



Artificial Intelligence of Things (AIoT): A Systematic Review of Smart Applications

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Abstract

With the rapid growth of the Internet of Things (IoT), ever greater quantities of complex data are created. To analyze this data and take better decisions, Artificial Intelligence (AI) especially in the form of Machine Learning (ML) and Deep Learning (DL) has been widely adopted, which has led to the rise of Artificial Intelligence of Things (AIoT). This study is a systematic literature review consisting of 79 peer-reviewed articles published in the last five years (from 2019 to 2024), following the PRISMA guidelines. We thoroughly searched major databases, and used strict quality assessment and inclusion/exclusion criteria for assessing the influence of the AI in five fields, namely, Smart Home, Smart Transportation, Smart Education, Smart Grid, and Robotics. Based on our quantitative results, we notice that the most studied domain is the Smart Transportation, and the most used technologies are recurrent models such as LSTM and convolutional networks (CNN). The review compares the performance of the models critically, by considering the evaluation metrics including accuracy, latency, and computational cost. Moreover, the paper discusses key challenges and limitations in the existing AIoT deployments such as data privacy, cybersecurity threats, power consumption and explainability of the models. This review aims to fill the gap of literature by providing a structured reference towards future research on scalable, secure and energy-efficient AIoT systems.

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1. Introduction

The Internet of Things (IoT) is now a giant network of billions of physical devices around the world, producing vast amounts of complex, high-speed, and diverse data unlike anything that has come before it. This constant stream of data offers some tremendous opportunities to monitor and automate in real-time, but the challenge of managing, processing and turning this vast and varied big data into actionable insight is overwhelming on the infrastructure and compute side. In the past, traditional data processing protocols had a hard time scaling efficiently to handle the variety and volume of today's IoT network streams. This huge amount of data is as main driver for the current technological shift toward Industry 4.0 paradigms.

To make the best use of this data, Artificial Intelligence (AI) – specifically Machine Learning (ML) and Deep

Learning (DL) – is being embedded within IoT systems and the term Artificial Intelligence of Things (AIoT) is introduced, which is expected to lead to technological autonomy and intelligent decision making [1], [2]. In the context of modern architectures, advanced deep learning models are very good at processing complex sensory streams. In smart home, for example, ML can be utilized to predict user behaviors that, in turn, enhances the security and energy efficiency [3]. In the same manner, the use of ML and DL techniques enables the prediction of smart grids, leading to efficient maintenance plans and even energy distribution [4]. AI-powered IoT solutions enable real-time evaluation of student performance in educational settings [5]. AI has introduced a new perspective in daily life, for example, recent extensive studies [6] suggest how the AIoT frameworks are helpful in optimizing real-time data processing and autonomous decision-making in a variety of smart applications from intelligent transportation

to urban infrastructures. At the same time, AI-powered systems can also help to detect security weaknesses in IoT devices before they even occur, including DDoS attacks [7]. In addition, ML/DL integrated IoT allows real-time processing which is best performed by CNN and RNN models for image analysis and natural language processing respectively [8], [9]. Computational, data, and security issues are critical for successful AIoT implementation [10], while AI enhances data-driven decision-making and operational efficiency [11].

The disruptive potential of AI is illustrated in the literature with many examples of AIoT applications that are extremely specialized. As an example, the deep learning frameworks have been successfully used to optimize smart home energy management systems [12]. LSTM networks are used to make strong short-term traffic flow forecasts for smart transportation systems [13]. Moreover, the use of AI has yielded impressive outcomes in the development of smart grids using deep learning integrated blockchain solutions for cyber-intrusion detection [14] and optimization of resource allocation in large-scale IoT architectures [15]. Further, in the field of robotics, deep reinforcement learning algorithms are being actively used to optimize autonomous UAV trajectories, and also to integrate sensing operations into the same [16]. Nevertheless, this wide scope is not matched by the current research landscape, which is fragmented. The surveys in the past tend to be either a general narrative description or analysis of an individual engineering layer. A detailed and systematic literature review to critically and quantitatively compare the execution time and specific performance of the models in relation to the accuracy, latency and energy efficiency for multiple interrelated smart everyday applications is lacking. This review aims to fill that gap by systematically and analytically reviewing the latest advancements in AIoT from 2019 to 2024.

To overcome the gaps in the literature, this study is based on a thorough study of 79 peer-reviewed articles. This paper has the following main contributions:

- We define a systematic taxonomy that covers 5 main applications of AIoT: Smart Home, Smart Transportation, Smart Education, Smart Grid and Robotics.
- We provide a comprehensive comparison of ML and DL models, assessing key metrics such as model performance, latency, and computational limitations in various research studies.
- We investigate some of the recurring issues with deployment, such as data privacy, cybersecurity, energy consumption, and explainable models, and chart an empirical course for further research.

The rest of this paper will be structured as follows: Section 2 describes the methodology and review protocol used in the systematic mapping study, based on the

PRISMA framework. The detailed review of section 3 identifies and tabulates the ML and DL applications pertaining to the selected IoT domains and summarizes the key findings from this section. Section 4 presents a detailed discussion of cross-domain trends, critical analysis and methodological limitations. Section 5 concludes the paper and proposes future research directions.

2. Method and Systematic Mapping Study's Approach

Internet of Things (IoT) devices incorporate and augment perception, learning, reasoning, and behavioral functions using (AI) technologies, particularly Machine Learning (ML) and Deep Learning (DL). Since there is lots of scientific work on AI-powered IoT systems, it's not feasible to consider all preliminary research. Hence, this systematic mapping review will help in determining the main research directions, emerging technologies, and disruptive potential of AIoT in five key domains: Smart Home, Smart Transportation, Smart Education, Smart Grid, and Robotics.

The study is conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure scientific rigor, transparency and reproducibility. We apply these standards to offer a comprehensive mapping that goes beyond general narrative descriptions of AI models that optimize IoT frameworks, and provides a structured evaluation of technological advancements in this space.

2.1 Search Strategy

The research was done through literature research, from January 2019 to early 2024. The main electronic databases that were used were Wiley Online Library, IEEE Xplore, Springer Nature, Elsevier, Taylor and Francis, ACM Digital Library, and Scopus. The search string was designed to use the Boolean operator OR between the five application domains, to obtain a broad search and retrieve relevant literature throughout the scope of our multi-domains. The search equation used was very refined:

("Internet of Things" OR "IoT") AND ("Artificial Intelligence" OR "AI" OR "AIoT") AND ("Smart Home" OR "Robotics" OR "Smart Grid" OR "Smart Education" OR "Smart Transportation").

2.2 Inclusion and Exclusion Criteria

To preserve the breadth as well as the-depth of this study, our eligibility criteria were further refined as follows:

- ❖ Inclusion Criteria:

English Language papers published from the year 2019 to 2024:

- Peer-reviewed journal articles and high-quality

conference proceedings, with the understanding that pioneering AIoT innovations often come from these types of publications.

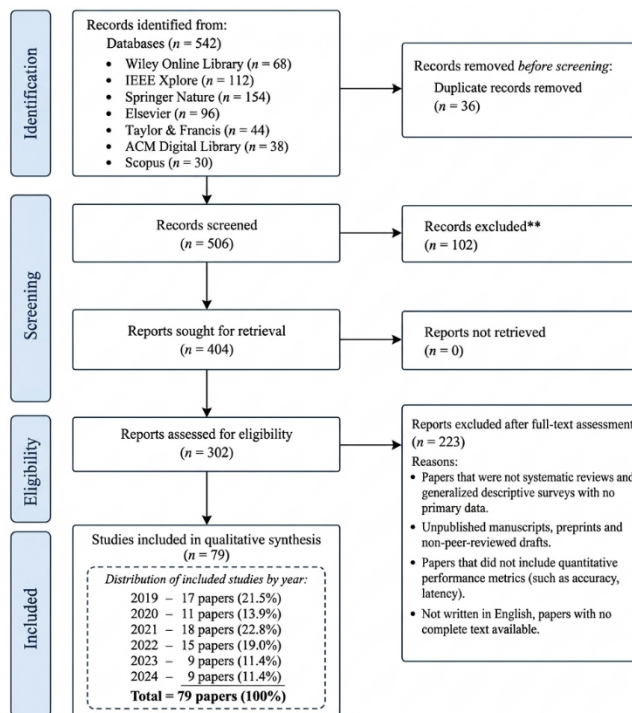
- Research that uses ML or DL models in one of the five domains.
- systematic reviews and comparative surveys that offer useful benchmarks and insights.

❖ Exclusion Criteria:

- Papers that were not systematic reviews and generalized descriptive surveys with no primary data.
- Unpublished manuscripts, preprints and non-peer-reviewed drafts.
- Papers that did not include quantitative performance metrics (such as accuracy, latency).
- Not written in English, papers with no complete text available.

2.3 Data Extraction and PRISMA Flow

The systematic selection process is shown in the PRISMA 2020 flow diagram **Figure 1**. During the first phase of identification, 542 records were retrieved from 7 main electronic databases (IEEE Xplore, Springer Nature, ScienceDirect etc.). Of the 506 articles which had been screened, 102 articles were excluded after removing 36 duplicate records by screening the articles according to their title and abstract. Then, it was requested that the 404 reports be retrieved and all were retrieved. Of the 302 reports assessed for eligibility, 223 were excluded because we did not have primary data or quantitative measurement of performance or were not systemic/unpublished draft reports. Finally, 79 peer-reviewed articles were retained for final qualitative synthesis that fulfilled all quality criteria. These annual distributions are indicative of the high-quality studies that have been selected for inclusion between 2019 and 2024 as part of the final stage in the PRISMA process.



* Database search was limited to publications between 2019 and 2024.
 ** Records excluded after screening titles and abstracts.

Figure 1. PRISMA 2020 flow diagram to show the systematic selection of the included studies.

The annual distribution of these 79 publications from 2019 to 2024 is illustrated in **Figure 2**, showing 17 papers in 2019, 11 in 2020, 18 in 2021, 15 in 2022, and 9 papers each in 2023 and 2024. This is only natural, but with the advancement of technology and the significance of IoT and the use of AI in IoT, one should expect to see more research papers published. However, due to the fact that this study was limited to only free and open-source research papers, we found a relative decline in the number of studies included from more recent years, as many impactful journals have moved towards closed source or paid access.

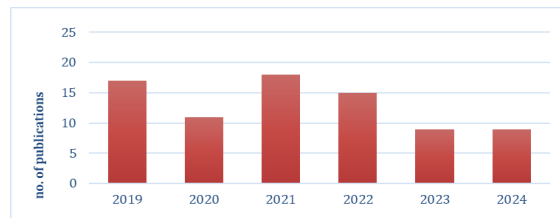


Figure 2. Publications annually for this study (2019-2024).

3. ML and DL in IoT applications

The amalgamation of machine learning (ML) and deep learning (DL) within Internet of Things (IoT) architectures augments applications by analyzing extensive datasets produced by IoT devices, with deep learning leveraging sophisticated models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)

to enhance IoT functionalities through superior data processing and decision-making for precise, real-time analytics. Applications AI in IoT systems are shown in **Figure 3**. The function of ML and DL in IoT applications is covered in these subsections.

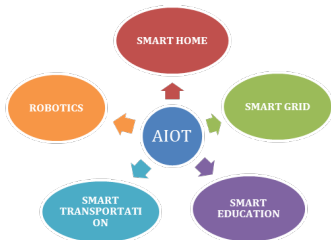


Figure 3. AIoT Applications.

3.1 Smart Home

AI integration in smart homes enhances security, efficiency, and convenience. It automates tasks like lighting, security, and thermostat management, and can send predictive maintenance signals. Future smart homes will be more intuitive, connected, and enjoyable, making daily life easier.

1. Human Emotion Detection, Recognition and Automation

Human Emotion Detection, Recognition and Automation (HEDRA) utilizing DL (CNN-LSTM hybrid model) and sensor data analysis is a useful method for classifying human emotions, according to [18]. Data from smartphones and wearable gadgets are utilized. Also [19] proposed Human Activity Recognition system (HAR) using DL Stacking Denoising Autoencoder (SDAE), Light GBM and sensor data. In [20] suggested a smart home system that employs DL, Long Short-Term Memory (LSTM) to identify human activity and carry out preset operations in response to the activity. This system is efficient at identifying patterns in sequential data.

2. Smart Home Ecosystems

In the context of smart home ecosystems (SH-Eco), the article [21] examines AI applications in insurance by using DI (Neural Networks) to determine the patterns and obstacles in the application of AI in insurance. In order to improve user experience, the study [22] investigated how ML such as Decision Trees maybe included into smart home ecosystems. Results are highly interpretable. This

study [23] examined the ways in which the Internet of Everything (IoE) links individuals, institutions, and intelligent objects. It examines service ecosystems and networked business models, offers a new classification of smart objects using ML.

3. Smart Home Data Transmission

To improve efficiency and lower latency in Smart Home Data Transmission (SHDT) this research [24] proposed a ML method for data transmission optimization by using Support Vector Machines (SVM) to streamline data transfer procedures in IoT networks in smart homes this method consumed lowers latency and increases efficiency.

4. Smart Home Security

The studies establish a robust framework for Smart Home Security (SH-Sec), employing ML and DL techniques to identify and mitigate security threats, ANN for multiclass classification and LSTM for binary classification, the study [25] introduced a revolutionary SDN architecture intended to improve security in smart homes settings. The study [26] investigated how Deep Neural Network (DNN)), which can dynamically adjust to emerging threats, can improve the security of smart home IoT networks. The goal of [27] is to increase detection accuracy and decrease false positives by creating DL(CNN) model for RT-anomaly detection in smart home IoT networks. Study of [28] investigates DL and ML strategies intended to defend smart home IoT devices against Man-in-the-Middle (MitM) assaults. The goal is to create strong AI models capable of identifying and stopping MitM assaults. This study [29] presents an innovative framework for bolstering cybersecurity in IoT ecosystems through the integration of an ensemble learning model with the Artificial Orca Algorithm, aimed at safeguarding IoT devices against diverse cyber threats. The study [30] offers a framework for using distributed ML approaches to improve the MQTT protocol’s security. Its main goal is to create a safe improvement for the MQTT protocol and fix security flaws.

5. Intelligent HVAC

Intelligent HVAC (Int-HVAC) systems use sensors to monitor and regulate airflow, utilizing ML to enhance performance, improve occupant comfort, and reduce energy use [31].

Table 1 provides a summary of the major applications and the impact of ML and DL on Smart Home.

Table I. Summary of Applications and Impact of ML and DL on Smart Home.

Ref.	year	IoT Domains	aim	Tech. Used	Algorithms Used	AI impact
[18]	2019	HEDRA	Identify/track human emotion and activity	DL	CNN-LSTM hybrid model	Accurate activity and emotion ID

[19]	2019	HEDRA	Sensor-driven activity recognition	DL	SDAE and Light-GBM	Capable of identifying human activity
[20]	2020	HEDRA	HAR-driven home automation.	DL	LSTM	High-efficiency sequence analysis.
[21]	2021	SH-Eco	Insurance AI-obstacles Analysis.	DL	NNs	high prediction accuracy for claims.
[22]	2021	SH Eco	Analyzing interaction responsiveness	ML	Decision Trees	Results are highly interpretable.
[23]	2021	SH-Eco	Capability-aware smart thing classification	ML	RF	Cross-sector efficiency/decision making
[24]	2023	SHDT	Streamline smart home IoT data transfer	ML	SVM	lowers latency and increases efficiency.
[25]	2022	SH-Sec	SDN-AI SH-security integration	ML, DL	ANN and LSTM	Adaptive resource/threat management.
[26]	2023	SH-Sec	Enhance adaptive smart home threat defense	DL	DNN	Real-time adaptation to emerging dangers.
[27]	2023	SH-Sec	Enhance smart home anomaly detection accuracy	DL	CNN	high precision in identifying irregularities.
[28]	2024	SH-Sec	Secure AI-driven MitM mitigation.	ML, DL	CNN,RF, kNN, and NB.	Robust MitM Protection
[29]	2024	SH-Sec	Robust multi-attack IoT defense	ML, DL	Ensemble ELM/ GRU/ BiLSTM via AOA and MPA	Precision-driven IoT sensing.
[30]	2024	SH-Sec	Secure MQTT	ML	Distributed ML	Optimized IoT-MQTT Comm
[31]	2022	Int-HVAC	Non-intrusive ML occupancy sensing	ML	RF	High accuracy (99.7%)

3.2 Smart Transportation

With IoT and AI at the front, smart transportation gets to evolve through the capabilities it imposes on traffic control, safety, and efficiency. The AI-powered systems analyze the large registers of IoT data to forecast and control the traffic flow more precisely.

1. Traffic Flow Prediction and Control

Traffic Flow Prediction and Control (TFPC) is an area that uses complex models to control urban traffic. There have been several studies on spatial and temporal forecasting. For instance, in [32] spatially and temporarily forecasted traffic behavior through K-Nearest Neighbors (KNN) and LSTM, thus enhancing the accuracy of the traffic flow predictions. the authors in [33] used LSTM-RNN to predict traffic conditions well ahead of time in smaller areas in the urban zone. the article [34] was able to use deep autoencoders to predict short-term traffic congestion very accurately. by using RNN and GPS Data, the study [35] was able to predict the traffic congestion in large transits. A hybrid deep learning architectures with the ability to model complex spatio-temporal dependencies have been increasingly adopted in recent advances in traffic flow management. To combine the advantages of spatial relationship and the temporal feature, Li et al. [36] proposed to use a hybrid of Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM) networks, which achieves to improve the prediction accuracy. Now by building on this, Yang et al. [37] proposed feature enhancement methods by applying attention mechanism on LSTM, which successfully tackled the potential long-term dependency problem in the traffic flow forecasting. In addition, Zhang [38] conducted a detailed summary of the existing mainstream methods, and Yin et al. [39] performed a detailed analysis on the deep learning-based methods, proposed a taxonomy, and marked the potential research

directions regarding deep learning in the intelligent transportation system. All these studies show that deep learning models perform better in predicting real-world traffic situations. The researchers in [40] experimented by integrating Ensemble Tree-Based models with the sensor data and they found themselves with the best urban congestion forecasts. in [41] handled the problem of disordered traffic by using DL(LSTM) to maximize IoT data. The authors [42] involved Gradient Boosted Decision Trees (GBDT) models to check out weather conditions on traffic congestion.[43] brainstormed ideas in relation to ML, Elastic Net Regression (ENR)that have to do with network optimization in transportation. about Comparative ML Analysis for Traffic Forecasting,[44] devised a plan for ML models' analysis to track the trends achieving 90% of the real value. At a higher efficiency level, [45] proposed TD2-DL, a novel DL-based model for predicting the speed of traffic propagation. in [46] have advanced the technologies by proposed DL model which is used in traffic congestion control in the form of Intelligent Adaptive On-Demand Learning- Traffic Congestion Control (IAOADL-TCC).

2. Traffic Signal Control

This study [47] proposed a deep reinforcement learning-based traffic light control method using high-resolution event-based data. Aiming to achieve cost-effective and efficient adaptive traffic signal control (TSC). Paper [48] proposed a deep reinforcement learning model to control and optimize traffic signal cycles in order to improve traffic flow and reduce intersection congestion. Study [49] adapted the asynchronous n-step Q-learning method to adaptive signal regulation using a two-hidden-layer artificial neural network in order to optimize traffic flow. The model presented in this study [50] was built on a DL framework and uses a multi-layer Extreme Learning Machine (ELM) to smooth a signal by taking into account congestion

information at all potential connection points and control traffic at intersections.

3. Traffic Accident Detection and Prevention

The Traffic Accident Detection and Prevention (TADP) systems are essential to improving road safety. Lately, some of the methods foreseen were based on the combination of Machine Learning (ML) and IoT devices , such as a paper [51] utilized ML and a Raspberry Pi camera to detect objects in real time and classify various objects, such as automobiles, animals, and humans, then uses voice messages to advise drivers to slow down, was able to increase road safety by reducing collisions. A sophisticated system [52] used AI and IoT to identify mishaps and instantly upload data to the cloud. After that, a DL model verifies the information and starts the rescue effort and emergency response delays. A ML Support Vector Machine (SVM), Pi camera, Raspberry Pi and other sensors were used in [53] to create prototype, track driver behavior and avert collisions.

4. Car Park Occupancy Prediction

To enhance the efficiency of urban traffic, Car Park Occupancy Prediction (CPOP) plays a crucial role. Recent approaches have included integrating Energy harvesting and Transport Mode Detection (TMD) utilizing DL attention-based LSTM were used in the study [54], to

identify the mode of transportation using a kinetic energy harvester, and 97% accuracy was achieved.

5. Ride-Hailing Demand prediction

Accurate Ride-Hailing Demand Prediction (RHDP) is essential for efficient resource allocation in urban transportation. A new spatiotemporal multi-graph Deep Learning (DL) convolution architecture has been proposed recently [55] for ride-hailing demand estimation, which has greatly enhanced the forecasting accuracy.

6. Route Planning-Urban Navigation

The effective planning of an urban road network is a key factor for improving transportation efficiency, which is called Route Planning - Urban Navigation (URP). Recent research works [56] have used Deep Learning (DL) for the design of optimized routes and traffic pattern estimation using double-rewarded value iteration network.

Table 2 provides a summary of the major applications and the impact of ML and DL on Smart Transportation.

Table 2. Summary of Applications and Impact of ML and DL on Smart Transportation

Ref.	year	IoT Domains	aim	Tech. Used	Algorithms Used	AI impact
[32]	2019	TFPC	Enhanced traffic flow forecasting	ML, DL	KNN and LSTM	Spatio-temporal feature fusion
[33]	2019	TFPC	Enhanced ST-urban traffic forecasting	DL	LSTM-RNN	Precise ST-forecasting
[34]	2019	TFPC	Optimize ST-congestion forecasting	DL	Autoencoders	High ST-Precision
[35]	2019	TFPC	GPS-based congestion forecasting	DL	RNN	Optimal congestion accuracy
[36]	2019	TFPC	Traffic flow prediction	DL	GCN, LSTM	Enhanced spatio-temporal accuracy.
[37]	2019	TFPC	Feature enhancement for prediction	DL	Attention-LSTM	Optimized long-term dependency capture.
[38]	2020	TFPC	to improve urban planning.	DL	Generic	Established baseline for model performance metrics.
[39]	2021	TFPC	Analysis of deep learning traffic methods	DL	Generic/Deep Learning	Formulated taxonomy for adaptive learning architectures.
[40]	2021	TFPC	Optimizing traffic forecast precision.	ML	(ETB) models	High efficiency/XAI.
[41]	2022	TFPC	Enhanced IoT-driven traffic management.	DL	LSTM	Captures long-term patterns.
[42]	2022	TFPC	Weather-congestion analysis	ML	GBDT	High generalizability.
[43]	2022	TFPC	Optimize transport network efficiency.	ML	(BRR)	High data-efficiency.
[44]	2023	TFPC	Evaluating optimal traffic models.	ML	(ENR)	Interpretable and adaptable.

[45]	2023	TFPC	Forecast speed propagation	DL	LSTM model	high accuracy of predictions
[46]	2024	TFPC	Optimize urban traffic efficiency	DL	HCNN-ALSTM	Optimal traffic management
[47]	2019	TSC	Efficient adaptive signal control.	DL	(DRL)	Improving throughput
[48]	2019	TSC	Optimizing intersection flow.	DL	DRL	High-performance signal control
[49]	2019	TSC	Adaptive flow control.	ML	Dual-layer ANN	Responsive flow adjustment
[50]	2022	TSC	Regulating intersection traffic.	DL	Deep Extreme ML	RT congestion awareness
[51]	2020	TADP	Alert-driven collision avoidance.	ML	RF	high accuracy of object detection
[52]	2022	TADP	to reduce emergency response delays.	DL	CNN	Precise incident detection
[53]	2022	TADP	Incident prevention and rapid response.	ML	SVM	High-efficiency RT tracking
[54]	2019	CPOP	Bespoke kinetic TMD	DL	Attention-based LSTM	Accurate and energy-efficient detection
[55]	2019	RHDP	Optimize ride-hailing demand forecasting.	DL	(ST-MGCN)	High-accuracy forecasting
[56]	2019	URP	Route optimization.	DL	(DRVIN)	High-precision routing

3.3 Smart Education

Through the creation of more individualized, effective, and captivating learning experiences, the confluence of machine learning (ML), deep learning (DL), and the internet of things (IoT) is revolutionizing the education. Large volumes of data may be gathered and analyzed thanks to these technologies, which can improve education in a number of ways.

1. Personalized Learning

Personalized Learning (PL) is increasingly empowered by IoT technologies. For instance, an RFID and IoT-based attendance system with ML verification is proposed in the study [57]. A camera with a Multi-task Cascaded Convolutional Network (MTCNN) model is used to perform the Verification Step. Once both parties agree, the students' attendance will be noted. If not, parents will receive a notification about the student's attendance. Boost attendance accuracy and security. paper [58] suggested a smart learning environment for STEM education that teaches data-driven thinking. This study [59] discusses online education using CNN as ways to increase student engagement in online learning environments. Study [60] developed a framework to increase the effectiveness of intelligent educational systems by integrating cloud computing with ML hybrids (LSTM and 1D CNN) on edge devices. This study [61] explained how IoT integration with AI can be utilized in education to transform traditional teaching, and producing an innovative method of

instruction and improved campus management.

2. Intelligent Tutoring

The domain of Intelligent Tutoring (IT) explores the integration of robotics with DL adaptive learning algorithms to revolutionize education are described in the study [62], Clever tutoring robots and adaptive learning in smart education. Using ML, Paper [63] examined the effectiveness of robotic process automation in the classroom. Compare human and robot teachers in early-warning systems, and to enhance English learning, the study [64] investigated whether secondary students intend to continue using AI-powered tutoring.

3. Higher Education Students' Performance

The study about Higher Education Students' Performance (HESP) is directed towards predictive analytics to improve academic outcomes. For instance, article [65] developed a model to forecast university course dropout rates using ensemble ML with two layers (stacked generalization) to predict student dropout rates. paper [66] Develop a model to predict exam outcomes, utilizing various ML approaches (SVM, decision trees) to forecast exam results for students.

4. On Line Education Students' Outcomes

For optimizing e-learning environments, it is important

to be able to predict Online Education Students' Outcomes (OESO). Several recent studies have used a variety of ML approaches, including logistic regression and random forest, the study [67] developed a model to forecast the success of students in online courses. **Table 3** provides a

summary of the major applications and the impact of ML and DL on Smart Education.

Table 3. Summary of Applications and Impact of ML and DL on Smart Education

Ref.	year	IoT Domains	aim	Tech. Used	Algorithms Used	AI impact
[57]	2021	PL	Secure-Accurate Attendance	ML	MTCNN	High security and accuracy
[58]	2021	PL	DL-driven STEM optimization.	DL	DL, customize learning	Enhanced Learning Outcomes
[59]	2023	PL	Enhanced E-learning Engagement.	DL	VD-CNN, All-CNN, and NiN-CNN	Optimal Net-metrics/Design
[60]	2024	PL	Optimized IES Efficiency.	DL	Hybrid LSTM and 1D CNN	Enhanced personalized learning/engagement
[61]	2024	PL	Transforming Traditional Pedagogy.	ML and DL	AI, AR, VR, gamification, and adaptive learning	Innovative Pedagogy and Admin
[62]	2022	IT	AI-driven Pedagogy.	DL	Robotics and Adaptive Learning	Optimal Individualized Aid
[63]	2023	IT	In early-warning systems, contrast human teachers with robots.	ML	NLP, predictive analytics, RPA	Enhanced Monitoring and Response
[64]	2023	IT	Use AI to improve English learning.	ML	AI-driven tutoring algorithms	Optimized Learning Performance
[65]	2021	HESP	Student Dropout Forecasting.	ML	Stacked Ensemble	Predictive accuracy and prompt action
[66]	2022	HESP	Exam Result Prediction.	ML	SVM	Academic Decision-Support
[67]	2022	OESO	E-learning Result Prediction.	ML	RF, logistic regression	Improved design of online courses

3.4 Smart grid

Smart grids, advanced electrical systems, use real-time energy consumption data and IoT devices to control electricity effectively. Machine Learning and Deep Learning are integrated to improve performance, optimize energy management, protect against threats, estimate state, detect faults, and predict energy demand, ensuring reliable power supply.

1. Energy Management

In a study by [68] a new hybrid model of forecasting electrical Energy Management (EM) was proposed using deep DL Genetic Wind Driven Optimization (GWDO) in combination with the Factored Conditional Restricted Boltzmann Machine (FCRBM). To predict future electrical energy consumption. By [69], the authors presented a study assessing the grid impact from using ML and smart grids for the IoT. The focus was on the two applications that arise, namely demand-side management (DSM) for renewables and energy storage for grids. IoT-based smart energy management system with accurate forecasting and load planning for renewable energy using an ML SVM regression model based on PSO, was proposed in study

[70]. A real-time smart building management system that uses ML to integrate physical and computational components was proposed in a work by [71], To create a comfortable, safe, and energy efficient space.

2. Smart Grid Cybersecurity

Smart Grid Cybersecurity (SGC) is a critical domain in modern power systems. Currently, only by using the neural network model (NNM) in combination with an RF model it is possible to improve theft detection.[72] proposed CNN-RF to identify instances of electricity theft with even more accuracy, improving both recall and precision. The authors in [73] utilized ANN trained with Whale Optimization Algorithm (WOA) to implement cyber intrusion detection, improving the detection accuracy of the algorithms. Unlike other researchers that have only used Naive Bayes classifiers, the authors in [74] presented a security system for the IoT-based smart grid, which combines ML, NB and IoT. Moreover, discuss how the combined solution enhances protection systems and vulnerability

management.

3. Smart Grid Stability

Power distribution cannot be relied upon without Smart Grid Stability (SGS). Recent efforts have involved a use of an Iterated Random Forest (IRF) and Partial- Mutual-Information (PMI) among the features of different datasets,

has been successfully used by [75] to describe the test results of one of the experiments. According to [76], AI ensemble techniques, such as DS based DL and voting algorithms, have been proposed to improve the reliability and stability of the smart grid system. **Table 4** provides a summary of the major applications and the impact of ML and DL on Smart Grid.

Table 4. Summary of Applications and Impact of ML and DL on Smart Grid

Ref.	year	IoT Domains	aim	Tech. Used	Algorithms Used	AI impact
[68]	2020	EM	Smart grid energy load forecasting.	DL	GWDO with Factored FCRBM	High precision and quick convergence
[69]	2020	EM	Secure energy-efficient grid.	ML	ML classifier	Robust grid efficiency
[70]	2020	EM	Predictive energy optimization.	ML	SVM regression based on PSO	Precise prediction/energy management
[71]	2021	EM	Secure energy-efficient comfort.	ML	RT-learning and model-based control	Subjective-aware building optimization
[72]	2019	SGC	Optimize electricity theft detection	ML	RF and CNN	High-performance electricity theft detection
[73]	2020	SGC	Enhance cyber intrusion detection accuracy.	ML	ANN and WOA	Precise multi-attack detection
[74]	2021	SGC	Secure grid management	ML	(NB)	Enhanced Grid Operations
[75]	2021	SGS	Robust stability evaluation.	ML	(IRF) and (PMI)	High-precision efficiency
[76]	2024	SGS	Improve smart grid stability/dependability	DL	DS-based and Voting Ensembles	High dependability and stability

3.5 Robotics

The amalgamation of Machine Learning and Deep Learning with the Internet of Things (IoT) facilitates robots in managing extensive data, refining autonomous navigation, and enhancing performance.

1. Unmanned Aerial Vehicles

The article [77] used drone imagery with DL(CNN) for surveillance to improve the monitoring of scenes and smart agricultural environments.[78] Utilized DL to plan Unmanned Aerial Vehicles (UAVs) trajectories, establishing the Age of Information (AoI) concept to ensure information freshness, and applying the DDPG approach to plan UAV trajectories, ensuring freshness with low throughput constraints. A study [79] proposed a private blockchain-envisioned security architecture for drone-assisted healthcare, utilizing a car network to monitor health and prevent crashes, enhancing security in ML-powered IoT-based healthcare systems. A blockchain-based outdoor medical service delivery system that makes use of UAVs was proposed by a study [80]. The new blockchain technology presents a viable answer to this data security and privacy challenge. the study [81] used reinforcement

learning plans Using Deep Q-Network Reinforcement Learning (DQN), efficient and well-designed UAV routes are created to optimize UAV routes for intelligent farming. [82] described how to use ML Methods for Scheduling Tasks(MLTS Strategies) to schedule multi-service UAV emergency tasks. To optimize the scheduling of UAV tasks during emergencies. A study by [83] explored the use of UAVs as flying base stations in emergency communication systems, proposing a Deep Q-Network DQN-based resource distribution strategy for optimal system efficiency. A network of several UAVs for ML-based surveillance was proposed by [84]. Computational UAVs employed ML techniques to forecast criminal activity, subsequently deploying deterrence UAVs to enhance predictive surveillance efficacy. Researchers in [85] a cooperative, model-free Deep Reinforcement Learning (DRL) approach for multiagent UAV management is introduced to optimize energy utilization and enhance user surveillance capabilities. Study [86] used DL for data analytics and privacy protection in IoT-enabled healthcare.

2. Cleaning Robots

A real-time obstacle avoidance for mobile robots using DL-CNN has been presented in [87]. At the same time, about

the robot autonomous operating room cleaner, [88] had proposed a robot with DL techniques for path planning and image recognition function which is effective and healthy in the operating room cleaning. Study [89] combined the model of an Artificial Potential Function (APF) and a PID Controller to the cleaning robot, which thus had a complete improvement in performance. In order to enhance the autonomous navigation capability of mobile robots in unknown environments and thus improve their adaptability and efficiency, [90] employed deep reinforcement learning (DQN and DDQN). According to the study by [91] they were the first to invent the first intelligent floor cleaning robot that incorporated IoT and ML algorithms to enhance removal of obstacles and planning of paths, thus upgrading the efficiency. In order to improve the capability of the Hybrid Automated and Manual Floor Cleaning Robots, [92] reexamined the ML-based path planning and control systems for these robots which led to greater versatility and

efficiency.

3. Voice assistant

To build a more accurate and efficient local voice assistant, a study [93] presented deep learning-based techniques such as multichannel acoustic echo cancellation and acoustic modeling to improve the quality and recognition of voice signals. In [94] ML and natural language processing (ML) were used to develop a voice controlled IoT solution that improved the control and interaction with IoT devices. The study [95] discussed the problems of voice liveness detection based on IoT technologies, and proposed a hybrid (self-attentional ResNet) model combined with LightGBM for voice classification. **Table 5** provides a summary of the major applications and the impact of ML and DL on Robotics.

Table 5. Summary of Applications and Impact of ML and DL on Robotics

Ref.	year	IoT Domains	aim	Tech. Used	Algorithms Used	AI impact
[77]	2019	UAVs	Enhance smart agricultural environment monitoring	DL	CNN	High-capacity Monitoring
[78]	2020	UAVs	Optimal UAV trajectory for ITS.	DL	DL-based trajectory planning and AoI	Timely AoI and efficient trajectory
[79]	2020	UAVs	Secure AI-IoT healthcare systems.	ML	Secure AI/ Blockchain algorithms	Secure/private medical services
[80]	2020	UAVs	Optimize healthcare delivery security	ML	BC/ML delivery	Secure-Efficient Delivery
[81]	2021	UAVs	UAV route optimization.	ML	(DQN)	Effective and well-designed UAV routes
[82]	2021	UAVs	Emergency UAV scheduling optimization.	ML	MLTS Strategies	Optimal task resource scheduling and allocation
[83]	2021	UAVs	Optimal UAV-UDN resource allocation.	DL	DQN, or Deep Q-Network	Enhanced effectiveness in allocating resources
[84]	2022	UAVs	To enhance predictive surveillance.	ML, DL	MAS-based predictive ML algorithms	Optimize surveillance precision/efficiency
[85]	2022	UAVs	Enhanced autonomous UAV surveillance.	DL	(MADRL)	Optimize UAV reliability/ collaboration
[86]	2022	UAVs	Enhance healthcare analytics and privacy.	DL	DL: Analytics /Privacy	Increased analytics efficiency/privacy
[87]	2020	Cleaning Robots	Enhance vacuum navigation and obstacle avoidance.	DL	CNN	High-accuracy real-time detection
[88]	2021	Cleaning Robots	Optimize operating room hygiene/ cleaning effectiveness.	DL	DL and Image Recognition	Improved efficiency and cleanliness
[89]	2021	Cleaning Robots	Closing theory/practice gap.	ML	Hybrid ML/APF/PID controller.	Optimize performance/flexibility/ efficiency
[90]	2022	Cleaning Robots	Improved navigation/ flexibility	DL	DQN/DDQN	Flexible, efficient navigation
[91]	2023	Cleaning Robots	Optimize robotic cleaning intelligence/efficiency	ML	Avoidance ML-Nav and Avoidance	Optimized cleaning/obstacle management
[92]	2023	Cleaning Robots	Optimize adaptive robotic cleaning.	ML	ML-based path planning and control	Flexible and effective cleaning abilities

[93]	2019	Voice assistant	Speech signal enhancement	DL	Statistical/Acoustic models	Robust speech recognition via deep learning integration.
[94]	2021	Voice assistant	Enhanced IoT device control.	ML	ML,NLP	Improved voice-based control
[95]	2023	Voice assistant	Enhanced Voice Liveness Detection	ML/DL	ResNet , LightGBM	Accurate voice classification for IoT

4. Results and discussion

The following application domains were identified in the study, as illustrated in **Figure 4**, and our analysis showed 5 application domains and that smart transportation is the top AIoT application domain, followed by robotics:

a. Smart Home: Includes Human Emotion Detection, Recognition and Automation (3 papers), Smart Home Ecosystems (3 papers), Smart Home Data Transmission (1 paper), Smart Home Security (6 papers) and Intelligent HVAC (1 paper).

b. Smart Transportation: Includes Traffic Flow Prediction and control (15 papers), Traffic Signal Control (4 papers), Traffic Accident Detection and prevention (3 papers), Car park occupancy prediction (1 paper), Ride-Hailing Demand prediction (1 paper), and Route Planning (Urban Navigation) (1 paper).

c. Smart Education: Includes Personalized learning (5 papers), intelligent tutoring (3 papers), Higher education students ‘performance (2 papers) and Online education students’ outcomes (1 paper).

d. Smart Grid: Includes Energy Management (4 papers), Smart Grid Cybersecurity (3 papers) and Smart Grid Stability (2 papers).

e. Robotics: Includes Unmanned Aerial Vehicles (UAVs) (10 papers), Cleaning Robots (6 papers) and Voice assistant (4 papers).

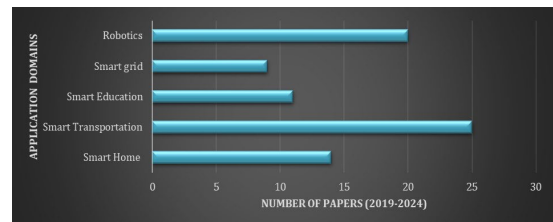


Figure 4. Application domains of AI in IoT.

Typical AI Tasks for the five IoT Domains:

a. Smart Home: The third domain identified in the reviewed literature highlights AI’s role in enhancing efficiency and innovation, primarily through object detection, recognition, and automation, with a focus on smart home ecosystems, data transmission, security, and intelligent HVAC systems. The literature on smart homes underscores the significance of AI integration in enhancing human activity recognition, system reactivity, and cybersecurity within IoT domestic settings. Current research trends are gravitating towards federated learning, privacy-preserving edge intelligence, and adaptive cybersecurity frameworks to tackle persistent issues related to data privacy and device interoperability. **Table 6** summarizes a thorough critical evaluation of IoT-Enabled Smart Home Systems.

Table 6. Comprehensive Critical Analysis of IoT-Enabled Smart Home Systems

Sub-Domain	Ref.	Primary AI Algorithms	Data Sources & Input Types	Critical Findings & Analysis	Future Research Path
HEDRA (Human Emotion Detection, Recognition and Automation)	[18–20]	CNN-LSTM, SDAE, LightGBM, LSTM	Wearable sensors, motion sensors, environmental sensors, behavioral activity logs	<ul style="list-style-type: none"> • Surely useful for emotional state detection and activities. • Hybrid CNN-LSTM models: They are used to capture the spatial-temporal dynamics. • Challenge: Privacy, real time processing. 	<ul style="list-style-type: none"> • Multimodal sensor fusion integration. • Construct privacy-preserving edge AI.
SH-Eco (Smart Home Ecosystem)	[21–23]	Neural Networks, Decision Trees, Random Forest	Smart appliance logs, user interaction data, IoT device telemetry	<ul style="list-style-type: none"> • Improves decision making and resource allocation. • Tree-Based models offer Interpretability. • Challenges: scalability, and interoperability issues. 	<ul style="list-style-type: none"> • Explore explainable AI (XAI) models. • Coherent IoT systems for data aggregation. • Improve adaptive residential settings.

SHDT (Smart Home Data Transmission)	[24]	SVM	IoT network traffic, communication logs	<ul style="list-style-type: none"> Increases the effectiveness of data transmission. Diminishes communication latency. SVM models are successfully used to classify network behavior. 	<ul style="list-style-type: none"> Focus on Smart Edge Networking. AI-enhanced communication protocols. Enable Smart Home Scalability.
SH-Sec (Smart Home Security)	[25–30]	ANN, LSTM, DNN, CNN, RF, kNN, NB, Ensemble DL	IoT network traffic, device activity logs, intrusion detection datasets	<ul style="list-style-type: none"> The accuracy of detection is enhanced by using ensemble methods. Recognizes anomalies, cyber threats, and intrusions. Complexity of IoT networks is a challenge. 	<ul style="list-style-type: none"> Federate cybersecurity education. Zero-trust IoT frameworks. Self-contained threat management systems.
Int-HVAC (Intelligent HVAC Systems)	[31]	Random Forest	Environmental sensors, occupancy sensors, temperature and motion data	<ul style="list-style-type: none"> Improves energy efficiency of HVAC systems. Allows real time management with occupancy data. Random Forest has a high level of predictive accuracy. 	<ul style="list-style-type: none"> Multimodal occupancy detection. Computer vision and sensor fusion. Energy optimization using reinforcement learning.

This critical evaluation, shown in **Table 6**, reveals the evolution from basic automated control systems to advanced and adaptive AI models in smart homes. For spatial-temporal behavior recognition and anomaly detection tasks, a comparative analysis shows that hybrid models (CNN-LSTM, HEDRA and SH-Sec) perform consistently better than conventional single-algorithm based models. But there is a significant difference in the terms of prediction accuracy and practicality: models that focus on security (SH-Sec) are able to obtain high detection accuracy by using ensemble

b. Smart Transportation: Our research indicates that the primary domain of application for artificial intelligence is intelligent transportation systems, with traffic signal control, traffic accident detection and prevention, demand prediction, car park occupancy prediction, and route planning as sub tasks of the main AI task of flow prediction and control. Current studies on IoT-driven smart transportation emphasize the utilization of spatio-temporal machine learning and deep learning techniques for traffic forecasting and management, with recurrent neural networks like LSTM and BiLSTM being particularly

learning, but they also raise the difficulty of IoT network management, which is often at the cost of real-time response. This is a performance trade-off that indicates that the present research environment is focused mostly on accuracy optimization at the expense of the important constraint of latency and decentralized data privacy. This implies that future research needs to shift from more performance-centric metrics to privacy-preserving edge-native AI paradigms to bridge the gaps of interoperability and scalability found in each of the smart home sub-domains.

effective. Moreover, challenges related to data heterogeneity and real-time scalability have prompted research into advanced methodologies such as graph neural networks and multi-agent reinforcement learning for enhanced traffic system integration. **Table 7** summarizes a thorough critical evaluation of IoT-Enabled Smart transportation Systems.

Table 7. Comprehensive Critical Analysis of IoT-Enabled Smart Transportation Systems

Sub-Domain	Ref.	Primary AI Algorithms	Data Sources & Input Types	Critical Findings & Analysis	Future Research Path
TFPC (Traffic Flow Prediction and Control)	[32–46]	KNN, LSTM, RNN, Autoencoders, RNN, GCN, Attention-LSTM, Generic, (ETB) models, (GBDT), (BRR), (ENR), HCNN-ALSTM	Traffic sensors, GPS trajectories, road cameras, historical traffic data, weather data	<ul style="list-style-type: none"> The LSTM models are particularly good at modelling temporal patterns in traffic. Using ensemble techniques increases reliability. Challenge: Environmental influence & data diversity. 	<ul style="list-style-type: none"> Explore Graph Neural Networks (GNN). Multimodal spatio-temporal learning. Digital twin architectures.
TSC (Traffic Signal Control)	[47–50]	Deep Reinforcement Learning, ANN, Deep Extreme ML	Traffic cameras, intersection sensors, vehicle counters	<ul style="list-style-type: none"> Adaptive signal control is optimized with deep RL. Supports higher traffic levels & decreases traffic jams. Challenge: Large urban networks—scalability. 	<ul style="list-style-type: none"> Multi-agent Reinforcement Learning (MARL). Coordination of complex dense urban networks.
TADP (Traffic	[51–	Random Forest,	Traffic cameras,	<ul style="list-style-type: none"> CNNs enhance safety by proactively 	<ul style="list-style-type: none"> Edge-centric video analytics.

Accident Detection and Prevention)	[53]	CNN, SVM	vehicle sensors, surveillance systems	<ul style="list-style-type: none"> detecting objects. Computer vision enhances accuracy of incident detection. 	<ul style="list-style-type: none"> Embedded in independent safety systems
CPOP (Car Park Occupancy Prediction)	[54]	Attention-based LSTM (ST-MGCN)	Traffic motion datasets, spatio-temporal mobility data	<ul style="list-style-type: none"> The attention-driven models improve congestion prediction. Reduces energy consumption in extensive networks. 	<ul style="list-style-type: none"> Transformer-driven traffic forecasting. Cross-city transfer learning.
RHDP (Ride-Hailing Demand Prediction)	[55]	Deep Learning	Mobility datasets, ride-hailing demand data	<ul style="list-style-type: none"> DL optimizes resource allocation for ride hailing. Improves service effectiveness in urban areas. 	<ul style="list-style-type: none"> Federated learning architectures. Combining different types of urban data.
URP (Urban Route Planning)	[56]	Deep Reinforcement Learning (DRVIN)	Road network graphs, GPS navigation data	<ul style="list-style-type: none"> Route optimization is better achieved in RL. Good selection of routes in the changing city environment. 	<ul style="list-style-type: none"> Collaborative AI navigation. Vehicle-to-infrastructure communication.

AS shown in **Table 7**, the systematic mapping of the domain of Smart Transportation which was found to be the most mature sector of AIoT, with the most prominent being the deep learning models, particularly LSTM and Deep Reinforcement Learning (DRL) architectures. One of the key differences is the paradigm shift from reactive to proactive traffic control, where static flow is addressed by traditional models, and temporal dynamics (TFPC) and adaptive signal control (TSC) are addressed by models developed using AI. A major difference, however, lies in the scalability of such

models: DRL models work well in micro-simulations, but in large urban areas, they suffer from high latency and computational burden. Moreover, the models such as ST-MGCN have a certain tradeoff between model complexity and energy efficiency in edge-deployed setting. As per literature, collaborative AI (moving from isolated to federated and multi-agent) is the future of this domain to address the challenges of data-siloing that hold back city-scale implementation.

c. Smart Education: Upon analysis of the reviewed literature, we identified that the fourth domain wherein A enhances efficacy and fosters innovation is within the realm of Smart Education. Personalized learning, intelligent tutoring, higher education students’ performance, and online education students’ results classification, prediction, and monitoring have emerged as the main AI tasks. AI-driven IoT advancements in smart education focus on improving personalized learning and predicting student

performance through sophisticated deep learning methodologies, including CNN engagement analysis and hybrid LSTM–CNN models. Despite these innovations, challenges concerning data privacy, AI fairness, and the interpretability of deep learning necessitate future exploration in explainable AI, multimodal analytics, and conversational AI tutors for enhanced educational frameworks. **Table 8** summarizes a thorough critical evaluation of IoT-Enabled Smart Education Systems.

Table 8. Comprehensive Critical Analysis of IoT-Enabled Smart Education Systems

Sub-Domain	Ref.	Primary AI Algorithms	Data Sources & Input Types	Critical Findings & Analysis	Future Research Path
PL (Personalized Learning Systems)	[57–61]	MTCNN, CNN variants, LSTM-CNN, AI/AR/VR Learning Models	Facial recognition cameras, learning management systems, student interaction logs	<ul style="list-style-type: none"> Personalized learning enhances learning effectiveness. The integration of AR/VR leads to a higher immersive engagement. Uses facial recognition and interaction logs. 	<ul style="list-style-type: none"> Expand Large Language Models (LLMs). Multimodal learning analytics.
IT (Intelligent Tutoring Systems)	[62–64]	Adaptive Learning Algorithms, NLP, Predictive Analytics	Student performance datasets, educational interaction logs, language learning datasets	<ul style="list-style-type: none"> Enhances support through anticipatory performance evaluation. Natural Language Processing enhances linguistic acquisition capabilities. 	<ul style="list-style-type: none"> Dialog-based AI pedagogical agents. Affective computing in educational frameworks.
HESP (Higher Education Student Performance)	[65–66]	Stacked SVM, Ensemble	Academic records, student behavioral datasets	<ul style="list-style-type: none"> Predictive analytics determines the likelihood of student dropout. Ensemble methodologies exhibit substantial predictive validity. 	<ul style="list-style-type: none"> Clear and accountable academic governance. Illuminative artificial intelligence methodologies.
OESO (Online Education)	[67]	Random Forest, Logistic Regression	E-learning interaction data, course analytics	<ul style="list-style-type: none"> Machine Learning augments the evaluation 	<ul style="list-style-type: none"> Employs multimodal analytics encompassing

Students' Outcomes)				of instructional effectiveness. <ul style="list-style-type: none"> Refines course design and enhances student performance outcomes. 	video, behavioral data, and textual information.
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The assessment delineated in **Table 8** elucidates that the incorporation of artificial intelligence within educational contexts is evolving from merely passive management frameworks to dynamic and individualized learning ecosystems. The findings indicate that hybrid architectures, particularly those that amalgamate computer vision with deep learning methodologies (MTCNN, LSTM-CNN), play a crucial role in enhancing student engagement; nevertheless, this customization engenders apprehensions regarding the transparency of the decision-making mechanisms, particularly in critical domains such as student performance forecasting (HESP). A significant observation is the

d. Smart Grid: the fifth most notable application domain is smart grid, the primary AI tasks were data management, decision-making, and authentication in energy management, smart grid cybersecurity, and smart grid stability. Research on IoT-integrated smart grids underscores the pivotal function of artificial intelligence in enhancing energy forecasting, grid security, and operational stability. Advanced machine learning approaches, including SVM and Random Forest, are instrumental in predicting energy consumption and identifying security threats, while innovative strategies such as reinforcement learning are

pronounced dependence on predictive analytics (IT, OESO) that frequently emphasizes output metrics rather than the underlying pedagogical processes themselves. This examination underscores a deficit wherein contemporary research favors 'performance prediction' at the expense of 'explainable learning pathways.' As a result, forthcoming advancements must pivot towards the development of emotionally intelligent artificial intelligence and multimodal analytics to cultivate human-centric educational environments that emphasize pedagogical transparency in conjunction with technological effectiveness.

being investigated for adaptive energy management, despite ongoing challenges like cybersecurity issues and the integration of renewable energy sources. **Table 9** summarizes a thorough critical evaluation of IoT-Enabled Smart Grid Systems.

Table 9. Comprehensive Critical Analysis of IoT-Enabled Smart Grid Systems

Sub-Domain	Ref.	Primary AI Algorithms	Data Sources & Input Types	Critical Findings & Analysis	Future Research Path
EM (Energy Management)	[68–71]	GWDO-FCRBM, ML classifiers, SVM-PSO, Reinforcement Learning	Smart meters, energy consumption data, grid sensors	<ul style="list-style-type: none"> Improves the accuracy of load forecasting and promotes energy efficiency. Predictive optimization strengthens system resilience. 	<ul style="list-style-type: none"> Grid management informed by reinforcement learning methodologies. Artificial intelligence-augmented digital twins for energy systems.
SGC (Smart Grid Cybersecurity)	[72–74]	RF, CNN, ANN, WOA, Naive Bayes	Smart meter datasets, grid network traffic, cyber intrusion logs	<ul style="list-style-type: none"> Expert in the discernment of illicit electricity appropriation and cyber vulnerabilities. Hybrid optimization enhances the accuracy of detection mechanisms. 	<ul style="list-style-type: none"> Smart grids enhanced by blockchain technology. Federated artificial intelligence-based cybersecurity infrastructures.
SGS (Smart Grid Stability)	[75–76]	IRF, PMI, Ensemble Deep Learning	Grid stability sensors, operational monitoring data	<ul style="list-style-type: none"> Enhances the assessment of grid reliability and stability. Ensemble deep learning methodologies produce enhanced system resilience. 	<ul style="list-style-type: none"> Autonomous fault detection systems. Self-repairing intelligent grid infrastructures.

The rigorous examination of **Table 9** elucidates that the integration of artificial intelligence within smart grids has progressed from rudimentary monitoring capabilities to intricate, self-optimizing control systems. Although machine learning frameworks, particularly those that incorporate reinforcement learning along with ensemble deep learning methodologies, have markedly enhanced grid resilience (SGS) and energy management (EM), the analysis uncovers a significant performance disparity concerning the scalability of security protocols. The extant literature predominantly

accentuates the precision of individual models; nonetheless, there exists a deficiency in addressing how these predictive models sustain efficacy amidst the decentralized and non-stationary conditions characteristic of contemporary smart grids. Moreover, the evolution towards blockchain-integrated and federated artificial intelligence frameworks (SGC) signifies a paradigm shift within the discipline, transitioning from centralized predictive models to trust-less, collaborative intelligence systems. This highlights a pivotal transformation within the smart grid sector: evolving from

'predictive efficiency' to 'autonomous, self-healing infrastructures' that possess the capacity to avert systemic

failures in real-time.

e. Robotics: AI played a significant role in robotics, which surfaced as a notable secondary application area from the reviewed literature. This included improved monitoring, security, and privacy, increased precision, enhanced dependability, RT object detection and increased flexibility and efficiency in UAVs, Cleaning Robots, and Voice Assistants. The amalgamation of IoT and AI in robotic systems has profoundly enhanced various applications, including autonomous UAV operations, intelligent cleaning robots, and voice-driven human-machine interfaces. While

these advancements leverage sophisticated algorithms for efficiency and effectiveness, challenges pertaining to energy efficiency, scalability, privacy, and real-time processing persist, necessitating ongoing research into swarm intelligence, edge AI, and context-aware interfaces for future intelligent IoT robotic ecosystems. **Table 10** summarizes a thorough critical evaluation of IoT-Enabled Robotics Systems.

Table 10. Comprehensive Critical Analysis of IoT-Enabled Robotics Systems

Sub-Domain	Ref.	Primary AI Algorithms	Data Sources & Input Types	Critical Findings & Analysis	Future Research Path
UAVs	[77–86]	CNN, DL trajectory planning, ML, Blockchain-ML, DQN, MAS-based ML, MADRL	UAV sensors, GPS trajectories, aerial imagery, IoT healthcare delivery data, surveillance cameras	<ul style="list-style-type: none"> The enhancement of trajectory optimization, resource allocation, and surveillance methodologies. The implementation of real-time oversight in logistical operations and emergency management. Challenge: The pursuit of energy efficiency and synchronization within swarm systems. 	<ul style="list-style-type: none"> Advancement of swarm intelligence paradigms. The integration of multi-agent reinforcement learning and edge artificial intelligence frameworks.
Cleaning Robots	[87–92]	CNN, Image Recognition DL, Hybrid ML/APF/PID, RNN, ML Navigation Models	Indoor cameras, LiDAR sensors, environmental mapping data, obstacle detection sensors	<ul style="list-style-type: none"> Computer vision and machine learning techniques significantly improve navigational efficiency and obstacle identification. Hybrid control systems augment operational adaptability. Challenge: Ensuring reliability in variable indoor environments. 	<ul style="list-style-type: none"> Navigation systems driven by reinforcement learning methodologies. Collaborative frameworks for domestic robotics.
Voice Assistants	[93–95]	Statistical/Acoustic models, ML, NLP, ResNet, LightGBM	Voice commands, speech datasets, IoT device interaction logs	<ul style="list-style-type: none"> The integration of AI-driven speech recognition and natural language processing (NLP) facilitates an instinctive mode of control for the Internet of Things (IoT). Promotes user contentment by enabling interactions that are more aligned with natural communication. Challenge: The necessity for multilingual functionalities alongside the imperative of data privacy. 	<ul style="list-style-type: none"> Contextually aware conversational artificial intelligence. Integration of localized speech processing with large language models (LLMs).

The examination of **Table 10** elucidates a pivotal transition in robotic systems from segregated task execution towards collective, swarm-based cognition (UAVs) and highly adaptable interior navigation (Cleaning Robots). A salient observation is that while contemporary AI algorithms markedly enhance environmental perception, there persists a fundamental 'reliability deficiency' when these systems function in dynamic, non-deterministic environments. The data indicates that hybrid control frameworks, which amalgamate traditional robotics controllers (PID/APF) with deep learning, are presently the most feasible trajectory

towards resilient indoor performance; however, this engenders a trade-off between computational burden and real-time adaptability. In the sphere of vocal assistants, the literature denotes a shift towards localized, privacy-centric processing; nevertheless, extant solutions grapple with context-awareness in multilingual, cacophonous IoT environments. This evidence substantiates that the predominant challenge across these robotics sub-domains is no longer merely 'perception,' but rather the 'autonomous coordination' and 'long-term environmental adaptation' requisite for seamless human-robot interaction

Conclusion

This comprehensive literature analysis investigated 79 peer-reviewed publications (2019–2024) sourced from a variety of databases to identify the essential roles of Artificial Intelligence (AI) in the context of Internet of Things (IoT) applications. The findings provide significant insights for researchers, concluding that functions such as pattern recognition, object categorization, decision-making

support, and predictive analytics are the most prevalent AI activities within these domains. Notably, Smart Transportation has emerged as the foremost sector for AI integration, closely followed by Robotics, with significant contributions also noted in Smart Home, Smart Grid, and Smart Education. The present research demonstrates the extensive potential of Machine Learning (ML) and Deep Learning (DL) in transforming the interactions between everyday applications and human involvement. Ultimately,

the relationship between AI and IoT fosters a transition towards more proactive, efficient, and innovative decision-making paradigms, thereby laying a robust groundwork for future advancements in autonomous industrial and residential systems.

This investigation has meticulously scrutinized the AIoT domain; however, it is subject to specific constraints. The dependence on a methodical selection procedure, while formidable, may engender publication bias favoring affirmative performance outcomes, potentially eclipsing unsuccessful experimental results. Moreover, the variability of metrics across the 79 examined studies complicates direct quantitative benchmarking. These elements should be contemplated when interpreting our discoveries regarding model prevalence and precision.

Future Research Directions

Based on a comprehensive and methodical analysis of a total of 79 scholarly publications that have been rigorously scrutinized and evaluated, the subsequent strategic pathways are recommended with the express purpose of effectively addressing and mitigating the existing deficiencies that have been discerned in the contemporary body of research.

1. Edge-AI & Latency Optimization: Addressing the performance disparity delineated in Section 4, where sophisticated models presently encounter challenges with real-time responsiveness on resource-constrained devices, forthcoming research endeavors must emphasize the imperative of converting intricate architectures such as Transformers into streamlined, quantized forms suitable for deployment in Internet of Things (IoT) edge environments.

2. Privacy-Preserving Frameworks: In order to address the privacy issues identified in our examination of the Smart Home and Education sectors, it is imperative that the advancement of Federated Learning (FL) and Differential Privacy be prioritized to guarantee that user data is preserved in an unblemished state throughout the model training process.

3. Explainable AI (XAI) in Critical Infrastructure: As delineated in the HESP sub-domain, within which 'black-box' models presently prevail, there exists a pressing necessity for transparent artificial intelligence frameworks that furnish defensible rationale for determinations in safety-critical domains such as Robotics.

4. Multi-Modal Data Fusion: Based on the fragmentation of data identified within contemporary diagnostic frameworks, subsequent research endeavors should emphasize the integration of diverse data sources to improve the resilience and dependability of AI-enhanced diagnostic methodologies.

5. Resilience Against Adversarial Attacks: Recognizing the susceptibility of AI-integrated Smart Transportation and Home systems to unauthorized access, forthcoming initiatives should prioritize the enhancement of security

protocols through the implementation of zero-trust architectures in order to safeguard against progressively advanced adversarial threats.

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Conflict of interest

None.

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Abbreviations and Acronyms

Abbreviation	Full Term
AIoT	Artificial Intelligence of Things
IoE	Internet of Everything
ANN	Artificial Neural Network
ASR	Automatic Speech Recognition
BiLSTM	Bidirectional Long Short-Term Memory
CNN	Convolutional Neural Network
CPOP	Car Park Occupancy Prediction
DL	Deep Learning
DNN	Deep Neural Network
DQN	Deep Q-Network
DRL	Deep Reinforcement Learning
EM	Energy Management
HEADRA	Human Emotion Detection, Recognition and Automation
HESP	Higher Education Students’ Performance
Int-HVAC	Intelligent Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
IT	Intelligent Tutoring
LSTM	Long Short-Term Memory
ML	Machine Learning
NER	Named Entity Recognition
NLU	Natural Language Understanding
NLP	Natural Language Processing
OESO	Online Education Students’ Outcomes
PL	Personalized Learning
RHDP	Ride-Hailing Demand Prediction
RNN	Recurrent Neural Network
SGC	Smart Grid Cybersecurity
SGS	Smart Grid Stability
SH-Eco	Smart Home Ecosystem
SHDT	Smart Home Data Transmission

SH-Sec	Smart Home Security
SVM	Support Vector Machine
TADP	Traffic Accident Detection and Prevention
TFPC	Traffic Flow Prediction and Control
TSC	Traffic Signal Control
TTS	Text-to-Speech
UAV	Unmanned Aerial Vehicle
URP	Urban Route Planning