging approach without field validation among the included studies.

The photographs of the solar-powered smart street lighting systems presented in this paper (Figures 1 and 2) illustrate real-world examples of modern public street lighting infrastructure that provide the physical platform for AI implementation. When integrated with appropriate AI technologies, such systems can evolve from simple lighting devices into intelligent nodes within a smart city ecosystem.

The benchmark against non-AI control constitutes the main contribution of this review: rule-based full-adaptive installations achieved savings of 22.5–56.2%, comparable to the AI-attributable saving reported in the included field study. The incremental value of AI therefore lies less in raw energy reduction than in capabilities that simpler automation lacks, namely forecasting for off-grid solar luminaires, reuse of existing cameras, and classification of road users. For regions such as West Papua and Southwest Papua, where solar-powered luminaires are a practical option, forecast-based energy management is likely to be the most relevant AI function, although the illustrative estimate presented here must be confirmed by field measurements. However, realizing their full potential requires stakeholders to address several critical challenges, including initial investment costs, cybersecurity, data privacy, and system standardization. With well-designed implementation strategies and supportive public policies, AI-powered smart street lighting systems will not only illuminate urban environments more efficiently but also serve as a fundamental pillar for developing smarter, safer, more sustainable, and more livable cities.

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