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Review

The Role of the Industrial IoT in Advancing Electric Vehicle Technology: A Review

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Abstract

The use of the Industrial Internet of Things within the domain of electric vehicles signifies a paradigm shift toward advanced, integrated, and optimized transport systems. This study thoroughly investigates the pivotal role of the Industrial Internet of Things in elevating various features of electric vehicle technology, comprising predictive maintenance, vehicle connectivity, personalized user management, energy and fleet optimization, and independent functionalities. Key IIoT applications, such as Vehicle-to-Grid integration and advanced driver-assistance systems, are examined alongside case studies highlighting real-world implementations. The findings demonstrate that IIoT-enabled advanced charging stations lower charging time, while grid stabilization lowers electricity demand, boosting functional sustainability. Battery Management Systems (BMSs) prolong battery lifespan and minimize maintenance intervals. The integration of the IIoT with artificial intelligence (AI) optimizes route planning, driving behavior, and energy consumption, resulting in safer and more efficient autonomous EV operations. Various issues, such as cybersecurity, connectivity, and integration with outdated systems, are also tackled in this study, while emerging trends powered by artificial intelligence, machine learning, and emerging IIoT technologies are also deliberated. This study emphasizes the capacity for IIoT to speed up the worldwide shift to eco-friendly and smart transportation solutions by evaluating the overlap of IIoT and EVs.

Keywords: Industrial Internet of Things (IoT); electric vehicles (EVs); predictive maintenance; fleet energy management; IIoT applications

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1. Introduction

The progression of the EV industry signifies a turning point in dealing with universal problems such as global warming, metropolitan traffic, and long-term energy solutions [1]. The adoption of EVs has been notably propelled as countries aspire to reach lower emission milestones [2]. However, this development calls for the need for smarter, streamlined, and deeply networked EV ecosystems that are able to resolve challenges linked to battery performance, EV charging setup, vehicle upkeep, and customer experience. This is where the Internet of Things appears to be a ground-breaking digital framework, facilitating the flawless integration of online platforms with industrial workflows to streamline effectiveness and stimulate new ideas [3].

The Industrial Internet of Things is established on the larger notion of IoT, expanding its potential for a large-scale industrial system [4]. The IIoT makes possible live tracking, predictive analysis, and adaptive regulation of vehicle systems in the context of EVs, guaranteeing optimal performance across a broad spectrum of applications [5]. IIoT technologies play a critical role in the revolutionizing of EVs into smart, self-driven, and versatile devices, whether it is Vehicle-to-Grid (V2G), fleet energy management, or Advanced Driver-Assistance Systems (ADASs) [6]. Vehicle-to-Grid technology enables EVs to directly interact with the power grid, thus allowing for the storage of excess energy and supplying it back to the grid when needed. Artificial intelligence significantly enhances energy storage systems (ESSs), improving efficiency and accuracy in power systems that are essential for renewable energy integration [7]. Meanwhile, an ADAS refers to a system that boosts driving ease and reinforces safety. Furthermore, the IIoT allows for the accumulation of assessments of larger datasets, empowering contributors to make analytics-based decisions that improve the safety, long-term viability, and optimization of EV operations [8]. Optimization techniques, such as hybrid metaheuristic algorithms, are invaluable for managing the complexities of interconnected systems, ensuring efficient resource allocation and faster decision-making in real-time scenarios, which are critical for IIoT applications in EVs [9]. Similar optimization frameworks have also been explored in other domains such as photovoltaic systems [10].

The application of the IIoT to EVs has its own challenges. Various obstacles remain substantial barriers to extensive adoption [11]. Such issues involve cybersecurity, risk identification [12], cross system communication, and the integration of IIoT technology with pre-existing infrastructure [13]. In addition, there is a lack of global adoption for IIoT protocols, which further complicates the process of creating a connected ecosystem [14]. Tackling these challenges calls for cross-functional strategies encompassing cooperation among decision-makers, market pioneers, and tech innovators to set up firm models and secure expendable infrastructure for IIoT-enabled EVs [15].

This review delves into the convergence of IIoT and EV technologies, showcasing a thorough examination of primary uses, benefits, and challenges. This discussion opens with an outline of IoT's transformation into IIoT, including successes around its structural elements and standardization requirements. We then study IIoT's role in various EV applications, for example, predictive maintenance, automated driving, and V2G integration, explained by real-world case studies. To the end, this study emphasizes the upcoming trends, including the overlap of AI and ML, which are set to reinvent the potential of IIoT use in the EV sector. This study aims to understand the transformative potential of the IIoT in shaping the next generation of eco-friendly and smart transportation systems.

Research Questions, Aims, and Objectives

This review is guided by the following questions: How is the IIoT currently applied across the EV ecosystem? What are its primary technological enablers? What measurable impacts have these applications demonstrated in terms of performance, safety, cost, and sustainability? What technical, organizational, and regulatory barriers impede wider adoption? Which research gaps and innovation opportunities are most critical for advancing IIoT-enabled EV systems?

This review is aimed at three main audiences: (1) academic researchers investigating IIoT architecture and applications in the electric mobility domain; (2) engineers, system integrators, and technology managers in the EV industry; and (3) policy-makers and infrastructure planners concerned with interoperability, safety, and sustainability.

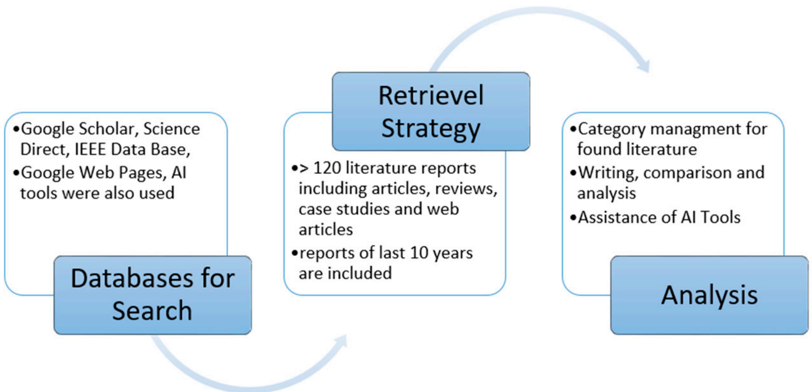
Our motivation is to consolidate fragmented technical and empirical insights from diverse sources into a single, structured synthesis that covers both technological enablers and real-world deployments. Readers will gain the following insights: (i) a taxonomy of IIoT application areas in EVs; (ii) a comparative analysis of enabling technologies; (iii) summaries of representative deployments; (iv) the identification of implementation challenges; and (v) research directions for the next generation of IIoT-enabled EV infrastructure.

2. Methodology

The literature review was systematically written by following the data retrieval strategy, inclusion criteria, and analysis of over 150 literature resources, including peer-reviewed articles, review papers, case studies, and credible web resources.

Data Retrieval Strategy and Inclusion Criteria: Peer-reviewed journal articles, conference proceedings, reviews, case studies, and credible web articles focusing on IIoT technologies, architecture, applications, or challenges in the context of electric vehicles were explored. The relevant literature was retrieved from academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. Priority was given to works published in the last 10 years to ensure contemporary relevance. Keywords, such as "Industrial Internet of Things," "Electric Vehicles," "IIoT Applications," "V2G Integration," "Predictive Maintenance," were included in the literature search. Abstracts and summaries were screened to assess relevance.

Analysis: The selected literature was categorized into thematic areas, including IIoT architecture, connectivity standards, applications in EVs, implementation challenges, and emerging trends. Each study was examined for its methodology, findings, and overall contribution to the field. Qualitative analysis was used to synthesize our findings, while case studies provided real-world insights into IIoT's impact on EV technologies. Our methodological approach is visually summarized in Scheme 1, which outlines the steps of the literature identification, selection, and analysis.



Scheme 1. Methodological approach used for this review.

The searches were conducted in IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar using keywords such as "Industrial Internet of Things", "Electric Vehicles", "V2G", "Predictive Maintenance", and "IIoT applications in EVs" to ensure broad representation. Peer-reviewed publications from the last 10 years were prioritized to include high-quality case reports and industry white papers to evaluate the deployed solutions. To reduce regional bias, geographic origins based on author affiliation and deployment locations were recorded to ensure coverage across Asia, Europe, North America, and other regions. Each study's technological maturity, i.e., proof-of-concept, pilot, deployed, or mature, was classified, and we organized the results to reflect both research maturity and real-world deployments. This process yielded over 150 sources that balanced academic, industrial, and regional perspectives.

3. Internet of Things (IoT) and Industrial Internet of Things (IIoT)

The word IoT was coined by University of Massachusetts researchers in 1999 [16]. The IoT is commonly considered as a network of physical objects that rely on embedded technologies enabling interaction with the external environment, transmit information about their status, and receive input from external sources [17]. The integration of information technology (IT) and operational technology (OT) drives the IIoT [18]. It is a matrix of networks linking devices and equipment, gathering data via sensor technologies, analyzing it, and integrating it directly into platforms as a service [19]. IoT is mainly expanded into consumer based IoT and Industrial IoT which is compared in Figure 1.

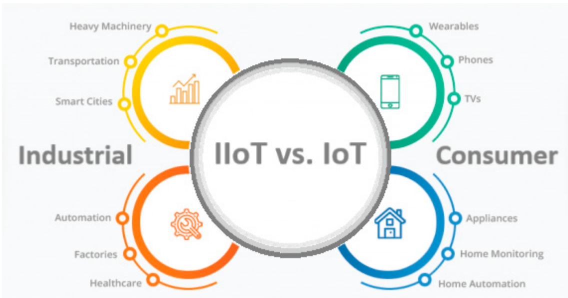


Figure 1. Comparison of consumer and Industrial IoT applications.

In this review, IIoT is used to denote industrial-scale IoT deployments and the operational and organizational practices that accompany them (industrial sensors [20], OT/IT integration, industrial communication stacks, and lifecycle management). While IoT deployments are often associated with consumer-facing applications and IIoT with industrial environments, in practice, both paradigms overlap. The distinction lies in the requirements: IIoT systems typically demand higher reliability, deterministic performance, integration with industrial control systems, and compliance with industry standards. Consumer-oriented IoT solutions can also be deployed in industrial contexts (e.g., small-scale fleet tracking). Conversely, IIoT technologies can enhance consumer services (e.g., connected EV dashboards). Cloud computing, edge analytics, and AI/ML are treated as enabling layers: cloud provides centralized storage and service orchestration; edge computing provides low-latency local processing; and AI/ML provide analytical models and decision logic that operate on IIoT data. While tightly coupled in practice, this distinction is necessary: IIoT refers to the operational system and deployments, while cloud/edge/AI denote the technology layers used within that system [21].

3.1. IIoT Architecture, Connectivity, and Standardization

Implementing IIoT in the EV industry is challenging and requires a well-crafted strategy. The IIoT framework combines edge computing, interfaces, cloud platforms, and data tools in order to carry out smooth data collection, optimization, and decision-making [22]. This framework supports automated services, energy optimization, and decision-making for the real-time monitoring of critical benchmarks and to maximize charging and grid integration [23]. A typical Industrial IoT architecture or IIoT architecture describes the arrangement of digital systems so that they collectively provide network and data connectivity between sensors, IoT devices, data storage, and other layers [24]. The IIoT architectural components are depicted in Figure 2.

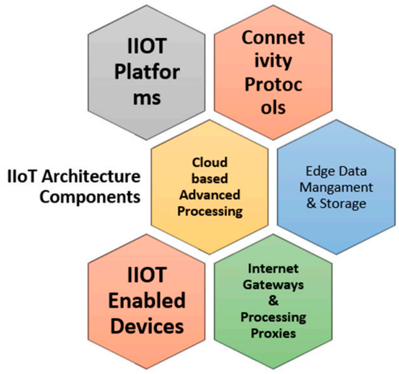


Figure 2. Architectural components of IIoT.

To usefully integrate IIoT systems in the EV industry, standardization and easy access are critical elements [25]. Rigorous guidelines and compatibility specifications are necessary to smoothly integrate diverse sensors, devices, and systems in IIoT environments. Secure data communication is currently possible due to technologies like Fifth Generation (5G), Long Range Wide Area Network (LoRaWAN), and Message Queuing Telemetry Transport (MQTT), as standardization attempts efforts ensure security and integration across multiple systems [26]. The IIoT communication stack for EV systems spans multiple layers, for example, physical layer, i.e., Power Line Communication (PLC, often OFDM-based) for ISO 15118 [27] in conductive charging; LTE/5G NR with OFDM for wide-area connectivity; IEEE 802.11p/DSRC for low-latency V2X; and sub-GHz FSK/LoRa for low-power telemetry. The data link and network layers include Ethernet, CAN bus (in-vehicle), IPv6, 6LoWPAN, and proprietary fieldbus systems. At the transport layer, for example, TCP/UDP for IP-based networks, while MQTT over TCP or CoAP over UDP for serves constrained devices. At the application layer, i.e., protocols like OCPP, the ISO 15118 application profile, and proprietary APIs for fleet and energy management. Physical and link layer choices directly affect achievable latency, throughput, and resilience, which in turn shape higher-layer application design [28].

By connecting IIoT and IoT sectors, the EV industry is destined to reach advanced levels of productivity, integration, and sustainability. Achievable pathways include the following factors:

(1) Adoption and harmonization of existing standards (e.g., ISO 15118 for V2G communications and OCPP for charging station control) as baseline protocols.
(2) Industry consortia and open reference implementations that demonstrate interoperability (manufacturers, utilities, and software vendors).
(3) Middleware/gateway layers that translate between vendor-specific APIs and common schemas, enabling backward compatibility for legacy assets.
(4) Regulatory and procurement incentives that require or reward adherence to open standards.
(5) Phased certification programs (testbeds and interoperability plugfests) to reduce risk for OEMs and operators.

These combined technical, organizational, and regulatory steps create a practical, incremental route toward cross-platform interoperability.

3.2. IoT Transition to IIoT

In recent years, new concepts like IoT and Industrial IoT have emerged with the active penetration of information and communication technologies into industrial processes. Interrelationships between these concepts and their degree of integration are considered the apotheosis of modern industry [29]. The transition of IoT to IIoT represents a very historic change, as there is a range of user-friendly features to industrial-scale systems that support operations at a very large scale. IoT integration in EVs mostly involves personal and individual vehicles or localized systems; integration of the IIoT is a comprehensive upgrade [30]. For example, the IIoT may analyze the output of the entire EV industry, foresee potential system failures, and reduce the overall cost of maintenance (Table 1) [31]. Emerging technologies such as edge computing, which minimizes processing delays, and AI-driven networks, which extract valuable knowledge from complex datasets, have significantly contributed to this major industrial shift [32].

Table 1. Comparative role of IoT and IIoT in EVs.

Application Area	IoT in EVs	IIoT in EVs	Key Outcomes	Ref.
Predictive Maintenance	Basic predictive maintenance systems for early fault detection. Relies on cloud-based solutions but faces latency issues.	Integration of sensors for real-time vehicle health monitoring. Advanced connectivity with real-time data exchange and edge analysis. AI and machine learning for battery health diagnostics and motor efficiency. Uses robust industrial-grade IoT sensors for continuous monitoring.	IoT in EVs: Reduces maintenance costs by 10–20%. IIoT in EVs: Achieves 20–30% cost reduction with enhanced uptime. IIoT offers an edge in minimizing downtime for commercial fleets.	[31,33]
Energy Management	Monitors energy usage via sensors. Optimizes charging cycles. Analyzes consumption trends.	Real-time optimization with edge computing. AI-based intelligent charging strategies. Prevents energy loss and extends battery life.	IoT: Efficient energy monitoring. IIoT: 15–25% cost reduction and improved battery life.	[34,35]
Vehicle Connectivity	Real-time data exchange via IoV. Support V2V, V2I, and V2X for safety.	Advanced sensors with edge computing for real-time decisions. Predictive traffic management and dynamic routing.	IoT: Improved traffic flow, reduced accidents. IIoT: 20–30% congestion reduction, better autonomy.	[36,37]

4. Applications of IoT and IIoT

The expansion of IoT to the IIoT has made a significant impact in various applications (elaborated in Table 2 in detail) [13]. Both provide platforms for different technologies by connecting devices, and they automate processes using sensors. They build a platform and are responsible for the functioning of various smart devices over a range. Once IoT and IIoT are installed into a device, they can communicate with each other without human–computer interaction. They are widely used across multiple fields, as no human intervention is required in IoT-based applications [38]. A comparative analysis of applications of IoT and IIoT in various sectors is summarized in Table 2.

IoT and IIoT applications in EVs face limitations such as data security vulnerabilities, interoperability issues arising from diverse systems, and scalability challenges with growing fleets. High implementation costs and limited network reliability, especially in remote areas, hinder widespread adoption. Additionally, real-time data processing demands and seamless integration with existing infrastructure can complicate deployment. To overcome these limitations, robust cybersecurity, standardized protocols, and scalable cloud solutions are crucial. Enhancing network infrastructure and leveraging edge computing can ensure reliable, real-time data processing.

Table 2. Comparison of IoT and IIoT applications in various fields.

Domain	Application of IoT	Application of IIoT	Ref.
Healthcare	Remote patient monitoring through wearable IoT devices. Telemedicine platforms enabling real-time doctor-patient consultations. Tracking medication adherence using IoT-enabled reminders.	Smart hospital management with interconnected equipment and predictive maintenance. Real-time analytics for critical equipment in operating rooms and ICUs. Supply chain optimization for pharmaceutical manufacturing and distribution.	[39,40]
Agriculture	Precision farming uses IoT sensors for soil moisture and weather monitoring. Livestock health monitoring through IoT-enabled collars and tags.	Smart irrigation systems are integrated with large-scale farming operations. Automation of food processing and storage systems to reduce waste.	[41,42]
Manufacturing	Asset tracking and monitoring for production line equipment. IoT-enabled employee safety monitoring in hazardous environments.	Predictive maintenance for machinery to reduce downtime and increase efficiency. -Industrial automation using robotics and IIoT-integrated control systems.	[43,44]
Energy Management	Smart meters for tracking energy consumption in households. IoT-based solar panel performance monitoring.	Real-time optimization of power grids to balance load and manage outages. -Integration of renewable energy sources with IIoT-enabled grid management systems.	[35,45,46]
Retail	Personalized shopping experiences through IoT-based recommendation systems. Smart shelves that track product availability and expiration dates.	Automated warehousing and logistics using IIoT-powered robotics and analytics. Large-scale building management systems with IIoT integration for HVAC, security, and energy control.	[47,48]
Transportation and EVs	IoT-enabled vehicle tracking and route optimization for public and private transportation and EVs. Real-time passenger information systems for smart transit networks.	Fleet management systems with predictive analytics to improve fuel efficiency and reduce operational costs. Integration of IIoT in autonomous vehicles for real-time decision-making.	[5,49,50]
Logistics	IoT-based package tracking for last-mile delivery. Monitoring warehouse inventory with IoT sensors.	IIoT-powered supply chain visibility with real-time analytics. Automation of freight loading and unloading with robotics and IIoT-integrated systems.	[51,52]
Environmental Monitoring	IoT sensors for detecting water quality and pollution levels in rivers and oceans. Air quality monitoring in urban areas.	Large-scale IIoT systems for climate monitoring and forecasting. Disaster response systems powered by IIoT analytics for real-time decision-making.	[53,54]
Education	Smart classrooms with IoT-enabled devices for interactive learning. IoT-based attendance and resource management systems.	IIoT-powered infrastructure for smart campus management, including HVAC, lighting, and security systems. Predictive maintenance of educational facilities.	[55,56]
Smart Cities	IoT-enabled smart street lighting for energy efficiency. Monitoring air quality and environmental conditions.	Large-scale traffic management systems using IIoT analytics and edge computing. Centralized control systems for utilities, waste management, and public safety.	[53,57,58]

5. IIoT Integration in Electric Vehicles (EVs)

In the automobile market, the utilization of the IIoT in the EV industry is a notable development [5]. Recent studies on the integration of the IIoT into EVs highlight its transformative potential in enhancing performance, efficiency, and connectivity [49]. Researchers have explored the role of the IIoT in predictive maintenance, where real-time sensor data and analytics reduce downtime and improve battery health management [50]. Advanced IIoT architectures have been proposed to facilitate Vehicle-to-Grid (V2G) communication, optimizing energy usage by leveraging EVs as mobile energy storage systems [59]. Furthermore, security frameworks for the IIoT in EVs have garnered attention, addressing vulnerabilities in communication protocols and data handling to ensure robust and secure operations. Despite these advancements, challenges, such as interoperability between diverse IIoT platforms and scalability in large-scale EV networks, remain critical areas for research. Several factors impact IIoT integration in the EV sector, as shown in Figure 3.

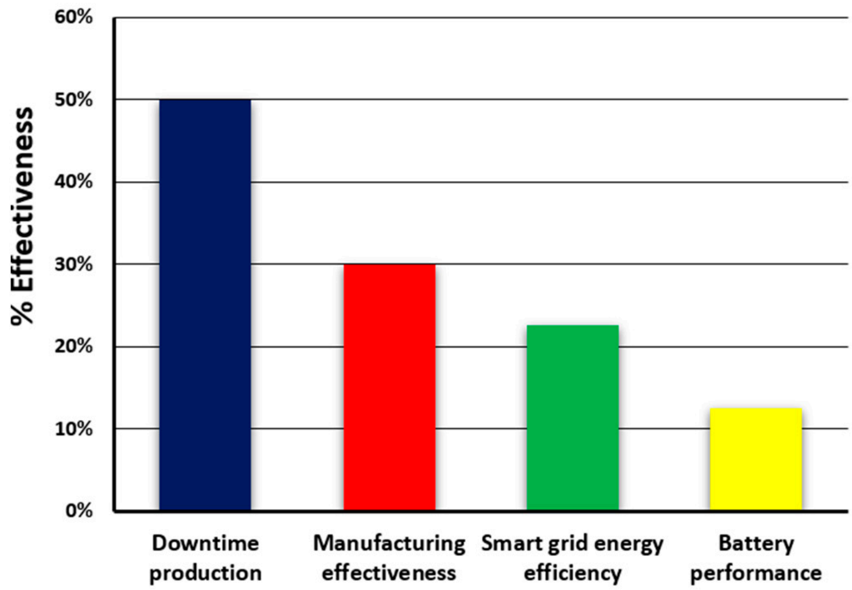


Figure 3. Comparison of factors making an impact on IIoT integration in the EVs sector.

Figure 3 shows that the EV sector has seen significant advantages from IIoT adoption. For example, IIoT-powered predictive maintenance systems boost total equipment effectiveness by 30% and decrease unscheduled downtime in manufacturing by up to 50%. Advanced analytics improve battery performance by increasing its lifespan by 10–15%, while IIoT-driven smart grids increase energy efficiency in charging infrastructure by 20–25%. Furthermore, security frameworks for IIoT in EVs have garnered attention, addressing vulnerabilities in communication protocols such as MQTT (Message Queuing Telemetry Transport), CoAP (Constrained Application Protocol), DSRC (Dedicated Short-Range Communications), and data handling to ensure robust and secure operations [38]. IIoT uses cloud-powered systems, on-site devices, and linked sensors to monitor and analyze the data [60]. These systems adopt forecast approaches and AI-driven models to gather significant data to guarantee optimal system efficiency and reduce hazards. Just like simulated models, analytical methods, without any real prototypes, help in the testing and refining of systems by replicating tangible EV procedures [61]. A comparative analysis of the IoT and IIoT features and available communication systems in EVs is presented in Tables 3 and 4.

Table 3. Comparative analysis of various features of IoT and IIoT in EVs.

Feature	IoT in EVs	IIoT in EVs	Ref.
Focus	User-centric applications	Industrial-scale infrastructure	[36]
Data Processing	Cloud-based	Edge computing with local processing	[62]
Scalability	Limited to individual vehicles	Designed for large-scale operations	[62]
Advantages	Improved user experience, route planning	Grid optimization, manufacturing efficiency	[36]
Disadvantages	Cybersecurity risks, high costs	Privacy concerns, over-reliance on automation	[62]
Communication	Vehicle-to-Cloud (V2C) interactions	Vehicle-to-Everything (V2X) integration	[63]
Application	Navigation, smart charging	Fleet management, predictive maintenance	[63]
Ecosystem	Isolated device interaction	Integrated supply chain and operations	[36]
Latency	Higher latency due to cloud reliance	Low latency for critical decisions	[61]
Reliability	Depending on network availability	Designed for high uptime and redundancy	[61]
Energy efficiency	Focus on vehicle-level optimization	System-wide energy management	[61]
Cost	Lower initial deployment cost	Higher investment but long-term efficiency	[63]
Security protocols	Standard encryption methods	Advanced, industrial-grade security measures	[63]
Maintenance	Reactive, user-initiated	Predictive, automated through sensors	[64]
Integration	Focused on individual systems	Seamless integration across industries	[64]
Data sharing	Limited to vehicle-owner interactions	Extensive sharing with industrial networks	[64]
Decision-making	User or cloud-driven	Automated and real-time	[60]
Standards	Consumer-grade protocols	Industrial compliance standards	[60]
Testing	Functional and usability testing	Stress-tested for harsh industrial conditions	[62]
Use case example	Personalized driving analytics	Real-time EV production monitoring	[62]

Table 4. Comparison of available communication systems [65,66] for connected EVs [67].

Wireless Option	Bluetooth	ZigBee	LTE-M (LTE Cat-M1)	Passive RFID	UWB	60 GHz mm Wave	LoRa/LoRaWAN
Frequency band	2.4 GHz	868 MHz, 915 MHz, 2.4 GHz	Licensed LTE bands	915 MHz	3.1–10.6 GHz	57–64 GHz	Sub-GHz ISM
Data rate	1, 2, 3 Mb/s	20–250 kb/s	Up to 1 Mbps	<4 Mb/s	53.5–480 Mb/s	>1 Gb/s	0.3 kbps to 50 kbps
TX power	1, 2.5, 100 mW	<1 mW	~23 dBm (200 mW)	0	1 mW/Mb/s	10 mW	14 dBm (25 mW), up to 20 dBm (100 mW)
MAC Protocol	TDMA	CSMA/CA	LTE-based	EPC global	CSMA/CA and TDMA	CSMA/CA and TDMA	ALOHA-based
Modulation	GFSK (1 Mb/s) π/4-DQPSK (2 Mb/s) 8DPSK	BPSK (868 MHz) BPSK (915 MHz) O-QPSK (2.4 GHz)	QPSK, 16QAM	BPSK	MB-OFDM	Single carrier, OFDM	Chirp Spread Spectrum (CSS)
Application	Multimedia	Monitoring/ Control	Mobile IoT	Monitoring/ Control	Multimedia	Multimedia	Long-range, Wireless

5.1. Predictive Maintenance (PdM)

Maintenance includes steps to keep a system operating in its designated mode, either by fixing malfunctions or by adopting preventative precautions. It is categorized into corrective, preventive, and predictive maintenance. Using past maintenance data and/or information about the system's health, the PdM seeks to forecast the best time point for maintenance activities. It seeks to guarantee prompt repair before a problem occurs while also attempting to prevent the needless and expensive repair of a system. In order to estimate the remaining useful life, advanced technologies try to forecast when a failure is expected to occur [68].

Predictive maintenance is one of the most beneficial uses of IIoT in the EV industry. The IIoT system predicts possible faults even before they emerge. It is performed by constantly tracking key features like engine efficiency, tire pressure, battery life, and thermal regulation [69]. These systems use a fusion of contemporary and prior information that has been processed through intricate algorithmic models and machine learning models to anticipate component breakdown and start necessary preventive measures. Thus, this process reduces the downtime period and enhances system efficiency.

Studies have focused on deploying sensor networks and real-time data analytics to monitor key components such as batteries, motors, and braking systems. Machine learning algorithms, particularly neural networks and decision tree models, have been applied to predict failures and optimize maintenance schedules, reducing unexpected breakdowns and operational costs [68]. Figure 4 have compared the benefits of predictive maintenance in repair and production, showing that repair expenses reduce by 25% and throughput increases by 30% due to fewer production disruptions throughout real-time monitoring [70].

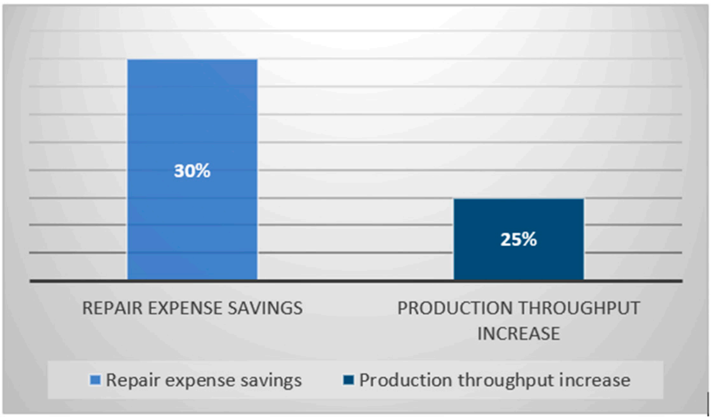


Figure 4. Comparison of predictive maintenance throughput in repair and production.

For high-frequency telemetry in EVs, temporal and deep-sequence models commonly adopted include LSTM/GRU, which are effective for moderate-length time series and RUL prediction; Temporal Convolutional Networks (TCN) and 1-D CNNs are good for high-rate sensor streams, and are often faster to train and deploy than RNNs. Transformer-/attention-based models are increasingly used for longer sequences and multimodal fusion, although they are more computing-intensive. Tree-based ensembles (Random Forest, XGBoost) are robust for tabular features, feature importance, and low-latency inference on aggregated windows. Lightweight models and model compression (e.g., pruned neural nets, quantized trees) are used for edge inference where memory and compute resources are constrained. Model choice depends on the prediction task (RUL, anomaly detection, classification), data volume, and the deployment target (cloud vs. edge). Hybrid pipelines, e.g., edge preprocessing coined using cloud training with model distillation for edge inference, are a practical pattern for EV IIoT.

IIoT-enabled predictive maintenance frameworks also facilitate seamless communication between EVs, charging stations, and maintenance centers, ensuring timely interventions [71]. However, challenges such as data privacy, the integration of diverse IoT devices, and the computational overhead of real-time processing remain significant barriers to widespread implementation. Researchers are actively exploring edge computing and blockchain technologies that address these limitations and enhance the scalability and security of PdM systems in EVs [72].

5.2. Vehicle Connectivity and Personalized User Management

Globally, the number of IIoT-connected EVs is projected to exceed 70 million by 2030, highlighting the growing reliance on connectivity technologies [73]. Recent advancements in vehicle connectivity, driven by IoT and IIoT technologies, have revolutionized interactions between electric vehicles (EVs), the supporting infrastructure, and end-users. Vehicle connectivity has been significantly improved by enabling smooth interactions between electric vehicles, infrastructure, and consumers [74]. The concept of Vehicle-to-Everything (V2X) communication [75] covers various elements like Vehicle-to-Grid (V2G) [76], Vehicle-to-Vehicle (V2V) [77], and Vehicle-to-Infrastructure (V2I) interactions [78]. A comparative analysis of vehicle connectivity in V2G, V2V, and V2I is described in Figure 5.

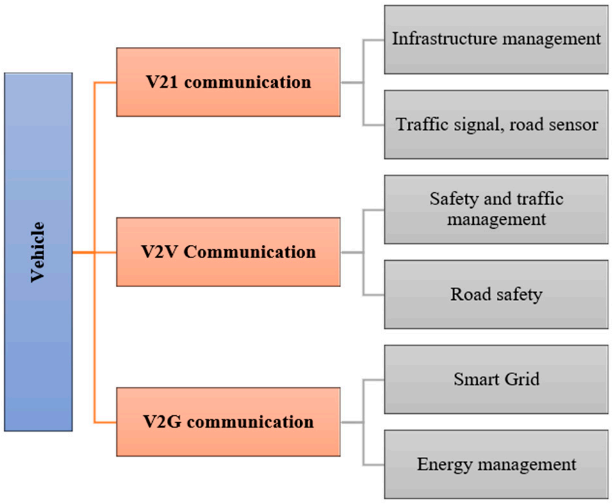


Figure 5. Comparison of vehicle connectivity applications in V2V, V2I, and V2G communication flow.

This integration depends on fast and sturdy analytical and computational frameworks, including networking protocols such as Message Queuing Telemetry Transport (MQTT), Constrained Application Protocol (CoAP), and other streamlined messaging systems. IIoT integration has greatly influenced vehicles in all of these vehicle connectivity types, as is shown in Table 5.

Table 5. Comparison of IIoT integration in various vehicle communication systems.

Vehicle Communication System	Effect of IIoT Integration	Ref.
V2X	It dynamically balancing grid demand and charging rates, ensuring grid stability and efficiency It reduced traffic congestion by 40% and improve road safety by 30% reported by IoT analytics firms	[73,75,79]
V2G	IIoT-based energy management systems in V2G networks are the reason for the decreased grid dependency during peak hours by 15–20%	[76,80]
V2I	It builds the ability to enhance intelligent infrastructure from traffic flow optimization to the efficient management of charging stations	[72,78,81]
V2V	It focuses on real-time data sharing to improve road safety, traffic efficiency, and hazard management	[77,81,82]

The recent literature underscores the transformative impact of IIoT on personalized user experiences in EVs [83]. Embedded sensors in EVs continuously collect data on driver behavior, preferences, and environmental conditions, enabling the development of adaptive systems [82]. A comparative analysis of various factors impacting personalized user management is shown in Figure 6.

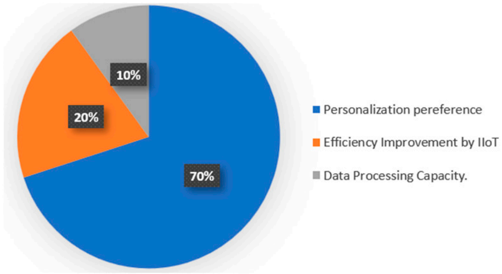


Figure 6. Comparison of impact of personalization and IIoT on EV user preferences, efficiency, and data analytics.

The comparison in Figure 6 shows that 70% of EV users express a preference for vehicles with advanced personalization features, highlighting strong consumer demand for these capabilities. IIoT-powered personalization algorithms can enhance driving efficiency by up to 20%, improving both performance and energy consumption. Large-scale IIoT systems can process massive amounts of user data, such as 50 terabytes annually, to generate in-depth analytics and provide highly customized services.

IIoT-enabled personalization raises ethical issues, including surveillance risks, loss of user autonomy, and algorithmic bias. Mitigation strategies include the following:

(1) Privacy-by-design minimizes data collection, keeps personal data on-device where possible, and apply anonymization.
(2) Federated learning and differential privacy enable model training without centralizing raw user data.
(3) User control and consent with clear opt-in/opt-out controls and granular consent for data uses.
(4) Transparency and explainability: Provide interpretable explanations for personalization decisions and allow for users to review and correct preference models.
(5) Fairness audits and bias testing: Regularly test personalization outcomes across demographic groups.
(6) Regulatory compliance and governance that align design with GDPR/CCPA and maintain logging/audit trails for automated decisions. These practices reduce surveillance risk and preserve user autonomy while allowing for beneficial personalization.

Studies emphasize the role of AI and ML algorithms, such as collaborative filtering and natural language processing (NLP), in creating tailored user profiles which facilitate dynamic adjustments to vehicle settings, including steering responsiveness, energy optimization, and climate control, based on real-time driving patterns and user preferences [84]. IIoT-enabled personalization offers notable benefits; however, limitations such as data privacy, system interoperability, and the computational demands of real-time data processing remain critical areas for exploration [85]. Ongoing advancements in edge computing, block chain, and secure data-sharing protocols are being investigated to address these limitations and further enhance the personalization capabilities of IIoT in EVs [86].

5.3. Energy and Fleet Management

Energy and fleet management are increasingly critical in the deployment and operation of EVs, particularly in commercial and industrial contexts, and IIoT technologies are proving to be essential in addressing these challenges [87]. Dynamic charging strategies facilitated by IIoT systems adjust charging schedules based on grid load, vehicle usage patterns, and energy prices, minimizing peak electricity charges and energy waste while ensuring that vehicles are adequately charged during optimal periods [88]. Battery health monitoring with IIoT-enabled tracking allows for fleet managers to anticipate maintenance needs and reduce downtime, thereby improving overall fleet reliability [89]. By offering centralized systems that compile real-time data on vehicle location, charging status, maintenance needs, and fleet health, these systems promote operational efficiency. Table 6 shows a comparative study of several IIoT integration factors in energy and fleet management.

Table 6. A comparative analysis of various aspects of IIoT integration in energy and fleet management.

IIoT Integration	Energy Management	Fleet Management	Ref.
Primary Focus	Optimization of charging cycles, energy consumption, and cost reduction.	Monitoring and optimizing vehicle operations, routes, and maintenance.	[35,45,90]
Role of IIoT	Tracks real-time energy consumption. Optimizes charging schedules. Reduces energy waste.	Collects and analyzes real-time data on fleet performance. Enables predictive maintenance.	[35,45,90]
Key Benefits	20–30% reduction in energy consumption for fleets. 15–20% reduction in charging times. Reduced energy costs by 10–25%.	Early detection of inefficiencies. Better coordination across vehicles. Reduced operational costs.	[35,45,90]
Technologies Used	Intelligent Energy Management Systems (EMS). Smart grids. Real-time IoT sensors.	The management of information and communication technology assets. Advanced analytics. Management and planning tools—predictive maintenance tools.	[47,91,92]
Cost Saving	Performed using energy efficiency and demand management techniques.	By reducing time when the platform is inoperable and simultaneously enhancing a range of performance indicators.	[92,93]
Operational Improvement	Reduces the load on the grid during some of the most critical hours. It also manages to extend periods of charging the batteries to improve their long periods of charges.	Reduces cases of accidental occurrences and energy loss. Improves assets productivity and protection.	[92,93]
Sustainability Impact	Lowered emission of green-house gases due to efficient energy utilization.	Enables the improvement of the sustainable practices of the fleets by reducing Emissions and fuel waste.	[92,93]
Scalability	Designed for individual and grid-wide applications.	Suitable for managing small to large-scale fleet operations.	[84,85,94]
Data Management	Rely on real-time energy data aggregation and predictive models.	Utilizes historical and live fleet data to optimize decision-making.	[84,85,94]
Collaboration	Integrates with utility companies and smart grid systems.	Connects with logistics, supply chains, and dispatching platforms.	[36,45]
Challenges	Investment in smart grid related Infrastructure. Uncertainty of energy projection models.	High initial setup costs. Security in computer and communication networks for protection of data.	[36,45]
Energy Sources	These integrate batteries storage systems for peak shaving and load balancing.	Controls battery conditions, and sets reminders for battery replacement, to minimize interruptions.	[84,85,93]

Table 6. *Cont.*

IIoT Integration	Energy Management	Fleet Management	Ref.
Predictive Analytics	Predicts the customer's energy requirement and adjusts the charging schedule for lower expenses.	Identifies when a vehicle component is faulty so that more	[93–95]
Real-time Insights	Provides live updates on energy grid performance and usage trends.	Tracks vehicle locations, fuel consumption, and driver behaviors.	[93–95]
Maintenance	Facilitating the same by assuring timely maintenance, mostly lightening infrastructural facilities to avoid time wastage.	It helps in fixing timely maintenance measures depending on its usage by the vehicles.	[93–95]
Revenue Generation	In particular, it engages in energy trading markets in order to purchase excess energy it will retail in the markets.	Improves the revenues by optimizing fleets and spending less time associated with fleets that are not generating any income.	[93–95]
Integration with AI	It actively participates in energy trading markets for purposes of purchasing excess energy that it can retail to the energy trading markets.	Uses Advanced Intelligent Automation for better routing, shorter time taken, and conservation of fuel.	[95,96]
Grid Resilience	Enhances depot security from malicious attacks and prevents energy loss by planning EV recharging during late hours.	Improves resource utility by allowing fleet adaptability during crisis situations.	[95,96]
User Experience	Offers end-users benefits in making informed decisions on charging stations that are cheap to manage.	Improves fleet management decision-making process by providing clear and easy to understand visualizations.	[96–98]
Compliance	Comply with energy norms and supports the consumption of renewable energy sources.	It complies with the company policy on emissions on their fleets as well as the operational safety standards.	[99,100]
Resource Allocation	Optimizes energy distribution among multiple charging stations.	Allocates vehicles dynamically based on demand and availability.	[99,100]
Performance metrics	The tracking of energy consumption, charging time effectiveness, and the stability of the grid.	Monitors fleets productivity, maintenance milestones as well as operational down time.	[99,100]
Long-term Viability	Encourages investment in renewable energy integration.	Facilitates long-term sustainability of fleet operations.	[99,100]
Cybersecurity	Implement robust measures to secure energy grid data and prevent breaches.	Employs advanced cybersecurity protocols to protect fleet data and communications.	[101,102]
Lifecycle Management	Manages the lifecycles of the stations to understand when charging stations need upgrades or replacements.	Tracks the lifecycle of vehicles and parts to maximize ROI and minimize waste.	[101,102]
Training and Support	Enables operators to examine energy systems and advance their utilization.	Offers fleet managers training on data interpretation and predictive tools.	[101,102]

IIoT systems help optimize the charging and discharging cycles of EVs, especially when these vehicles are part of a fleet. Intelligent energy management systems (EMS) are deployed to balance the power demands from EVs, charging stations, and the grid [103]. These systems collect data on the vehicle's battery State of Charge, temperature, and health, which is then analyzed to provide predictions on optimal charging times and battery life extension [102]. A comparison of minimum and maximum IIoT integration benefits in energy optimization is depicted in Figure 7.

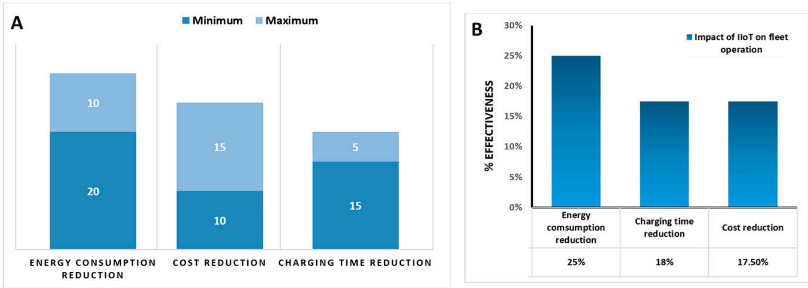


Figure 7. Comparison of IIoT integration levels (%) in (**A**) energy optimization and (**B**) fleet operations.

In fleet management, IIoT-enabled systems provide a robust framework for collecting and processing large volumes of data from vehicles, charging stations, and infrastructure in real-time [104]. This data is analyzed using sophisticated analytics platforms such as Amazon Web Services (AWS IoT Core) or Google Cloud IoT to generate actionable insights into fleet performance, energy usage, and maintenance needs. By leveraging advanced analytics, fleet operators can predict vehicle failures before they occur and optimize route planning. Real-time data analytics help in the evaluation of driver behavior, which can lead to the development of tailored training programs to improve driving efficiency and reduce energy consumption [105]. This comprehensive, data-driven approach ensures that fleet operations are optimized, cost-effective, and sustainable. A comparison of different effects of IIoT on fleet operations is depicted in Figure 7.

Despite the many benefits of IIoT integration in energy and fleet management for EVs, several limitations remain. The enormous volumes of private data shared among connected devices gives rise to security and privacy concerns. As the number of EVs and charging stations rises, scalability problems may arise, making it more difficult for the infrastructure to manage growing data loads. Furthermore, interoperability is still a challenge because different software and hardware systems often lack established protocols for smooth integration. Adoption may be hampered by the high upfront costs associated with deploying IIoT technologies, such as sensors and network equipment. To address IIoT limitations, robust cybersecurity, standardized protocols, and scalable cloud solutions are essential. Affordable IoT hardware and improved network infrastructure, including edge computing, can enhance reliability and reduce costs.

5.4. EV Charging and Battery Management

A recent study by Canilang et al. emphasized the pivotal role of IIoT in enhancing EV charging infrastructure and battery management, which are the key components for ensuring efficient and reliable EV operation [92]. IIoT-enabled systems optimize charging processes, balancing grid demand and vehicle requirements to minimize downtime and energy waste [106]. Research highlights that load-balancing during peak demand can reduce grid energy consumption by 20–25%, lowering costs for consumers and utilities, while smart charging features reduce charging times by up to 30% through efficient power distribution [107]. A novel bi-level four-stage optimization framework was reported to address the operational challenges of renewable energy variability and uncoordinated electric vehicle (EV) charging in Active Distribution Networks (ADNs) [108]. Battery management, another critical focus area, benefits significantly from IIoT-enabled Battery Management Systems (BMS). At the cell level, these systems track variables including temperature, State of Charge (SoC), and State of Health (SoH) [109]. BMS can increase battery longevity by 10–15% and decrease operational downtime by 30–40% by using predictive analytics to optimize charging cycles, regulate battery temperature, and anticipate faults [110]. The comparison of the impact percentage of IIoT in battery management and EV charging in depicted in Figure 8, which includes smart charging (reduction in charging time), load-balancing (reduction in grid energy consumption), IIoT-enabled BMS (extension in battery lifespan), and downtime reduction (predictive analytics for battery health). These advancements underscore the potential of IIoT to transform EV ecosystems by enhancing charging efficiency, prolonging battery life, and reducing maintenance costs. However, further research is needed to address scalability, cybersecurity risks, and integration challenges.

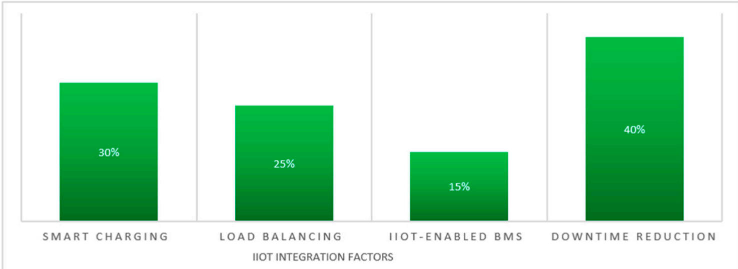


Figure 8. Comparison of impact percentage of IIoT in battery management and EV charging.

Power load management is a key issue in smart grids, since the widespread adoption of EVs is generally expected to increase energy efficiency and reduce greenhouse gas emissions. The creation of a demand-response model for residential clients dealing with EV penetration was examined by researchers [111]. They investigated how distribution-level load-shaping is affected by customers' responses to different pricing regimes under various EV penetration scenarios. According to this analysis, peak demand can be decreased by appropriately designing the time-of-use rate. From a V2G perspective, grid-connected EV batteries can also serve as a distributed energy storage system by storing excess energy from renewable sources and releasing it when needed [112]. Recent advances in self-supervised and generative learning improve demand forecasting and provide resilience against cyber-attacks on charging infrastructure; for example, generative self-supervised models have been shown to increase forecast robustness under adversarial input scenarios for EV charging demand [113].

5.5. Autonomous EVs, Cyber Security, and Advanced Charging Systems

The integration of the IIoT in EV charging systems is crucial for improving charging efficiency, optimizing energy distribution, and enhancing the overall user experience [88]. Intelligent charging solutions can dynamically adjust charging speeds, monitor energy consumption, and provide real-time updates to both the user and charging stations [114]. Furthermore, IIoT can enable integration with renewable energy sources, such as solar or wind power, ensuring that EVs are charged with sustainable energy whenever possible [115]. With IIoT, charging stations can communicate with the EV to identify the optimal time for charging, considering factors like grid demand, energy prices, and the vehicle's State of Charge. Advanced charging algorithms can help minimize waiting times and reduce the burden on the grid during peak hours [116]. Additionally, IIoT systems can monitor charging infrastructure health, alerting operators to malfunctions and preventing downtime. Various proposed advanced charging systems using IIoT integration are depicted in Figure 9.

The convergence of autonomous driving technologies and the IIoT presents significant advancements in EV safety and operational efficiency [117]. IIoT-enabled autonomous EVs use real-time sensor data to dynamically modify their driving style in response to road dangers, traffic conditions, and vehicle health, especially the battery state [118]. Due to enhanced real-time decision-making capabilities, research indicates that this integration may result in a 40–50% decrease in traffic accidents. Autonomous EVs can improve route planning and energy efficiency by lowering energy consumption by 10%–15% by choosing better routes and modifying their driving [119]. The likelihood of cyberattacks increases with the number of connected vehicles. EVs with IIoT-enabled systems are susceptible to hostile intervention and data intrusions [120]. To guarantee the secure data transfer, communication, and functioning of connected EVs, research into EV cybersecurity standards and solutions is crucial. Research is also focused on the development of blockchain and advanced encryption technologies to secure data transmission between EVs and charging stations. In addition, machine learning-based intrusion detection systems are being implemented to proactively identify potential threats in real-time [101].

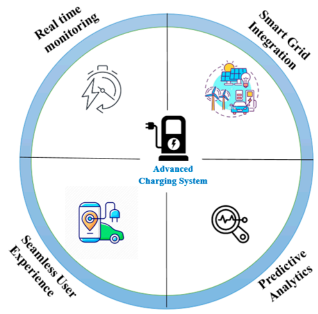


Figure 9. Different IIoT integration benefits in advanced charging systems.

5.6. Advanced Driver-Assistance Systems (ADASs)

The integration of the IIoT into ADASs within EVs offers significant enhancements in safety and driver experience. IIoT sensors and systems can provide real-time data on the vehicle's surroundings, including traffic, road conditions, and other vehicles, to support systems such as adaptive cruise control, lane-keeping assistance, automatic emergency braking, and parking assist [121]. Additionally, data from IIoT sensors can be used to improve the accuracy and reliability of ADAS, ensuring that safety features are activated at the right time and in the correct conditions [122]. The global advanced ADAS market was valued at USD 33.00 billion in 2023 and is expected to grow at a CAGR of 9.5% during the forecast period. A comparison of ADASs' market size by region proposed for 2019–2032 is shown in Figure 10, as reported by Polaris Market Research [123].

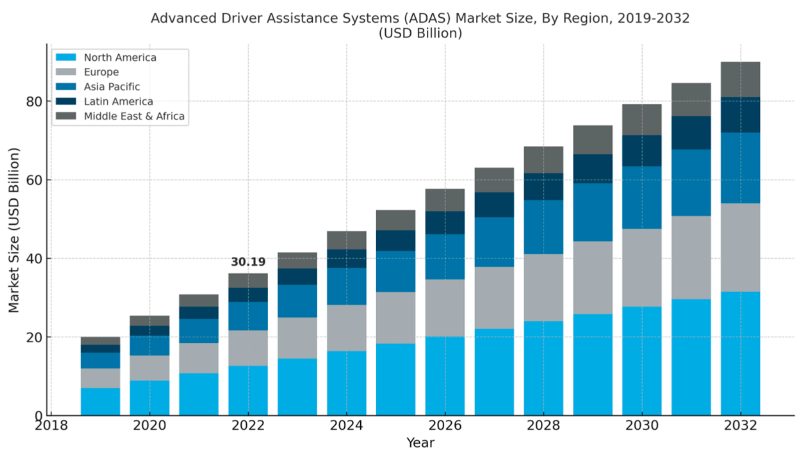


Figure 10. A comparison of ADAS market size by region proposed for 2019–2032 (reported in the 'Polaris Market Research Report', ID: PM1359, published on January 2024) [123].

The role of the IIoT in an ADAS includes the following factors:

- Real-time sensor data for detecting obstacles, pedestrians, or other vehicles, enhancing the vehicle's decision-making capabilities.
- Integration with outside data sources to enhance the vehicle's awareness and reaction to its surroundings, such as weather and traffic data.
- Constant system tuning using machine learning methods to enhance the ADAS' performance and adjust to various driving situations.

As ADASs become more widely used, providing solid security measures within these systems remains essential, as the limitations of ADASs could be exploited by attackers. For example, a defect might allow for a potential attacker to remotely access the car's system and control its functions [124]. Vulnerabilities may be introduced by updates and patches that are not fully assessed before being implemented. Real-life incidents underscore the dangers posed by vulnerabilities in ADASs, such as the well-documented issue of phantom braking. These systems can sometimes misinterpret shadows or objects as pedestrians or vehicles, leading to sudden and unnecessary braking, especially on high-speed roads like motorways.

6. Case Studies

By examining real-world applications in diverse contexts, we aim to provide a comprehensive understanding of how IIoT drives innovation and addresses critical challenges in fleet management, charging infrastructure, and personalized user experiences. This section delves into three prominent case studies that exemplify the potential of IIoT in revolutionizing the EV sector. An overview of individual case study projects and their results, advantages, and limitations is discussed in detail below and in Table 5 (IIoT integration into electric bus fleets in Shenzhen China [125]), Table 6 (EV charging network in the Netherlands [126]), and Table 7 (personalized user management from Tesla [127]).

Table 7. Overview of proposed solution, obtained results, advantages and limitations of IIoT integration in EVs: a case study of electric bus fleets in Shenzhen, China.

Case Study	**Electric Bus Fleets Shenzhen, China**		
Proposed Solution	**Obtained Results**	**Advantages**	**Limitations**
IIoT sensors monitored battery status, vehicle location, energy consumption, and charging cycles. Real-time data collected via a cloud-based platform for optimization.	Energy Optimization: Reduced charging costs by 20–30%.	Cost reduction.	Managing large fleet data, optimizing charging schedules.
	Cost Reduction Maintenance costs were reduced by 15%.	Scalability for large scale fleet operations.	Complex system High initial cost.
	Predictive Maintenance: Reduced downtime and maintenance costs by 15%.	Reduced downtime and maintenance costs.	Continuous need for upgradation and monitoring.
	Fleet Utilization: Improved efficiency by 35%.	Efficiency is improved by optimized fleet scheduling.	

6.1. Case Study 1: Electric Bus Fleets in Shenzhen, China

Background: Shenzhen's journey toward a fully electric bus fleet began in 2010 as part of China's ambitious efforts to combat urban air pollution and promote sustainable mobility. By 2017, Shenzhen successfully electrified all 16,000 of its buses, becoming the first city in the world to achieve this milestone. However, this large-scale transition brought significant operational challenges, including managing energy consumption, optimizing charging schedules, and maintaining vehicle health across such a vast fleet.

Project Overview: To address these issues, the city formulated an IIoT-based fleet management system. IIoT sensors were installed to monitor critical parameters like battery status, vehicle location, charging cycles, and real-time energy consumption. A centralized cloud-based platform was integrated to process and analyze this data, facilitating predictive maintenance, smart charging, and route optimization. These innovations not only reduced operational costs, but also enhanced energy efficiency and improved fleet utilization by 35%. Shenzhen's success underscores how advanced IIoT solutions can scale to meet the challenges of large urban transportation systems while paving the way for sustainable and efficient public mobility. An overview of the proposed solutions, obtained results, advantages, and limitations are discussed in Table 7.

Advantages and Limitations: Shenzhen's IIoT-based fleet-management system achieved notable advantages, including streamlined charging plans that minimized energy costs by 20–30% and predictive maintenance that minimized maintenance expenditures by 15%. Improved fleet scheduling improved performance efficiency by 35%, while the system's scalability and environmental gains set a global benchmark for electric public transportation. However, the project faced high initial costs for IIoT infrastructure, technical difficulties in handling data from 16,000 buses, and dependency on a stable electricity supply [125].

6.2. Case Study 2: The Netherlands' EV Charging Network

Background: A pioneer of electric transportation systems, the Netherlands encountered increasing pressure on its power grid due to the increasing volume of electric vehicles. The Dutch government, acknowledging the necessity to align energy demand and supply optimization, collaborated with power suppliers and IIoT technology companies in 2018 to develop a country-wide automated charging network.

Project Overview: This initiative aimed to optimize EV charging sessions while minimizing grid strain, especially during peak hours. The system incorporated IIoT sensors across over 40,000 charging stations to gather real-time data on energy demand, vehicle battery SoC, and user charging patterns. Furthermore, the integration of V2G technology allowed for EVs to act as dynamic energy reserves, sending power back to the grid during peak times. Dynamic pricing models were implemented to incentivize off-peak charging, reducing costs for consumers and improving grid stability. This case study highlighted the critical role of IIoT in modernizing energy infrastructure, demonstrating how smart charging solutions can enhance energy efficiency, grid resilience, and cost optimization in regions with significant EV adoption. The proposed solutions, obtained results, advantages, and limitations are discussed in Table 8.

Advantages and Limitations: The Netherlands' smart charging system effectively minimized high grid load and, using dynamic pricing, lowered user charges [126]. For example, Utrecht's smart solar charging project [128], ElaadNL's smart charging demonstrations [129], and research on dynamic pricing and grid impact by TU Delft [130] have conducted significant research on this topic. While these initiatives have demonstrated the potential benefits of minimizing grid load and reducing user charges, they also underscore the need for the careful consideration of grid infrastructure capabilities and consumer perceptions to ensure successful and equitable outcomes. Moreover, V2G technology lowered grid strain demonstrating optimized energy usage while incorporating renewable sources. Regardless of these advantages, high setup expenses and the reliance on broad V2G adoption posed hurdles. Also, concerns around data security surfaced due to real-time monitoring, and integrating IIoT into current grid infrastructure required major updates and technical proficiency.

Table 8. Overview of proposed solution, obtained results, advantages and limitations of IIoT integration in EVs: a case study of the Netherlands' EV charging network.

Case Study	Netherlands EV Charging Network		
Proposed Solution	**Obtained Results**	**Advantages**	**Limitations**
IIoT sensors monitored State of Charge (SoC), peak demand times, and dynamically adjusted charging rates. Integrated Vehicle-to-Grid (V2G) technology for grid balancing.	Load Balancing: Reduced peak grid load by 15–20%.	During high demand hours, reduction in peak grid loads.	Grid capacity management and charging station distribution challenges.
	Cost Reduction Charging costs reduced by 25% during off-peak hours.	Reduction in charging cost.	Possible delay in communication.
	Dynamic Pricing: Lowered consumer charging costs by 25% during off-peak hours.	V2G technology reduces strain of grid system. Improved energy efficiency and grid reliability.	Require high investments Challenges in the worldwide accessibility of V2G technology.
	Energy Efficiency: Reduced grid strain by 18%.	Possible delay in communication.	

6.3. Case Study 3: Tesla Personalized User Management

Background: Tesla's journey with electric vehicles (EVs) began in 2003, founded by engineers Martin Eberhard and Marc Tarpenning, aimed at proving that electric vehicles could be better, faster, and more enjoyable to drive than gasoline cars. Their idea was to create electric cars that could not only be environmentally friendly, but also offer unmatched performance and be desirable to mainstream consumers. Since the release of its early EV models, Tesla has integrated IoT and machine learning capabilities to deliver highly customized and efficient driving experiences. By leveraging IIoT, Tesla's vehicles collect and analyze vast amounts of real-time data on driving behavior, road conditions, battery performance, and environmental factors.

Project Overview: This study powers Tesla's personalized in-vehicle systems, enabling features like adaptive driving modes (e.g., energy-saving, performance), dynamic climate control settings, and predictive battery management. For instance, the system automatically adjusts energy consumption based on user's driving habits and external factors like traffic conditions and terrain. Tesla's reliance on IIoT extends beyond personalization-predictive analytics, also using it to optimize battery charging cycles, ultimately extending battery life by 10–12%. Additionally, these data-driven enhancements have significantly increased user satisfaction, with 70% of Tesla owners reporting a better driving experience due to the intuitive and adaptive features. Tesla's case study exemplifies how IIoT and machine learning can revolutionize modern vehicles by combining sustainability, technological intelligence, and user-centric design, reshaping the future of automotive innovation. An overview of the proposed solutions, obtained results, advantages, and limitations are discussed in Table 9.

Advantages and Limitations: Tesla's personalized user management offers several benefits that enhance the user's driving experience. Tailored settings, such as energy-saving and performance modes, provide users with a driving experience that meets their specific needs, significantly boosting satisfaction. Predictive analytics optimize battery charging cycles, resulting in extended battery life of up to 12%, which also contributes to the vehicle's overall longevity. Real-time data processing enables dynamic adjustments, ensuring efficient energy consumption and reducing the environmental impact of driving. Furthermore, these adaptive and intuitive features have greatly improved user engagement, as reflected in a 70% positive feedback rate from Tesla owners, who appreciate the seamless and intelligent functionality [126].

Table 9. Overview of proposed solution, obtained results, advantages and limitations of IIoT integration in EVs: a case study of Tesla personalized user management.

Case Study	**Tesla Personalized User Management**		
Proposed Solution	**Obtained Results**	**Advantages**	**Limitations**
IIoT collected data on driving behavior, vehicle usage, and battery health Personalized features like adaptive driving modes and predictive energy consumption	Driving Efficiency: Improved by 15–20%	Extended battery life	Continuous need of upgradation High initial investment
	Fleet efficiency Enhanced through adaptive driving modes	High user satisfaction	Risk of cyberbullying
	Battery Life: Extended by 10–12%	Improved driving efficiency	Continuous need for upgradation Ensuring seamless adaptation to individual driving styles
	User Satisfaction: 70% of users reported enhanced satisfaction with adaptive features	Better consumption based on driving tactics and road conditions	

Despite its advantages, Tesla's system faces several limitations. The continuous collection of real-time data raises concerns about user privacy and data security. Additionally, the integration of advanced IIoT and machine learning technologies comes with high development and maintenance costs, requiring significant investment. Moreover, limited infrastructure in certain regions—such as insufficient charging stations or weak connectivity—can hinder the full functionality of some features.

6.4. Emerging Markets

Although IIoT–EV adoption in Africa and South America is in an earlier stage, notable initiatives exist. In South Africa, the Rea Vaya bus rapid transit system in Johannesburg is piloting IIoT-enabled fleet management, with telematics for preventive maintenance and route optimization [131]. In Brazil, São Paulo has deployed a small network of IIoT-connected EV charging stations integrated with local renewable generation, using mobile-payment–based access control [132]. Chile operates one of the largest electric bus fleets outside China, with ongoing trials of V2G functionality and predictive battery health monitoring in Santiago [133]. These examples illustrate that emerging markets can act as testbeds for cost-optimized, context-specific IIoT solutions, even in the presence of infrastructure and policy constraints.

7. Discussion and Analysis

The findings of this study showcase various advantages that IIoT technologies bring to the EV sector, focusing on their part in the development of power optimization, extending battery life span, fleet management, and automated driving abilities. While these findings exhibit the groundbreaking promise of IIoT, an in-depth study, with a comparison of the technologies, their statistical influence, and related methods, reveals pivotal understandings into their benefits, challenges, limitations, and comprehensive consequences.

Smart charging stations, which support IIoT for real-time energy distribution, significantly decrease charging duration by up to 30% [134]. This upgrade is highly competitive compared to traditional charging terminologies, where time duration is a primary issue for consumers. The integration of load-balancing, reducing grid energy utilization by 20–25% [135], is another value-added benefit. However, these milestones rely on advanced communication protocols and high-bandwidth infrastructure, such as 5G, which may not always be accessible in developing regions. Additionally, the development cost of such smart systems can be prohibitive for smaller-scale operators, creating disparities in access.

Battery Management Systems (BMSs) represent another area where IIoT technologies advance, achieving a 10–15% extension in battery lifespan and a 30–40% reduction in operational downtime using predictive analytics [136]. These improvements mark a significant advancement in conventional battery management techniques, where such precise monitoring and optimization are largely absent. However, the accuracy of predictive analytics heavily relies on the quality and quantity of sensor data, as well as the robustness of machine learning models. Systems that depend on AI models must also address computational resource demands, as complex training and processing can challenge real-time responsiveness.

Vehicle-to-Grid (V2G) systems represent the relationship between IIoT and renewable energy. Allowing for bidirectional energy flow, they contribute to a 15–20% reduction in peak energy demand, refining grid stability and reducing costs during high-demand periods [137,138]. While conceptually strong, this technology's success hinges on the adoption of standard protocols, interoperability across manufacturers, and regulatory support. Inconsistent global regulations and infrastructural readiness remain hurdles, making V2G adoption slower than desired. The use of IIoT in fleet management and automated EV sector demonstrates the prospect of real-time data for efficiency enhancements and safety. The automated system [139] lessens the likelihood of road accidents by 40–50% via improved decision-making on IIoT tracking data, while enhanced path scheduling can cut power usage by 10–15%. However, these innovations come with certain challenges, including moral issues in AI-powered decision-making, responsibility in case of accidents, and the integration of diverse datasets [140].

The performance improvements cited in this review (e.g., battery life extensions, reductions in accidents) are typically the result of combined interventions. IIoT provides standardization, connectivity, and operational data; AI/ML provides analytics and decision logic; and embedded systems, such as ADASs, deliver real-time vehicle control. Thus, improvements, such as a 40–50% reduction in accidents, are most often attributable to ADAS/vehicle control algorithms enabled by IIoT data streams, whereas battery life improvements (10–15%) are commonly driven by BMS algorithms and predictive analytics operating on IIoT-collected telemetry. We revised our wording throughout the manuscript to avoid implying that IIoT alone is the sole cause of these gains, and, where possible, indicate the primary contributor.

Regarding cybersecurity, this study showcases decentralized systems and AI-powered security monitoring systems as potential solutions. While a decentralized system guarantees safe data transfer, its high operational and energy costs can be obstructive for an industry dedicated to long-term stability [141]. Also, intrusion detection systems provide real-time tracking, but are triggered by actions, which calls for a reliable protective framework. In terms of approaches, a striking difference lies in centralized vs. decentralized models. Technologies such as smart charging stations rely on centralized data processing, which can create single points of failure and increase vulnerability. Decentralized solutions, like blockchain, aim to remove these issues, but introduce complexity and scalability challenges [142].

Authors' perspective: From our synthesis, the primary advantages of IIoT adoption in EV systems include improved predictive maintenance accuracy, enhanced fleet efficiency, and integration with smart grids for energy optimization. However, disadvantages include higher upfront costs, increased cybersecurity exposure, and the complexity of integrating heterogeneous systems. While the technological trajectory is clear toward more interconnected EV ecosystems, success will depend on solving interoperability and governance challenges alongside technical innovation.

The integration of IIoT into EVs presents various benefits. It improves efficiency and performance indicators, specifically in charging systems and power consumption, thus resulting in more intelligent and more eco-friendly practices. Additionally, IIoT facilitates considerable safety improvements in automated EVs through live senor integration, permitting vehicles to react adaptively to their vicinity. Furthermore, preventive maintenance is a major advantage, as IIoT enables the lifecycle efficiency of batteries, lowering overall costs and improving sturdiness [143]. On the other hand, this incorporation comes with difficulties. The high upfront costs of launching the foundational framework can be a major obstacle for producers, manufacturers, and consumers. Additionally, the reliance on advanced technologies such as 5G, which are currently inaccessible in various regions across the world, constrains the growth potential of these systems. Data standardization, compatibility between various systems, and meeting legal adherence increase challenges for deployment. Another primary issue is the increased risk of cybersecurity threats, which necessitate considerable perpetual expenditure in security measures to protect confidential data and systems [144].

In conclusion, while our findings exhibit the huge impact of IIoT in EVs, these technologies' benefits must be carefully weighed against their associated costs and practical challenges. Future implementations should focus on scalability, cost efficiency, and robust regulatory frameworks to ensure equitable and sustainable adoption.

7.1. Challenges and Solutions

Despite being extraordinary beneficial, the adoption of IIoT in EVs introduces numerous challenges, ranging from data security to interoperability and legacy system integration [145]. National and regional regulations shape IIoT–EV deployments in distinct ways. In the EU, GDPR imposes strict constraints on personal data processing, requiring local storage or anonymization for IIoT telemetry. China's GB/T charging standards and cybersecurity law dictate physical connectors, communication protocols, and domestic data localization. In the U.S., fragmented state-level regulations create variability in V2G market participation rules [33]. In emerging markets, the absence of comprehensive EV/IIoT regulations can accelerate pilots, but also create uncertainty for scaling. These differences impact hardware choices, software architectures, and cross-border interoperability, underscoring the value of global standard alignment. These hurdles, if not addressed, can impede the widespread adoption and efficient functioning of IIoT-enabled EV ecosystems. In Table 10, key challenges are compared, along with their possible solutions and implementable steps.

Table 10. Challenges, possible solutions, and implementation steps for IIoT integration in EVs.

Challenge	Description	Possible Solutions	Implementable Steps	Ref.
Data Security and Privacy	The vast amount of sensitive data exchanged between vehicles and external systems, such as user info, telemetry, and energy consumption, increases the risk of breaches	Implement robust encryption Secure communication protocols Regular security audits and updates	Use of encryption methods (e.g., AES) Employ secure communication protocols (e.g., MQTT) Performance vulnerability assessments and audits regularly	[14,63,145]
Interoperability and Standardization	Lack of universal standards complicates seamless integration of various hardware and software platforms, causing compatibility issues	Establishing universal protocols and standards Foster industry collaboration to define common frameworks	Adopting standards like ISO 15118 (Vehicle-to-Grid communication) Engage in industry collaborations for developing protocols Standardize data formats	[145–147]

Table 10. *Cont.*

Challenge	Description	Possible Solutions	Implementable Steps	Ref.
Integration with Legacy Systems	Older EV models and manufacturing systems may not be designed for IIoT integration, leading to challenges in retrofitting and system compatibility	Use of IoT gateways for system integration Developing hybrid solutions for legacy and modern systems	Install IoT gateways to bridge legacy systems with IoT platforms Planning phased upgrades to minimize downtime and ensure compatibility with newer technology	[145,147]
Scalability	Ensuring that IIoT systems can handle growing numbers of EVs and infrastructure without performance bottlenecks	Designing of modular systems Use of cloud-based architectures Optimize data storage	Adoption of scalable cloud platforms Implement modular architectures Regularly upgrade system capacity	[62,148,149]
Real-Time Data Processing	Managing high volumes of data from numerous devices in real-time to support instant decision-making	Use of edge computing Implementing high-speed data processing algorithms	Deploying edge devices for localized computing Optimize data pipelines for real-time analytics	[64,149,150]
Cost of Implementation	High initial investment in IIoT systems, including hardware, software, and integration processes, can deter adoption	Leverage government subsidies Optimizing resource allocation Use of open-source solutions	Applying for grants and incentives Allocating resources strategically Use of cost-effective open-source tools	[33,150]
User Adoption	Resistance from stakeholders due to lack of awareness or training regarding IIoT benefits and usage	Conducting training programs Highlighting cost and efficiency benefits Providing user-friendly interfaces	Organizing stakeholder workshops Develop easy-to-use interfaces for IIoT systems	[33,150]
Regulatory Compliance	Adhering to national and international regulations governing data usage, privacy, and energy consumption	Staying updated with legal requirements Implement compliance monitoring tools	Regularly reviewing relevant regulations Use of monitoring tools for continuous compliance	[150,151]
Energy Demand Forecasting	Predicting energy requirements accurately to avoid grid overloads and optimize charging schedules	Implementing AI-based forecasting models Using historical and real-time data	Developing predictive models with AI Integrating weather and usage patterns for forecasting	[64,152,153]
Maintenance and Support	Ensuring the reliability and longevity of IIoT devices and infrastructure through proper maintenance	Setting up predictive maintenance tools Schedule regular inspections	Using IIoT sensors for condition monitoring Automate scheduling for preventive maintenance	[64,152,153]
Cybersecurity Threats	The risk of cyberattacks on IIoT networks and infrastructure, disrupting services and compromising data	Employing intrusion detection systems (IDS) Regularly updating security protocols	Installing IDS tools Regularly updating firewalls and encryption techniques	[154,155]
Environmental Impact	Managing the ecological footprint of IIoT systems, including energy consumption and e-waste generation	Use of energy-efficient devices Development of recycling programs for outdated hardware	Choosing low-energy IoT devices Partner with e-waste recycling organizations	[156]

7.2. Future Trends

The following subsections elaborate on the emerging technological trends shaping IIoT adoption in electric vehicles. Each trend is discussed with respect to its underlying principles, current applications, and potential implications for scalability, performance, and sustainability.

7.2.1. Use of AI and ML

AI and ML are driving innovation in the EV industry by enabling vehicles to become more intelligent, adaptive, and user-friendly [157]. AI can analyze data from IIoT sensors to predict battery degradation, ensuring timely interventions that extend battery life and improve overall reliability [155]. Similarly, ML models can refine algorithms for regenerative braking, energy consumption, and charging cycles based on driving patterns and environmental factors [158]. In autonomous driving, AI plays a pivotal role in processing vast amounts of real-time sensor data, enabling vehicles to navigate complex environments with greater safety and precision. By analyzing traffic patterns, road conditions, and nearby vehicles, AI-driven systems make informed decisions that enhance navigation and reduce accidents [159]. Machine learning models also continuously adapt to new scenarios, improving performance over time [160]. Future applications will include adaptive charging schedules that align with grid conditions [135], predictive route planning to avoid congestion, and personalized driving modes that are tailored to individual preferences. Generative self-supervised learning approaches have also been proposed to make demand forecasts and control strategies robust to adversarial or missing data, improving the cyber-resilience of smart charging systems [113]. Additionally, as these technologies integrate further into IIoT platforms, they will facilitate innovations such as self-healing systems, where vehicles can autonomously detect and resolve minor faults before they escalate [161].

7.2.2. Technological Advancements

Technological breakthroughs, particularly in quantum computing and edge computing, are set to redefine the capabilities of IIoT-enabled EV systems [162]. Quantum computing could revolutionize route planning by dynamically adjusting paths based on traffic [163], energy availability, and vehicle range. It also could enable optimal energy distribution within charging networks, significantly reducing charging times and enhancing the efficiency of renewable energy integration. Edge computing, on the other hand, addresses the challenges of latency and connectivity by processing data locally on the vehicle or near the source [164]. These advancements will also support the scalability of IIoT systems as the number of connected devices in EV ecosystems continues to grow. By decentralizing data processing, edge computing alleviates the burden on cloud infrastructure, ensuring seamless operation, even during peak loads. The combination of quantum and edge computing will empower industry to achieve new levels of efficiency, reliability, and responsiveness, fostering innovation across the EV value chain.

7.2.3. Introducing New Models

The future of EV design is increasingly leaning toward modular and customizable architectures, enabling the seamless integration of IIoT technologies. Modular designs will allow for manufacturers to upgrade or replace individual components, such as batteries, control units, or IIoT sensors, without requiring a complete vehicle overhaul [165]. For instance, cars with a modular design can easily be adapted to integrate the latest IIoT features, such as better AI algorithms or the latest communication standards, as this market is fast evolving [166]. Standardized modules also help to maintain a circular economy, since they prolong the number of years that a vehicle will serve the public and, at the same time, help with the efficient maintenance of vehicles. Moreover, using this strategy, overall scalability may be improved, manufacturing can be standardized, and new models can be developed to meet the increased call for sustainable, advanced automobiles.

7.2.4. Unified Evaluation Framework

To enable consistent benchmarking, future IIoT–EV studies should adopt a unified evaluation index system integrating technical KPIs, for example, network latency, data packet delivery ratio, predictive maintenance accuracy, and mean time to repair (MTTR) reduction. Economic metrics can evaluate total cost of ownership (TCO), return on investment (ROI), payback period, and operating cost reduction. Sustainability indicators can record CO_2 emissions avoided per km, grid load reduction, and the percentage of renewable energy utilized. Comparative analyses should normalize these metrics to a defined baseline (e.g., equivalent non-IIoT system) to facilitate cross-study comparison. Frameworks such as ISO 50001 (energy management) can be adapted to provide a structure for reporting [167].

7.2.5. IoT and IIoT Expansion

A new generation of networked ecosystems enhancing EV's operation, connectivity, and (often) user experience is emerging through the junction of IoT and IIoT. While IIoT covers factory-level programs such as resource-tracking systems or prognosis systems, IoT is more oriented toward use cases that involve common people, such as using a smart phone application to monitor an electric vehicle, or smart home charging stations [168].

These two domains work together to comprise integrated networks that ensure the seamless transmission of data through different contact points. To reduce expenditure and decrease grid stress, for instance, IoT-integrated home charging may organize charging sessions based on IIoT-integrated grid handling systems [169]. In the same regard, the coupled fleets may coordinate charging and routing schemes in a bid to optimize operations and reduce energy consumption. Both the IoT and IIoT have the capability to create novelties involving industrial symbiosis and cooperation across these sectors.

8. Conclusions

The revolutionary influence of IIoT in the EV industry enables the advancements of smarter, more optimized, and renewable transportation solutions. This review has collected research from over 120 studies to provide a complete understanding of IIoT's applications, issues, advantages, and upcoming trends in the EV industry. Predictive maintenance, vehicle connectivity, energy and fleet management, and self-driving systems are some core applications that showcase the capacity of IIoT to revolutionize the EV network. Case studies additionally emphasize the tangible gains of IIoT, depicting its potential to boost operational efficiency and customer satisfaction. The findings of this study showcase the transformative potential of IIoT in advancing EV technology, specifically through smart charging systems, load-balancing, and real-time data analytics. These innovations contribute to enhanced operational sustainability by lowering grid energy consumption, extending battery lifespan, and minimizing downtime.

Despite its various benefits, the integration of the IIoT into EVs is not without challenges. Challenges such as cybersecurity, connectivity, and the integration of IIoT technologies with pre-existing systems remain significant barriers. These issues can be resolved, as they necessitate cooperation among legislators, involved parties, and technology developers to set up uniform structures and fast, secure architectures. Moving forward, progress in artificial intelligence and machine learning are likely to improve the capacities of the IIoT in EVs, laying the foundation for smarter and more automated transportation systems. In addition to that, continued innovation in connectivity technologies and charging infrastructures will play a critical role in accelerating the adoption of IIoT-enabled EVs.

In conclusion, the coupling of IIoT and EVs carries significant possibilities for propelling a worldwide shift towards eco-friendly and smart transportation. By addressing the ongoing challenges and harnessing rising technologies, the IIoT-enabled EV industry can play a vital role in influencing the future trajectory of the transport industry.

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Acronyms

The following abbreviations are used in this manuscript:

5G	Fifth Generation
ADAS	Advanced Driver-Assistance Systems
AI	Artificial Intelligence
BMS	Battery Management Systems
CCPA	California Consumer Privacy Act
EMS	Electric Vehicles
EVs	Energy Management Systems
GDPR	General Data Protection Regulation
HMI	Human–Machine Interface
IDS	Intrusion Detection Systems
IIoT	Industrial Internet of Things
IoT	Internet of Things
ISO	International Organization for Standardization
IT	Information Technology
LoRaWAN	Long Range Wide Area Network
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NLP	Natural Language Processing
OT	Operational Technology
SoC	State of Charge
SoH	State of Health
TLS	Transport Layer Security
V2C	Vehicle-to-Cloud
V2G	Vehicle-to-Grid
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything

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