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An AI-Powered Integrated Management Model for a Sustainable Electric Vehicle Charging Infrastructure

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Abstract

The rapid increase of electric mobility is challenging the deployment design and operation of electric vehicle charging infrastructure in a scalable, sustainable, operationally reliable, and regulation-compliant manner. Although advances in both digitization and artificial intelligence in recent years have made smarter charging solutions possible, today's approaches tend to concentrate on individual technical parts without considering holistic views. This paper introduces an AI-driven integrated management model for sustainable EV charging infrastructures, composed of four interconnected layers, namely, Eco-Design, Digital Tools, Risk Management, and Governance. In particular, each layer focuses on specific aspects of functionality, including environmentally friendly design decisions, digital monitoring capabilities, proactive risk reduction, and strategic coordination. Compared with existing approaches that address isolated technical or operational aspects, the proposed model provides an integrated, multi-layer architecture that unifies eco-design, digital intelligence, risk management and governance, offering a more holistic and scalable foundation for sustainable EV charging infrastructures. It represents the conceptual output of a structured integration of existing technologies, design principles and governance needs. Considering that fragmented, solution-specific advances are reduced by including interdependencies between layers, the model allows us to better integrate technical operations, resilience mechanisms and sustainability goals. The model is theoretical and offers a scalable point of reference for researchers, as well as infrastructure operators and politicians.

Keywords: electric vehicle charging; artificial intelligence; digital twins; sustainability; risk management

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1. Introduction

The proliferation of electric mobility is accelerating the demand for deployment and operation of electric vehicle (EV) charging infrastructure. Despite the rapid growth in global EV usage, charging infrastructures continue to experience high scalability, energy efficiency, operational reliability, and long-term sustainability challenges. These challenges are further exacerbated by the infusion of renewable generation, fluctuating user demand, and compliance with changing regulations. As a result, traditional approaches to EV charging infrastructure management, often based on isolated optimization strategies, are proving insufficient to address the systemic complexity of modern charging ecosystems [1,2].

The deployment of EV charging infrastructure has become a critical component of the global energy transition. Several studies have addressed infrastructure planning, optimal charging station placement, grid integration, and smart charging strategies. These works highlight key challenges related to demand uncertainty, renewable energy integration, grid stability, and infrastructure scalability [3,4].

Latest progress in digitalization and AI has offered new choices in enhancing the efficiency of electric vehicle charging systems. Among these, the most relevant are Internet of Things (IoT) sensors, digital twins of devices [5] and infrastructure elements [6], data analytics, and machine learning models that support real-time monitoring (e.g., predictive maintenance or adaptive energy management). However, existing research usually addresses aspects of the infrastructure in isolation (e.g., smart charging algorithms, load balancing, or predictive maintenance) and does not provide a framework to integrate them with technical operations towards sustainability objectives, risk management, and governance mechanisms [2,7].

This fragmentation limits the capacity of current solutions to address long-term resilience, lifecycle sustainability, and coordinated decision-making. On the other hand, from a sustainability and design point of view, lifecycle-based and circular economy principles emphasize modularity, material efficiency, and long-term adaptability related to energy infrastructures [8,9]. Governance and resilience studies, in turn, stress that sustainable infrastructure systems need anticipatory, coordinated, and adaptive management models able to cope with systemic risks and disruptive events [10–13]. Yet these governance-oriented resilience paradigms have not been transferred systematically so far to the design and operation of EV charging infrastructures.

To fill this gap, this study contributes by presenting an AI-based integration management model of sustainable EV charging infrastructures. The model is divided into four interconnected layers: Eco-Design, Digital Tools, Risk Management, and Governance. In this regard, every layer provides a particular asset function view, while AI represents a horizontal enabler helping to optimize, predict, and decide across the whole system. By emphasizing a stratified, holistic approach, this model promotes breaking down siloed solutions and addresses the coherence of design decisions, operational intelligence, resilience strategies, and strategic planning. Moreover, the model emphasizes the importance of stakeholder involvement, recognizing that sustainable and resilient EV charging infrastructures require coordinated contributions from technical, institutional and user-side actors. The research question (RQ) guiding this research study is as follows:

RQ: How can an AI-driven, multi-layer management model systematically integrate eco-design principles, digital monitoring tools, risk management mechanisms, and governance processes across the lifecycle of EV charging infrastructures to support sustainability and resilience?

The contribution of this work can be summarized as follows:

- Development of a multi-layer conceptual model including eco-design, digital solutions, risk management, and governance of EV charging infrastructures.
- Identification of artificial intelligence as an enabling mechanism between layers and supporting optimization and decision support tools.
- Conceptual unification of sustainability-based design principles with operational intelligence and resilience-based management of EV charging infrastructures.

The paper is structured as follows: Section 2 introduces related research on smart and sustainable charging infrastructure for electric vehicles. In Section 3, the methodological steps followed for defining the integrated management model of EV charging infrastructures are illustrated. The different layers of the integrated management model and the role of AI are described in Section 4. In Section 5, the integration of the different layers of the integrated management model is illustrated. Section 6 concludes the paper.

2. Related Work

There has been a lot of research related to smart and sustainable charging infrastructure for electric vehicles because of the fast growth in the use of electric mobility. In earlier work, the deterministic and rule-based charging concept dominated the literature, but more recent publications often use artificial intelligence to tackle the increasing complexity in interaction with the grid, renewable sources, and managing the demand.

The second important thread of research revolves around smart charging and load management. Adaptive charging networks using distributed optimization techniques have been proposed by Lee et al. [1], showing how charging points can be coordinated through algorithms to better stabilize and optimize energy use in the grid. More contemporary work in AI is using machine learning and reinforcement learning to adapt charging patterns in response to evolving conditions in the grid, availability of RE, and uncertainties in demand [14–16]. The applications and results mostly pertain to real-time control, and any implications related to sustainability and governance are negligible. Another integrated area of study is digital twins and IoT-based monitoring. Digital twins have been identified as important enabling techniques for real-time simulation, predictive analysis, and scenario analysis of smart energy systems [6]. In terms of EV charging infrastructure, Yu et al. [2] illustrated the concept of digital twin architectures for planning, optimizing, and resilience analysis for the infrastructure. However, this approach is technology-based and is rarely, if ever, integrated with a governing or sustainability-oriented design approach.

Predictive maintenance, resilience, or risk management can be considered a third area that dominates many recent studies. AI models are increasingly used for diagnosis to forecast failures in system components and minimize overall system downtime [16,17]. Cybersecurity considerations have become paramount for charging infrastructure. Sarieddine et al. [18] showed that edge-based AI methods have been used to identify oscillatory load attacks and cyber threats, while Razzaque et al. [7] gave a comprehensive perspective on cyber–physical threats within vehicle-to-grid systems. These techniques align with other disaster management theories that propose management strategies that focus on anticipatory systems, adaptiveness, or risk management strategies to handle overall disaster risk [11–13]. Nonetheless, its application to EV charging infrastructure management as a resilience strategy is an area that remains largely uninvestigated.

The above-mentioned studies also examined the interaction between electricity market dynamics and electric vehicle charging systems. In particular, risk-aware optimization approaches have been proposed to incorporate financial entities into spot electricity markets with high shares of renewable energy, enabling more resilient and economically sustainable charging strategies [19–21]. A multi-objective optimization approach that analyses how investment decisions can balance economic costs, environmental sustainability, and energy policy goals has been proposed to support the energy transition [22].

Finally, a stream of research on governance and regulation studies, which emphasizes coordination, accountability, and transparency in the smart energy grid, must also be noted. It is within this context that the concept of governance created by Kooiman [10] is a process of multi-actor coordination, while the growing regulatory issues concerning the use of AI in the energy sector were emphasized by Jørgensen [23]. Nonetheless, governance research is often separated from AI-driven operational design.

Overall, the literature shows great developments in the areas of smart charging, digital twins, predictive maintenance, cybersecurity, sustainability, and governance. Most of the above-mentioned studies have emphasized the importance of operational modeling and optimization of energy infrastructure, which address specific aspects of this infrastructure. Indeed, the literature lacks an integrated, multi-layered model capable of coordinating eco-design, digital intelligence, resilience-based risk management, and governance within a unified AI-driven architecture. This fragmentation motivates the holistic integrated management model proposed in this paper. Specifically, this study consists of the definition and structured articulation of an AI-powered integrated management model for sustainable electric vehicle charging infrastructure. The study does not present empirical findings but, instead, a conceptual and architectural model, which represents the result of synthesizing evidence based upon technologies in existence, design principles, and governance needs according to a systematic pattern. The proposed model formalizes the way in which artificial intelligence can be properly integrated through a specific number of layers to ensure sustainability, operational efficiency, and resilience of EV charging systems. More specifically, outcomes are articulated within a four-dimensional model that includes Eco-Design, Digital Tools, Risk Management, and Governance, addressing specific aspects of the charging infrastructure lifecycle (see Sections 4.1–4.4). In this context, AI represents a cross-cutting enabler supporting data-light optimization techniques, as well as exploiting predictive analytics and decision support mechanisms over layers. Moreover, the model emphasizes relationships between design decisions, digital surveillance, risk management approaches, and strategic oversight in a coherent manner that contrasts with single-tiered approaches.

The theoretical foundation of the proposed model builds on a few widely recognized perspectives of complexity in contemporary energy systems. In particular, socio-technical transition theory emphasizes that energy systems are co-evolving via the interplay of technological innovation with institutional arrangements and societal actors [24]. Parallel to this, the interfacing of digital monitoring technologies and physical infrastructures is in accordance with tenets of cyber–physical systems, whereby dynamic data streams allow for adaptive management of the system [25]. In conclusion, the risk management component of the model is related to establishing structured processes to identify and react to systemic risks in complex technological systems [26]. These aspects serve as a conceptual background for the analysis of eco-design, digital monitoring tools, risk mitigation mechanisms, and governance processes in EV charging infrastructures in order to answer the research question defined in the paper.

3. Methodology

The research methodology employed in the present study is based on a multi-step approach that aims to develop an integrated AI-enabled management model for the development of sustainable EV charging infrastructure. Since the research aims to contribute to the field conceptually, the applied research methodology consists of the following three main steps:

1. Literature overview and knowledge mapping (Sections 2 and 4): the research methodology employed in the present study begins with the analysis of the scientific literature related to the four major thematic domains of the research, named principles of eco-design and circularity, digital monitoring and AI-based tools for operation of electric vehicle charging infrastructure, risk management of complex energy systems, and the role of governance in developing sustainable mobility. The objective of this phase was to have an overview of existing approaches, the fragmentation of these approaches, the identification of the interdependencies between the four thematic domains, and the absence of a unifying model that incorporates design, operation, risk, and governance dimensions.

2. Model definition (Section 4): as a result of the mapping process, the second step entailed the structured development of the proposed AI-integrated management model. In this regard, this step adopted a conceptual modeling approach to define the structure of the proposed management model into its four interconnected layers (i.e., Eco-Design, Digital Tools, Risk Management, and Governance). The development of each layer was conducted according to: (i) its functional objectives within the EV charging infrastructure lifecycle, (ii) related technologies and AI paradigms, as well as (iii) interactions between different layers of the proposed management model.
3. Scenario illustration (Section 5): while considering the potential for empirical validation as being out of the scope of this research work, the proposed management model's internal consistency was analyzed by developing an illustrative scenario that shows how the proposed management model operates within its four interconnected layers. In this regard, it serves as a preliminary assessment of its potential applicability and benefits.

4. The Integrated Management Model of Electric Vehicle Charging Infrastructures

This section describes the integrated management model of EV charging infrastructures. The proposed model is largely prescriptive as it outlines a detailed, multi-layer structure aimed at assisting the design, operation, and governance of sustainable EV charging infrastructures. Yet it is based on a descriptive summary of current technological, research, and governance methods that form the basis of the prescriptive structure.

The integrated management model comprises the following four layers:

- **Eco-Design Layer**: it is concerned with the green EV charging infrastructure design. It includes Life Cycle Assessment (LCA), modularity, integration of renewable energy supply, and circular economy requirements.
- **Digital Tools Layer**: it contains digital monitoring and optimization tools. It includes IoT, sensors, digital twin, GIS, data analytics dashboards, and simulation software.
- **Risk Management Layer**: it ensures technical, operational, and financial strength. It comprises predictive maintenance, electrical and structural safety, high-demand readiness, and economic risk analysis.
- **Governance Layer**: it ensures scalability as well as implementation. Consists of centralized platforms for decision-making, monitoring, and reporting, and action integration from the previous layers to rational control over operations.

Table 1 reports the conceptual structure of the proposed model by defining each layer, its main functions and technologies, and its relationships with existing research. Table 2 shows how the role of AI varies across the different layers of the model.

While optimization and predictive analytics support operational monitoring and infrastructure management, reinforcement learning techniques enable adaptive responses to dynamic system conditions. In particular, at the governance level, explainable AI approaches can improve transparency and support data-driven policy evaluation.

The following subsections describe in detail the structure and functional role of each layer, outlining how their integration contributes to a scalable and sustainable management model for EV charging infrastructures. Moreover, the interaction between the four layers is operational rather than conceptual. For example, eco-design choices related to modular architecture and energy efficiency have a direct impact on risk management parameters, including system reliability, maintenance intervals, and contingencies for component failures. Likewise, information obtained from digital tools (i.e., IoT sensors and digital twins) flows into predictive analytics models that underpin risk assessment and governance-level decision-making. In this way, outputs generated within one layer can become inputs for the others, enabling a continuous feedback loop across the infrastructure lifecycle.

Table 1. Conceptual structure of the proposed model.

Layer	Definition	Main Functions	Key Technologies/Mechanisms	Related Research
Eco-Design Layer	Design-oriented layer that integrates sustainability principles into the planning and development of EV charging infrastructure.	Infrastructure planning, lifecycle optimization, renewable energy integration.	Modular infrastructure design, lifecycle assessment, circular economy principles.	Sustainable infrastructure design; energy transition studies [8,9].
Digital Tools Layer	Operational layer that enables real-time monitoring and data-driven management of EV charging infrastructures.	Data collection, system monitoring, predictive analytics.	IoT sensors, digital twins, GIS systems, data analytics platforms.	Smart energy systems; cyber–physical systems [1,2,6,14–16].
Risk Management Layer	Analytical layer that identifies, evaluates, and mitigates operational and systemic risks affecting EV charging networks.	Risk detection, anomaly identification, preventive maintenance.	Predictive models, anomaly-detection algorithms, load balancing strategies.	Risk governance; infrastructure resilience studies [7,11–13,18].
Governance Layer	Strategic coordination layer that supports policy alignment, stakeholder coordination, and performance monitoring.	Strategic planning, regulatory compliance, performance evaluation.	Decision support systems, performance dashboards, multi-criteria decision tools.	Energy governance; socio-technical transitions [10,23].

Table 2. AI paradigms in the layers of the model.

Layer	AI paradigm/Technique	Operational Role	Example Application
Eco-Design Layer	Machine learning optimization	Support sustainable infrastructure planning.	Optimization of charging station placement considering demand, grid capacity, and environmental constraints.
Digital Tools Layer	Predictive analytics and anomaly detection	Monitor system performance and detect operational anomalies.	Predictive maintenance of charging equipment based on sensor data.
Risk Management Layer	Reinforcement learning	Dynamic risk mitigation and load balancing.	Adaptive control strategies to prevent grid overload during peak charging demand.
Governance Layer	Explainable machine learning (XAI)	Support transparent decision-making and policy evaluation.	Evaluation of infrastructure performance indicators for strategic planning and regulatory compliance.

4.1. Eco-Design Layer

The Eco-Design Layer [8] targets the early design phases of EV charging infrastructure to directly impact decisions that will shape its ecological impact, from environmental impact and resource efficiency to long-life system performance. This eco-design principle, inspired by the concept of circular economy and life cycle thinking, aims at considering the charging infrastructure as a sustainable asset (and not simply as a technical entity). Among key considerations, materials, modular principles, energy issues, and the integration with renewable energies represent relevant aspects.

By taking a lifecycle view [9], the Eco-Design Layer focuses on reducing embodied energy and making maintenance and component replacement simpler, whilst also extending the lifespan of infrastructure. In this scenario, modularity is central and provides scalability with high flexibility of deployment and dynamic reconfiguration based on the prevailing demand and technology [27].

Based on eco-design principles that go beyond energy efficiency, the Eco-Design Layer is focused on maximizing the value through avoiding resource use and extending infrastructure life. In particular, the modular design allows components to be replaced and contemporary technologies to be incorporated, reducing material waste while enabling infrastructure to evolve with users' needs. This kind of approach promotes circular economy principles, focusing on reuse, repair, and optimizing the lifecycle of existing technological assets. Moreover, eco-design choices within this layer have a direct impact on downstream operational efficiency and risk exposure, so there are tight interactions with digital monitoring, risk management, and governance mechanisms. Furthermore, eco-design decisions are by their very nature multi-stakeholder activities that involve operators of infrastructure, urban planners, technology providers, as well as local authorities.

Within the proposed model, the Eco-Design Layer provides the structural foundation upon which AI-driven optimization and management processes can be effectively applied, aligning infrastructure design with sustainability and resilience objectives.

4.1.1. AI Governance in the Eco-Design Layer: Intelligent Material and Modularity Optimization

The Eco-Design Layer integrates sustainability principles deeply into the planning and building of EV charging infrastructures, thus affecting their design both in terms of architecture and used materials [6,23]. In this case, artificial intelligence (AI) is the main actor in the background as a tool that analyzes data and supports decisions, thus enabling the engineers and designers to pick the solutions that are the most efficient, longest-lasting, and cause the least environmental impact.

Rather than relying on static, regulation-driven design approaches, the use of AI in eco-design marks a shift toward flexible, data-informed models that can anticipate how materials, structures, and energy systems perform throughout their entire lifecycle [2].

The following paragraphs will be focused on material and modularity optimization, lifecycle, and sustainability.

4.1.1.1. Material and Modularity Optimization

In this context, AI governance focuses on ensuring that intelligent technologies are used responsibly from the earliest phases of infrastructure development. Machine learning models enable one to estimate the eco-footprint resulting from different design choices by way of handling information from materials libraries, as well as from weather and lifecycle analyses [28]. For example, the algorithms for reinforcement learning might determine the combinations of modular components that can result in the lowest embodied energy used for the production of the product, without at the same time the structure or the visual side being compromised [29]. Moreover, optimization algorithms might evaluate and juxtapose hundreds of likely design scenarios, allowing the identification of the best balance between cost, sustainability, and spatial efficiency [1].

From a materials standpoint, AI contributes to the transition toward circular economy principles by evaluating factors such as recyclability, durability, and maintenance needs [30]. Through the use of predictive analytics, it is possible to anticipate the way in which a particular material degrades under different environmental conditions. In this way, AI can make specific preventive choices in an attempt to extend product lifespan and reduce waste. In this regard, Figure 1 represents the conceptual workflow for sustainable EV charging infrastructure design. The initial phase involves selecting materials that are good for the environment to ensure minimal environmental footprint from the very start of the infrastructure development process. The second phase highlights the need to ensure flexibility in charging units, station designs, and upgradeability of system components. The last phase of this workflow is lifecycle prediction to facilitate proactive rather than reactive interventions, as well as reliability and sustainability.

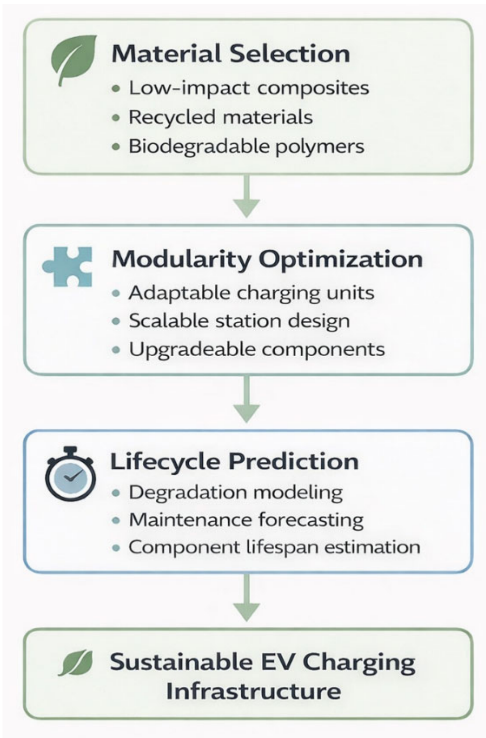

Figure 1. AI-supported eco-design workflow.

In addition, as previously discussed in the Digital Tools Layer Section, digital twins can be applied in this context to model how materials behave over time. This provides engineers and designers with real-time performance feedback during the development process [6]. These kinds of iterative simulation loops encourage adaptive design methods, in which predictive models would be continuously refined when new operational data are gathered from functioning charging infrastructures.

4.1.1.2. Lifecycle and Sustainability Forecasting

The modular nature of EV charging infrastructures can benefit greatly from the careful use of AI in design and planning. A modular setup makes it easier to replace or upgrade individual parts instead of entire systems, helping to extend the life of the infrastructure and cut down on emissions that come from large-scale replacements [14]. With the help of AI techniques, such as clustering and optimization, designers can figure out the best ways to connect modules such as charging units, power converters, and cooling systems [17]. In this kind of approach, the system would become flexible and easier to expand, and new modules can be added as electric vehicle use increases. In other words, the design process does not have to start over again.

Within this layer, the contribution would be related to guaranteeing that clear and transparent rules for how AI is used in eco-design are established. It is not only a technical issue but also an ethical one; aspects like where the data come from, how the models make their decisions, and how much energy is spent in the computation process all need to be taken into account from the very beginning [31]. Jørgensen [23] points out that the use of AI within the energy sector has to keep pace with the changing European rules in the area of sustainable digitalization. The main concern is to make sure that the environmental progress achieved through AI does not end up being offset by the high energy use required to run very large models. In this respect, it would be relevant not only to manage the technical aspects but also to connect them with policy decisions. The aim is to define clear and workable standards for AI-based eco-design that keep innovation aligned with sustainability goals.

The link between AI and eco-design also works through feedback from real operations. In fact, the most relevant data collected from charging infrastructures, such as energy efficiency levels, hardware breakdowns, or user habits, should be part of the design process [32]. This method can generate a continuous loop, where each generation of charging infrastructures can improve through a machine learning process. Over time, this approach supports a more predictive form of maintenance, with design parameters adjusting naturally in response to actual environmental data rather than fixed expectations.

AI governance and sustainability targets are becoming more connected, and this helps the Eco-Design Layer fit into larger goals like the European Green Deal on clean and affordable energy. Hossen et al. [33] highlight the need to incorporate intelligent systems within clear rules in an attempt to make their operation transparent and accountable, even in relation to the importance of good data and fair access to technology. When these elements are part of the process, AI can support sustainable development instead of adding new layers of complexity or uncertainty.

The AI-based Eco-Design Layer pulls together different strands (e.g., modeling, lifecycle studies, and ethical management) into a single way of thinking about design. It moves the focus from reacting to problems to improving things before they happen. In this context, it would be possible to build sustainability within each step of a charging infrastructure's life, instead of checking it at the end of the process. In this way, AI would turn into a practical tool for designing flexible and EV infrastructures, also ready to adapt to future needs.

4.2. Digital Tools Layer

The Digital Tools Layer represents the technological foundation of the integrated management model for sustainable EV charging infrastructures. As shown in Figure 2, it relies on a combination of Internet of Things (IoT) devices, digital twins, Geographic Information Systems (GIS), simulation tools, and big data analytics platforms to enable continuous monitoring and intelligent control of charging infrastructures [2,6]. In addition, the data and decision-making workflows outlined in Figure 2 underscore the importance of lifecycle-oriented design decisions, modular architecture, and renewable energy integration during the development of sustainable infrastructure. Organizing these components in a cohesive design process within the model can enable environmentally sound and flexible infrastructure solutions capable of accommodating future technology and operational needs. Within this model, digitalization serves as both a data source and a coordination hub, connecting the physical infrastructure of chargers with virtual analytical environments that support predictive maintenance, energy optimization, and operational efficiency [1].

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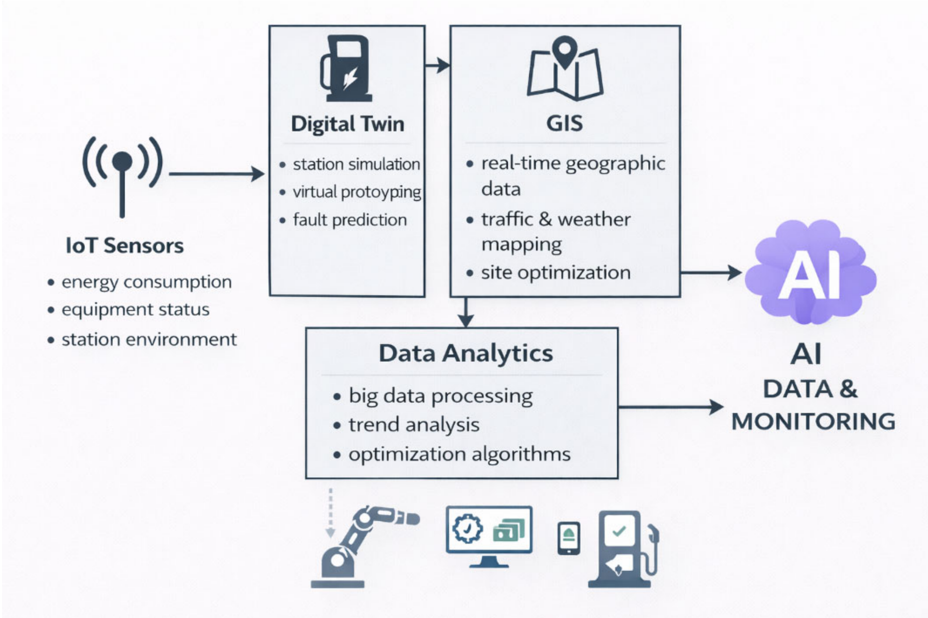

Figure 2. Data pipeline illustrating how IoT, digital twins, GIS, and analytics feed into AI within the Digital Tools Layer.

In the Digital Tools Layer, rather than isolated technologies, IoT sensors, digital twins, and GIS platforms act as interconnected elements. Internet of Things (IoT) devices provide real-time data to charging stations on energy usage charges, machine functioning, and environmental factors. Such streams of data feed into the digital twin environment that models the physical infrastructure to simulate operational use-cases. This architecture is complemented by GIS systems providing spatial context, enabling visualization and spatial analysis of the distribution of charging infrastructure, demand patterns, and connectivity to the grid. Together, these tools can build an integrated data ecosystem capable of supporting predictive analytics and informed decision-making. The use of digital tools requires taking into account the perspectives of various stakeholders such as operators of infrastructure, providers of charging services, as well as urban planners.

In the following subsections, digital infrastructure, data processing, and simulation tools will be described and discussed.

4.2.1. Digital Infrastructure (IoT, GIS, Digital Twin)

IoT and sensor networks are combined to make every charging station act as a "data node" which shares the usage pattern, environmental conditions, and technical performance information in real-time [32]. These streams of data are fed into cloud–edge architectures that distribute the computational load more evenly while providing low-latency responses, even reaching near-real-time [17]. In addition, in this process, digital twins are of great significance because they serve as virtual representations of physical systems and dynamic behavior modeling for charging equipment and energy flow, enabling operators to simulate various operational scenarios before their field implementation [6]. In fact, with the use of such simulations, one can derive the best configuration of a charging infrastructure, predict system bottlenecks, and prevent overload conditions on any part of the system [2].

Both GIS and sophisticated visualization dashboards are employed to increase spatial awareness, improving accessibility, decisions about where to locate the stations, and how demand clusters across each of them [28]. Such mapping tools are vital to ensure that infrastructure development is in concert with regional mobility demand and renewable energy potential. Blockchain applications and their synergies with AI-controlled monitoring systems can also improve data integrity as well as transparency between a variety of players, ranging from grid operators to end users [29,34].

4.2.2. Data Processing and Simulation Tools

Within this layer, the contribution focuses on interoperability and standardization processes guaranteeing that the set of heterogeneous digital components, such as sensors, software, and control system communication, are effectively working over common data protocols. The scalability is also a key value: based on standard and open source modular architectures, the system can grow as EV networks mature [15]. This scalability is directly related to sustainability, as digital tools enable optimized load balancing, thus minimizing energy waste and supporting renewable integration [16].

Moreover, the Digital Tools layer enables pre-emptive tasks with AI boosted analytics. In fact, machine learning techniques could be used to predict demand variance by learning from historical and near-ready demand signals and update the charging schemes [14]. These predictive models are critical in order to prevent peak-load stress and grid stability, while keeping user satisfaction with dynamic pricing and queue maintenance [17]. Then, the advent of edge computing enables distributed intelligence, and it is especially practical in the case of large networks of geographically distributed charging points [18].

In system terms, digital tools are also a source of cybersecurity and resilience. As noted by Razzaque et al. [7], the integration of EV stations with macroscopic various levels energy/data networks brings potential risks for attacks, leading to the need for anomaly detection and secure communication protocols. AI models at the edge, for example, can detect unusual consumption patterns that could come from cyberattacks or components failing [18]. Such schemes are used to improve the robustness of the overall charging system and prevent a failure cascade in critical mechanisms.

Thus, this is where the Digital Tools Layer acts as the glue of the integrated farm management model that converts dumb hardware into a responsive, smart network. It represents which higher-level layers (AI eco-design, risk management, and governance) can operate to feed them with accurate, interoperable, and actionable data. This digital confluence optimizes not only the technical performance of electric vehicle charging infrastructures but also serves the environment by optimizing energy consumption through greater energy efficiency and less downtime, and enabling informed governance decisions [23,30,33].

In conclusion, the digitalization process of EV charging infrastructures represents a strategic enabler for sustainability and resilience. In other words, the Digital Tools Layer acts as a bridge between physical and virtual environments, transforming raw data into intelligent operations, supporting both real-time control and long-term planning within an integrated, AI-powered management model.

4.2.3. AI's Role in the Digital Tools Layer: Predictive Failure Diagnosis, Load Optimization, and Real-Time Decision-Making

In the integrated management model, the Digital Tools Layer is where AI really gets to work. In particular, this Section focuses on how AI functions as the analytical core that drives prediction, optimization, and real-time control across the EV charging network [2,6]. The use of AI within this layer enhances system resilience, operational efficiency, and user satisfaction. Figure 3 depicts the use of a combination of predictive control strategies for the efficient running of the EV charging system: the predictive control strategy for predicting the future demand by analyzing the traffic information, the load management strategy for balancing the energy load and prevent congestion on the grid, and the energy storage integration strategy, where the batteries are managed intelligently through the use of smart charging and discharging. In other words, this digital ecosystem serves as the technological spine for the model, allowing predictive analytics and contextualized operational decision-making. In this way, the gap between digital data collection and strategic decision-making can be reduced.

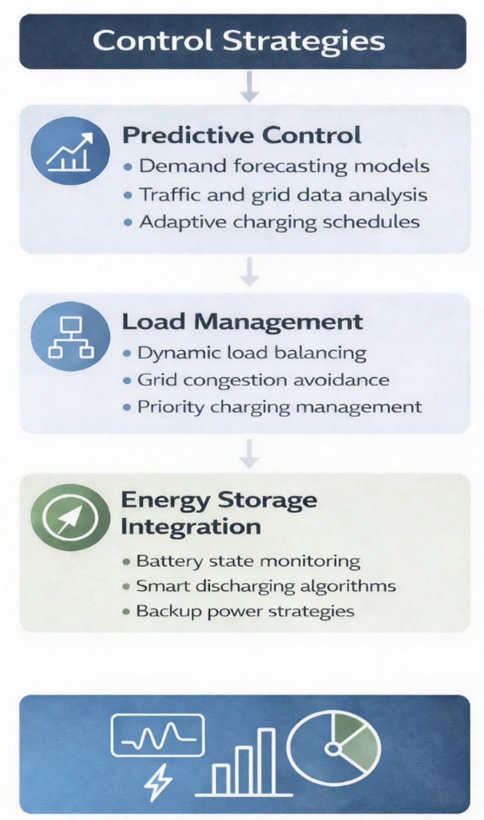

Figure 3. Overview of AI-enhanced operational control strategies for EV charging systems.

4.2.3.1. Predictive Diagnostics and Load Management

AI's biggest impact shows up in predictive failure diagnosis. Here, machine learning and deep learning models pick out technical problems before they happen. They look at sensor data and old maintenance logs to spot early warning signs in things like power converters, connectors, or cooling systems [15]. So instead of waiting for something to break, the system can fix it before it becomes a problem. Some other methods, like the convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were also used to model multivariate time series for detecting subtle variations before hardware failures [17]. This method minimizes the downtime and maintenance cost through proactive intervention instead of reactive repair [33].

AI also helps with load optimization, as it is a challenge in large-scale deployment infrastructure. By understanding consumption behavior, grid limitations, and the potential energy input from renewables, AI systems can tune energetic flows on-the-fly to avoid peak demands [14]. For example, reinforcement learning algorithms dynamically adapt the charging rates of individual stations based on the states of the grid, weather predictions, and user preferences [16].

This efficient and dynamic orchestration represents a help in involving stations in demand-response programs to stabilize the grid and integrate fluctuating renewable assets such as solar or wind on the AC bus [15]. In this regard, AI is what makes the charging network an active agent in the larger energy system, able to learn and continuously optimize, adapting for drivers and optimizing for grid operators.

Moreover, AI supports real-time decision-making by being able to digest large amounts and disparate sources of data from IoT sensors, geographical information platforms (GIS), as well as digital twin simulations. Cloud–edge architecture allows inferring and deciding to be processed between local units and cloud centers in an optimized way [18]. Edge-based models can promptly react to local evidence of error or congestion (e.g., voltage instability, and occupancy on load), while cloud-based models coordinate the entire charging network globally with respect to an optimal performance goal [1]. Dashboards based on AI-supported analytics visualize this data for operators and allow a simple, data-based management of energy assets [6,35].

The management of these AI systems also needs to be focused on explainability, transparency, and interoperability [31]. Because the Digital Tools Layer increasingly incorporates a mix of data sources such as public utilities, private operators, and user devices, ethical and security frameworks should make sure that predictive models run under responsible and auditable governance [23]. Furthermore, due to the nature of charging data (e.g., it may contain geolocation or user identity), preserving privacy in machine learning and federated solutions is critical to guarantee compliance with European data protection standards [7].

4.2.3.2. Real-Time and Cybersecure Operations

In this context, cybersecurity plays a decisive role in maintaining trust in AI-driven infrastructures. Both adversarial and oscillatory attacks against charging networks can lead to cascading failures, as demonstrated by Sarieddine et al. [18]. AI can detect and counteract such threats: anomaly-detection algorithms monitor data flows in real time, identifying compromised nodes and rerouting energy distribution to preserve service delivery. By baking in these protections, the AI layer helps build resilience and long-term stability into the charging ecosystem.

Finally, the AI-enabled Digital Tools Layer acts as a bridge between technical operation and strategic management. Predictive insights generated from this layer direct the upper Governance Layer and inform investment preferences, maintenance schedules, and sustainability. AI models learn and develop iteratively with each cycle of operation, making predictions more accurate and optimization effective [17].

In summary, the role of AI within the Digital Tools Layer is crucial to transform digital infrastructure into a self-learning, adaptive network. If predictive diagnosis is possible to prevent failures before they occur, then load optimization can ensure efficient energy use. Moreover, real-time decision-making maintains stability across distributed systems. Through proper governance and cybersecurity protocols, AI can be used not only to enhance the operational intelligence of EV charging infrastructures but also to provide the foundation for sustainable, data-driven management in the next generation of smart mobility ecosystems.

4.3. Risk Management Layer

The Risk Management Layer deals with the vulnerabilities concealed in electric vehicle charging infrastructure, and analyses technical, operational, and economic risks that threaten system robustness and service completeness [36,37]. With charging networks growing in scale and complexity, the increasingly visible interplay between power grids, digital platforms and user-generated demand means that a deep understanding of risk—and how to mitigate it—represents an important skill set. This layer aims at the identification of sources of disruption, such as failed equipment, unstable load corresponding to energy supply variation (feed-in and wind), or external events.

The risk management included in the proposed model is based on prevention rather than reactive intervention [38]. By framing risk as a property of the system itself, and not just that of its components, this layer supports methods for coordinated risk mitigation leading to reduced downtime, prevention of cascading failures and preserved value of investment. The Risk Management Layer is closely linked to digital monitoring technologies that feed early warning mechanisms, and to governance processes that translate risk indicators into strategic choices.

Within the integrated model, this layer establishes the conditions under which AI-driven prediction and scenario analysis can support resilient and adaptive EV charging operations. This layer benefits from a multi-stakeholder approach that involves operators of infrastructure, experts in cybersecurity, energy sector regulators, as well as emergency response bodies, to support the definition of the risk management practices.

4.3.1. AI's Role in the Risk Management Layer: Risk Detection, Scenario Simulation, and Downtime Mitigation

The Risk Management Layer focuses on the different types of critical vulnerabilities that can affect EV charging infrastructure, whether they are technical, operational, or even economic. In this context, AI has a practical role: it helps predict possible disruptions, understand how different parts of the network interact, and support strategies that keep the system running smoothly and financially stable. As charging networks become more tightly connected with the power grid, cloud services, and the shifting patterns of user demand, having AI tools that can assess risks becomes increasingly important for maintaining overall resilience [7,23].

The following paragraphs will be focused on the topics of risk detection and mitigation, scenario modeling and downtime prevention.

4.3.1.1. Risk Detection and Scenario Modeling

One of the first areas where AI proves genuinely useful is risk detection. This usually involves anomaly-detection tools that sift through different streams of information coming from sensors, usage logs, cybersecurity systems, and even environmental data. These models can flag early warnings of stress in the system—things like odd voltage swings, connectors heating up more than they should, communication glitches, or sudden and unexplained jumps in demand [18]. By learning from past failure patterns, predictive models can classify potential threats into categories, such as technical, cyber-related, environmental, or caused by users, enabling operators to respond promptly [33]. In this way, the ability of AI systems to highlight all those deviations that human operators may overlook significantly reduces failures. Figure 4 depicts a series of operational issues that the integrated model proposed here seeks to address. It identifies the major sources of complexity, which are the forecasting problems, the data quality problems, and the grid constraints, as commonly discussed in the literature as the structural limitations of the current EV charging infrastructures. By solving these operational issues, risk management becomes a continuous process that enhances the resilience and reliability of EV charging infrastructures.

AI is not just operative to catch problems as they show up. It is also used to try out different scenarios, which is becoming a pretty normal part of risk management now. People rely on things like digital twins or agent-based models to test a bunch of "what if" situations, such as an unexpected jump in demand, a piece of hardware breaks, or part of the grid goes down for a while. It could even be changes in renewable supply or some kind of coordinated cyberattack [2,6]. Running these simulations gives everyone involved a much clearer idea of how bad things could get and what reactions might actually help. For example, some solutions could comprehend load redistributions, temporary isolation of nodes, or emergency storage activations in an attempt to maintain overall system stability [15]. Moreover, reinforcement learning models are now increasingly adopted in the adaptive responses evaluations, improving system efficiency under specific and uncertain and dynamic conditions [17].

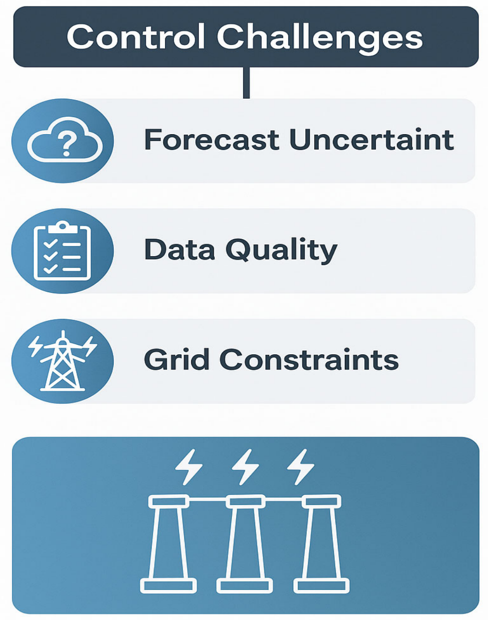

Figure 4. AI prediction of potential threats.

4.3.1.2. Downtime Prevention and Risk Mitigation

AI also has even more at stake when it comes to preventing downtime, which is a top priority for operators with the financial and social consequences of service disruption. Using predictive maintenance with failure-forecasting models, AI systems minimize unforeseen failures and maintain schedules [16]. This is not only cost-effective but also provides a better user experience, because charging locations are always readily accessible. AI-driven load balancing algorithm minimizes pressure on weak spots in peak times and helps prolong the life of equipment, with less likely for technical failures [14].

Cybersecurity is another important domain of risk governance. With charging infrastructure to be an increasing target of adversarial attacks such as spoofed communication signals and oscillatory load manipulation, AI-based intrusion-detection systems are imperative for recognizing anomalous behaviors [18]. AI builds resiliency into systems by automatically isolating affected parts of the system in order to reconfigure power flows, stopping localized attacks from spreading throughout the system [7].

Moreover, from the governance point of view, AI helps to ensure that operational-level insights are connected with high-level planning by enabling risk-aware decision-making. In fact, AI-based predictive measures are fed into tracking tools for managers, city planners, and energy authorities to assess investment priorities, warranty strategies, and risk-adjusted sustainability targets [23]. This connection between short-term and long-term decision-making reinforces the integrity of the overall management model.

In short, the Risk Management Layer changes from a reactive to being more backward-looking locking system to a proactive intelligence machine. AI improves the technical and operational resilience of EV charging networks by early warning, complex risk simulation, and downtime reduction. With the backing of effective governance and cybersecurity policies, AI in risk management further ensures that EV infrastructures source adequate support to cope with the exponential shift towards electric mobility.

4.4. Governance Layer

The Governance Layer offers a strategic and institutional framework to structure the functioning, evolution and regulation of electric vehicles charging infrastructures [10]. This layer participates in the alignment of technical operations with business objectives, compliance constraints, and sustainability targets. It includes a variety of decision-making tasks concerning planning, control, policy compliance and stakeholder coordination by public and private actors [39]. From an operational perspective, the governance aspect of the proposed model provides decision support mechanisms that translate technical data into high-level strategic actions. Performance dashboards give operators and policymakers the tools to measure key performance indicators, including system uptime, energy efficiency, charging demand patterns and cybersecurity incidents. Such governance processes are in accordance with the multi-actors and multi-criteria coordination models discussed within governance theory [10]. Additionally, governance mechanisms need to align with wider energy transition policies and regulatory frameworks that require coordinated decision processes across technological, institutional and societal actors [27]. In this respect, Table 3 summarizes the main governance mechanisms and their interactions with the other layers of the model.

Table 3. Governance mechanisms and interaction with layers.

Governance Mechanism	Function	Layer
Performance dashboards	Monitor KPIs	Digital Tools layer
Decision support systems	Evaluate infrastructure strategies	Eco-Design + Risk
Compliance monitoring tools	Ensure regulatory alignment	Governance layer
Stakeholder coordination platforms	Support multi-actor decisions	All layers

Because of large scales and decentralization properties in EV charging networks, governance is fundamental to make sure to have a unified and coherent system. It determines how accountabilities are assigned, how appraisal can be measured by means of key performance indicators and how information is shared between the operational and strategic levels [40]. Efficient governance also facilitates transparency, accountability and flexibility in the context of changing regulations and technology innovation.

The governance dimension also includes the coordinated participation of many stakeholders such as infrastructure operators, energy providers, policymakers, technology developers and end users. In this regard, governance mechanisms link operational actions to sustainability policies; for instance, using performance monitoring and data-driven decision support systems for collaborative planning.

Within the proposed model, the Governance Layer acts as the integrative interface that connects design, digital operations, and risk management. In this way, it can be possible to ensure that the overall system evolves in a coordinated, resilient, and sustainable manner.

4.4.1. AI's Role in the Governance Layer: Strategic Planning, Key Performance Indicators (KPI) Management, and Cross-Layer Coordination

The Governance Layer takes care of the Strategic, Regulatory, and Operational coordination of the complete EV charging ecosystem. As shown in Figure 5, in this architecture, AI is relevant to enhancing control systems and converting governance into a static, compliance-based activity to one based on data and analytics. This figure illustrates a series of measures to be implemented to manage the energy systems, divided into four thematic blocks. It emphasizes the improvement of the forecasting results by means of prediction models, the use of analytics with big data and machine learning, the improvement of security by means of threat detection and encryption, and the use of automation tools to enable smart and remote control. When integrating increasingly larger smart charging platforms, AI becomes a necessity when designing actions across eco-design, digital operations, and risk management to ensure that sustainability, reliability, and economic returns are balanced [23]. In these contexts, the following paragraphs will address the topics of strategic forecasting, KPI management, cross-layer coordination, and regulation.

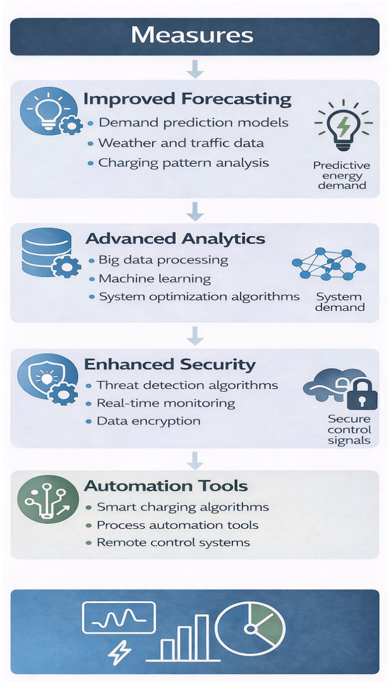

Figure 5. Enhancing control systems through AI in the governance layer.

4.4.1.1. Strategic Forecasting and KPI Management

A key role that AI will play in this layer is mainly to inform strategic planning, adopting predictive analytics for long-term forecasting around demand growth, infrastructure requirements, and energy needs. Through data fusion from digital twins, climate models, and mobility trend/market scenarios, AI assists decision makers in assessing policy actions and investment strategies [2,6]. Machine learning models can test how different tariff structures, renewable penetration, and grid constraints could impact charging behavior in the future [15]. In this way, it could be possible to incorporate evidence-based planning consistent with national sustainability strategies and European regulatory frameworks, in relation to AI and energy governance [23].

Moreover, AI also enhances KPI management, through which it is possible to continuously and automatically monitor performance indicators like uptime, power efficiency, grid interaction, user satisfaction, carbon footprint, and cybersecurity response. Real-time data is streamed through the AI-enabled dashboards to enable governing bodies to track any deviations from the anticipated level of performance, thus modifying operational protocols in turn [17]. In consequence of this, it is possible to use predictive models to help both operators and policymakers to achieve more ambitious environmental and service-quality goals [16]. In addition, explainable AI methods ensure high levels of transparency in KPI-related decisions, and this would be in line with emerging ethical requirements for AI in public infrastructure [31].

4.4.1.2. Cross-Layer Coordination and Regulation

Cross-layer coordination is a key aspect of governance, and AI assists in implementing the latter with multi-level optimization algorithms and integrative control architectures. In particular, results of the Eco-Design Layer, e.g., derating projections, are used as an input to the planning of maintenance. Predictions from the Digital Tools Layer support energy allocation, IFAS alert informs contingency [33]. In this context, AI serves as such a central brain, bringing together the wisdom in between layers and providing adaptive global governance for it. This orchestration should ensure high levels of consistency between day-to-day operations and broader sustainability goals, with the consequence of reducing fragmentation and enhancing institutional coherence [7].

Additionally, AI can assist with compliance and ethics, using algorithms to help organizations ensure that they are in line with safety requirements, privacy requirements, and environmental standards. Process-based compliance analysts enable checking whether operational activities comply with European AI regulations and energy directives [23]. Relying on model interpretability, traceability, and data quality control, AI governance builds trust among the operators, regulators, and users.

In conclusion, AI of the Governance Layer should not only be used for accountability but rather as a strategic orchestrator that integrates forecasting, KPI management, and cross-layer coordination. With well-transparent and accountable AI governance models, this layer takes care that the EV charging infrastructure grows coherently, efficiently, and environmentally responsibly to fit social and environmental needs relating to technological innovation.

5. From Concept to Deployment

The various components (AI-based eco-design, digital tools, risk-management, and governance layers) integrated in this model make it a comprehensive approach for the management of the EV charging stations. In particular, Figure 6 describes the way in which the four layers interact within the lifecycle of EV charging infrastructure, with a coordinated approach that combines sustainable design, digital monitoring, risk mitigation, and strategic governance. This conclusion demonstrates how these pieces fit together in operational terms, laying out the way to a real-life deployment.

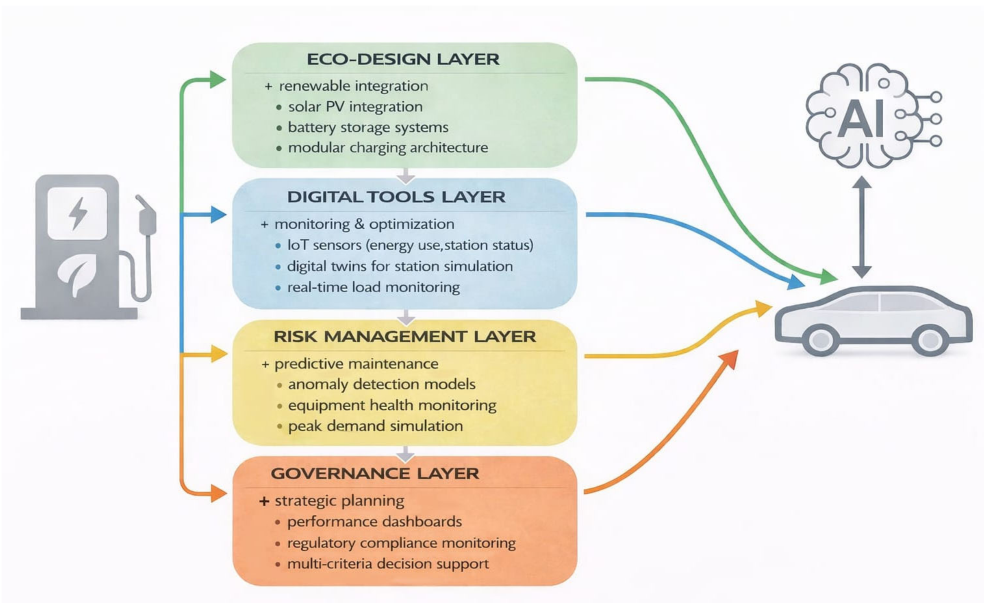

Figure 6. Integrated management model for EV charging stations.

The integrated model is built upon data, simulation environment, and decision support system interoperability. Outputs from the Eco-Design Layer (e.g., material durability predictions, modularity assessments) feed into digital twin models residing in the Digital Tools Layer [6]. These models generate operational data for input to predictive analytics and risk assessment algorithms [7,18]. The synthesized inputs feed into the Governance Layer for long-term planning, KPI monitoring, and regulation compliance [23]. This two-way flow helps in continued infrastructure innovations by having a feedback loop between them, allowing for better, faster, and cleaner management of the system.

This model can be operationalized, but it requires a structured deployment path. In this regard, a preliminary phase is represented by pilot deployment, in which a fraction of charging stations will be outfitted with IoT monitoring, local AI inference modules, and digital twin links. This simulated environment permits operators to verify prediction validity, examine cybersecurity measures, and evaluate operating performance indicators. Feedback from the pilot phase informs system modification before scale-up [15,33].

The second stage will address scaling and interoperability to make a new station, module, or software component a seamless addition to the already existing network. Open data exchange standards, communication protocols, and AI model deployment are essential to prevent vendor lock-in and enable cross-operator collaboration [31]. At this stage, centralized dashboards begin aggregating data from multiple nodes, enabling multi-site optimization and network-level scenario simulation [17].

A third phase is centered on periodical evaluation and adaptive governance, where real-time AI-augmented KPIs allow for monitoring success in both the environmental, operational, and economic domains. In particular, indicators such as reduction in downtime, energy-efficiency enhancement, and reduction in carbon footprints will help demonstrate impact and enable opportunity for iterative policy improvement [14,16]. These mechanisms provide a means whereby governance remains dynamic in response to emerging issues and changing legislation.

Furthermore, a long-term commitment to empowerment and continuous improvement cycles is necessary. In this regard, operators, policymakers, and technical staff are being empowered to learn and institutionalize capabilities for sustainable growth in the system. Thus, training programs, model-explainability frameworks, and recurring auditing ensure that AI is dependable, transparent, and meets the expectations of society [23].

In summary, the integration and roadmap phase turns the abstract model into a practical evolving system. Through the integration of smart design, business operational intelligence, predictive risk management, and strategic governance principles embedded into the analysis-based grid deployment approach, it would be possible to provide a feasible route for the mass roll-out of sustainable EV charging infrastructure. By bringing together environmental targets, technological progress, and user needs at once, this integrated approach will facilitate the larger shift towards clean energy and intelligent mobility.

Illustrative Application Scenario

To illustrate the practical implications of the proposed model, we considered a hypothetical deployment scenario involving a network of electric vehicle charging stations in a medium-sized urban area. In particular, the Eco-Design Layer enables decision support during the planning phase regarding the modularity of charging infrastructure components, integration strategies for renewable energy sources, and lifecycle-oriented design decisions targeting reduced environmental impact and increased adaptability of infrastructure.

When in operation, the Digital Tools Layer gathers up-to-date operating data through IoT sensors, digital twins, and spatial analysis tools. These technologies facilitate real-time tracking of energy usage, charging demand trends, equipment conditions, and environmental factors. The collected data are analyzed through predictive analytics models that help with demand forecasting, maintenance scheduling, and operational optimization.

The Risk Management Layer translates these predictive insights to find potential disruptions like peak-demand surges, equipment failures, or cybersecurity anomalies. Through anomaly detection and forecasting techniques, operators can predict critical events and take proactive measures like adaptive load balancing or maintenance scheduling.

The Governance Layer summarizes operational indicators as completion dashboards and decision support systems for infrastructure operators or policymakers; after the first pilot projects with appropriate key performance indicators such as system reliability, energy efficiency and carbon footprint will be evaluated. The integrated decision process that this entails aids strategic planning, aligning activities with sustainability goals and regulatory environments. While this is a highly simplified illustrative representation, it demonstrates how the proposed model supports all factors involved in decision-making that are inherently interconnected between design, operation, and risk mitigation and governance processes for EV charging infrastructures.

As shown in Table 4, this model provides a much more integrated view, which enriches previous approaches of managing existing EV charging infrastructure that mainly work on separate optimization problems (i.e., load balancing, infrastructure location, or energy scheduling).

Table 4. Conceptual comparison between existing EV charging management approaches and the proposed integrated model.

Aspect	Aspects of Existing EV Charging Management	Innovative Aspects of the Proposed Model
Infrastructure design	Often treated independently [1,8,9]	Integrated through eco-design principles
Data monitoring	Limited operational monitoring [2,6]	Integrated digital ecosystem (IoT, digital twins, GIS)
Risk management	Reactive response to failures [11–13,17]	Predictive and proactive risk mitigation
Decision processes	Fragmented operational decisions [10–12]	Coordinated governance mechanisms
Strategic alignment	Weak connection with sustainability goals [8,9,23]	Integrated with energy transition and sustainability objectives

Conventional approaches view these dimensions independently, resulting in fragmented decisions and limited operational–strategic coordination [39].

This study's layered architecture facilitates the co-alignment of information flows between the following aspects: (1) infrastructure design; (2) operational monitoring technologies and risk assessment mechanisms, which link to operational process structures and performance measures; (3) strategic decision processes.

6. Conclusions

This paper suggested a next-generation enabled AI-based integrated management model for sustainable EV charging infrastructure to cope with the increasing complexity of the evolving EV ecosystem in a holistic manner. By structuring the model into four interconnected layers (i.e., Eco-Design, Digital Tools, Risk Management, and Governance) the study moves beyond fragmented optimization approaches and emphasizes the systemic nature of sustainability, operational intelligence, and resilience.

In this sense, the novelty of the work resides in showing that artificial intelligence may indeed operate as a transversal enabler across designing, operating safely, mitigating risk, and coordinating strategically. Whereas existing research has tended to discuss isolated technological options, the proposed model emphasizes how infrastructure design choices are enmeshed with digitally enabled monitoring capacity and a system of proactive risk management, as well as governance activities.

Although the model is theoretical, it serves as a scaffold for researchers, infrastructure operators, and policymakers interested in implementing AI-based EV charging systems. One limitation of the present approach is that it must still be validated empirically to demonstrate its performance in practice. Next steps will include carrying out pilot projects, quantifying performance indicators, and adapting governance provisions to changes in regulation.

Overall, the proposed model offers a coherent and extensible foundation for advancing the design and management of sustainable, resilient, and intelligent EV charging infrastructures. The proposed model also has a number of other implications at the theoretical, operational, and policy levels. From a theoretical point of view, it offers a basis that can be utilized to overcome the current fragmentation of research findings related to smart charging, sustainability, digitalization, and risk governance. From an operational point of view, the multi-layer structure of the proposed model has the potential to be utilized by infrastructure operators, as well as by various authorities, to enhance coordination between design decisions, digitalization instruments, and management practices. From a policy point of view, the proposed model has the potential to facilitate a better match between technological innovation and regulatory needs. Moreover, it can enhance the efficiency of decision processes that are data-driven and AI-enabled and expedite the development of more effective and sustainable charging infrastructures for EVs.

However, despite its conceptual contribution, the proposed model presents certain limitations. In particular, its applicability may vary depending on regulatory contexts, electricity market structures, and infrastructure scales. Starting with these aspects, future work should therefore explore how the model can be adapted to different national regulatory environments and operational settings through empirical validation and pilot implementations.

In this direction, empirical validation of the presented theoretical model will be conducted on pilot deployments at actual EV charging scenarios. This comprehends the statistical assessment of performance indicators that relate to energy, system security, and sustainability results. Further research will also focus on the model's combination with regulatory frameworks and new standards, and its adjustment to different territorial or operational conditions.

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