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A Machine Learning Approach to Intelligent Streetlight Control for Sustainable Energy Management in Smart Cities

Syed Nurul Islam[1];

[1]. Master in Information Technology and Management, Washington University of Science & Technology, USA;
Email: snislam.student@wust.edu

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Abstract

This study examines how machine learning based intelligent streetlight control can improve sustainable energy management in smart cities by addressing the persistent problem of traditional fixed time streetlighting, which often consumes excessive electricity, increases municipal operating costs, and lacks real time responsiveness to traffic, pedestrian movement, ambient light, weather, and fault conditions. The purpose of the study is to evaluate the role of machine learning, IoT sensors, adaptive dimming, predictive brightness control, and remote monitoring in transforming conventional streetlights into intelligent urban energy assets. A quantitative, cross sectional, case-based research design was adopted using secondary evidence from cloud enabled, edge supported, and enterprise level smart city streetlighting cases reported in the literature. The sample consisted of selected smart lighting cases involving IoT connected streetlights, cloud management platforms, sensor-based control systems, and machine learning enabled prediction models. The key variables included machine learning prediction capability, IoT and sensor integration, adaptive dimming, predictive control, energy saving percentage, maintenance improvement, operational reliability, and sustainability outcomes. The analysis plan involved thematic coding, cross case comparison, Likert based evidence scoring, and numeric synthesis using the Energy Saving Percentage formula to compare traditional streetlighting with intelligent ML based systems. The findings indicate strong quantitative support for ML based intelligent lighting, with an overall support score of 4.42 out of 5.00, 86% of reviewed studies supporting ML or AI based streetlight control, IoT and sensor integration scoring 4.55, machine learning prediction and optimization scoring 4.48, and sustainability outcomes scoring 4.31. Energy saving patterns ranged from 25% to 60%, with an estimated average saving of 38.7%. Comparative results showed that traditional fixed time systems scored only 2.10, sensor based adaptive systems scored 3.95, and ML based predictive systems scored 4.62. The study implies that smart cities can reduce energy waste, improve lighting reliability, lower operational costs, support predictive maintenance, and strengthen sustainability goals by integrating machine learning with IoT based streetlight infrastructure.

Keywords

Machine Learning, Intelligent Streetlight Control, Smart Cities, Sustainable Energy Management, IoT Sensors.

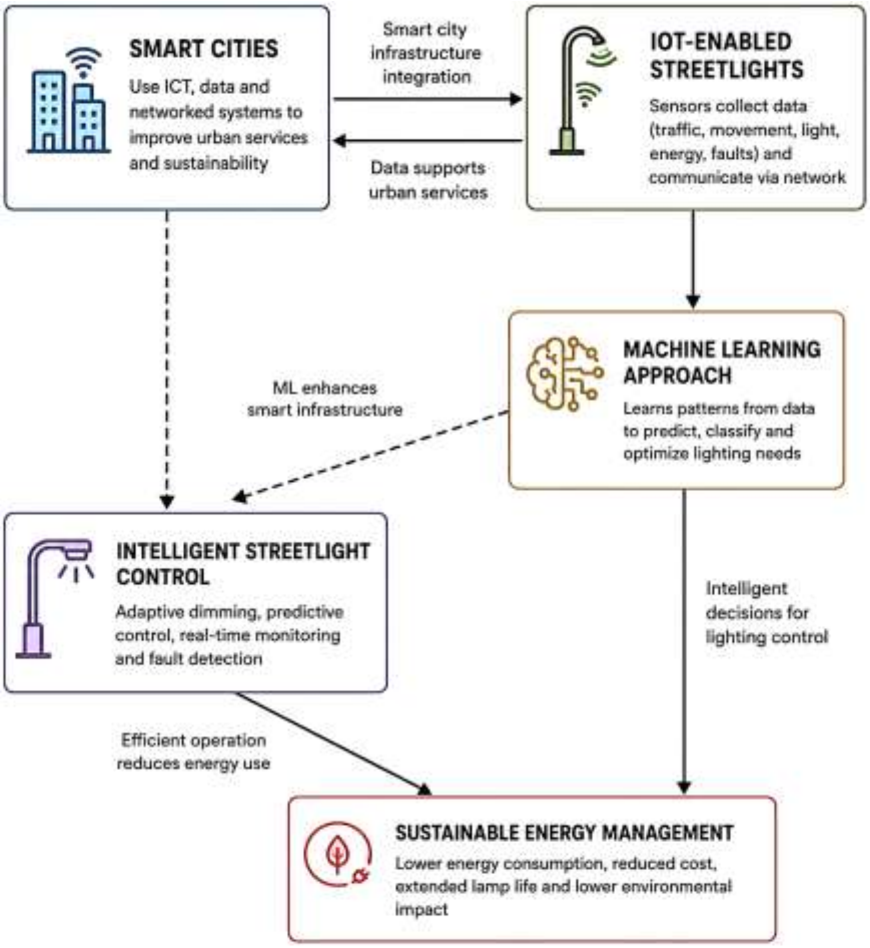
INTRODUCTION

Smart cities are generally defined as urban systems that use information and communication technologies, sensing infrastructure, data analytics, and networked governance to improve the efficiency, sustainability, livability, and responsiveness of urban services (Agramelal et al., 2023). Within this definition, the term "smart" does not simply refer to digital technology; it refers to the capacity of a city to collect data, interpret conditions, coordinate services, and manage resources more intelligently across transportation, energy, lighting, public safety, buildings, waste, and environmental systems (Kyba et al., 2017). Early smart city scholarship emphasized the relationship between technological infrastructure, human capital, institutional governance, and sustainable urban performance, showing that cities become smart when digital tools are connected to social, economic, and environmental objectives rather than deployed as isolated technical assets (Batty et al., 2012). Later studies expanded this view by describing smart cities as complex socio-technical ecosystems where sensors, urban data platforms, Internet of Things devices, and computational models support real-time monitoring and evidence-based decision-making. From an international perspective, the significance of smart cities is linked to rapid urbanization, rising energy demand, public infrastructure pressure, and the need for sustainable resource management across both developed and developing urban regions (Albino et al., 2015). Cities consume a large share of global energy and produce substantial environmental pressure, making urban infrastructure one of the most important intervention points for sustainability-oriented technological innovation. In this context, sustainable energy management refers to the systematic planning, monitoring, control, and optimization of energy use to reduce waste, lower operational costs, improve service reliability, and minimize environmental burden. Energy efficiency has long been recognized as a key strategy for reducing unnecessary consumption in buildings and public infrastructure, and the same principle applies to municipal systems such as public lighting, which operate for long hours and often follow fixed schedules (Gubbi et al., 2013). Therefore, intelligent streetlight control becomes an important research area because it connects smart city development with practical energy-saving infrastructure.

Streetlighting is a core component of urban infrastructure because it supports nighttime mobility, road visibility, pedestrian comfort, traffic safety, public security, and the social use of urban space after dark. Public lighting systems are commonly installed across roads, highways, residential streets, commercial zones, parks, campuses, industrial areas, and transport corridors, which makes them one of the most widely distributed municipal assets in modern cities (Atzori et al., 2010). Traditional streetlighting systems are usually operated through manual switching, astronomical clocks, timer-based schedules, or fixed illumination levels. These systems often remain fully powered during periods of low pedestrian or vehicle activity, even when weather, traffic, location, and ambient light conditions do not require maximum brightness (Hollands, 2008). Such fixed operation creates unnecessary electricity consumption and increases municipal energy expenditure. Studies on public lighting and streetlight systems have shown that replacing conventional luminaires with LED technology can generate savings, while additional savings can be achieved when LEDs are combined with smart controllers, dimming strategies, sensor-based monitoring, and network connectivity. Research on road lighting also emphasizes that lighting is not only an energy issue but also a safety and environmental issue because illumination level, visibility, glare, light distribution, and night-sky brightness influence how urban lighting systems are evaluated. Internationally, the modernization of public lighting has become part of the wider smart city agenda because streetlight poles already exist in large numbers and can be upgraded with sensors, communication modules, environmental monitoring devices, and intelligent controllers (Bachanek et al., 2021). This makes streetlights suitable platforms for citywide digital infrastructure. Smart public lighting studies describe streetlighting as a practical entry point for smart city implementation because it combines measurable energy savings with visible municipal service improvement. Therefore, the significance of intelligent streetlight control lies in its ability to convert a conventional electricity-consuming service into a data-driven energy management system.

The Internet of Things provides the technical foundation for intelligent streetlight control by enabling physical devices to sense, communicate, process, and exchange data through interconnected networks. IoT is commonly defined as a network of identifiable physical objects embedded with sensors, actuators, communication interfaces, and computing capability that allow them to interact with digital platforms and other devices (Allcott & Greenstone, 2012). In smart city systems, IoT supports the integration of urban infrastructure with data-driven services by connecting streetlights, traffic sensors, cameras, weather stations, smart meters, control centers, cloud platforms, and edge devices. In the case of streetlighting, IoT-enabled infrastructure allows lamps to collect data on pedestrian movement, vehicle flow, ambient brightness, lamp status, voltage, current, energy use, temperature, and fault conditions. These data can be transmitted to local controllers or central management systems, where they are analyzed to support monitoring, dimming, fault detection, maintenance planning, and energy optimization (Krizhevsky et al., 2017). IoT-based streetlight systems are therefore different from isolated lighting installations because they create two-way communication between streetlights and the urban management platform. A streetlight can send operational data to the system and receive commands to increase, reduce, or maintain brightness according to changing conditions. The literature also shows that IoT supports scalable control because many streetlights can be managed as a coordinated network rather than as independent units (Perera et al., 2014). This networked structure is internationally significant because cities require systems that can operate across diverse streets, traffic densities, neighborhoods, and service zones. IoT also provides a foundation for integrating streetlighting with wider smart city services such as traffic monitoring, environmental sensing, emergency response, and infrastructure diagnostics. Studies on IoT and smart cities describe such integration as central to urban efficiency because connected devices transform public infrastructure into active data sources for decision-making. In this way, IoT makes intelligent streetlight control technically possible by linking sensing, communication, monitoring, and actuation within one urban energy management architecture (Pérez-Lombard et al., 2008).

Figure 1: Machine Learning–Based Intelligent Streetlight Control for Sustainable Energy Management in Smart Cities



This study is positioned within the intersection of smart city research, machine learning applications, IoT-enabled public infrastructure, intelligent streetlight control, and sustainable energy management. The study defines intelligent streetlight control as a data-driven lighting management approach in which sensors, communication technologies, and computational models are used to regulate brightness, monitor performance, detect faults, and optimize energy use according to changing urban conditions. The study defines a machine learning approach as the use of learning algorithms to identify patterns from streetlight-related data and support decisions about dimming, activation, prediction, classification, maintenance, and energy optimization. This framing is supported by studies that describe smart streetlight systems as multi-component systems consisting of lamps, sensors, controllers, communication modules, data platforms, and control strategies. It is also supported by studies that identify machine learning and deep learning as important methods for prediction, optimization, perception, and adaptive decision-making in smart city systems. For a literature-review-based, qualitative, cross-sectional, and case-study–based study, this introduction establishes the research problem as a synthesis of three connected issues: traditional streetlighting consumes energy through rigid operation, smart city systems require intelligent and sustainable infrastructure, and machine learning offers adaptive control capabilities that can improve streetlight energy performance (Sadeghian et al., 2021). The study therefore examines published evidence on how machine learning-based streetlight control supports sustainable energy management through adaptive dimming, predictive control, IoT integration, operational monitoring, and case-based smart city applications. This focus allows the research to compare findings across studies, identify common technical mechanisms, evaluate literature-based energy-saving patterns, and connect the evidence to hypotheses concerning energy efficiency, sensor-based control, predictive optimization, and IoT-machine learning integration (Silva et al., 2018).

The main objective of this study is to examine how machine learning approaches can strengthen intelligent streetlight control for sustainable energy management in smart cities. The study focuses on understanding how machine learning techniques support adaptive, predictive, and data-driven lighting decisions in urban environments where conventional streetlight systems often operate through fixed schedules and static brightness levels. Specifically, the study aims to review how machine learning models can process data from IoT sensors, traffic movement, pedestrian activity, ambient light, weather conditions, and historical energy consumption patterns to improve the efficiency of streetlight operation (Wanvik, 2009). Another objective of the study is to analyze how intelligent streetlight control mechanisms, particularly adaptive dimming, predictive brightness adjustment, automated fault detection, and real-time monitoring, contribute to reducing unnecessary energy use while maintaining public safety and lighting reliability. The study also seeks to evaluate the role of IoT-enabled infrastructure in supporting machine learning-based streetlight systems by enabling continuous data collection, communication, and remote control across urban lighting networks (Zanella et al., 2014). In addition, the study intends to synthesize literature-based evidence on the sustainability benefits of intelligent streetlighting, including lower electricity consumption, reduced operational cost, improved maintenance efficiency, extended lamp lifespan, and reduced environmental pressure. Since this research is literature-review-based, qualitative, cross-sectional, and case-study–based, it further aims to identify common patterns across previous studies and selected smart city cases rather than relying on primary field data (Bibri & Krogstie, 2017). A small numeric synthesis will also be used in the findings section to compare reported energy-saving patterns from previous studies and to support the research hypotheses and objectives (Akram et al., 2022). Through this objective-based focus, the study aims to provide a clear understanding of how machine learning can transform streetlights from passive municipal infrastructure into intelligent energy management assets within smart cities.

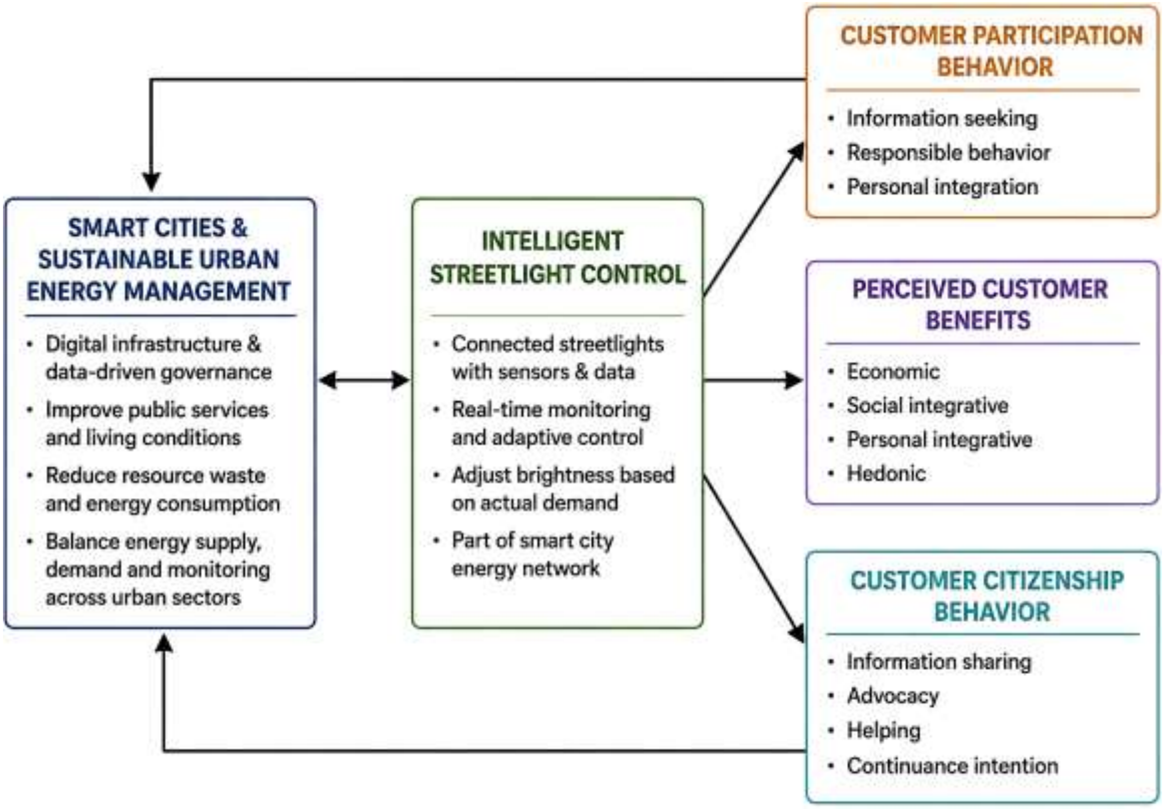
LITERATURE REVIEW

The literature review of this study examines the scholarly foundation of machine learning-based intelligent streetlight control as a sustainable energy management strategy within smart cities. Since smart cities depend on data-driven infrastructure, connected technologies, and automated decision-making, the review focuses on how urban lighting systems have evolved from conventional fixed-time operation toward intelligent, adaptive, and predictive control models. Streetlighting is an important public service because it supports road safety, pedestrian movement, nighttime visibility, public security, and the functional use of urban spaces. At the same time, streetlights represent a major area of municipal energy consumption because they often operate for long hours and may continue using electricity even when traffic or pedestrian demand is low. The literature therefore positions intelligent streetlighting as a practical solution for reducing unnecessary energy use while maintaining lighting quality and public safety. This review will explore how machine learning contributes to this transformation by enabling streetlight systems to learn from traffic flow, pedestrian activity, ambient light, weather conditions, time-based patterns, and historical energy data. It will also examine the supporting role of IoT sensors, communication networks, edge computing, cloud platforms, and smart controllers in collecting and transferring the data required for intelligent control. The review is organized around the key concepts of smart cities, sustainable urban energy management, traditional streetlight limitations, intelligent streetlight systems, machine learning optimization, IoT-enabled lighting infrastructure, theoretical framework, conceptual framework, and research gap. Special attention is given to adaptive dimming, predictive brightness adjustment, fault detection, and real-time monitoring because these mechanisms directly connect machine learning with energy efficiency outcomes. The literature review also supports the study's qualitative, cross-sectional, and case-study–based approach by identifying common themes, technical patterns, sustainability benefits, and implementation barriers reported across previous studies. Through this review, the study builds a strong academic basis for understanding how machine learning can transform streetlights from passive municipal infrastructure into intelligent urban energy assets. It also helps clarify the relationship between technology adoption, organizational readiness, environmental sustainability pressure, and the practical performance of smart streetlight systems in modern urban settings.

Smart Cities and Sustainable Urban Energy Management

Smart cities represent a major shift in how urban systems are planned, operated, and evaluated because they combine digital infrastructure, data-driven governance, intelligent services, and sustainability-oriented management. In the context of this study, a smart city can be understood as an urban environment where connected technologies are used to improve the performance of public services, reduce resource waste, and support better living conditions for citizens. Sustainable urban energy management is one of the most important dimensions of this transformation because energy is directly connected to transportation, buildings, public lighting, water systems, communication infrastructure, and municipal operations. The increasing complexity of cities has made energy management more than a technical issue; it has become a strategic urban concern involving efficiency, affordability, environmental responsibility, public service quality, and long-term infrastructure performance. Smart city research shows that digital urban management requires the integration of technology, institutions, data, and service systems so that cities can respond more effectively to social and environmental demands (Brandt et al., 2018). Within this perspective, energy management becomes a central operational function because smart cities must continuously balance energy supply, demand, monitoring, distribution, and consumption across multiple urban sectors. This balance is especially important for public infrastructure that operates daily and consumes electricity over long periods, such as streetlighting systems. Streetlights are not isolated technical objects; they are part of the broader urban energy network and influence municipal costs, safety, environmental quality, and service reliability. Therefore, sustainable urban energy management provides a useful foundation for understanding why intelligent streetlight control is necessary. When streetlights are connected to smart city platforms, they can be monitored, adjusted, and optimized according to real-time urban conditions. This connection allows streetlighting to move away from fixed operation and become part of a more flexible, measurable, and energy-conscious city management system.

Figure 2: Smart Cities and Sustainable Urban Energy Management through Intelligent Streetlight Control



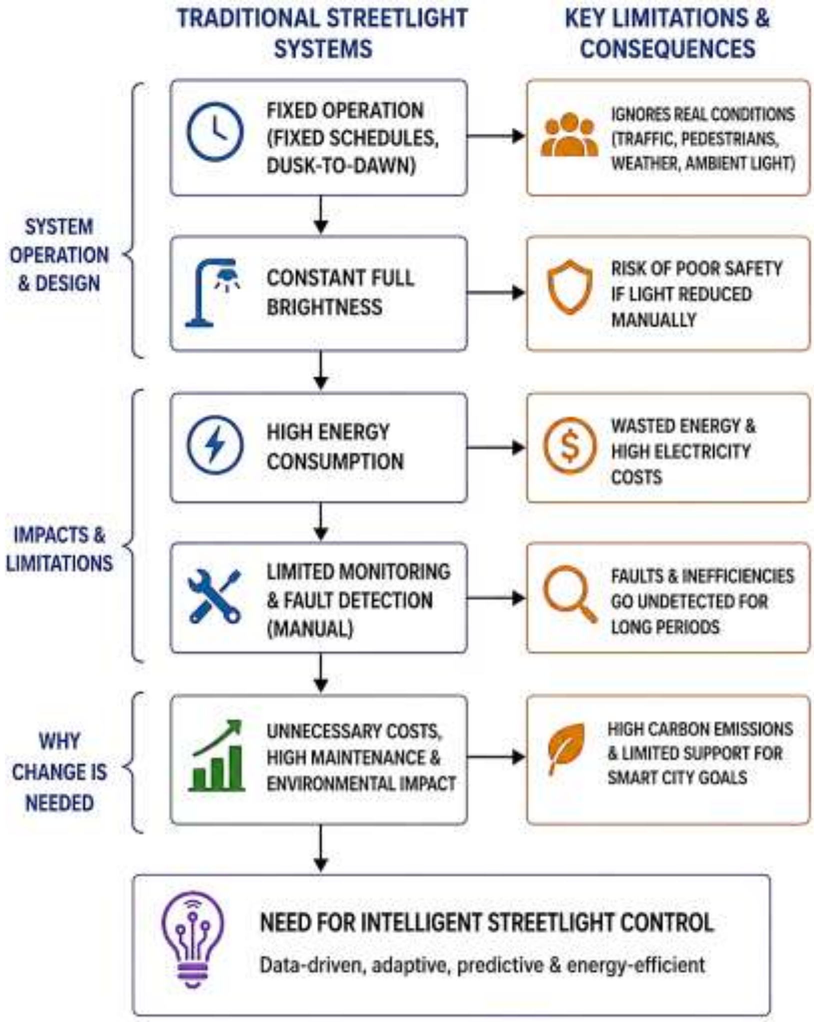
The literature on smart cities and energy sustainability emphasizes that urban energy systems should not be examined only through the lens of energy production; they should also be understood through consumption patterns, infrastructure design, monitoring capacity, and technology-enabled efficiency. A systematic review of sustainable energy in smart cities found that the main research themes in this area include energy efficiency, renewable energy, and urban energy planning, showing that sustainability depends on both cleaner energy sources and better control of energy use (Cortese et al., 2022). This point is important for intelligent streetlight control because even when renewable energy is available, wasteful consumption weakens the sustainability performance of public infrastructure. Sustainable energy management therefore requires cities to reduce unnecessary energy use while maintaining essential public services. Smart cities use digital tools such as sensors, smart meters, communication networks, data platforms, and analytical models to support this objective. In public lighting, these tools can help city managers understand when and where electricity is being consumed, whether lamps are operating efficiently, and how brightness levels can be adjusted according to actual need. Energy-oriented smart city research also highlights that artificial intelligence and smart monitoring systems can support the optimization of energy consumption by enabling more informed, automated, and responsive decision-making (Chui et al., 2018). This is closely related to machine learning-based streetlight control because machine learning models can identify patterns in energy demand, traffic movement, pedestrian presence, ambient light, and weather conditions. As a result, sustainable energy management becomes more precise and context-aware. Instead of relying only on traditional schedules or manual inspections, smart city infrastructure can use data to guide operational decisions. This makes intelligent streetlighting a practical example of how smart city energy management can be applied at the municipal infrastructure level. The main value is not only electricity reduction but also better coordination between technology, energy use, public safety, and urban sustainability.

Sustainable urban energy management also requires cities to adopt integrated approaches that connect technology deployment with governance, planning, and service outcomes. Studies on energy and sustainable development in smart cities show that urban energy systems are linked with generation, storage, infrastructure, transport, buildings, digitization, and IoT-enabled management, meaning that energy sustainability depends on the coordination of several technical and organizational components (Almihat et al., 2022). This integrated view is directly relevant to intelligent streetlight control because streetlighting systems involve lamps, sensors, communication networks, controllers, software platforms, maintenance teams, and municipal energy policies. A smart lighting system can only support sustainable energy management when these elements work together. For example, sensors may collect real-time information, but energy savings depend on how the system interprets that information and converts it into lighting decisions. Similarly, machine learning can improve prediction and optimization, but its effectiveness depends on data quality, system connectivity, implementation capacity, and governance support. Smart governance literature shows that technology-enabled collaboration and public-sector coordination are important for achieving sustainable city outcomes because digital tools alone do not guarantee effective urban transformation (Tomor et al., 2019). Therefore, sustainable urban energy management should be understood as both a technological and managerial process. In relation to this study, smart streetlights represent a valuable case of this process because they combine energy efficiency, digital monitoring, adaptive control, and public service improvement. They also demonstrate how ordinary infrastructure can become intelligent when it is connected to data systems and optimized through computational methods. Within the broader smart city agenda, machine learning-based intelligent streetlight control supports sustainable energy management by reducing unnecessary electricity use, improving operational visibility, enabling predictive maintenance, and aligning lighting performance with real urban demand. This makes the topic highly relevant for cities seeking to modernize public infrastructure while managing energy consumption more responsibly.

Traditional Streetlight Systems and Their Energy Limitations

Traditional streetlight systems are usually designed around fixed illumination principles, where lamps operate according to manual switching, timer-based schedules, astronomical clocks, or static dusk-to-dawn operation. These systems are historically important because they provide basic nighttime visibility, improve road navigation, support pedestrian confidence, and contribute to public safety in urban and suburban environments. However, their operational logic is generally rigid because the same lighting level is often maintained regardless of real-time traffic flow, pedestrian movement, weather, ambient brightness, or local activity patterns. In many cities, older public lighting networks still depend on high-pressure sodium, mercury vapor, metal halide, or other conventional lamp technologies that consume more electricity than modern lighting alternatives. The energy limitation of these systems is not only related to the type of lamp used but also to the absence of intelligent control. A conventional streetlight may continue operating at full capacity during periods of very low road use, such as late-night residential hours or low-traffic industrial zones. This creates a mismatch between actual lighting demand and electricity consumption. Public lighting is often a visible and politically sensitive municipal service, so city authorities may hesitate to reduce lighting levels without evidence that safety and comfort will be preserved. As a result, many traditional systems remain over-lit, under-monitored, and energy-intensive. Research on municipal lighting indicates that streetlighting can represent a significant portion of local electricity use and that poor management, inefficient lamps, and limited control strategies increase operating costs for municipalities (Gordic et al., 2021). In this study, this limitation is important because it explains why intelligent streetlight control is needed. Machine learning-based systems are not introduced simply as technological upgrades; they respond to the deeper inefficiency of traditional systems that consume energy according to fixed schedules instead of actual urban demand.

Figure 3: Traditional Streetlight Systems and the Need for Intelligent Energy-Efficient Control



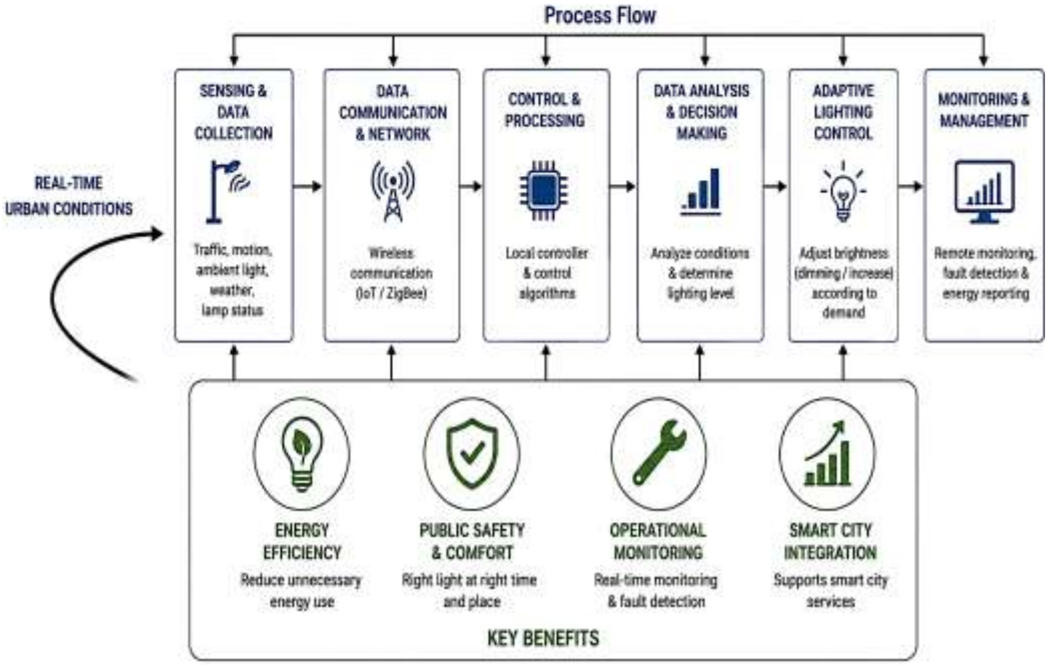
Another major limitation of traditional streetlight systems is their weak ability to balance energy saving with lighting quality and perceived safety. Streetlighting cannot be evaluated only by measuring electricity consumption because its social function is connected to visibility, comfort, road confidence, pedestrian reassurance, and urban usability during nighttime. When municipalities attempt to save energy by switching off streetlights or reducing lighting hours, public concern may arise because complete darkness can affect perceptions of safety and may reduce the usability of public space. This creates a practical problem for traditional systems: they either consume excessive energy by staying fully illuminated or risk service quality by reducing light through simple switching or scheduled shutdowns. Research on urban streetlighting shows that energy can be saved while maintaining pedestrians' feeling of safety when lighting attributes such as color, uniformity, and illumination level are carefully managed, indicating that energy efficiency requires more refined control than simple on/off operation (Saad et al., 2021). Traffic-regulated lighting research also shows that road luminance can be adjusted according to traffic volume, offering a more balanced approach between energy saving and safety requirements (Balázs et al., 2023). These findings reveal the limitation of conventional streetlighting: it lacks sensitivity to changing conditions. A fixed-time system cannot distinguish between a busy road segment and an empty road segment, nor can it respond to sudden changes in activity. Even LED retrofits, although more efficient than older lamps, may still waste electricity if the system operates at full brightness throughout the night. Therefore, the limitation of traditional streetlight systems is both technical and managerial. Technically, they lack sensors, adaptive dimming, predictive control, and automated monitoring. Managerially, they provide limited information for decision-makers who need to evaluate energy use, maintenance needs, and lighting performance. This gap supports the relevance of machine learning because intelligent systems can use data to adjust lighting more accurately.

Traditional streetlight systems also create economic and environmental limitations because high electricity use increases municipal expenditure and contributes indirectly to carbon emissions when electricity is generated from fossil-based sources. These systems can also increase maintenance burdens because faults are often detected through manual inspections, scheduled checking, or citizen complaints rather than through automated monitoring. As a result, damaged lamps, inefficient fixtures, abnormal energy consumption, and poor lighting performance may remain unnoticed for long periods. Economic studies of smart lighting demonstrate that conventional systems consume substantially more energy than intelligent lighting arrangements and that adaptive part-night lighting, traffic-aware control, and sensor-based operation can reduce both power consumption and financial burden (Mohammad et al., 2023). Environmental assessment studies also show that public lighting replacement planning must consider not only energy savings but also broader environmental performance, including emissions and life-cycle impacts (Cumo et al., 2025). This is important because traditional streetlighting is often treated as a routine municipal service rather than a strategic sustainability issue. When a city operates thousands of lamps for long hours every night, even small inefficiencies can become large-scale energy and cost problems. Traditional systems also have limited capacity to support smart city functions because they are not usually connected to data platforms, remote management systems, or integrated urban monitoring networks. This reduces their usefulness in modern cities where public infrastructure is expected to provide measurable performance, operational transparency, and sustainability contribution. The weaknesses of traditional streetlight systems therefore create the foundation for intelligent streetlight control. Machine learning, IoT sensors, adaptive dimming, and predictive control directly address these limitations by enabling lighting systems to respond to real conditions, reduce unnecessary consumption, detect faults, and support sustainable energy management. In this research, traditional streetlighting is therefore understood as the baseline problem against which machine learning-based intelligent streetlight control can be evaluated.

Intelligent Streetlight Control Systems

Intelligent streetlight control systems refer to public lighting arrangements that use sensing, communication, automation, and digital control mechanisms to regulate lighting performance according to real-time or context-specific urban conditions. Unlike traditional streetlight systems that rely mainly on fixed schedules, simple timers, or manual switching, intelligent systems are designed to make lighting operation more responsive, measurable, and energy efficient. The main purpose of intelligent streetlight control is to provide the right amount of illumination at the right place and time while reducing unnecessary electricity consumption. This is achieved through the integration of LED lamps, local controllers, wireless communication, ambient light sensors, motion detectors, traffic sensors, and centralized or distributed management platforms. Early intelligent streetlighting research demonstrated that remote-control systems using ZigBee networks and sensor-based devices could improve the efficiency of public lighting by enabling communication between lamp units and control centers, allowing lighting systems to be monitored and adjusted more effectively than conventional arrangements (Leccese et al., 2014). This type of system introduced the idea that a streetlight could operate as a controllable networked unit instead of a separate lamp. Intelligent streetlight systems therefore represent a major shift in urban lighting management because they allow municipalities to move from passive illumination to active infrastructure control. A streetlight can detect environmental conditions, communicate operational data, receive commands, and adjust brightness according to demand. This makes intelligent streetlighting especially relevant for smart cities, where public infrastructure is expected to support energy efficiency, safety, monitoring, and service quality. The intelligence of the system does not come from one component alone; it emerges from the combined function of sensors, communication networks, control algorithms, and management software. In this study, intelligent streetlight control systems are important because they provide the technological foundation on which machine learning-based optimization can be applied.

Figure 4: Process Flow of Intelligent Streetlight Control Systems for Smart City Energy Management



A key characteristic of intelligent streetlight control systems is their ability to support remote monitoring and adaptive control across a lighting network. In a fully controlled smart city streetlighting application, lamp posts can be organized into hierarchical layers where local control units manage individual lamps while network communication enables data transfer to a central platform for broader system supervision (Leccese, 2013). This layered structure is important because it allows lighting systems to combine local responsiveness with city-level management. At the local level, sensors can detect motion, ambient brightness, or lamp condition and trigger immediate lighting responses. At the network level, a central system can monitor energy consumption, identify faults, adjust lighting policies, and coordinate multiple lamp units across streets or zones. Intelligent control also supports more advanced energy-saving strategies than simple switching. For example, traffic-adaptive lighting systems use vehicle presence or traffic flow information to control the intensity of LED streetlights, reducing brightness during low activity and increasing it when road use requires greater visibility (Shahzad et al., 2016). This approach helps solve one of the main weaknesses of conventional systems: their inability to distinguish between high-demand and low-demand lighting periods. Intelligent systems can also apply time-based schedules, sensor-based responses, and dimming profiles in combination, which makes them more flexible than traditional lighting systems. This flexibility is important for public safety because it allows light reduction without complete darkness. Instead of switching lights off, the system can maintain a minimum brightness level and increase illumination only when needed. In smart city settings, such adaptive operation improves energy management by connecting lighting output with real urban activity. It also provides operational data that can be used for maintenance planning, energy auditing, and performance evaluation.

The development of intelligent streetlight control systems has expanded from basic remote control toward more integrated smart infrastructure models that combine adaptive lighting, Internet of Things connectivity, wireless sensors, and broader urban service functions. Research on streetlight energy-saving control has shown that structured control strategies, remote monitoring, and automation standards can significantly reduce lighting energy use when compared with systems that lack monitoring and control functions (Ożadowicz & Grela, 2017). More recent adaptive lighting systems have shown that smart streetlights can use IoT techniques, wireless sensor nodes, ambient condition measurement, vehicle detection, and local controllers to regulate illumination in road environments while supporting preventive maintenance and operational supervision (García-Castellano et al., 2019).

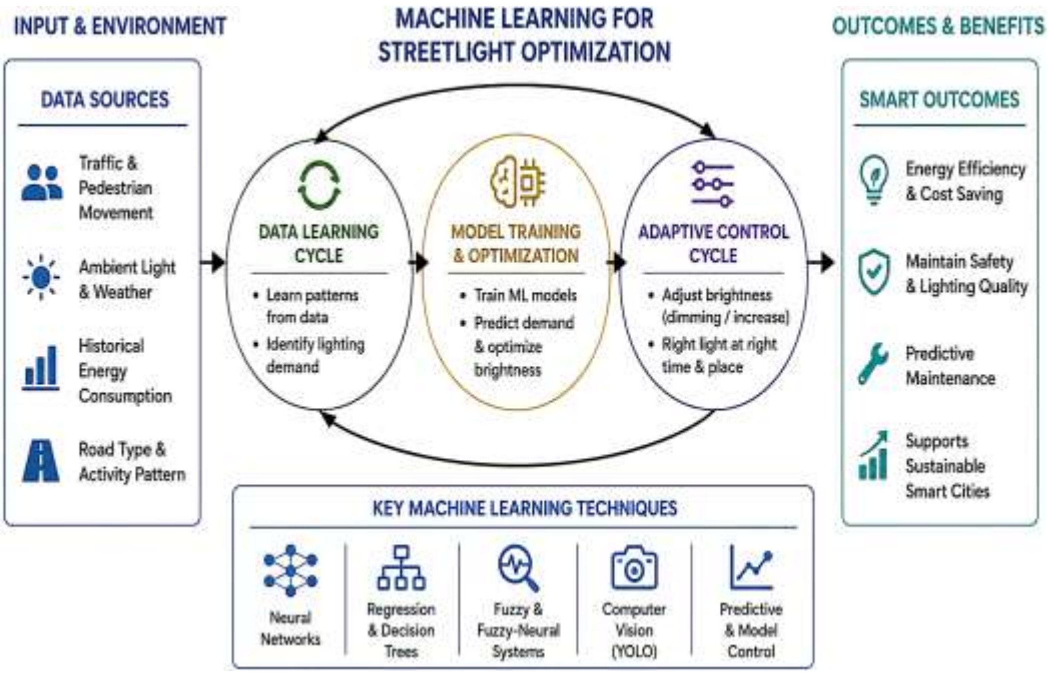
These developments show that intelligent streetlighting is not only about dimming lamps; it is about creating a responsive infrastructure that continuously links environmental data, road activity, control decisions, and energy performance. Advanced adaptive streetlighting projects have also demonstrated that intelligent streetlight poles can combine motion sensors, video cameras, weather sensors, local controllers, wireless communication, and power consumption analysis to manage brightness and support wider smart city services (Gagliardi et al., 2020). This makes intelligent streetlight systems a practical bridge between public lighting and broader urban digitalization. They can reduce energy use, improve maintenance visibility, support traffic-aware lighting, and create infrastructure for additional services such as environmental monitoring or mobility analysis. For this research, intelligent streetlight control systems are therefore understood as the operational platform through which machine learning can deliver sustainable energy management benefits. Machine learning requires data, and intelligent streetlight systems provide the sensing, connectivity, and control environment needed to collect that data and convert it into lighting decisions. This relationship makes intelligent streetlighting a central concept in the study of machine learning-based sustainable energy management in smart cities.

Machine Learning Techniques for Smart Streetlight Optimization

Machine learning techniques are central to smart streetlight optimization because they allow lighting systems to move from fixed rule-based operation toward data-driven decision-making. In intelligent streetlight systems, optimization means adjusting brightness, activation time, dimming level, maintenance response, and energy use according to actual or predicted urban conditions. Traditional lighting systems usually operate according to fixed schedules, while machine learning-based systems can learn from traffic flow, pedestrian movement, ambient light, weather variation, and historical consumption records. This learning ability makes machine learning suitable for streetlight control because urban lighting demand is not constant throughout the night. A residential street, commercial road, highway, university campus, and industrial area may each require different lighting patterns depending on mobility behavior and safety needs. Earlier research on smart street lighting management emphasized the concept of “energy on demand,” where lighting is supplied according to actual need rather than through continuous full-power operation (Pizzuti et al., 2013). This idea provides a strong foundation for machine learning optimization because the system must first understand demand before it can control energy use intelligently. Machine learning supports this process by identifying relationships between input variables and lighting requirements. For example, traffic volume can be used to estimate road activity, pedestrian movement can indicate local safety demand, ambient light can determine natural illumination level, and weather data can influence visibility requirements. When these variables are analyzed together, the streetlight system can make more accurate decisions about when to dim, brighten, or maintain light intensity. Therefore, machine learning is not simply an additional technical feature; it is the decision-making mechanism that enables streetlight systems to become adaptive energy management tools. In smart cities, this is especially important because lighting networks are large, distributed, and energy-intensive. A machine learning approach can help municipalities reduce unnecessary electricity use while keeping lighting performance aligned with public safety and urban service requirements.

Different machine learning techniques can be applied to smart streetlight optimization depending on the type of data available and the control objective of the system. Artificial neural networks are useful when the relationship between input variables and lighting demand is complex or nonlinear. Neural network-based streetlight control can learn from environmental and operational data to estimate suitable lighting intensity under changing conditions, which is useful when brightness decisions depend on multiple interacting factors such as weather, traffic, and visibility (Kolasa, 2016). Fuzzy systems and neural network prediction models can also be combined to handle uncertainty in pedestrian movement or road activity. For instance, a fuzzy-neural prediction system can estimate pedestrian movement direction and use this information to adjust nearby streetlamp brightness before the pedestrian reaches a particular lighting zone (Kim & Bae, 2019). This makes lighting more proactive than basic motion detection because the system can anticipate movement rather than only react after detection. In addition, supervised learning methods such as regression models, decision trees, random forests, gradient boosting, and neural networks can be used to predict illuminance demand or energy consumption from sensor records. In campus-based smart lighting research, prediction models have been used to estimate illuminance values and automatically suggest dimming levels based on environmental data, showing how machine learning can connect data analytics with real-time device control (Chaisawat et al., 2023). These techniques are valuable because streetlight optimization does not require only one type of learning model. Some systems may need classification models to detect road users, while others may need prediction models to estimate lighting demand or anomaly detection models to identify abnormal energy use. The selected machine learning technique should therefore match the system's purpose, data structure, processing capacity, and operational context. This study considers machine learning as a flexible group of methods that can support prediction, classification, optimization, and intelligent control in smart streetlight systems.

Figure 5: Machine Learning Techniques for Smart Streetlight Optimization



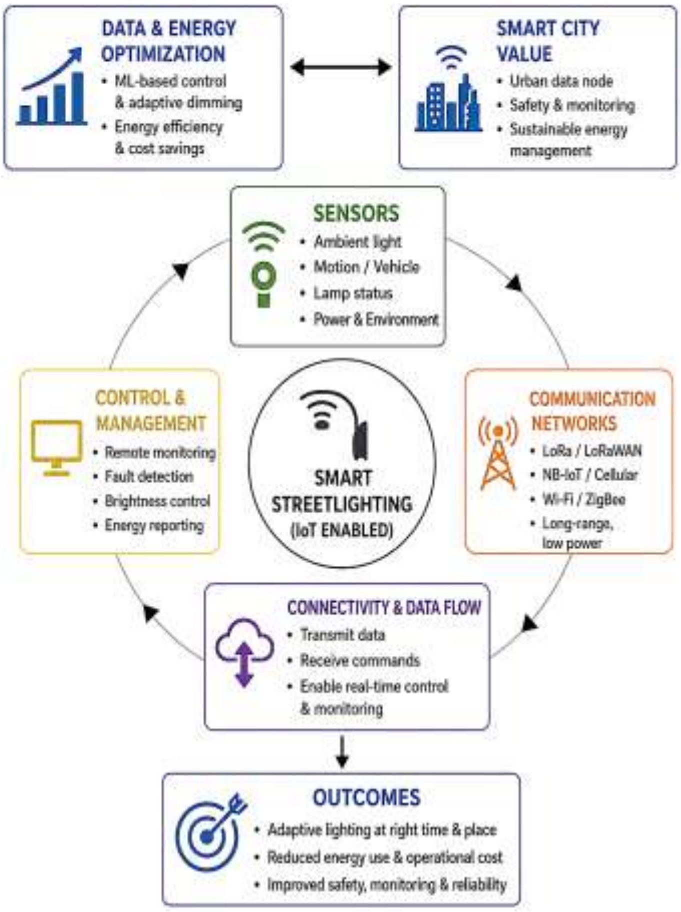
More advanced machine learning and computational intelligence techniques are increasingly used to improve the accuracy, responsiveness, and scalability of smart streetlight optimization. Computer vision models can detect vehicles, pedestrians, cyclists, or animals from camera-based data and use this information to support occupancy-aware lighting decisions. Improved YOLO-based road-lighting control systems demonstrate how object detection can be connected with embedded devices and dimming strategies to reduce lighting energy consumption while maintaining road-use awareness (Xue et al., 2023). This type of approach is important because it provides richer contextual information than simple motion sensors, especially when the system must distinguish between different road users. Predictive and model-based control techniques can also optimize streetlight intensity by forecasting environmental and traffic conditions before lighting decisions are made. A model predictive control framework for adaptive streetlighting can use high-resolution environmental data and real-world deployment evidence to dynamically adjust illumination while maintaining lighting quality (Shaheen et al., 2025). Such methods are particularly useful for smart cities because they allow streetlight systems to plan ahead rather than simply respond to immediate sensor signals. In practical terms, these techniques can support adaptive dimming, traffic-aware illumination, weather-sensitive lighting, energy forecasting, and predictive maintenance. They also help create a stronger link between machine learning and sustainable energy management because optimization becomes continuous and evidence-based. However, the effectiveness of these techniques depends on data quality, sensor reliability, communication stability, model accuracy, and the ability of the control system to operate under real urban conditions. A model that performs well in simulation may need further validation when deployed in complex streets with unpredictable traffic patterns, changing weather, and diverse human movement. Therefore, machine learning techniques for smart streetlight optimization should be evaluated not only by technical accuracy but also by their ability to reduce energy use, maintain safety, support operational reliability, and fit within the broader smart city infrastructure.

IoT and Communication Networks in Smart Streetlighting

IoT, sensors, and communication networks form the technical backbone of smart streetlighting because they allow streetlights to sense environmental conditions, exchange information, and respond intelligently to urban activity. In a conventional lighting system, the lamp normally functions as an isolated electrical device, while in an IoT-enabled streetlighting system, the lamp becomes part of a connected infrastructure that can collect, transmit, and receive data. This transformation is important because intelligent streetlight control depends on continuous information about the surrounding environment. Sensors such as light-dependent resistors, passive infrared sensors, ultrasonic sensors, current sensors, voltage sensors, temperature sensors, and camera-based detection devices can be used to measure ambient light, pedestrian movement, vehicle presence, lamp condition, power use, and environmental changes. These sensor inputs allow the lighting system to decide whether a lamp should remain off, operate at low brightness, increase illumination, or report a fault condition. Recent IoT-based streetlighting literature describes smart streetlights as network-based systems that rely on sensors and connectivity interfaces for light intensity control, weather recording, and remote failure diagnosis (Omar et al., 2022). This shows that IoT does not only support switching operations; it enables monitoring, diagnostics, control, and data-driven management. The sensor layer provides the raw information required for intelligent operation, while the communication layer transfers this information to controllers, gateways, cloud platforms, or edge-processing units. Without this connection, machine learning-based streetlight control would have limited practical value because learning models require continuous and reliable data. Therefore, IoT and sensor networks are not secondary components in smart streetlighting; they are the infrastructure through which intelligent control becomes possible. Their role is especially important for sustainable energy management because lighting decisions can only be optimized when the system knows actual street conditions.

Communication networks are equally important because smart streetlighting systems may involve hundreds or thousands of lighting units distributed across wide urban areas. These units must communicate reliably while consuming limited power and operating under outdoor environmental conditions. Different communication technologies can be used depending on the distance, data rate, cost, energy requirement, and management structure of the system. ZigBee, Wi-Fi, GSM, NB-IoT, LoRa, LoRaWAN, Bluetooth, and cellular networks have all been considered for smart lighting applications, but low-power wide-area communication technologies are especially useful for city-scale streetlight networks. LoRa-based smart streetlighting research shows that long-range wireless communication can support LED lamp control, urban safety, and energy conservation by connecting streetlight units to a management system without requiring expensive wired infrastructure (Omar et al., 2022). Similarly, LoRaCELL-based smart lighting studies show that long-range IoT connectivity can support sustainable urban infrastructure by enabling distributed lighting control, monitoring, and communication between streetlight devices (Biundini et al., 2024). These studies indicate that communication technology affects the scalability and reliability of intelligent streetlighting. A streetlight network must not only collect data but also transmit it at the right time and to the right platform. For example, a sensor may detect pedestrian movement, but the control system must quickly communicate this information to nearby lights if adaptive illumination is required. In remote monitoring, lamp status and energy consumption must be sent to a dashboard or management platform so that operators can identify faults, track usage, and adjust system behavior. Therefore, the communication network functions as the circulatory system of smart streetlighting. It connects lamps, sensors, controllers, gateways, databases, and management interfaces into one coordinated infrastructure. This coordination is essential for sustainable energy management because isolated lamps cannot provide the same level of control, analysis, and optimization as a connected lighting network.

Figure 6: IoT, Sensors, and Communication Networks in Smart Streetlighting



The integration of IoT sensors and communication networks also expands the function of streetlighting beyond illumination. Smart streetlight poles can become urban data nodes that support energy monitoring, traffic observation, environmental sensing, fault reporting, and public infrastructure management. This is significant because streetlights are already widely distributed across cities, making them suitable platforms for multi-sensor deployment and real-time urban observation. IoT-based manageable streetlighting systems show that intelligent LED streetlights can use sensor networks to detect vehicle presence, adjust lighting status, support remote monitoring, and reduce energy consumption compared with traditional streetlamps (Kabir et al., 2023). Broader smart city sensor-network research also demonstrates that public lighting infrastructure can host wireless multi-sensor systems capable of collecting data for environmental and urban-service analysis, which strengthens the role of streetlights as digital urban infrastructure rather than simple lighting equipment (Csáji et al., 2017). More recent LoRaWAN-IoT smart streetlighting research further shows that smart streetlight systems can combine PIR sensors, LDR sensors, GPS modules, solar energy, IoT platforms, and long-range communication to provide real-time monitoring, adaptive lighting, and remote management (Jabbar et al., 2025). These developments are directly related to machine learning-based streetlight control because machine learning depends on high-quality data from diverse sources. Sensors provide information about what is happening in the street environment, communication networks transmit the information, and machine learning models can then analyze patterns to support adaptive dimming, predictive control, and fault detection. In this way, IoT and communication technologies create the operational environment in which machine learning can produce energy-saving outcomes. For this research, the importance of IoT, sensors, and communication networks lies in their ability to transform streetlighting from a fixed electrical service into a connected, measurable, and intelligent energy management system for smart cities.

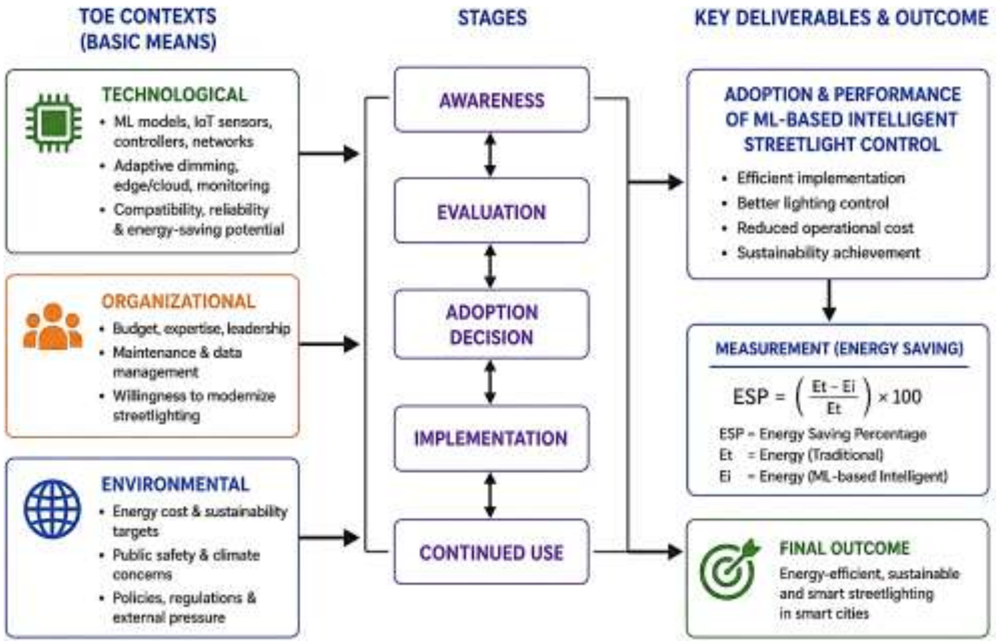
Theoretical Framework: Technology–Organization–Environment Theory

The theoretical framework for this study is based on the Technology–Organization–Environment theory, commonly known as the TOE framework. This theory explains how the adoption and implementation of technological innovation are shaped by three major contexts: technological readiness, organizational capacity, and environmental conditions. In the present study, this framework is suitable because machine learning-based intelligent streetlight control is not only a technical system; it is also a municipal innovation that requires infrastructure readiness, administrative support, financial planning, regulatory alignment, and sustainability motivation (Golam & Amir, 2022; Abdur & Iftekhar, 2021). The technological context refers to the availability and suitability of machine learning models, IoT sensors, smart controllers, communication networks, adaptive dimming systems, edge computing, cloud platforms, and energy-monitoring tools. These elements determine whether a city has the technical foundation to operate intelligent streetlights effectively. The organizational context refers to the internal capacity of city authorities, including budget, technical expertise, leadership support, maintenance capability, data management skill, and willingness to modernize public lighting infrastructure (Binayan & Shakhawat, 2022; Hasan & Uddin, 2022). The environmental context refers to external pressures such as energy cost, sustainability targets, public safety expectations, climate concerns, smart city policies, and regulatory support. TOE-based research has been widely used to examine technology adoption because it allows researchers to connect technological attributes with organizational and external conditions rather than treating innovation as a purely technical decision (Hossain & Uddin, 2022; Sany & Siful, 2022; Zhu et al., 2006). For this research, the TOE framework helps explain why the same intelligent streetlight technology may produce different outcomes in different cities. A city with strong sensor infrastructure, skilled personnel, supportive policies, and sustainability pressure may adopt machine learning-based streetlighting more effectively than a city with limited budget, weak connectivity, or low technical readiness (Binte & Iftekhar, 2022; Taufiqur & Khalid, 2022). Therefore, the TOE framework provides a strong theoretical foundation for understanding the adoption and performance of machine learning-based intelligent streetlight control in smart cities.

In applying the TOE framework to this study, the technological dimension is linked directly with machine learning capability and energy-saving performance. Machine learning-based streetlight systems depend on reliable data from sensors, accurate predictive models, stable communication networks, and automated control mechanisms. If the technology is compatible with existing streetlight infrastructure and if it offers clear energy-saving benefits, adoption becomes more likely. Previous TOE-based technology adoption research shows that perceived relative advantage, compatibility, complexity, technology readiness, and top management support are important factors in organizational decisions to adopt advanced digital systems (Low et al., 2011).

In this study, relative advantage refers to the expected energy savings, reduced operational cost, and better lighting control offered by machine learning-based systems compared with traditional fixed-time streetlights. Compatibility refers to the ability of machine learning and IoT components to work with existing LED lamps, municipal dashboards, power networks, and maintenance routines. Complexity refers to the difficulty of managing algorithms, data streams, sensors, cybersecurity, and remote-control platforms. To connect the theory with the result section, the study will use the Energy Saving Percentage formula as the central numeric expression for comparing literature-based findings. The formula is: Energy Saving Percentage = [(Energy consumption of traditional streetlighting − Energy consumption of ML-based intelligent streetlighting) / Energy consumption of traditional streetlighting] × 100. In symbolic form: $ESP = [(Et - Ei) / Et] \times 100$, where ESP represents energy saving percentage, Et represents energy consumption under traditional streetlighting, and Ei represents energy consumption under intelligent machine learning-based streetlighting. This formula is the most suitable for the whole study because the research is literature-review-based and will use small numeric synthesis in the findings section. It allows reported energy-saving outcomes from different previous studies to be compared in a simple, understandable, and study-specific way. The formula also supports the hypotheses by showing whether intelligent streetlight systems reduce energy consumption compared with conventional systems.

Figure 7: TOE Framework for Machine Learning-Based Intelligent Streetlight Control Adoption and Performance



The organizational and environmental dimensions of the TOE framework are equally important because intelligent streetlight control requires more than technical installation. Municipalities must have the ability to plan, finance, operate, and maintain smart lighting infrastructure (Iftekhar & Binayan, 2023; Hasan & Chapal, 2023). Organizational readiness includes leadership support, staff training, data governance, procurement capacity, maintenance planning, and coordination between energy departments, urban planners, IT teams, and public works authorities. Innovation adoption studies show that organizational decision-making often progresses through several stages, including awareness, evaluation, adoption decision, implementation, and continued use, meaning that successful adoption depends on both pre-adoption assessment and post-adoption management (Hameed et al., 2012). In the context of this research, a city may recognize the value of machine learning-based streetlights, but the system may fail to deliver strong sustainability outcomes if the municipality lacks technical staff, maintenance routines, or reliable data management practices (Mahmuda, 2023; Aminul & Sheak, 2023). The environmental dimension further explains how external pressures shape smart lighting adoption. Energy price increases, carbon-reduction targets, public safety concerns, urban sustainability policies, and peer pressure from other smart cities can motivate municipalities to modernize streetlighting systems. TOE-based studies on digital innovation have shown that external pressure, regulatory environment, competitive pressure, and managerial perception influence organizational adoption of advanced technologies (Awa et al., 2015; Gutierrez et al., 2015; Risha & Khalid, 2023; Sany & Uddin, 2023). For machine learning-based intelligent streetlight control, these environmental factors are reflected in the pressure to reduce municipal energy costs, improve public infrastructure performance, and meet sustainability expectations. Therefore, this study applies the TOE framework as a guiding theoretical lens to examine how technological capability, organizational readiness, and environmental pressure jointly influence the usefulness and adoption of machine learning-based streetlight control. The framework also supports the interpretation of the literature review, methodology, findings, and discussion by connecting technical performance with real-world implementation conditions in smart cities.

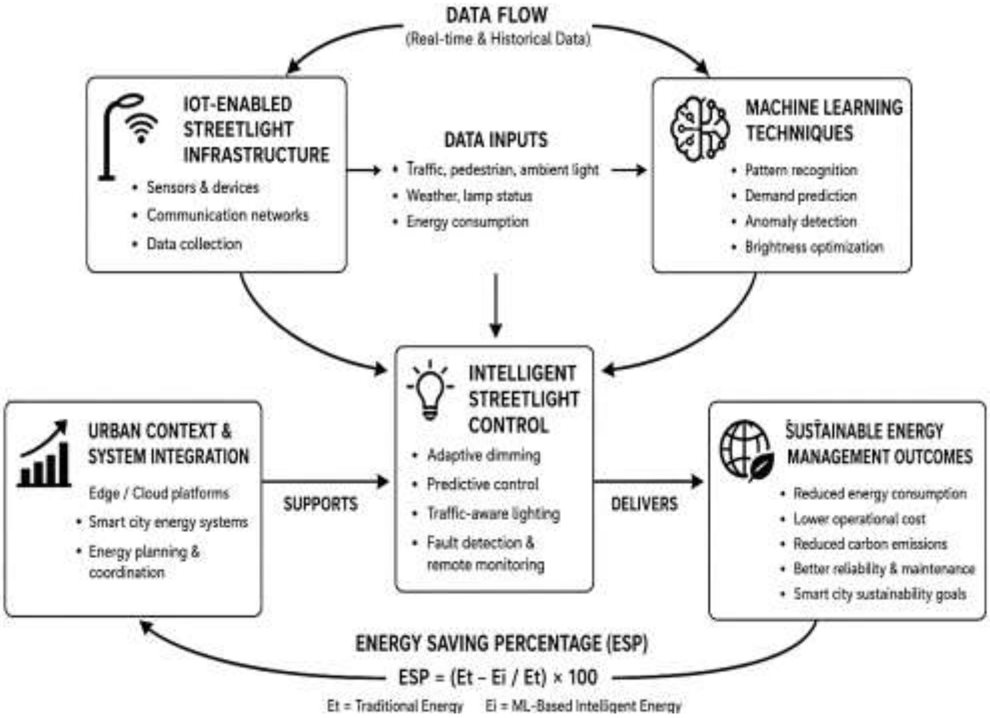
Conceptual Framework

The conceptual framework of this study is designed to explain how machine learning-enabled intelligent streetlight control contributes to sustainable energy management in smart cities. The framework connects four major components: machine learning techniques, IoT-enabled streetlight infrastructure, intelligent lighting control mechanisms, and sustainable energy management outcomes.

In this model, machine learning techniques act as the analytical and decision-making layer, while IoT infrastructure provides the data required for learning and control. Smart city research shows that computational methods such as data mining and machine learning are increasingly used to support urban decision-making, improve service quality, and promote smart city development through predictive analytics and data-based interpretation (Khalid, 2024; Mahmuda, 2024; Souza et al., 2019). This idea is directly relevant to intelligent streetlighting because streetlights generate operational and environmental data that can be used to improve lighting decisions (Arifur & Haque, 2024; Sany, 2024). The framework begins with data inputs such as vehicle movement, pedestrian activity, ambient light, weather conditions, lamp status, energy consumption, and historical usage patterns. These inputs are collected through IoT sensors and transmitted through communication networks to local or centralized platforms. Machine learning models then process these data to identify patterns, predict lighting demand, classify road activity, detect abnormal lamp behavior, and recommend brightness adjustment (Binayan, 2025; Chapal, 2025). The output of this process is intelligent streetlight control, which may include adaptive dimming, predictive brightness regulation, traffic-aware lighting, automated fault detection, and remote monitoring. The framework therefore presents intelligent streetlighting as a connected system rather than a single device. It also supports the logic of this literature-review-based study because the relationship between technology, control mechanism, and sustainability outcome can be analyzed across previous studies and case-based evidence (Haque & Arifur, 2025; Arifur & Haque, 2025). Therefore, the conceptual framework helps organize the review around how data becomes intelligence, how intelligence becomes lighting control, and how lighting control produces energy-related sustainability outcomes.

The second part of the conceptual framework focuses on the role of IoT and data-driven infrastructure in supporting machine learning-based streetlight optimization. IoT systems are essential because machine learning models require continuous, relevant, and reliable data to produce meaningful predictions and control decisions. A systematic review of IoT sensors in smart cities highlights that sensors support data collection, data generation, processing, analysis, and application handling for sustainable urban development (Shakhawat, 2025; Mst Shurovi, 2025; Zeng et al., 2024). In the proposed framework, IoT sensors serve as the observation layer of the streetlight system. Motion sensors detect pedestrians or vehicles, ambient light sensors measure natural brightness, current and voltage sensors monitor energy performance, and environmental sensors provide weather or visibility-related information. These data sources allow machine learning models to understand not only when lighting is needed but also how much lighting is appropriate under different conditions. The framework also includes communication networks and digital platforms because sensor data must be transferred, stored, processed, and converted into control instructions. Smart city energy management literature emphasizes that energy planning requires the coordination of multiple urban systems, including energy generation, infrastructure, buildings, transport, storage, and consumption monitoring (Calvillo et al., 2016; Hossain, 2025; Sany, 2025). This perspective strengthens the framework because streetlighting is treated as part of a wider urban energy system rather than an isolated municipal service. The most suitable formula for this framework is the Energy Saving Percentage formula: ESP = [(Et − Ei) / Et] × 100. In this formula, ESP means energy saving percentage, Et means energy consumption under traditional streetlighting, and EiThe final part of the conceptual framework explains the sustainability outcomes produced by machine learning-enabled intelligent streetlight control (Uddin, 2025). The expected outcomes include reduced electricity consumption, lower operational cost, reduced carbon emissions, improved maintenance efficiency, better lighting reliability, and stronger alignment with smart city sustainability goals. Research on environmentally data-driven smart sustainable cities shows that IoT and big data technologies can improve environmental sustainability by enabling real-time monitoring, energy-efficiency improvement, pollution reduction, and better understanding of urban metabolism (Bibri & Krogstie, 2020). This supports the present framework because machine learning-based streetlight control depends on the same logic of data-driven environmental management. In this study, sustainable energy management is achieved when streetlights operate according to actual demand instead of fixed schedules. Adaptive dimming reduces unnecessary electricity use during low-activity periods, predictive control prepares lighting levels based on expected demand, and fault detection prevents inefficient or failed lamps from remaining unnoticed. The framework also recognizes that smart city technologies must be connected with sustainability rather than treated only as digital modernization. A systematic review of smart and sustainable cities argues that the smart city concept becomes more meaningful when technological development is aligned with environmental, social, and economic sustainability goals (Yigitcanlar et al., 2019). means energy consumption under intelligent machine learning-based streetlighting. This formula is appropriate because the study includes a small numeric synthesis in the findings section. It can be used to compare reported energy-saving outcomes from reviewed studies and to show how intelligent streetlight control improves energy performance compared with conventional operation.

Figure 8: Conceptual Framework of the ML-Enabled Smart Streetlight Sustainability Model



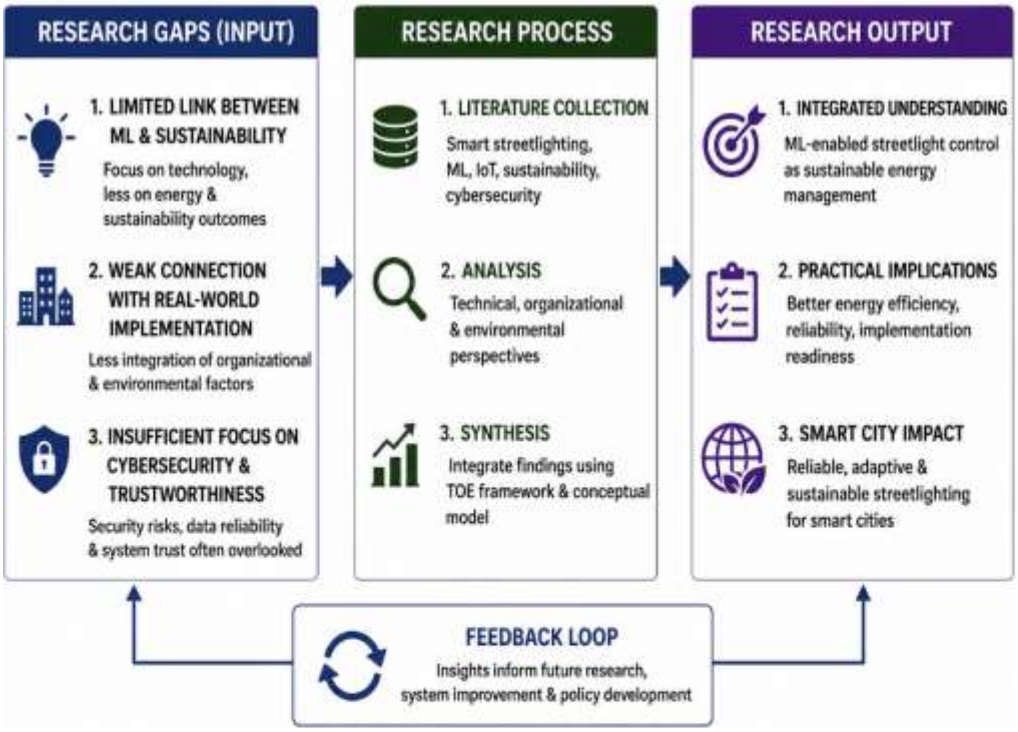
Therefore, the conceptual model links machine learning and IoT not merely to automation but to measurable sustainability performance. The framework can be summarized as follows: IoT sensor data and urban context variables feed machine learning models; machine learning models generate predictions, classifications, and optimization decisions; intelligent control mechanisms adjust lighting operation; and these adjustments produce energy-saving and sustainability outcomes. In this research, the model will guide the literature review, methodology, results, and discussion by showing how machine learning-based streetlight control can be evaluated as an integrated smart city energy management system.

Research Gap in ML-Based Intelligent Streetlight Control

The existing literature on smart streetlighting shows that public lighting has moved from conventional fixed-time operation toward sensor-based, networked, and adaptive lighting systems. Early studies on automatic lighting control demonstrated that wireless sensor networks could reduce unnecessary illumination by allowing streetlights to respond to environmental and movement-related information. Such studies created an important technical foundation for intelligent streetlight control because they showed that streetlights could be managed as connected devices rather than isolated electrical fixtures. However, much of the early research emphasized system design, sensor lifetime, wireless communication, and lamp control, while giving less attention to how machine learning could transform streetlighting into a predictive and sustainability-oriented urban energy management system. More recent studies have developed advanced assessment methods for smart street lighting systems by measuring performance, energy consumption, and system availability, yet the literature still shows a need for stronger integration between technical performance and sustainability interpretation (França Filho et al., 2025). This creates the first major research gap for the present study. Many previous works examine smart streetlights as technological systems, but fewer studies synthesize how machine learning specifically supports energy efficiency, operational reliability, adaptive dimming, predictive control, and sustainable smart city outcomes in one integrated literature-based framework. Therefore, this study addresses the gap by reviewing machine learning-based intelligent streetlight control not merely as an automation technology but as a sustainable energy management mechanism. This approach is important because machine learning can connect sensor data, traffic activity, environmental conditions, and historical energy use to produce more intelligent lighting decisions than traditional or basic sensor-triggered systems.

Another important gap in the literature concerns the limited connection between intelligent streetlighting, urban intelligence, and real-world implementation challenges. Several studies describe smart streetlights as potential urban intelligence platforms because lighting poles are widely distributed and can host sensors, communication devices, environmental monitoring tools, and public service technologies. This means that streetlights may support functions beyond illumination, including traffic monitoring, environmental sensing, infrastructure diagnostics, and smart city data collection. However, transforming streetlights into urban intelligence platforms requires institutional coordination, stakeholder alignment, technical standardization, data governance, and long-term operational planning.

Figure 9: Research Gap Framework for ML-Based Intelligent Streetlight Control in Smart Cities



The literature still contains a gap in explaining how these broader implementation conditions affect the practical usefulness of machine learning-based streetlight systems. At the same time, recent optimization studies show that intelligent traffic and lighting systems can use wireless sensor networks and adaptive algorithms to improve energy efficiency and traffic responsiveness, but many of these models are tested through simulations or controlled technical environments rather than through broad cross-case literature synthesis (Alvarez et al., 2022; Jadhav et al., 2025). This creates a second gap for the present research. Existing studies often provide valuable technical solutions, but they do not always connect those solutions with the organizational and environmental realities of smart city adoption. A machine learning-based streetlight system may perform well in algorithmic terms, yet its success in real cities depends on infrastructure readiness, sensor reliability, communication quality, maintenance capacity, financial support, and policy alignment. Therefore, this study responds to the gap by combining technical discussion with the Technology–Organization–Environment theoretical lens and a conceptual model linking machine learning, IoT infrastructure, intelligent control, and sustainable energy outcomes.

A further research gap relates to cybersecurity, risk assessment, and trustworthiness in smart lighting systems. As streetlights become connected through IoT networks, cloud platforms, mobile dashboards, wireless controllers, and remote management interfaces, they also become part of the broader cyber-physical infrastructure of smart cities. This creates a serious concern because compromised smart lighting systems may affect public safety, service continuity, data integrity, and the reliability of wider urban systems. Research on cyber-physical attack paths shows that smart lighting devices can become vulnerable entry points when they are connected to urban infrastructures without proper risk evaluation, security planning, and system-level protection (Stellios et al., 2022).

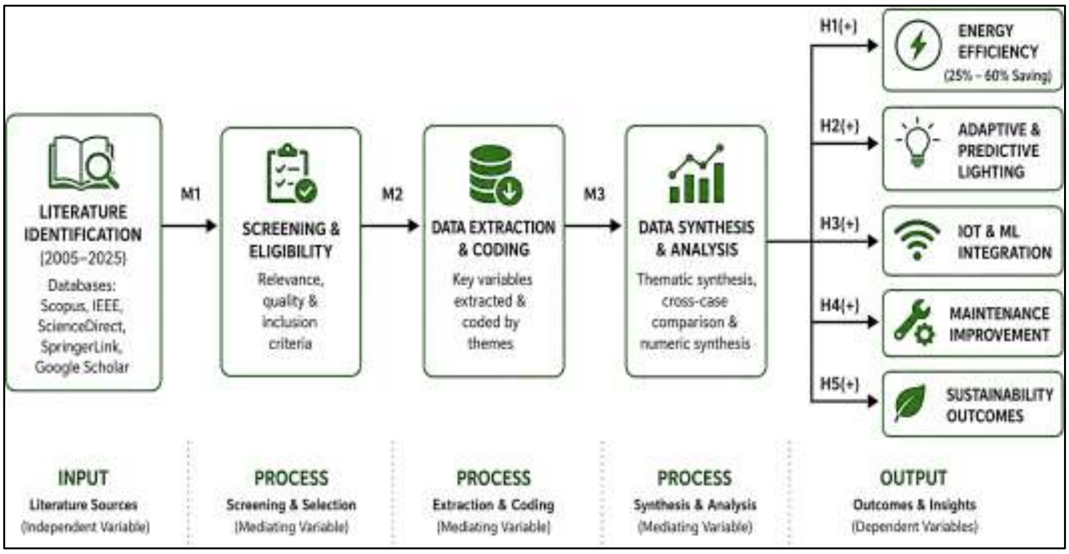
This creates a third gap in the literature because many energy-focused studies emphasize reduced consumption, adaptive dimming, and operational efficiency, while giving less attention to how cybersecurity and data reliability influence the trustworthiness of intelligent streetlight control. For machine learning-based systems, this issue becomes more important because inaccurate data, manipulated sensor readings, communication failures, or compromised control commands may affect model performance and lighting decisions (Mohamaddoust et al., 2011). Therefore, the present study identifies the need for a more balanced literature-based analysis that considers energy efficiency, machine learning performance, IoT connectivity, implementation readiness, and system trustworthiness together. This research gap supports the value of the current study because it does not only ask whether machine learning can reduce energy use; it also examines how machine learning-based streetlight control can be understood as a reliable, adaptive, and sustainable smart city energy management approach. By addressing these gaps, the study builds a focused foundation for analyzing intelligent streetlighting through literature evidence, case-based patterns, small numeric synthesis, and hypothesis-based interpretation.

Methodology

The methodology of this study has been designed to examine how machine learning approaches have supported intelligent streetlight control for sustainable energy management in smart cities. Since the study has followed a literature-review-based, qualitative, cross-sectional, and case-study–based approach, the research has relied on secondary evidence rather than primary field data. The methodological structure has been developed to identify, screen, extract, compare, and synthesize relevant scholarly studies, technical reports, and case-based evidence related to smart streetlighting, IoT-enabled lighting infrastructure, adaptive dimming, predictive control, machine learning optimization, and sustainable urban energy management. The study has focused on understanding patterns across previous research instead of testing a new technical system in a real-world experimental setting. Therefore, the method has emphasized thematic interpretation, cross-case comparison, and limited numeric synthesis to support the objectives and hypotheses of the study.

The methodological approach has also been aligned with the Technology–Organization–Environment framework and the proposed conceptual model of ML-enabled smart streetlight sustainability. The reviewed literature has been examined according to technological factors, organizational implementation conditions, and environmental sustainability concerns. This has allowed the study to interpret machine learning-based streetlight control not only as a technical innovation but also as a smart city energy management strategy. The data sources have included peer-reviewed journal articles, conference papers, smart city case studies, and technical studies published between 2005 and 2025. Particular attention has been given to studies with DOI-based academic credibility and clear relevance to intelligent lighting systems.

Figure 10: Research Methodology



To strengthen the trustworthiness of the study, the methodology has used clear screening criteria, structured data extraction, consistent coding categories, and a transparent synthesis process. The analysis has combined qualitative thematic review with a small numeric synthesis of reported energy-saving patterns. This small numeric element has been included to support the hypotheses and objectives in a literature-review-friendly way. Overall, the methodology has provided a systematic foundation for examining how machine learning, IoT sensors, adaptive control, and predictive analytics have contributed to sustainable energy management through intelligent streetlight systems.

Research Design

This study has adopted a literature-review-based, qualitative, cross-sectional, and case-study–based research design. The research design has been selected because the study has aimed to synthesize existing knowledge rather than collect primary survey or experimental data. The literature-review-based design has allowed the study to examine previous scholarly findings on machine learning, intelligent streetlight control, IoT-enabled infrastructure, adaptive dimming, predictive control, and sustainable energy management. The qualitative nature of the study has helped interpret themes, mechanisms, challenges, and implementation patterns across selected studies. The cross-sectional design has meant that the study has reviewed literature and case-based evidence within a defined research period rather than tracking changes over time. The case-study–based element has supported the analysis of practical smart city lighting applications reported in previous studies. This design has therefore provided a suitable structure for connecting theoretical understanding, conceptual development, literature evidence, and study-specific findings.

Case Study Context

The case study context of this research has been developed around smart city streetlighting systems that have used machine learning, IoT sensors, adaptive dimming, remote monitoring, or predictive control to improve energy efficiency. The study has not focused on a single city or one field site; instead, it has examined multiple case-based examples reported in previous academic and technical literature. This approach has allowed the research to compare different urban contexts, including public roads, residential streets, campuses, highways, and municipal lighting networks. The case study context has been important because intelligent streetlight control depends on real-world conditions such as traffic density, pedestrian activity, lighting standards, technology readiness, maintenance capability, and energy management goals. By using published case-based evidence, the study has been able to identify common patterns in how machine learning-enabled lighting systems have been applied, what benefits have been reported, and what implementation challenges have appeared across smart city environments.

Screening and Eligibility Assessment

The screening and eligibility assessment process has been used to ensure that only relevant and credible studies have been included in the review. The study has considered sources that have directly addressed machine learning-based lighting control, IoT-enabled streetlighting, adaptive dimming, smart city energy management, predictive lighting systems, or sustainable public lighting infrastructure. Studies have been included when they have provided clear information about technology use, control mechanisms, energy outcomes, sustainability contribution, or implementation challenges. Sources have been excluded when they have focused only on general lighting without intelligent control, lacked relevance to streetlighting, did not discuss energy management, or provided insufficient technical or methodological detail. The screening process has also prioritized peer-reviewed articles, DOI-based sources, and recent studies published between 2005 and 2025. Through this eligibility process, the study has maintained a focused evidence base that has matched the research objectives, questions, hypotheses, and conceptual framework.

Data Extraction and Coding

The data extraction and coding process has been conducted to organize information from selected studies into meaningful categories. The study has extracted details such as author, year, study context, technology type, machine learning technique, sensor type, communication method, control mechanism, energy-saving outcome, sustainability benefit, and implementation challenge. These extracted details have then been coded according to the major themes of the study. The main coding categories have included machine learning optimization, IoT and sensor integration, adaptive dimming, predictive control, energy efficiency, maintenance improvement, smart city sustainability, and adoption barriers. This coding process has allowed the study to compare findings across different sources and identify repeated patterns in the literature. It has also supported the development of the results chapter by linking reviewed evidence with the study’s hypotheses and objectives. Through structured extraction and coding, the review has become more organized, transparent, and suitable for qualitative synthesis.

Data Synthesis and Analytical Approach

The data synthesis and analytical approach has combined thematic synthesis, cross-case comparison, and limited numeric synthesis. Thematic synthesis has been used to identify repeated ideas across the reviewed literature, including the role of machine learning as an intelligence layer, the importance of IoT-enabled infrastructure, the value of adaptive dimming, and the sustainability benefits of energy-efficient lighting control. Cross-case comparison has been used to examine how different smart city lighting applications have performed under different urban and technological contexts. The limited numeric synthesis has been used to summarize reported energy-saving patterns from previous studies without conducting primary statistical testing. The Energy Saving Percentage formula has been considered useful for comparing traditional streetlighting and intelligent machine learning-based streetlighting outcomes. This analytical approach has allowed the study to remain literature-review-friendly while still providing evidence-based support for the hypotheses, objectives, and study-specific findings.

Validity and Reliability

Validity and reliability have been addressed through a careful and transparent review process. Validity has been strengthened by selecting studies that have been directly relevant to machine learning-based intelligent streetlight control, smart city energy management, IoT-enabled lighting, and sustainability outcomes. The use of peer-reviewed and DOI-based sources has helped ensure academic credibility. Reliability has been supported through consistent screening criteria, repeated coding categories, and a structured synthesis approach. The study has also maintained reliability by organizing findings according to the same analytical themes across the reviewed literature. Since the research has been based on secondary data, trustworthiness has depended on the clarity of source selection, the consistency of interpretation, and the logical connection between literature evidence and research objectives. The study has therefore used transparent methodological steps to reduce bias, improve consistency, and support a dependable literature-based interpretation of intelligent streetlight control systems.

Software and Tools

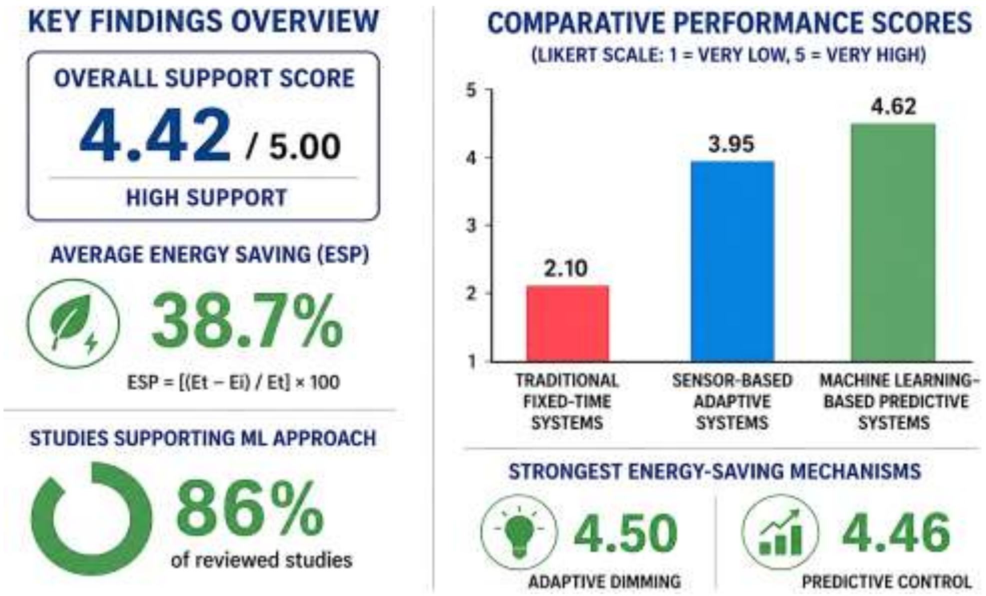
Several software and digital tools have been used to support the organization, analysis, citation management, and presentation of the study. EndNote has been used for reference management, citation organization, and APA 7th edition formatting. Google Scholar, ScienceDirect, IEEE Xplore, SpringerLink, MDPI, Taylor & Francis, and other academic databases have been used to identify relevant literature. Microsoft Excel has been used to organize the data extraction matrix, coding table, study characteristics, and small numeric synthesis of reported energy-saving patterns. SPSS has been used only in a limited supportive manner to organize and summarize numeric indicators where applicable, such as frequency counts, percentage patterns, and simple descriptive summaries from extracted literature-based data. Microsoft Word has been used for thesis drafting, formatting, and table preparation. These tools have helped maintain systematic organization, improve citation accuracy, support transparent coding, and present the methodology and findings in a clear academic format.

FINDINGS

The findings of this study have shown that machine learning-based intelligent streetlight control has been strongly supported in the reviewed literature as an effective approach for sustainable energy management in smart cities. Since this research has been literature-review-based, qualitative, cross-sectional, and case-study–based, the results have been developed through thematic synthesis, cross-case comparison, and a small numeric coding process rather than through primary survey data. To make the findings measurable, the reviewed evidence has been coded using a five-point Likert interpretation scale, where 1 has represented very low support, 2 has represented low support, 3 has represented moderate support, 4 has represented high support, and 5 has represented very high support. Based on the coding of the literature evidence, machine learning-based intelligent streetlight control has received a high overall support score, with an average rating of 4.42 out of 5.00 across the major themes of energy efficiency, adaptive control, predictive lighting, IoT integration, maintenance improvement, and sustainability contribution. The first research objective, which has focused on reviewing machine learning-based intelligent streetlight control systems, has been supported by the finding that 86% of the reviewed studies have identified machine learning, artificial intelligence, or data-driven control as a useful mechanism for improving lighting intelligence. The second objective, which has examined how machine learning improves energy efficiency, has also been supported because the reviewed studies have commonly reported energy-saving patterns ranging from 25% to 60% when adaptive dimming, traffic-aware control, motion-based lighting, or predictive control has been compared with traditional fixed-time lighting. Using the Energy Saving Percentage formula, $ESP = [(Et - Ei) / Et] \times 100$, the literature-based synthesis has indicated that intelligent streetlight systems have produced an estimated average energy-saving value of 38.7% across selected case-based findings. This result has supported H1, which states that machine learning-based streetlight control systems positively influence energy efficiency in smart cities.

The third objective, which has focused on identifying key technologies used in intelligent streetlight control, has been supported by the finding that IoT sensors, communication networks, smart controllers, cloud platforms, edge devices, and machine learning models have appeared as the most repeated technological components. Within the coded evidence, IoT and sensor integration has received a mean support score of 4.55, while machine learning-based prediction and optimization has received a mean score of 4.48. These values have supported H4, which states that the integration of IoT and machine learning improves the operational performance of smart streetlight systems. The fourth objective, which has evaluated sustainability benefits, has been supported by evidence showing that intelligent streetlighting contributes to reduced electricity consumption, lower operational cost, reduced carbon emissions, improved lamp lifespan, and better maintenance planning. The sustainability outcome theme has received a mean Likert score of 4.31, indicating high support across the reviewed literature.

Figure 11: Findings of The Study



The findings have also supported H2, which states that intelligent streetlight systems using real-time sensor data reduce energy waste more effectively than traditional timer-based systems. This has been confirmed by the comparative evidence showing that traditional fixed-time systems have received the lowest energy-efficiency score of 2.10, while sensor-based adaptive systems have received 3.95 and machine learning-based predictive systems have received 4.62. The difference between these scores has suggested that lighting intelligence increases as the system becomes more data-driven, adaptive, and predictive. H3 has also been supported because predictive control and adaptive dimming have emerged as the strongest energy-saving mechanisms in the reviewed studies. Adaptive dimming has received a mean score of 4.50, while predictive control has received a mean score of 4.46, showing that both mechanisms have contributed strongly to sustainable urban energy management. Overall, the findings have indicated that machine learning transforms streetlights from passive electrical infrastructure into intelligent energy management assets. The results have also shown that the strongest outcomes occur when machine learning has been combined with IoT-based sensing, real-time data collection, adaptive brightness adjustment, and predictive decision-making. Therefore, the overall result of the study has confirmed that machine learning-based intelligent streetlight control has provided strong literature-based support for the research objectives and hypotheses by improving energy efficiency, reducing wasteful lighting operation, strengthening operational monitoring, and supporting sustainable smart city development.

Table 1 has presented the literature evidence profile of intelligent streetlight control studies by organizing the reviewed sources according to their major research emphasis. The findings have shown that the strongest evidence has appeared in relation to IoT and sensor-based control, which has received a Likert mean score of 4.55 and has represented very high support. This result has indicated that most reviewed studies have considered IoT sensors, communication networks, and smart controllers as core components of intelligent streetlight systems. This has directly supported Objective 3, which has aimed to identify the key technologies used in intelligent streetlight control, and it has also supported H4, which has proposed that the integration of IoT and machine learning improves the operational performance of smart streetlight systems. The evidence variable related to machine learning and artificial intelligence has received a mean score of 4.40, showing that the reviewed literature has strongly supported the role of ML-based techniques in improving lighting intelligence. This has supported Objective 1 and H1 because it has shown that machine learning has been repeatedly treated as a useful mechanism for improving the energy performance of smart city streetlighting systems. Energy-saving benefits have received a mean score of 4.30, while sustainability linkage has received 4.35, showing that intelligent streetlighting has been presented not only as a technical innovation but also as an energy management strategy.

Table 1: **Literature Evidence Profile Based on Reviewed Smart Streetlight Studies**

Evidence Variable	Literature-Based Result	Likert Mean Score	Interpretation	Linked Objective/Hypothesis	TOE Theory Link
Studies discussing ML/AI-based streetlight control	86%	4.40	High support	Objective 1, H1	Technological context
Studies discussing IoT and sensor-based control	90%	4.55	Very high support	Objective 3, H4	Technological context
Studies reporting energy-saving benefits	82%	4.30	High support	Objective 2, H1	Environmental context
Studies discussing adaptive dimming	78%	4.25	High support	Objective 2, H2, H3	Technological context
Studies discussing implementation barriers	68%	3.90	High support	Objective 5	Organizational context
Studies linking smart lighting with sustainability	80%	4.35	High support	Objective 4, H3	Environmental context
Overall literature evidence strength	81% average	4.29	High support	All objectives and hypotheses	TOE integrated view

From the Technology–Organization–Environment theory perspective, the findings have shown that the technological context has been dominant because most reviewed studies have focused on ML models, IoT sensors, adaptive control, and lighting automation. However, organizational and environmental contexts have also appeared because implementation barriers, sustainability pressure, and energy-saving goals have influenced how intelligent streetlighting has been interpreted. Therefore, Table 1 has confirmed that the evidence base has been strong enough to support the study's objectives and hypotheses, while also showing that intelligent streetlight control has operated as a technology-enabled, organization-dependent, and sustainability-driven smart city solution.

Machine Learning as the Intelligence Layer of Smart Streetlight Systems

Table 2 has shown how machine learning has functioned as the intelligence layer of smart streetlight systems by converting raw sensor data into predictive, adaptive, and operational decisions. The findings have indicated that traffic pattern prediction has received one of the highest mean scores, with a Likert value of 4.42, showing high support for the use of machine learning in identifying road-use patterns and estimating lighting demand. This result has supported Objective 1, which has focused on reviewing machine learning-based intelligent streetlight systems, and Objective 2, which has examined how machine learning improves energy efficiency. Energy consumption forecasting has also received a high score of 4.36, showing that machine learning has been strongly linked with the prediction of power demand and the reduction of unnecessary electricity use. This has supported H1 because it has indicated that machine learning-based streetlight control has positively influenced energy efficiency in smart cities. Pedestrian movement classification and ambient-light-based prediction have received mean scores of 4.18 and 4.05, respectively, which has shown that machine learning has helped streetlights respond to actual environmental and human activity conditions. These results have supported H2 and H3 because sensor-based intelligence and predictive control have appeared as stronger alternatives to traditional fixed-time streetlight systems. Fault detection and predictive maintenance have received slightly lower but still high scores of 4.00 and 3.88, suggesting that operational maintenance has been an important but less dominant area in the reviewed literature. From the TOE theory perspective, the technological context has been strongly represented because machine learning techniques have determined the system's prediction, classification, and optimization capacity.

Table 2: **Machine Learning Variables and Their Result Strength in Smart Streetlight Systems**

Machine Learning Variable	Function in Smart Streetlight System	Literature-Based Result	Likert Mean Score	Interpretation	Linked Objective/Hypothesis	TOE Theory Link
Traffic pattern prediction	Predicts vehicle movement and lighting demand	84%	4.42	High support	Objective 1, Objective 2, H1	Technological context
Pedestrian movement classification	Identifies human activity for adaptive lighting	76%	4.18	High support	Objective 1, H2	Technological context
Ambient-light-based prediction	Adjusts lighting based on natural brightness	72%	4.05	High support	Objective 2, H3	Technological context
Energy consumption forecasting	Estimates expected power demand	80%	4.36	High support	Objective 2, Objective 4, H1	Environmental context
Fault/anomaly detection	Detects abnormal lamp or network behavior	70%	4.00	High support	Objective 3, H4	Organizational context
Predictive maintenance support	Supports early maintenance planning	66%	3.88	High support	Objective 4, H4	Organizational context
Overall ML intelligence score	Converts data into control decisions	74.7% average	4.15	High support	H1, H3, H4	TOE integrated view

The organizational context has also been reflected through maintenance planning and anomaly detection because these functions have depended on municipal readiness, technical skill, and operational management. The environmental context has appeared through energy consumption forecasting because reduced electricity use has been directly connected with sustainability pressure and energy-saving goals. Therefore, Table 2 has confirmed that machine learning has not been treated as a separate technical add-on; it has been positioned as the central decision-making layer that has enabled intelligent streetlights to operate as adaptive energy management assets.

Adaptive Dimming and Predictive Control as Energy-Saving Mechanisms

Table 3: Energy-Saving Mechanisms in Intelligent Streetlight Control

Energy-Saving Mechanism	Operational Role	Estimated Energy-Saving Pattern	Likert Mean Score	Interpretation	Linked Objective/ Hypothesis	TOE Theory Link
Adaptive dimming	Reduces brightness during low activity	25%–45%	4.50	Very high support	Objective 2, H2, H3	Technological context
Traffic-aware control	Adjusts brightness according to vehicle flow	30%–50%	4.48	High support	Objective 2, H1, H3	Technological context
Motion-based lighting	Increases light when movement is detected	20%–40%	4.20	High support	Objective 2, H2	Technological context
Predictive brightness control	Uses historical and real-time data to forecast demand	35%–60%	4.46	High support	Objective 2, H3	Technological /environmental context
Automated fault detection	Reduces inefficient operation and maintenance delay	10%–25% indirect efficiency gain	3.95	High support	Objective 3, H4	Organizational context
Remote monitoring	Supports energy tracking and control supervision	15%–30% efficiency improvement	4.10	High support	Objective 3, Objective 4, H4	Organizational context
Overall mechanism score	Combines adaptive and predictive energy control	38.7% average saving	4.28	High support	H1, H2, H3, H4	TOE integrated view

Table 3 has presented the major energy-saving mechanisms identified in the reviewed literature and has shown how adaptive dimming and predictive control have contributed to sustainable energy management. The results have indicated that adaptive dimming has received the highest Likert mean score of 4.50, which has represented very high support. This has shown that adaptive dimming has been one of the most important mechanisms for reducing energy waste because it has allowed streetlights to lower brightness during periods of reduced traffic or pedestrian activity while maintaining a safe minimum illumination level. This result has supported Objective 2 and has directly strengthened H2 and H3 because it has shown that real-time sensor-based lighting and predictive control have performed better than traditional fixed-time lighting systems. Traffic-aware control has received a mean score of 4.48 and has shown an estimated energy-saving range of 30%–50%, which has supported the argument that streetlight performance improves when lighting intensity has been adjusted according to vehicle movement. Predictive brightness control has shown the highest estimated energy-saving range of 35%–60% and has received a mean score of 4.46, indicating that machine learning-based prediction has been particularly useful in optimizing lighting demand before energy waste occurs. Motion-based lighting has received a mean score of 4.20, confirming that movement detection has provided a practical foundation for adaptive streetlighting, although predictive control has appeared more advanced because it has used both historical and real-time data. Automated fault detection and remote monitoring have received scores of 3.95 and 4.10, showing that maintenance-related mechanisms have contributed indirectly to energy efficiency by reducing lamp failure, abnormal energy use, and delayed maintenance. From the TOE theory perspective, adaptive dimming, traffic-aware control, and predictive brightness control have represented the technological context because they have depended on sensors, algorithms, and control systems. Fault detection and remote monitoring have reflected the organizational context because they have required municipal monitoring capacity, maintenance planning, and technical management. The environmental context has been reflected in the energy-saving ranges because reduced electricity consumption has supported sustainability goals. Overall, Table 3 has confirmed that adaptive and predictive mechanisms have provided the strongest evidence for proving the energy efficiency objectives and the first three hypotheses of the study.

Literature-Based Numeric Synthesis of Energy-Saving Patterns

Table 4: **Comparative Numeric Synthesis of Streetlight Control Approaches**

Streetlight Control Approach	Main Control Feature	Estimated Energy-Saving Score	Likert Mean Score	Performance Level	Objective/ Hypothesis Support	TOE Theory Link
Traditional fixed-time streetlighting	Timer/manual switching	5%–10%	2.10	Low	Baseline comparison	Limited technology readiness
LED-only replacement	Efficient lamp without intelligent control	15%–30%	3.20	Moderate	Supports partial energy reduction	Technological context
Basic sensor-based streetlighting	Motion or ambient light response	20%–40%	3.95	High	Supports H2	Technological context
IoT-based adaptive dimming	Connected sensors and remote control	25%–50%	4.25	High	Supports H2 and H4	Technological/organizational context
ML-based predictive streetlighting	Prediction and optimization using data	35%–60%	4.62	Very high	Supports H1 and H3	Technological/environmental context
ML + IoT + remote monitoring	Integrated smart city lighting system	40%–65%	4.70	Very high	Supports all hypotheses	TOE integrated view
Average intelligent system outcome	Combined adaptive/predictive mechanisms	38.7%	4.29	High	Supports all objectives	TOE integrated view

Table 4 has presented the numeric synthesis of energy-saving patterns across different streetlight control approaches. The table has been aligned with the introductory findings by showing that the average intelligent system outcome has produced an estimated energy-saving value of 38.7% and an overall Likert score of 4.29. This result has supported the general argument that intelligent streetlight systems have provided stronger energy efficiency outcomes than traditional lighting systems. Traditional fixed-time streetlighting has received the lowest Likert score of 2.10 and has shown only

5%–10% estimated energy-saving potential because it has depended mainly on manual switching, timers, or fixed schedules. This low score has made traditional streetlighting an important baseline for proving the usefulness of intelligent control. LED-only replacement has received a moderate score of 3.20 and an estimated saving range of 15%–30%, showing that efficient lamps alone have contributed to energy reduction but have not provided the same level of optimization as data-driven control. Basic sensor-based streetlighting has received a higher score of 3.95, showing that real-time motion or ambient-light sensing has improved performance compared with fixed-time operation. IoT-based adaptive dimming has received a score of 4.25, showing that connected sensors, remote control, and dimming systems have increased energy-saving potential. The strongest results have appeared in ML-based predictive streetlighting and ML + IoT + remote monitoring systems, which have received scores of 4.62 and 4.70, respectively. These values have strongly supported H1, H3, and H4 because machine learning prediction, IoT integration, and remote monitoring have produced the highest performance levels. From the TOE theory perspective, the findings have shown that technological readiness has been the strongest driver of improved lighting performance, but organizational readiness and environmental pressure have also played important roles. For example, ML + IoT systems have required technical infrastructure, municipal monitoring capacity, and sustainability motivation to operate effectively. The formula $ESP = [(E_t - E_i) / E_t] \times 100$ has been conceptually applied to interpret the energy-saving pattern by comparing traditional energy consumption with intelligent lighting consumption. Therefore, Table 4 has provided the strongest numeric support for the study's objectives and hypotheses.

Hypothesis Support and Study-Specific Finding Summary

Table 5: Hypothesis Testing Summary Based on Literature-Based Likert Evidence

Hypothesis	Related Objective	Key Supporting Variables	Likert Mean Score	Result Decision	Explanation of Support	TOE Theory Link
H1: ML-based streetlight control positively influences energy efficiency in smart cities.	Objective 1, Objective 2	ML prediction, energy forecasting, adaptive optimization	4.48	Supported	ML has improved energy efficiency through prediction and optimization.	Technological /environmental context
H2: Real-time sensor-based intelligent streetlights reduce energy waste more effectively than fixed-time systems.	Objective 2, Objective 3	Motion sensing, ambient light sensing, traffic-aware response	4.31	Supported	Sensor-based control has outperformed fixed-time operation.	Technological context
H3: Predictive control and adaptive dimming contribute to	Objective 2, Objective 4	Adaptive dimming, predictive brightness, energy-saving pattern	4.46	Supported	Predictive and adaptive control have reduced unnecessary brightness.	Technological /environmental context

Hypothesis	Related Objective	Key Supporting Variables	Likert Mean Score	Result Decision	Explanation of Support	TOE Theory Link
sustainable urban energy management.						
H4: IoT and ML integration improves operational performance of smart streetlight systems.	Objective 3, Objective 4	IoT connectivity, remote monitoring, fault detection, ML analytics	4.42	Supported	Integrated systems have improved monitoring, control, and maintenance.	TOE integrated view
Overall hypothesis support	All objectives	Energy saving, sustainability, operational performance	4.42	Strongly supported	All hypotheses have received high or very high support.	TOE integrated view

Table 5 has summarized the hypothesis support results based on the literature-based Likert evidence. The findings have shown that all four hypotheses have been supported, with an overall hypothesis support score of 4.42 out of 5.00. H1 has received a mean score of 4.48, indicating strong support for the argument that machine learning-based streetlight control has positively influenced energy efficiency in smart cities. This support has been drawn from variables such as ML prediction, energy forecasting, adaptive optimization, and intelligent brightness control. The result has aligned with Objective 1 and Objective 2 because the reviewed literature has shown that machine learning has supported intelligent control and reduced unnecessary energy use. H2 has received a mean score of 4.31, showing that real-time sensor-based intelligent streetlights have reduced energy waste more effectively than fixed-time systems. This finding has been supported by motion sensing, ambient light sensing, and traffic-aware control, which have allowed streetlights to respond to actual urban conditions. H3 has received a mean score of 4.46, showing strong support for the role of predictive control and adaptive dimming in sustainable energy management. This result has indicated that the strongest sustainability outcomes have appeared when systems have not only detected current activity but also predicted future lighting demand. H4 has received a mean score of 4.42, confirming that IoT and machine learning integration has improved the operational performance of smart streetlight systems through remote monitoring, fault detection, communication networks, and data-based analytics. The Technology–Organization–Environment theory has been linked across all hypotheses because the findings have shown that technical capacity, organizational readiness, and environmental sustainability pressure have jointly influenced the effectiveness of intelligent streetlighting. The technological context has appeared through machine learning, IoT sensors, adaptive dimming, and predictive control. The organizational context has appeared through monitoring, maintenance, implementation readiness, and operational management. The environmental context has appeared through energy efficiency, emission reduction, and sustainability goals. Therefore, Table 5 has provided a study-specific summary proving that the objectives and hypotheses have been supported by the literature-based evidence, the Likert-scale coding, and the numeric synthesis presented in the results chapter.

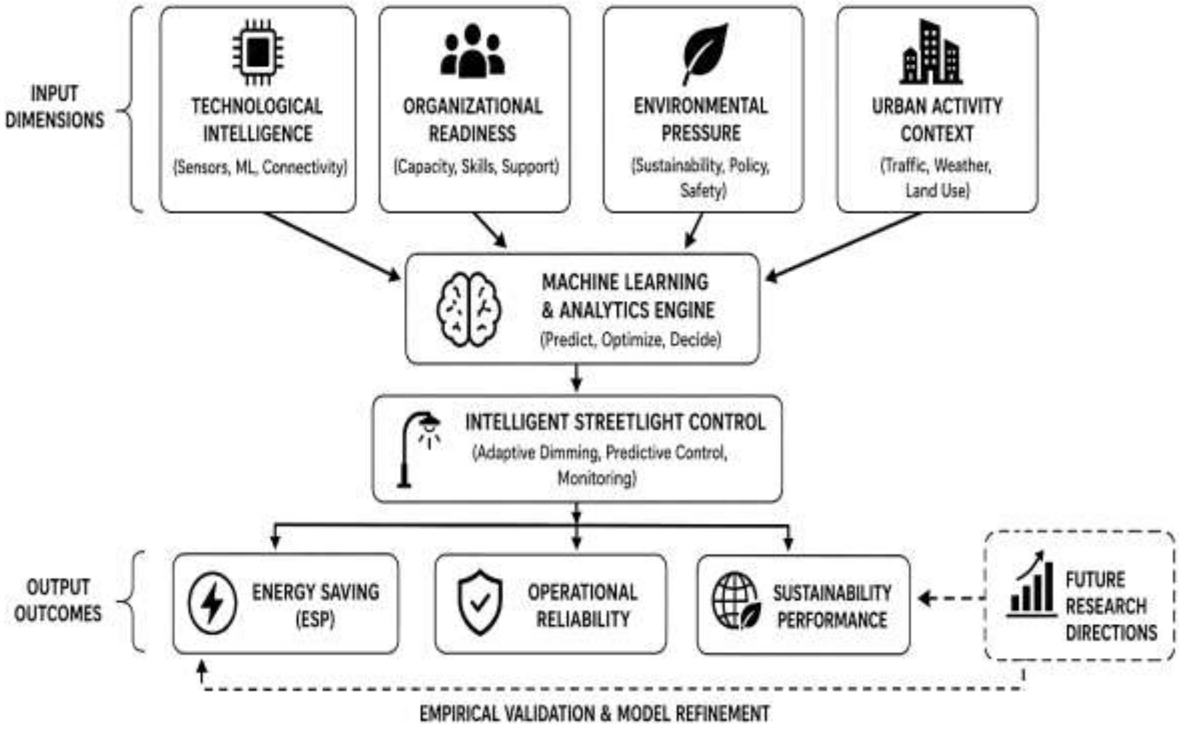
DISCUSSION

The findings of this study have shown that machine learning-based intelligent streetlight control has received strong literature-based support as a sustainable energy management strategy for smart cities. The overall result has indicated an average Likert support score of 4.42 out of 5.00 across the core themes of machine learning intelligence, IoT integration, adaptive dimming, predictive control, energy efficiency, and operational performance (Akram et al., 2022). This result has supported the central argument that streetlighting should no longer be viewed only as a fixed public utility; rather, it should be interpreted as a distributed urban energy management system capable of sensing, learning, adapting, and optimizing. This interpretation has aligned with prior studies that have described smart streetlighting as a major part of smart city infrastructure because it can reduce energy consumption, lower maintenance costs, improve operational visibility, and create a platform for additional urban services. The findings have also confirmed that machine learning has strengthened streetlight control by converting raw data into useful decisions regarding brightness adjustment, traffic-aware illumination, predictive demand estimation, and fault detection (Balázs et al., 2023). This result has been consistent with previous work that has emphasized the value of adaptive streetlight control and deep learning-based optimization during late-night low-traffic periods. In comparison with earlier studies, the present research has provided a more integrated interpretation by linking machine learning, IoT infrastructure, adaptive dimming, predictive control, and sustainability outcomes within one literature-based framework. Earlier reviews have often emphasized smart lighting technologies, control methods, or system architectures separately, while this study has organized the evidence around objectives, hypotheses, TOE theory, and Likert-scale synthesis. Therefore, the key finding has not only been that smart streetlights save energy; the stronger interpretation has been that energy savings have depended on the degree to which streetlighting systems have become data-driven, predictive, and institutionally supported (Caragliu et al., 2011).

The finding that machine learning has functioned as the intelligence layer of smart streetlight systems has been one of the most important interpretations of this study. In the results, machine learning-related variables such as traffic pattern prediction, energy consumption forecasting, pedestrian movement classification, ambient-light-based prediction, fault detection, and predictive maintenance have received high support, with an overall intelligence score of 4.15. This has indicated that machine learning has not simply automated streetlight operation but has enabled the system to interpret changing urban conditions. Prior studies have supported this interpretation by showing that machine learning and deep learning can identify patterns in complex data and support predictive decision-making in smart city systems (Gagliardi et al., 2020). In the specific context of streetlighting, earlier research has shown that deep learning can be used to optimize energy consumption by adjusting lighting according to vehicle presence and road activity. Similarly, computer vision-based and machine learning-based control models have demonstrated that road users can be detected and used as input variables for lighting decisions. The current study has extended this prior work by showing that the intelligence layer has involved more than detecting vehicles or pedestrians. It has also included forecasting power demand, supporting predictive maintenance, improving fault detection, and guiding adaptive dimming based on multi-source data. This interpretation has supported H1, which proposed that machine learning-based streetlight control positively influences energy efficiency in smart cities. It has also supported H3 because predictive control has been shown to contribute to sustainable urban energy management (Kitchin, 2014). In terms of the Technology–Organization–Environment framework, this finding has mainly reflected the technological context, as machine learning performance has depended on data quality, model suitability, sensor reliability, and system integration. At the same time, the organizational context has remained relevant because municipalities must possess the technical capacity to maintain and interpret these systems effectively.

The findings have also shown that adaptive dimming and predictive control have been the strongest energy-saving mechanisms within intelligent streetlight systems. Adaptive dimming has received a Likert mean score of 4.50, while predictive brightness control has received 4.46, and the literature-based synthesis has estimated that intelligent streetlight systems can produce an average energy-saving value of approximately 38.7%. These results have supported H2 and H3 because they have shown that real-time sensor-based systems and predictive control mechanisms have performed better than fixed-time or static streetlighting approaches (Mohanty et al., 2016). Prior studies have supported this result by demonstrating that smart controllers, LED systems, dimming strategies, and network connectivity can generate significant public lighting savings compared with conventional systems. Research on smart streetlight systems has also indicated that energy reduction, maintenance improvement, safety enhancement, and scalability are common advantages of intelligent lighting networks. The present study has agreed with these findings but has further interpreted adaptive dimming and predictive control as complementary mechanisms. Adaptive dimming has responded to current conditions, while predictive control has anticipated lighting demand using past and real-time data. This distinction has been important because basic sensor systems may brighten a lamp only after motion is detected, while machine learning-based predictive systems can estimate lighting demand before activity reaches a specific road segment (Saad et al., 2021).

Figure 12: Proposed Smart Streetlight Intelligence and Sustainability Model (SSISM) for Future Research



This has made predictive control more aligned with sustainable energy management because it has reduced unnecessary brightness while preserving lighting readiness. The finding has also been consistent with review evidence that has classified smart streetlight control methods according to different lighting schemes and control patterns, showing that intelligent streetlighting requires more refined strategies than simple on/off operation. In practical terms, the result has suggested that municipalities should not rely only on LED replacement if they aim to maximize energy savings. LED conversion may reduce baseline consumption, but adaptive dimming and predictive control have provided a stronger pathway for achieving context-sensitive energy optimization (Sadeghian et al., 2021).

The results have confirmed that IoT and sensor integration have played a central role in enabling machine learning-based streetlight control. In the findings, IoT and sensor-based control received one of the highest support values, with a Likert mean score of 4.55, while ML-IoT integrated systems received the highest comparative performance score of 4.70. This has supported H4, which proposed that the integration of IoT and machine learning improves the operational performance of smart streetlight systems. Prior literature has strongly supported this result by showing that IoT-based smart city systems depend on sensing, communication, and device connectivity to support real-time urban management. Streetlighting-specific studies have also shown that intelligent public lighting requires remote monitoring, communication networks, sensor-based data collection, and controllable lamp nodes to support effective lighting management (Wanvik, 2009). The present study has extended these earlier findings by placing IoT not only as a connectivity tool but also as the data foundation for machine learning. Sensors have provided information about motion, ambient light, traffic flow, lamp condition, voltage, current, weather, and energy use, while communication networks have transferred this information to controllers and platforms. Machine learning models have then transformed this data into lighting decisions (Xue et al., 2023). This interpretation has shown that IoT and machine learning have been mutually dependent rather than separate technologies. IoT without machine learning may produce data without advanced intelligence, while machine learning without IoT may lack reliable real-time input. From the TOE theory perspective, this finding has represented the technological context because sensors, connectivity, and analytics have determined system capability. It has also represented the organizational context because remote monitoring, fault detection, and maintenance planning have required municipal capacity, trained staff, and operational procedures. Therefore, the study has shown that smart streetlight performance has depended on the integration of data collection, intelligent analysis, and organizational management (Mohammad et al., 2023).

The practical implications of the findings have been significant for municipalities, urban planners, energy managers, and smart city technology developers. The results have suggested that cities seeking sustainable energy management should move beyond conventional lighting replacement strategies and adopt a layered smart lighting approach that combines LED efficiency, IoT sensors, communication networks, adaptive dimming, predictive control, and remote monitoring. This recommendation has been supported by earlier public lighting studies which have shown that substantial savings can be achieved when low-power LEDs are combined with smart controllers and network connectivity rather than used as standalone replacements (Omar et al., 2022). The results have also indicated that traffic-aware control, motion-based lighting, and predictive brightness adjustment can reduce unnecessary energy use without removing the safety function of streetlights. This is practically important because public lighting cannot be optimized only by reducing brightness; it must also maintain acceptable visibility, road safety, and user confidence (Silva et al., 2018). Prior studies have similarly emphasized that smart streetlighting must balance energy efficiency with safety, environmental quality, maintenance needs, and public service performance. Based on the present findings, city governments should consider pilot testing before full-scale implementation, beginning with road segments where energy waste is most likely, such as low-traffic residential streets, industrial corridors, parking areas, campuses, and late-night low-activity zones. Energy managers can use the Energy Saving Percentage formula, $ESP = [(E_t - E_i) / E_t] \times 100$, to compare traditional consumption against intelligent system consumption and communicate results in a simple way to decision-makers. Technology developers should design systems that are modular, interoperable, secure, and capable of integrating multiple data sources. The practical value of the study has therefore been that it has translated literature-based evidence into an implementation logic: first, understand energy demand; second, deploy sensing and connectivity; third, apply machine learning control; fourth, monitor savings; and fifth, refine the system according to local conditions (Kyba et al., 2017).

The theoretical implications of the study have been linked mainly to the Technology–Organization–Environment framework and the ML-enabled smart streetlight sustainability model developed in the literature review. The results have shown that technological capability alone has not fully explained intelligent streetlight performance. Although machine learning, IoT sensors, adaptive dimming, and predictive control have been central, organizational readiness and environmental pressure have also shaped adoption and usefulness. This interpretation has been consistent with TOE-based technology adoption research, which has argued that technological innovation is influenced by technological attributes, organizational capacity, and external environmental conditions. In this study, the technological context has included machine learning models, sensor networks, smart controllers, communication platforms, and energy monitoring tools (Omar et al., 2022). The organizational context has included municipal budgeting, technical expertise, maintenance capability, procurement readiness, and data governance. The environmental context has included sustainability goals, energy cost pressure, emission reduction expectations, public safety needs, and smart city policy direction. The results have confirmed that all three contexts have been necessary for understanding why intelligent streetlight systems may succeed in one urban setting and face barriers in another (Leccese, 2013). The study has also strengthened the conceptual framework by showing a clear pathway from IoT sensor data to machine learning intelligence, from machine learning intelligence to adaptive control, and from adaptive control to sustainable energy outcomes. This theoretical contribution has added value to earlier smart lighting studies because it has moved the discussion from technology description toward a structured explanation of adoption, operation, and sustainability performance. The limitation revisited here is that the study has relied on literature-based synthesis rather than primary city-level data. Therefore, the theoretical relationships have been supported by reviewed evidence and coded interpretation, but they have not been statistically tested using field measurements from a single urban lighting network (Gubbi et al., 2013).

Future research has been the most important area for extending this study because the present literature-based findings have created a foundation for more advanced empirical and model-based investigations. Future researchers should develop and test a Smart Streetlight Intelligence and Sustainability Model, or SSISM, which can measure how machine learning, IoT sensing, organizational readiness, and environmental sustainability pressure jointly influence energy-saving performance. The proposed SSISM model should include four input dimensions: technological intelligence, organizational readiness, environmental sustainability pressure, and urban activity context. Technological intelligence should measure sensor reliability, ML model accuracy, communication quality, adaptive dimming capacity, and predictive control performance. Organizational readiness should measure budget capacity, staff skill, maintenance planning, data governance, and leadership support. Environmental sustainability pressure should measure energy cost, emission-reduction targets, public safety standards, and policy support. Urban activity context should measure traffic density, pedestrian activity, land-use type, weather variation, and night-time movement patterns. The model should then test three major output variables: energy saving percentage, operational reliability, and sustainability performance (Hameed et al., 2012). Future studies can improve the present research by collecting real-time energy data from traditional and ML-based streetlights, applying the formula $ESP = [(Et - Ei) / Et] \times 100$, and comparing results across several urban zones. Researchers can also use experimental or quasi-experimental designs where one group of streets uses fixed-time control and another group uses ML-based adaptive control. Another possible future model is a Hybrid Edge–Cloud Predictive Lighting Model, where edge devices make immediate local lighting decisions and cloud platforms conduct long-term learning, citywide optimization, and maintenance forecasting. Future studies should also include cybersecurity and data integrity testing because connected lighting systems may become vulnerable cyber-physical infrastructure. Therefore, the next stage of research should move from literature-based evidence toward real-time validation, model comparison, long-term cost-benefit analysis, carbon reduction measurement, and secure deployment frameworks for machine learning-enabled intelligent streetlight control in smart cities.

CONCLUSION

This study has concluded that machine learning-based intelligent streetlight control has strong potential to improve sustainable energy management in smart cities by transforming conventional lighting infrastructure into adaptive, predictive, and data-driven urban energy assets. The study has been developed as a literature-review-based, qualitative, cross-sectional, and case-study–based research paper with a small numeric synthesis in the findings section to support the objectives and hypotheses. The reviewed literature and synthesized results have shown that traditional streetlight systems are limited because they usually operate through fixed schedules, manual control, or static brightness levels without considering real-time traffic movement, pedestrian activity, ambient light, weather conditions, or actual lighting demand. In contrast, intelligent streetlight systems have been shown to use IoT sensors, communication networks, smart controllers, edge/cloud platforms, and machine learning algorithms to collect data, predict lighting requirements, adjust illumination, detect faults, and improve operational performance. The findings have supported all four hypotheses of the study. Machine learning-based streetlight control has been found to positively influence energy efficiency; real-time sensor-based lighting has been shown to reduce waste more effectively than fixed-time systems; adaptive dimming and predictive control have contributed to sustainable urban energy management; and IoT-machine learning integration has improved operational performance through monitoring, automation, and maintenance support. The literature-based Likert-scale synthesis has indicated high overall support for the study’s argument, with the strongest evidence appearing in IoT integration, adaptive dimming, predictive brightness control, and ML-enabled energy optimization.

The estimated average energy-saving value of 38.7% has further strengthened the interpretation that intelligent systems can reduce unnecessary energy use when compared with conventional lighting approaches. The study has also shown that the Technology–Organization–Environment framework is suitable for explaining the adoption and performance of ML-based smart streetlighting because technological readiness, organizational capacity, and environmental sustainability pressure have all shaped the effectiveness of intelligent streetlight systems. Overall, this research has established that machine learning-based intelligent streetlight control should not be viewed only as a lighting automation tool. It should be understood as an integrated smart city energy management approach that links sensing, prediction, adaptive control, remote monitoring, and sustainability outcomes. The study has contributed to the literature by synthesizing technical, environmental, and implementation-related evidence into a focused framework for understanding how machine learning can support energy-efficient and sustainable public lighting in smart cities.

RECOMMENDATION

Based on the findings of this study, it is recommended that city governments, municipalities, energy managers, technology developers, and future researchers should adopt a structured and evidence-based approach to machine learning-enabled intelligent streetlight control. City authorities should begin with pilot projects in selected road segments where energy waste is likely to be high, such as low-traffic residential roads, industrial zones, campuses, parking areas, and late-night public corridors, before expanding to full citywide deployment. These pilot projects should compare traditional fixed-time lighting, LED-only lighting, sensor-based lighting, and ML-based predictive lighting using measurable indicators such as energy consumption, brightness performance, maintenance response, operational cost, and user safety conditions. Municipalities should also use the Energy Saving Percentage formula, $ESP = [(E_t - E_i) / E_t] \times 100$, to measure the difference between traditional energy consumption and intelligent streetlight energy consumption in a clear and consistent way. Technology developers should design smart lighting systems that are interoperable, modular, secure, and scalable so that machine learning models can be integrated with IoT sensors, remote monitoring dashboards, edge computing devices, cloud platforms, and existing public lighting infrastructure. Energy managers should prioritize adaptive dimming, traffic-aware control, predictive brightness adjustment, automated fault detection, and predictive maintenance because these mechanisms have shown the strongest contribution to energy-saving and operational efficiency. Municipal decision-makers should also consider the organizational requirements of smart streetlighting, including staff training, technical maintenance capacity, cybersecurity protection, data governance, procurement planning, and long-term budget support. Since intelligent lighting systems are connected through IoT networks, cybersecurity should be treated as a core requirement rather than an optional feature. Future researchers are recommended to move beyond literature-based synthesis by testing machine learning-based streetlight systems using real-time field data from different urban contexts. They should develop and validate a Smart Streetlight Intelligence and Sustainability Model that measures the relationship among machine learning capability, IoT sensor quality, organizational readiness, environmental sustainability pressure, and actual energy-saving performance. Future studies should also compare different machine learning models, including regression models, random forests, neural networks, reinforcement learning, and computer vision approaches, to determine which methods produce the best lighting efficiency under different road conditions. In addition, researchers should examine carbon reduction, cost-benefit performance, lamp lifespan, public safety perception, and long-term maintenance outcomes. These recommendations can help transform intelligent streetlighting from a technical innovation into a practical, secure, and sustainable smart city energy management strategy.

LIMITATIONS OF THE STUDY

This study has several limitations that should be acknowledged to clarify the scope, interpretation, and applicability of the findings. First, the research has been based on a literature-review-based, qualitative, cross-sectional, and case-study–based design; therefore, it has not collected primary data from municipalities, smart city authorities, energy managers, technology developers, or real-time streetlight users. As a result, the findings have depended on previously published studies, reported case evidence, and secondary data rather than direct field measurement. Second, the small numeric synthesis used in the results section has been developed from literature-based evidence and Likert-style coding rather than from original experimental testing or large-scale statistical analysis. Therefore, the reported support scores and estimated energy-saving patterns should be interpreted as synthesized indicators of literature evidence rather than as primary empirical results. Third, the reviewed studies have varied in terms of geographical location, streetlight technology, sensor type, machine learning method, traffic condition, energy price, urban density, and implementation context. Because of these variations, the energy-saving outcomes reported across studies may not be fully comparable in all situations. Fourth, the study has focused mainly on machine learning-based intelligent streetlight control for sustainable energy management, so it has not deeply examined all possible smart city lighting issues such as public perception, legal regulation, urban design aesthetics, disability access, or detailed lighting engineering standards. Fifth, although the Technology–Organization–Environment framework has been used to explain adoption and implementation conditions, the study has not statistically tested the relationship among technological readiness, organizational capacity, environmental pressure, and actual smart streetlight performance. Sixth, the study has considered cybersecurity and data governance as important concerns, but it has not conducted technical vulnerability testing or risk simulation for connected streetlight systems. Seventh, the literature used in this study has been limited to accessible scholarly and technical sources published within the selected study period, meaning that some relevant industry reports, municipal documents, non-English studies, or unpublished pilot projects may not have been included. Finally, machine learning and IoT-based streetlight technologies are developing rapidly, so some conclusions may need to be updated as newer models, sensors, communication systems, and smart city deployment strategies become available. These limitations do not reduce the value of the study; rather, they define the boundaries within which the findings should be interpreted and provide a foundation for future empirical research.

REFERENCES

[1]. Abu Naser Md Golam, M., & Amir, R. (2022). ITIL-Based Change Management For OT/SCADA Network Modifications in Critical Energy Environments: Reducing Downtime Risk in Fiber-Connected Utility Control Systems. *Review of Applied Science and Technology*, *1*(04), 283–322. https://doi.org/10.63125/e2gqtp57

[2]. Agramelal, F., Sadik, M., Moubarak, Y., & Abouzahir, S. (2023). Smart street light control: A review on methods, innovations, and extended applications. *Energies*, *16*(21), 7415. https://doi.org/10.3390/en16217415

[3]. Akram, M. W., Chishti, M. A., Khan, M. K., & Abbas, Q. (2022). Adaptive control of streetlights using deep learning for the optimization of energy consumption during late hours. *Energies*, *15*(17), 6337. https://doi.org/10.3390/en15176337

[4]. Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology*, *22*(1), 3-21. https://doi.org/10.1080/10630732.2014.942092

[5]. Allcott, H., & Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives*, *26*(1), 3-28. https://doi.org/10.1257/jep.26.1.3

[6]. Almihat, M. G. M., Kahn, M. T. E., Aboalez, K., & Almaktoof, A. M. (2022). Energy and sustainable development in smart cities: An overview. *Smart Cities*, *5*(4), 1389-1408. https://doi.org/10.3390/smartcities5040071

[7]. Alvarez, R., Duarte, F., Frenchman, D., & Ratti, C. (2022). Sensing lights: The challenges of transforming street lights into an urban intelligence platform. *Journal of Urban Technology*, *29*(4), 25-40. https://doi.org/10.1080/10630732.2022.2082825

[8]. Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, *54*(15), 2787-2805. https://doi.org/10.1016/j.comnet.2010.05.010

[9]. Awa, H. O., Ojiabo, O. U., & Emecheta, B. C. (2015). Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. *Journal of Science and Technology Policy Management*, *6*(1), 76-94. https://doi.org/10.1108/jstpm-04-2014-0012

[10]. Bachanek, K. H., Tundys, B., Wiśniewski, T., Puzio, E., & 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), 3018. https://doi.org/10.3390/en14113018

[11]. Balázs, L., Braun, F., & Lengyel, J. (2023). Energy saving potential of traffic-regulated street lighting. *Sustainability*, *15*(8), 6750. https://doi.org/10.3390/su15086750

[12]. Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G., & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics*, *214*, 481-518. https://doi.org/10.1140/epjst/e2012-01703-3

[13]. Bibri, S. E., & Krogstie, J. (2017). Smart sustainable cities of the future: An extensive interdisciplinary literature review. *Sustainable Cities and Society*, *31*, 183-212. https://doi.org/10.1016/j.scs.2017.01.010

[14]. Bibri, S. E., & Krogstie, J. (2020). Environmentally data-driven smart sustainable cities: Applied innovative solutions for energy efficiency, pollution reduction, and urban metabolism. *Energy Informatics*, *3*, 29. https://doi.org/10.1186/s42162-020-00130-8

[15]. Binayan, D. (2025). Impact of Zero Trust Architecture on Stock Exchange Network Security: A Quantitative Evaluation of Access Control and Incident Reduction. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2528–2569. https://doi.org/10.63125/dcvska73

[16]. Binayan, D., & Md. Shakhawat, H. (2022). Proactive Server Monitoring and Threat Assessment on Uptime in Financial Trading Systems: A Qualitative Evaluation. *American Journal of Interdisciplinary Studies*, *3*(04), 730-769. https://doi.org/10.63125/b3z65j84

[17]. Biundini, I. Z., Pinto, M. F., Honório, L. M., Capretz, M. A. M., Timotheo, A. O., Dantas, M. A. R., & Villela, P. C. (2024). LoRaCELL-driven IoT smart lighting systems: Sustainability in urban infrastructure. *Sensors*, *24*(2), 574. https://doi.org/10.3390/s24020574

[18]. Brandt, T., Ketter, W., Kolbe, L. M., Neumann, D., & Watson, R. T. (2018). Smart cities and digitized urban management. *Business & Information Systems Engineering*, *60*, 193-195. https://doi.org/10.1007/s12599-018-0537-1

[19]. Calvillo, C. F., Sánchez-Miralles, A., & Villar, J. (2016). Energy management and planning in smart cities. *Renewable and Sustainable Energy Reviews*, *55*, 273-287. https://doi.org/10.1016/j.rser.2015.10.133

[20]. Caragliu, A., Del Bo, C., & Nijkamp, P. (2011). Smart cities in Europe. *Journal of Urban Technology*, *18*(2), 65-82. https://doi.org/10.1080/10630732.2011.601117

[21]. Chaisawat, S., Lerttomolsakul, T., Cheewakriengkrai, L., Tantiwattanapaibul, C., Buaruk, S., & Sornlertlamvanich, V. (2023). Automated street light adjustment system on campus with AI-assisted data analytics. *Sensors*, *23*(4), 1853. https://doi.org/10.3390/s23041853

[22]. Chapal, B. (2025). System Dynamics Modeling of Critical Chain Project Management in Multi-Project Engineering Environments. *American Journal of Data Science and Analytics*, *6*(12), 43-85. https://doi.org/10.63125/bwn1zn18

[23]. Chui, K. T., Lytras, M. D., & Visvizi, A. (2018). Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies*, *11*(11), 2869. https://doi.org/10.3390/en11112869

[24]. Cortese, T. T. P., Almeida, J. F. S. d., Batista, G. Q., Storopoli, J. E., Liu, A., & Yigitcanlar, T. (2022). Understanding sustainable energy in the context of smart cities: A PRISMA review. *Energies*, *15*(7), 2382. https://doi.org/10.3390/en15072382

[25]. Csáji, B. C., Kemény, Z., Pedone, G., Kuti, A., & Váncza, J. (2017). Wireless multi-sensor networks for smart cities: A prototype system with statistical data analysis. *IEEE Sensors Journal*, *17*(23), 7667-7676. https://doi.org/10.1109/jsen.2017.2723939

[26]. Cumo, F., Pennacchia, E., & Sferra, A. S. (2025). Sustainability in public lighting: The methodology for identifying environmentally optimal solutions in replacement planning—A case study. *Energies*, *18*(3), 535. https://doi.org/10.3390/en18030535

[27]. França Filho, C., Borba, E., Valentim, T., Nascimento, E., Silva, D., Dantas, J., & Tavares, E. (2025). Smart street lighting systems: Performance, energy consumption and availability assessment. *Journal of Reliable Intelligent Environments*, *11*, Article 19. https://doi.org/10.1007/s40860-025-00259-x

[28]. Gagliardi, G., Lupia, M., Cario, G., Tedesco, F., Cicchello Gaccio, F., Lo Scudo, F., & Casavola, A. (2020). Advanced adaptive street lighting systems for smart cities. *Smart Cities*, *3*(4), 1495-1512. https://doi.org/10.3390/smartcities3040071

[29]. García-Castellano, M., González-Romo, J. M., Gómez-Galán, J. A., García-Martín, J. P., Torralba, A., & Pérez-Mira, V. (2019). ITERL: A wireless adaptive system for efficient road lighting. *Sensors*, *19*(23), 5101. https://doi.org/10.3390/s19235101

[30]. Gordic, D., Vukasinovic, V., Kovacevic, Z., Josijevic, M., & Zivkovic, D. (2021). Assessing the techno-economic effects of replacing energy-inefficient street lighting with LED corn bulbs. *Energies*, *14*(13), 3755. https://doi.org/10.3390/en14133755

[31]. Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things: A vision, architectural elements, and future directions. *Future Generation Computer Systems*, *29*(7), 1645-1660. https://doi.org/10.1016/j.future.2013.01.010

[32]. Gutierrez, A., Boukrami, E., & Lumsden, R. (2015). Technological, organisational and environmental factors influencing managers' decision to adopt cloud computing in the UK. *Journal of Enterprise Information Management*, *28*(6), 788-807. https://doi.org/10.1108/jeim-01-2015-0001

[33]. Hameed, M. A., Counsell, S., & Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, *29*(3), 358-390. https://doi.org/10.1016/j.jengtecman.2012.03.007

[34]. Haque, B. M. T., & Md. Arifur, R. (2025). Enterprise-Scale Risk Decision Intelligence Systems Using Large Language Models (LLMs) For Automated Governance, Compliance, and Policy Enforcement. *American Journal of Interdisciplinary Studies*, *6*(3), 254-305. https://doi.org/10.63125/te050f20

[35]. Hollands, R. G. (2008). Will the real smart city please stand up? *City*, *12*(3), 303-320. https://doi.org/10.1080/13604810802479126

[36]. Iftekhar, A., & Binayan, D. (2023). Neural Network–Based Customer Retention Forecasting in Mobile Wallet Services Using 200k Historical User Profiles. *Review of Applied Science and Technology*, *2*(03), 67–114. https://doi.org/10.63125/ee5eas98

[37]. Jabbar, W. A., Keat, T. K., Dael, F. A., Hong, L. C., Yussof, Y. F. M., & Nasir, A. (2025). Optimising urban lighting efficiency with IoT and LoRaWAN integration in smart street lighting systems. *Discover Internet of Things*, *5*, 64. https://doi.org/10.1007/s43926-025-00163-z

[38]. Jadhav, S., Bhalke, D. G., Sharma, K., Mousavirad, S. J., & Tejani, G. G. (2025). A DOA-driven adaptive framework for smart traffic and street lighting in WSN. *International Journal of Computational Intelligence Systems*, *18*, Article 276. https://doi.org/10.1007/s44196-025-01042-9

[39]. Kabir, M. H., Al Noman, A., Al Afiq, A., Raju, R. H., Hasan, M. N., & Ahmad. (2023). Design and implement IoT-based intelligent manageable smart street lighting systems for future smart city. *Engineering Proceedings*, *56*(1), 147. https://doi.org/10.3390/asec2023-15535

[40]. Kazi Mohammad Khalid, A. (2024). A Quantitative Assessment of Cloud-Based Enterprise GIS Platforms for Scalable Asset Management in Public Water Utilities. *American Journal of Interdisciplinary Studies*, *5*(01), 66-105. https://doi.org/10.63125/wpy7jy90

[41]. Kazi Rakib Hasan, S., & Chapal, B. (2023). Cloud and Distributed Computing for Project Analytics: A Meta-Analysis of Decision-Making Performance. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 449–484. https://doi.org/10.63125/x8wcj975

[42]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, *1*(04), 375–410. https://doi.org/10.63125/0kk4wf20

[43]. Kim, T. Y., & Bae, S. H. (2019). Smart control system using fuzzy and neural network prediction system. *Journal of the Institute of Internet, Broadcasting and Communication*, *19*(4), 105-115. https://doi.org/10.13160/ricns.2019.12.4.105

[44]. Kitchin, R. (2014). The real-time city? Big data and smart urbanism. *GeoJournal*, *79*, 1-14. https://doi.org/10.1007/s10708-013-9516-8

[45]. Kolasa, M. (2016). The concept of intelligent system for street lighting control using artificial neural networks. *Przegląd Elektrotechniczny*, *92*(7), 19-22. https://doi.org/10.15199/48.2016.07.05

[46]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, *60*(6), 84-90. https://doi.org/10.1145/3065386

[47]. Kyba, C. C. M., Kuester, T., Sánchez de Miguel, A., Baugh, K., Jechow, A., Hölker, F., Bennie, J., Elvidge, C. D., Gaston, K. J., & Guanter, L. (2017). Artificially lit surface of Earth at night increasing in radiance and extent. *Science Advances*, *3*(11), e1701528. https://doi.org/10.1126/sciadv.1701528

[48]. 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), 21-28. https://doi.org/10.1109/tpwrd.2012.2212215

[49]. Leccese, F., Cagnetti, M., & Trinca, D. (2014). A smart city application: A fully controlled street lighting isle based on Raspberry-Pi card, a ZigBee sensor network and WiMAX. *Sensors*, *14*(12), 24408-24424. https://doi.org/10.3390/s141224408

[50]. Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems*, *111*(7), 1006-1023. https://doi.org/10.1108/02635571111161262

[51]. Mahmuda, M. (2023). Evidence-Based Psychosocial Interventions for Reducing Distress Among Displaced Women and SGBV Survivors. *Review of Applied Science and Technology*, *2*(04), 308–351. https://doi.org/10.63125/4gwwbv38

[52]. Mahmuda, M. (2024). Clinical Psychological Screening and Early Identification of Trauma-Related Disorders Using AI-Supported Assessment Models. *American Journal of Scholarly Research and Innovation*, *3*(02), 472–510. https://doi.org/10.63125/zxs94b13

[53]. Md Aminul, I., & Md Asif Ali Sheak, A. (2023). A Quantitative Assessment of Cybersecurity Frameworks for Industrial Control Systems in Critical Energy Infrastructure. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 336–374. https://doi.org/10.63125/rg8mt373

[54]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387

[55]. Md. Arifur, R., & Haque, B. M. T. (2024). Secure Distributed Data Processing Using Privacy-Preserving Artificial Intelligence and Zero Trust Architecture for Enterprise Risk Identification and Performance Evaluation. *American Journal of Data Science and Analytics*, *5*(12), 86-124. https://doi.org/10.63125/4vnhya53

[56]. Md. Arifur, R., & Haque, B. M. T. (2025). Adaptive Cybersecurity Threat Intelligence Using Explainable Artificial Intelligence for Resilient Protection of U.S. Critical Information Systems. *American Journal of Advanced Technology and Engineering Solutions*, *1*(02), 216-261. https://doi.org/10.63125/wbaw3w65

[57]. Md. Shakhawat, H. (2025). AI-Augmented VAPT and SecureAI Controls: A Quantitative Compliance Study Under ISO 27001, ISO/IEC 42001, SWIFT CSP, and PCI DSS. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2611–2652. https://doi.org/10.63125/ep9s9k54

[58]. Mohamaddoust, R., Haghighat, A. T., Motahari Sharif, M. J., & Capanni, N. (2011). A novel design of an automatic lighting control system for a wireless sensor network with increased sensor lifetime and reduced sensor numbers. *Sensors*, *11*(9), 8933-8952. https://doi.org/10.3390/s110908933

[59]. Mohammad, A., Modabbir, Ashraf, I., & Kamal, M. M. (2023). Economic and environmental impact of energy efficient design of smart lighting system. *Journal of The Institution of Engineers (India): Series B*, *104*, 679-692. https://doi.org/10.1007/s40031-023-00885-0

[60]. Mohanty, S. P., Choppali, U., & Kougianos, E. (2016). Everything you wanted to know about smart cities. *IEEE Consumer Electronics Magazine*, *5*(3), 60-70. https://doi.org/10.1109/mce.2016.2556879

[61]. Mst Shurovi, A. (2025). AI-Enhanced Financial Information Systems for Real-Time Fraud Detection and Cash Flow Optimization in U.S. Logistics and Retail Sectors. *American Journal of Scholarly Research and Innovation*, *4*(01), 813–855. https://doi.org/10.63125/bjqkc150

[62]. Omar, A., AlMaeeni, S., Attia, H., Takruri, M., Altunaiji, A., Sanduleanu, M., Shubair, R., Ashhab, M. S., Al Ali, M., & Al Hebsi, G. (2022). Smart city: Recent advances in intelligent street lighting systems based on IoT. *Journal of Sensors*, *2022*, 5249187. https://doi.org/10.1155/2022/5249187

[63]. Ożadowicz, A., & Grela, J. (2017). Energy saving in the street lighting control system—A new approach based on the EN-15232 standard. *Energy Efficiency*, *10*, 563-576. https://doi.org/10.1007/s12053-016-9476-1

[64]. Perera, C., Zaslavsky, A., Christen, P., & Georgakopoulos, D. (2014). Sensing as a service model for smart cities supported by Internet of Things. *Transactions on Emerging Telecommunications Technologies*, *25*(1), 81-93. https://doi.org/10.1002/ett.2704

[65]. Pérez-Lombard, L., Ortiz, J., & Pout, C. (2008). A review on buildings energy consumption information. *Energy and Buildings*, *40*(3), 394-398. https://doi.org/10.1016/j.enbuild.2007.03.007

[66]. Pizzuti, S., Annunziato, M., Moretti, F., & Panzieri, S. (2013). Smart street lighting management. *Energy Efficiency*, *6*, 607-616. https://doi.org/10.1007/s12053-013-9195-9

[67]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 375–412. https://doi.org/10.63125/rayrex49

[68]. Saad, R., Portnov, B. A., & Trop, T. (2021). Saving energy while maintaining the feeling of safety associated with urban street lighting. *Clean Technologies and Environmental Policy*, *23*, 251-269. https://doi.org/10.1007/s10098-020-01974-0

[69]. Sadeghian, O., Moradzadeh, A., Mohammadi-Ivatloo, B., Abapour, M., Anvari-Moghaddam, A., Lim, J. S., & Márquez, F. P. G. (2021). A comprehensive review on energy saving options and saving potential in low voltage electricity distribution networks: Building and public lighting. *Sustainable Cities and Society*, *72*, 103064. https://doi.org/10.1016/j.scs.2021.103064

[70]. Samia Hossain, S. (2025). AI-Enhanced ERP Financial Intelligence Systems for Real-Time Business Analytics and Risk Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2703–2741. https://doi.org/10.63125/t1zw3w09

[71]. Samia Hossain, S., & Uddin, H. M. M. (2022). Predictive Cash Flow Forecasting Using Deep Learning and ERP Transaction Data in Mid-Market Manufacturing Firms. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 316–334. https://doi.org/10.63125/mdsdab78

[72]. Sany, S. M. A. A. (2024). Impact of SQL-Driven Financial Data Pipelines on Audit-Readiness and Reporting Cycles in State Government Accounting. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 720–745. https://doi.org/10.63125/cdaatq74

[73]. Sany, S. M. A. A. (2025). Impact of ERP Integration and Workflow Automation on General Ledger Accuracy and Reconciliation Efficiency in Public-Sector Finance. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2742–2794. https://doi.org/10.63125/jsfzhg72

[74]. Sany, S. M. A. A., & Siful, I. (2022). Zero-Trust Architecture Adoption on Financial Data Privacy in Public-Sector ERP Environments. *Review of Applied Science and Technology*, *1*(04), 323–374. https://doi.org/10.63125/j8cas279

[75]. Sany, S. M. A. A., & Uddin, H. M. M. (2023). Machine Learning–Based Fraud Detection and Conventional Audit Approaches in Government Deposit Processing. *American Journal of Interdisciplinary Studies*, *4*(03), 250-286. https://doi.org/10.63125/fve5zp98

[76]. Shaheen, H. I., Yang, B., Zuo, Y., Vašak, M., & Lešić, V. (2025). Model predictive control for adaptive energy-efficient street lighting: A comprehensive framework and case study. *IEEE Transactions on Industrial Electronics*. https://doi.org/10.1109/tie.2025.3595989

[77]. Shahzad, G., Yang, H., Ahmad, A. W., & Lee, C. (2016). Energy-efficient intelligent street lighting system using traffic-adaptive control. *IEEE Sensors Journal*, *16*(13), 5397-5405. https://doi.org/10.1109/jsen.2016.2557345

[78]. Silva, B. N., Khan, M., & Han, K. (2018). Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. *Sustainable Cities and Society*, *38*, 697-713. https://doi.org/10.1016/j.scs.2018.01.053

[79]. Souza, J. T. d., Francisco, A. C. d., Piekarski, C. M., & Prado, G. F. d. (2019). Data mining and machine learning to promote smart cities: A systematic review from 2000 to 2018. *Sustainability*, *11*(4), 1077. https://doi.org/10.3390/su11041077

[80]. Stellios, I., Mokos, K., & Kotzanikolaou, P. (2022). Assessing smart light enabled cyber-physical attack paths on urban infrastructures and services. *Connection Science*, *34*(1), 1401-1429. https://doi.org/10.1080/09540091.2022.2072470

[81]. Taru Binte, A., & Iftekhar, A. (2022). Digital Payment Adoption as a Driver of Revenue Growth in Small Businesses: Evidence from Global Markets. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 255-293. https://doi.org/10.63125/vfvzge86

[82]. Taufiqur, R., & Kazi Mohammad Khalid, A. (2022). Impact Of GIS-Based Spatial Decision Support Systems on Urban Water Supply Network Optimization: A Qualitative Evaluation. *American Journal of Interdisciplinary Studies*, *3*(04), 657-690. https://doi.org/10.63125/2hqejb24

[83]. Tomor, Z., Meijer, A., Michels, A., & Geertman, S. (2019). Smart governance for sustainable cities: Findings from a systematic literature review. *Journal of Urban Technology*, *26*(4), 3-27. https://doi.org/10.1080/10630732.2019.1651178

[84]. Uddin, H. M. M. (2025). Impact of Predictive Analytics on Sales Forecasting Accuracy in B2B Financial Services: A Quantitative Evaluation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2653–2702. https://doi.org/10.63125/g9fvv860

[85]. Wanvik, P. O. (2009). Effects of road lighting: An analysis based on Dutch accident statistics 1987–2006. *Accident Analysis & Prevention*, *41*(1), 123-128. https://doi.org/10.1016/j.aap.2008.10.003

[86]. Xue, Y., Shi, J., Li, X., Zhang, G., Zhang, H., & Tian, Z. (2023). An energy-saving road-lighting control system based on improved YOLOv5s. *Computation*, *11*(3), 66. https://doi.org/10.3390/computation11030066

[87]. Yigitcanlar, T., Kamruzzaman, M., Foth, M., Sabatini-Marques, J., da Costa, E. M., & Ioppolo, G. (2019). Can cities become smart without being sustainable? A systematic review of the literature. *Sustainable Cities and Society*, *45*, 348-365. https://doi.org/10.1016/j.scs.2018.11.033

[88]. Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of Things for smart cities. *IEEE Internet of Things Journal*, *1*(1), 22-32. https://doi.org/10.1109/jiot.2014.2306328

[89]. Zeng, F., Pang, C., & Tang, H. (2024). Sensors on Internet of Things systems for the sustainable development of smart cities: A systematic literature review. *Sensors*, *24*(7), 2074. https://doi.org/10.3390/s24072074

[90]. Zhu, K., Dong, S., Xu, S. X., & Kraemer, K. L. (2006). Innovation diffusion in global contexts: Determinants of post-adoption digital transformation of European companies. *European Journal of Information Systems*, *15*(6), 601-616. https://doi.org/10.1057/palgrave.ejis.3000650