Complex Systems Informatics and Modeling Quarterly (CSIMQ)
eISSN: 2255-9922
Published online by RTU Press, https://csimq-journals.rtu.lv
Article 231, Issue 42, March/April 2025, Pages 43–62
https://doi.org/10.7250/csimq.2025-42.03

AI-Enabled Predictive Analytics in Smart Grids: The Case of Sweden

Theodore Kindong*, Björn Johansson, and Victoria Paulsson

IEI/Division of Information Systems and Digitalization, Linkoping University, SE-581 83 Linköping, Sweden

Theodore.kindong@liu.se, bjorn.se.johansson@liu.se, victoria.paulsson@liu.se

Abstract. Smart grids (SGs) revolutionize existing power grids by using a wide range of developing disruptive technologies to generate clean, efficient, and predictable energy. Our study uses an action research method and focuses solely on the first two stages of the action research process, diagnosis and action planning, to evaluate ways to adopt artificial intelligence (AI) applications in SGs for predictive analytics in practice. The *diagnosis stage* of the study entails conducting a systematic literature review on AI applications in SGs, highlighting four areas of potential for predictive analytics: power outage prediction, demand response, control and coordination, and AI-enabled security to optimize decision-making, diagnose faults, and improve grid stability and security. The *action planning step* included a document analysis to devise methods to enable the practical implementation of AI in smart grids for predictive analytics. Finally, we address practical ways for implementing transparent AI for predictive analytics, followed by a conclusion and future research direction. The study's key conclusion is that more research is needed to complete the action taking (implementing the solution), evaluation (assessing the results), and learning (reflecting on lessons learned) phases of the action research cycle.
Keywords: Smart Grids, Artificial Intelligence, Predictive Analytics, AI Techniques, Smart Grids Stability, AI Interpretability.

1 Introduction

Smart grids (SGs) represent a significant departure from traditional, fixed grid infrastructure, transforming the energy system by integrating various advanced technologies. Integrating advanced technologies in SGs enhances stability, reliability, resilience, sustainability, and efficiency across the entire electricity value chain, from electricity generation to consumption [1]–[5]. Notably, SGs facilitate the integration of intermittent renewable energy sources, thereby

* Corresponding author

Reference: T. Kindong, B. Johansson, and V. Paulsson, "AI-Enabled Predictive Analytics in Smart Grids: The Case of Sweden," Complex Systems Informatics and Modeling Quarterly, CSIMQ, no. 42, pp. 43–62, 2025. Available: https://doi.org/10.7250/csimq.2025-42.03

Additional information. Author ORCID iD: T. Kindong – https://orcid.org/0009-0001-6502-8325, B. Johansson – https://orcid.org/0000-0002-3416-4412, V. Paulsson – https://orcid.org/0000-0001-6951-2985. PII S225599222500231X. Received: 31 January 2025. Accepted: 17 April 2025. Available online: 30 April 2025.

reducing pollution [6] and enabling bidirectional energy flow, empowering consumers to buy and sell energy [7]. However, operating these complex systems reliably presents challenges, including the inherent variability of weather-dependent energy sources and persistent security, stability, and reliability concerns. Consequently, there is growing interest in predictive analytics techniques, such as fault-tree analysis and Markov modeling [8], now further enhanced by the application of new artificial intelligence (AI) techniques [5].

AI has recently gained global prominence and is recognized for its innovative and transformative potential with applications across various sectors [7], [9]. The electric power sector has undergone a significant transformation driven by advanced technologies, and the advancement of AI has the potential to revolutionize electricity production, distribution, and consumption [1], [2], [4], [10]–[12]. Also, AI can modernize traditional electric power grids, initially controlled by electromechanical systems, into networks managed by Information and Communication Technologies (ICTs) [3], [10], [11] to address growing energy demands through predictive analytics. The AI application in the form of predictive analytics can transform SGs to be more efficient, intuitive, and cooperative for all actors involved [13]. Hence, enabling a fully collaborative operating mode where each participant relinquishes their decision-making autonomy to a centralized system, works towards achieving global optimization, and allocates the resulting expenses to each participant [13], [14]. Overall optimization, cost-sharing among actors, cost-effectiveness, environmental friendliness, stability analysis, and the generation of a reliable power grid are some of the potential benefits of AI applications in the context of SGs [5], [9].

However, despite the potential benefits of AI applications in SGs, a significant gap remains between research and practical implementation due to several challenges. These include, but are not limited to, demanding data requirements, difficulties with imbalanced data, interpretability issues, limitations in transfer learning, and vulnerability to communication disruptions and attacks [5], [9], [13]. This situation has highlighted the need for research to address these challenges and bridge the gap. Furthermore, studies on real-case scenarios of AI applications in SGs for tackling the increasing challenge of maintaining balance, stability, and reliability have not been thoroughly explored. Investigating the practical implementation of AI in SGs and how AI algorithms can address the challenges posed by increasing electricity demand, weather-dependent generation, and the necessity of maintaining grid stability and reliability is now essential.

This study aims to examine how the potential benefits of AI applications in SGs, as highlighted in the literature, can be applied in real-case scenarios by investigating the approaches and strategies required to ensure the practical implementation of AI in SGs to handle unexpected variations in supply and demand. Additionally, it seeks to investigate how these approaches can lead to the design and implementation of explainable AI in SGs for predictive analytics. This research distinguishes itself from previous studies on AI in SGs by focusing on practical implementations and real-case scenarios rather than solely on theoretical contributions. Previous research has primarily addressed theoretical aspects, including separate technical challenges such as efficient stability analysis and control through predictive analytics, power consumption, and peak hour prediction using Deep Learning (DL) [1], [5], [6], [13], [14]. This study adopts a different perspective, seeking to bridge the gap between research and practice of AI application in SGs through a collaborative practice research approach that investigates how AI's predictive models in SGs can be effectively implemented. It is the preliminary stage of a collaborative practice research initiative aiming to narrow the divide between AI in SGs research and practice through productive collaboration between scholars and practitioners. This collaboration will aid in the design, development, and implementation of transparent and easily understandable AI models in smart grids. Implementing a transparent and easily understandable AI model will enable users to intervene effectively when AI systems fail or become biased in addressing stability control, reliability, security, and transmission costs. Furthermore, our study intends to leverage recent research and development in AI and its applications, alongside big data and SG-generated data, as well as the expertise of industry practitioners, to lay a foundation on which explainable AI can be implemented in SGs. This will facilitate the adoption of a large machine-learning model in predictive analytics, ensuring improved accuracy while alleviating issues related to data interpretation and transparency. Additionally, it aims to enhance human understanding of AI decisions, increasing engagement and autonomy and thereby improving energy distribution and management in SGs. To achieve our aim, the study will attempt to address the following research question: *What strategies and approaches can enhance the practical implementation of transparent AI for predictive* analytics *in smart grids to improve energy generation and distribution?*

We develop the idea of what strategies and approaches are needed for smart grid operators to fully implement AI for predictive analytics in SGs as follows. First, we explore the background and related work (Section 2). We describe the used research method in Section 3. We then evaluate predictive analytics in smart grid literature and highlight four areas of predictive analytics applications in Section 4. Then, we present the results of our document analysis in Section 5. Finally, we discuss four strategies and approaches required to bridge the gap between research and practical implementation of AI in smart grids in Section 6 and provide conclusion and future research direction in Section 7.

2 Background and Related Work

A Smart grid (SG), as described in the US Department of Energy's Smart Grid System Report, encompasses information management, control technologies, digitally based sensors, ICTs, and field devices [9]. It is an integrated system that coordinates diverse electrical operations, generating a wealth of data that, through predictive analytics, offers insights into energy production, distribution, and consumption. Consequently, advanced technologies like AI are increasingly used in SG predictive analytics for monitoring, measuring, and reporting these key aspects of electricity flow. AI algorithms are being used to process and analyze generated data and produce patterns that assist human operators in accessing and utilizing data across the grid [9], [15].

Also, the integration of advanced metering infrastructure, control technologies, and sophisticated communication protocols enables SGs to acquire substantial volumes of heterogeneous, high-dimensional data about electric power grid operations. Consequently, the application of AI-based methods within SG environments is gaining increasing prominence. AI-based methods offer the potential to mitigate limitations inherent in conventional modeling, optimization, and control paradigms employed in traditional grid systems [9], thereby facilitating the development of a more efficient, stable, and reliable grid infrastructure. AI has demonstrated capabilities resembling human thought and behavior [5], [16]. Its application in SGs promises to reduce the need for human intervention in grid management. Following periods of fluctuating interest, advancements in computational power, data volume, and data modeling techniques have propelled AI to the forefront of various industries, economies, and daily life in the 2020s. This resurgence of AI, particularly within SGs, has enabled them to meet stringent dependability, security, and stability standards [5] through automated control and timely stability analysis.

More so, numerous AI techniques, such as machine learning, deep learning, and reinforcement learning, are continuously being integrated into SGs [1], [6], [17]–[19]. These techniques enhance SG performance in areas such as stability control, fault diagnosis, security evaluation, stability assessment, transmission cost reduction, and seamless demand-supply management [2], [8], [19], [20]. Research on AI applications in SGs has achieved significant milestones due to technological advancements in accuracy, security, speed, and effectiveness, coupled with a reduction in human workload [5]. However, an essential aspect largely overlooked in AI applications for SGs is interpretability, a key concern in social science research on algorithms [21]. This lack of interpretability raises concerns about trust and transparency [13], [22], as users may not understand AI models and decisions, which can potentially lead to inaccurate or biased predictions [13], [22]. The adoption of AI in SGs is largely driven by the desire to enhance predictive analytics for various operational improvements [13]. By leveraging such techniques as data mining, predictive modeling, and machine learning, AI enables SGs to improve fault diagnosis, predict future events, enhance decision-making, and optimize grid operations. This application of predictive analytics has made AI models indispensable tools for risk prediction and decision-making optimization [15], earning the description of "modern oracles of our networked digital age" [10].

Finally, prior studies on AI-enabled predictive analytics in SGs have attempted to address critical challenges related to energy consumption, climate change, energy transmission costs, and managing and predicting energy demand and grid stability [5], [13]. Predictive analytics is essential in environments with dynamic energy pricing based on peak consumption and short-term load forecasting [6]. Consequently, both energy producers and consumers are increasingly embracing predictive analytics and seeking ways to improve its accuracy [23]. Prior research has also demonstrated the potential of machine learning for energy prediction, such as Ahmad's et al. [24] work on predicting hourly solar thermal energy usefulness using experimental data and Bose's [1] overview of AI's power within SG power systems, focusing on expert systems, fuzzy logic, and artificial neural networks. Bhuiyan et al. [11] provide a comprehensive overview of predictive analytics in SGs for grid stability analysis and control. In contrast, others demonstrate AI's analytical capabilities for evaluating SG security, stability, fault diagnosis, and power [8]. However, as Latour [25] observes, the inner workings of successful technologies often become obscured by their achievements, focusing attention solely on inputs and outputs. This irony applies to AI in SGs: as its applications advance, their complexity increases, making them less comprehensible [25]. This lack of transparency raises trust concerns and limits the potential benefits. Therefore, AI model transparency is pivotal for realizing the full potential of AI in SGs and addressing challenges related to transfer learning, communication quality, security, and adversarial attacks [8], [18], [26]. To explore how to make AI models in SGs more transparent and human-understandable, particularly in contexts with high renewable energy integration, this study, which is part of a collaborative research practice, adopts an action-research approach to actively contribute to societal and behavior-oriented perspectives in research and development of SGs, focusing on integrating domain expertise into AI model training.

3 Research Method

The research presented in this article[†] builds on a study that, due to its emphasis on deep stakeholder involvement, was developed from the action research methodology. As outlined in the work of Susman and Evered [27], action research requires close researcher engagement with participants through a cyclical process: (1) Diagnosis – understanding the problem context; (2) Action Planning – devising a solution; (3) Action Taking – implementing the solution; (4) Evaluation – assessing the results; and (5) Learning – reflecting on lessons learned) [27], [28]. This study, being in its early stages of ongoing research, has implemented the first two stages as follows:

The Diagnosis Stage involves investigating and understanding the context of AI-enabled predictive analytics in SGs and identifying gaps in existing approaches for developing and implementing AI applications in SGs for predictive analytics. This was done by reviewing existing literature using the systematic literature review approach. The process involved conducting and describing a methodical and replicable procedure for searching all existing articles and reports on a specific topic of interest, evaluating identified articles, summarizing or synthesizing findings from the reviewed articles, and condensing or applying findings to yield new results or knowledge on a specific topic [29]–[31]. Unlike a classic narrative review, which consists of presenting a descriptive summary, overview, or synthesis of evidence from existing publications on a certain topic or theme, as well as evaluating the contents of the articles about the topic or theme of interest [29]–[31], our choice of review was based on the aim and scope of this study [31].

[†] An extended version of a BIR workshop paper: T. Kindong, B. Johansson, and V. Paulsson, "A systematic literature review of AI-enabled predictive analytics in smart grids," BIR-WS 2024, Prague, Czech Rep., September 11–13, 2024, vol. 3804, pp. 16–30.

Our literature review follows Webster and Watson's recommended systematic literature review approach [31]. The systematic literature review employed an inductive approach to address the research questions and clarify the research gap, enabling a broader perspective than a single, location-specific primary study and aligning with the diagnostic stage of the action research process [29]–[31]. Our search began with a comprehensive literature search across multiple databases to establish the scope of existing research on the intersection of artificial intelligence, smart grids, and predictive analytics. The study used the following keywords: ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("predictive analytics") AND ("smart grid"). It employed a combination of "OR" and "AND" operators to perform searches on Scopus. Additionally, "Artificial intelligence applications in Smart Grids" was used with predictive analytics and publication dates to conduct searches on IEEE Xplore, ACM, and Science Direct. "Artificial intelligence applications in Smart Grids" was also used to search for Google Scholar articles. Furthermore, backward and forward searches were performed to broaden the scope and improve the quality of our search. The backward search was conducted by reviewing the references in the initially selected papers published in the Renewable and Sustainable Energy Reviews and Elsevier journals and proceedings of the IEEE due to their high quality and reputation. In contrast, the forward search utilized the "cited by" operator to examine additional papers that have cited selected papers. This strategy aimed to capture prominent publications and potentially overlooked research, ensuring a thorough exploration of the topic. This ensured that the study began with high-quality papers, providing a solid foundation for the topic and considering other outlets that might have lesser visibility in more extensive databases or journal/conference rankings [31]. The "cited by" operator and the publication dates were also employed for filtering to yield promising results for further refining the search on Google Scholar. Finally, the study only reviewed papers published after 2015. This initial search yielded 847 articles across the five databases, which underwent a second screening process based on the following criteria: (1) published in English, (2) fully accessible through contracted repositories, and (3) peer-reviewed, resulting in 97 selected articles, as detailed in Table 1.

Table 1. Summary of selected papers from five databases used

Databases	1st search: string results	2nd screen: Relevant articles after	3rd screen: Selected articles	Percentage (%)
Google Scholar	426	30	6	23.1
ACM	47	10	2	7.7
Scopus	143	16	5	19.2
Science Direct	174	24	7	26.9
IEEE Xplore	57	17	6	23.1
Total	847	97	26	100

After the initial two-stage screening process, we applied inclusion and exclusion criteria to refine the selection of articles for this review. The inclusion criteria specified articles that (1) highlighted diverse technical AI application techniques within the context of SGs, such as machine learning, reinforcement learning, and deep learning, and (2) were published in or after 2015, reflecting the rapid evolution of these techniques. Conversely, articles were excluded if they: (1) lacked empirical data; (2) were unrelated to AI and larger-scale computing and/or networking infrastructure; or (3) focused on assistive devices. In cases of uncertainty regarding an article's relevance, its bibliography was consulted to assess its potential contribution and alignment with the review's focus [31]. This final screening process resulted in 26 articles being selected for review, as shown in Table 1. The literature review process is summarized in Figure 1. The literature review concludes the diagnosis stage and is preceded by the action planning phase described below.

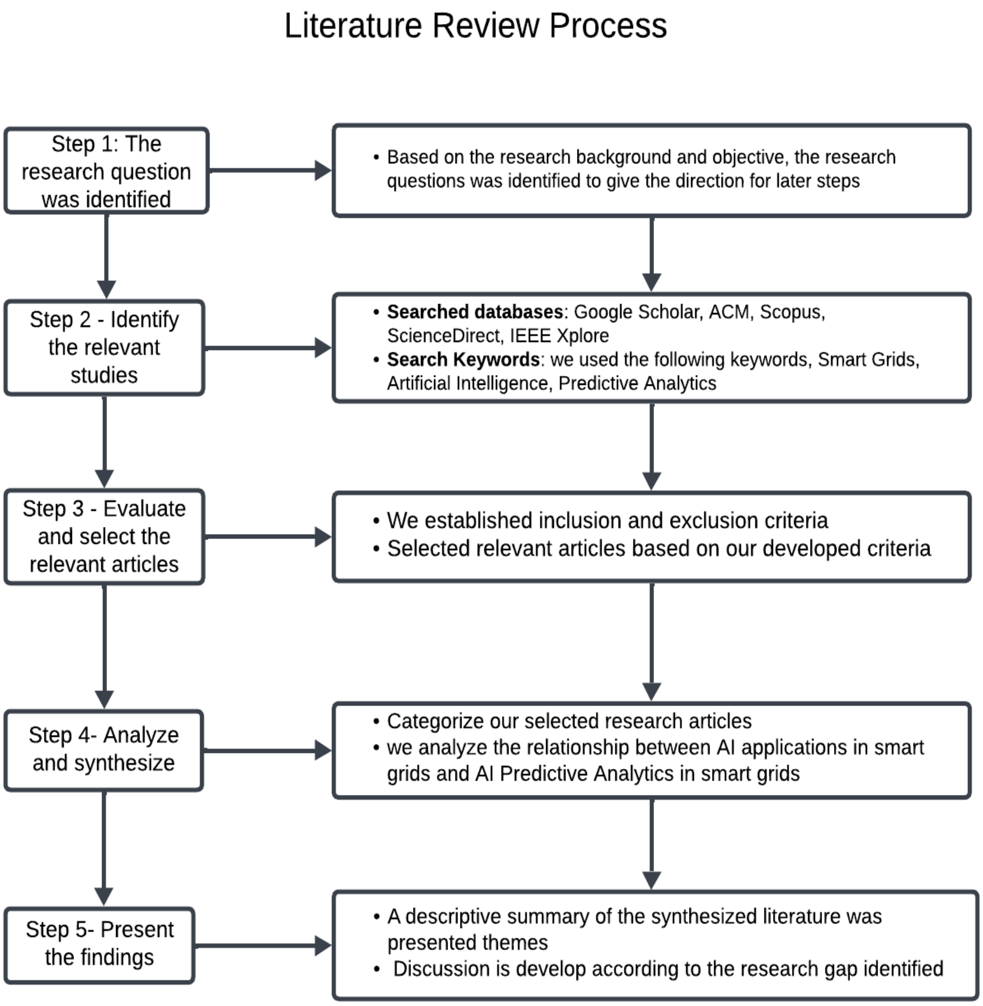

Figure 1. The literature review process

The Action Planning Stage involves designing strategies and approaches to address the identified gaps [28], [32]. This was achieved by analyzing documents from smart grid actors and exploring strategies and approaches that can facilitate the design and implementation of AI applications in SGs for predictive analytics. We analyzed existing documents from smart grid stakeholders in Sweden to gain insights into our domain of interest [33]. We collected and analyzed energy report documents, grid operations, project summaries [34], regulations, protocol implementation documents, meeting notes, company websites, informal conversations, official announcements, mobile app reviews, and industry conference papers, as seen in Table 2. The study also collected data and used content and topic analysis to extract significant information. This involved skimming (cursory review), reading (complete evaluation), and interpreting in an iterative process that combined material and thematic analysis. The study employed content analysis [33] to categorize relevant information and thematic analysis [35] to discover and explain themes. The literature review summary and the document analysis findings are discussed below.

Table 2. A Sample of Selected Documents and Data Analysed

Documents selected	Data analyzed
Meeting notes from research group meetings, and program conferences	Current trends, new actors, and emerging business models.
Stakeholders' portals, such as, svk.se, ediel.se, and indlov.se, tekniskaverken.se	Grid actors require communication protocols, information on renewable energy sources, step-by-step guidance for connecting to the grid, and ongoing innovation projects.
Energy reports, project reports, and practitioners conference papers	Energy usage trends, renewable energy statistics, technological adoption, grid improvement, and future projections.
Electricity Market Guide	Statistics for electricity production, consumption, imports and exports, electricity prices, grid capacity, electricity trade, forecasts, and analysis of energy markets.
Energy policies	Regulatory frameworks, compliance with energy standards for data gathering and consumption, as well as data protection and privacy.
National Grid development	Innovation projects related to building new lines and stations and also strengthening national grids

4 The Diagnosis Stage: Literature Review on AI Predictive Analytics in SG Context

Predictive analytics, powered by modern AI models, has become pivotal for risk prediction and optimizing decision-making processes [15]. By leveraging data mining, predictive modeling, and machine learning, predictive analytics analyses historical and real-time data to generate forecasts, describing "modern oracles of our networked digital age" [10]. Within SGs, AI-driven predictive analytics is vital in addressing key challenges related to energy consumption, climate change, transmission costs, demand forecasting, and grid stability. Predictive analytics is essential for managing energy consumption in dynamic pricing environments where costs are determined by peak consumption and short-term load forecasting of building electricity usage [36]. Recognizing this, both energy producers and consumers are increasingly embracing predictive analytics and seeking ways to enhance its predictive capabilities further [23].

Furthermore, Ahmad et al. [24] laid the groundwork for predicting solar thermal energy's hourly usefulness using machine learning algorithms. In their work, they trained and tested several machine-learning models using experimental data. Similarly, Bose [1] states that AI approaches are incredibly potent tools in SG power systems. Bose provides a concise but thorough overview of three significant areas of AI: expert systems (ES), fuzzy logic, and artificial neural networks. Also, Bhuiyan et al. [5] provide a detailed and understandable overview of the current adoption of predictive analytics in SGs to enable grid stability analysis and control. Finally, the review summary shows that AI in SGs has the potential to enhance analysis for SG security, stability, fault diagnosis, and stability control [18] to ensure transient, frequency [37], small signal, and voltage stability [38]. The summary of AI predictive analytics in smart grids is presented as follows: (I) power outage prediction, (II) demand response, (III) control and coordination, and (IV) AI-enhanced security.

The summary of the Diagnostic Stage on Results and Derived Insights are shown in Table 3.

Table 3. Summary of the Diagnostic Stage on Results and Derived Insights

Category	Description	Summary	Derived Insights
Publication & Temporal Analysis	Number of Papers Analyzed	The study analyzed 26 articles.	A clear trend emerges from the analyzed papers: The increasing interest in diverse AI techniques and applications, particularly machine and deep learning, artificial neural networks, and reinforcement learning for predictive analytics in SGs.
	Publication Outlets	Renewable and Sustainable Energy Reviews, Journal of Cleaner Production, Solar energy, Energy and AI.	Most of the literature on AI applications is published in energy related, and engineering journals and conference proceedings.
	Publication Year Distribution	Distribution of papers across time periods broken down into earlier (2015-2020) and recent (2021-2025) periods.	The analyzed research shows a marked evolution in AI's application within SGs. Early studies (2015-2020), representing 30% of the articles, focused on foundational uses like load forecasting and stability. However, recent publications (2021-2025), comprising 70% of the data, highlight a shift towards advanced predictive analytics for grid balancing and dynamic pricing.
AI Techniques & Applications	Prevalent AI techniques	Common AI techniques: Fuzzy logic, Machine learning (ML), Deep learning (DL), Artificial neural network (ANN), and reinforcement learning (RL).	Based on the reviewed papers, ML, DL, ANN, and RL are identified as the most prevalent and highly developed AI techniques utilized for predictive analytics.
	Specific Application Areas	Common application: Load forecasting, Fault detection, Renewable integration, and Grid stability.	The findings demonstrate AI's broad area of applications in SGs, that spans across enhancing system reliability and renewable energy integration to enabling complex energy scheduling and predictive modeling.
	Hybrid AI Approaches	Common hybrid approaches: Distributed AI using game theory and reinforcement learning, Complex-valued algorithms, and Federated learning.	There is a trend towards sophisticated AI in SGs, marked by hybrid models combining multiple techniques, like the complex-valued artificial hummingbird algorithm and ensemble methods, to achieve enhanced prediction and optimization.
Observations & Challenges	Key Observations Across Reviewed Papers	Synthesis of the findings from reviewed papers reveals that AI is predominantly used for (1) Power outage prediction, (2) Demand response optimization, (3) Control and coordination of grid resources, and (4) Enhancing grid security.	Practical implementation of AI applications in SGs for predictive analytics can enhance reliability and resilience, optimize renewable energy integration, improve stability and control, forecast energy consumption and fault detection, and grid security.
	Identified Challenges & Limitations	Vast heterogeneous data, Model interpretability, and Limited real-time implementation.	The primary obstacles to broader AI adoption in SGs include the challenges of model interpretability, large data requirements, and the limited deployment and proven reliability of AI algorithms in physical systems.
Trends and Future Directions	Emerging Trends	Federated learning and explainable AI.	Future research should focus on developing transparent AI models, validating AI algorithms within real-world grid environments to facilitate practical implementation and widespread integration.

4.1 Power Outage Prediction in Smart Grids

The growing demand for clean energy, integration of renewable energy sources, and the aging of most grid infrastructure highlights the risk of power outages in several global marketplaces [7]. The increasing complexity of modern electrical grids has driven a significant focus on predictive analytics for asset management and renewable energy integration. Firstly, predictive analytics identifies and mitigates risks associated with aging grid components, such as transmission lines, transformers, and substations [39]. Secondly, it plays a vital role in addressing the challenges posed by the variable and intermittent nature of renewable energy sources like solar and wind, ensuring grid stability and reliability.

Electricity demand continues to rise, and more weather-dependent electricity is added to the grid. This implies it is becoming increasingly complex to maintain the balance due to the possibility of probable power outages induced by bad weather [19], [24], [39]. Therefore, the stability and operational reliability of the electricity grid is a growing worry due to the unpredictability of weather-dependent renewable energy sources [19], [40]. Hence, grid actors increasingly seek ways to improve grid performance through power outage prediction and maintenance of poorly optimized structures, such as many lines and stations nearing their technical end [41]. Also, the heightened risk of power outages during severe weather events like snowfall, tornadoes, and cyclones [13], [40], [41] makes the grid vulnerable. Thus, power outage prediction is gaining attention to optimize power generation, delivery, and consumption within a smart grid [13], [40]. This emphasis has further intensified with the adoption of AI, which provides advanced capabilities like real-time communication and the ability to predict future events to address challenges posed by potential blackouts due to severe weather conditions [13], [19].

More so, the advent of AI in SGs has seen a strong interest in adopting AI algorithms for power outage prediction [13], [19], [24]. This is due to AI's potential to transform SGs into dependable yet cost-effective electricity for consumers across the network and predict future severe weather conditions to enable better planning. Also, AI's predictive analysis capabilities offer potential benefits in power outage prediction, especially if producers and consumers can understand and interpret AI decisions and plan for the future. Furthermore, AI-enabled predictive analytics across the grid is pivotal to taking necessary actions to avoid a power outage. For instance, electricity producers can incorporate future happenings forecasted by AI into their planning and strategy formulation to address potential blackouts. Also, AI power outage predictions in SGs bring about effective stability analysis and control, which are necessary to guarantee reliable operation, ensuring that electricity suppliers meet electricity demand during severe weather conditions and prevent potential blackouts [34]. Lastly, power outage prediction enhances demand response, which is discussed below.

4.2 Demand Response in Smart Grids

Demand response (DR) is a significant concept in SGs that encourages consumers to discharge non-essential electricity during peak hours to balance supply [42]. It is a concept that mandates electricity suppliers to ensure sufficient output to meet consumption [34]. Under the Swedish Electrical Act, an electrical supplier must provide as much electricity as its consumers consume [34]. The electricity supplier may take on this obligation for its electricity delivery or transfer it to another company, ensuring efficient demand response that always meets electricity needs. Also, consumers could commit to reducing unnecessary energy consumption during peak periods and store more energy for the future. This explains why household load forecasting plays an essential role in DR, especially when dealing with the unknown amount of energy a household uses [43]. Customer behavior is a significant factor in demand planning, making accurate predictions laborious and requiring demand response systems to handle the uncertainty that comes with it [43]. Moreover, DR continues to gain interest through employing semantic web methodologies [44] to develop an integrated smart grid information model and provide case studies for dynamic disaster recovery. Khan et al.[45] argue that the increasing complexity of demand-side management and the need for near real-time decision-making have positioned AI and Machine Learning (ML) as essential technologies in demand response. This is primarily due to their ability to handle the intricate tasks and massive data volumes inherent in effective demand response strategies [45].

Furthermore, the rapid proliferation of AI applications in different fields has also seen a rise in AI applications in SGs for demand response. AI applications in SGs for DR have the potential to optimize disaster recovery by merging several ways to estimate customer electricity use and automate the process. Authors of [18] investigated reinforcement learning (RL) usage for demand response applications in the SGs, including controlling energy systems such as electric vehicles, heating, ventilation, and air conditioning (HVAC) systems, smart appliances, and batteries. Ensemble-based AI methods, such as random forest (RF), are gaining popularity in prediction and are being used to predict hourly HVAC energy consumption [46]. Also, Ma et al. [47] developed a distribution optimization method for multi-agent systems to find optimal network weights for various stakeholders for an efficient and secure dynamic pricing strategy for SGs. Ma et al. [47] suggested that strategy enhances stakeholder privacy and decision-making autonomy and optimizes DR in SGs. Also, Boopathy et al. [6] investigated Deep Learning (DL) applications for smart grid demand response, presenting deep learning principles in SG demand response and exploring cutting-edge applications such as electric load forecasting, state estimation, energy theft detection, energy sharing, and trade [6]. Boopathy et al. [6] address current research challenges, key issues, and prospective future directions in deep learning for smart grids and demand response and conclude that DL models can identify patterns in vast SG network data to predict electricity demand during peak hours to help forecast future consumption [22], [43]. Furthermore, other studies have investigated the use of cutting-edge deep learning algorithms to directly learn uncertainties in demand response due to consumer behaviors [43]. This is essential for Demand Response in SGs to ensure a constant balance between the production and consumption of electricity [34]. Finally, demand response necessitates that suppliers and consumers both assume their responsibilities in a controlled and coordinated manner. Thus, efficient control and coordination in SGs is pivotal and is discussed in Section 4.3.

4.3 Control and Coordination in Smart Grids

Control and coordination have become pivotal in handling demand response in SGs, ensuring that balanced responsibility parties collaborate in a coordinated manner [42]. Control and coordination in SGs utilize advanced power electronics, computer systems, information technology, emerging technologies, and cyber technology to foster efficient and seamless control and coordination of the interactions within SGs. Efficient control and coordination are fundamental to achieving a sustainable and reliable power system. This is accomplished by accurately predicting energy production and consumption, which allows for optimized operation of energy consumers and battery systems, enabling responsive adjustments to grid price fluctuations while balancing energy output and user comfort [5], [42], [48]. Also, according to [44], the ability of SGs to collect large amounts of data allows for the development of new AI applications and tools to regulate power usage and meet escalating electricity demand through control and coordination. By analyzing vast datasets, grid operators can accurately forecast energy demand and supply fluctuations, allowing for proactive issue mitigation and optimized energy distribution, which is particularly important when dealing with the variable nature of renewable energy sources [49]. Moreover, AI techniques such as machine learning algorithms significantly enhance these predictive capabilities by effectively identifying complex data patterns and generating precise forecasts [39], [49].

AI has become a powerful tool for controlling and coordinating electricity generation, transmission, and distribution in SGs, allowing for real-time pricing by third-party service providers to control domestic energy use [44]. AI also enables real-time processing, ensuring stability analysis, thereby enhancing control and coordination in SGs [5], [42]. This is important as the SG continues to expand through interconnection, renewable energy integration, direct current power transmission technologies, and electricity market liberalization, which requires controlling and coordinating various actions of all stakeholders [5]. Also, AI applications in SGs can incorporate computer processing and leverage large database repositories and communication network connectivity [50]. Thereby, enhancing control and coordination, which is essential for facilitating or enabling specific tasks [1], [5], [14], [42]. Moreover, AI offers potential methods for analyzing and controlling smart grid stability by accessing data and other sensitive information, which creates security vulnerabilities that must be addressed through AI-enhanced security, as presented below.

4.4 AI-enabled Security in Smart Grids

AI-enhanced security in SGs can be defined as using AI techniques to improve the security and resilience of SG infrastructure [13]. This involves applying AI algorithms and models to various security tasks, such as intrusion detection, access control, and risk assessment [13], [38], [51]. These AI algorithms are trained to detect abnormalities and predict potential attacks to protect stakeholders' privacy by forbidding the exchange of personally identifiable information. Also, AI-enhanced security uses AI-based distributed optimization systems to improve trustworthiness. Furthermore, AI-enabled security combines AI algorithms and blockchain-enabled solutions for scheduling, managing, organizing, and optimizing SG power distribution for security in SGs [8]. The combination of AI algorithms and blockchain protects the integrity and secrecy of transaction executions to immutable storage in encrypted blocks. This will improve the security and performance of AI applications in SGs [8], demonstrating the primary advantages of SG innovation and how AI can advance SG security [52], [53].

Furthermore, AI capabilities provide a unique advantage since AI-enabled smart contracts respond quickly to emerging cyber threats, such as a cyber-physical fusion event or a climate calamity that occurs organically. Thus, AI-enabled security leads to automated and robust management of some power grid functions [8]. Integrating AI and blockchain technology may create a defense against unauthorized attempts to alter formations or web and sensor scenes instantly and simultaneously [8]. Thus, AI significantly bolsters smart grid security and intelligence by automating critical processes. This enhancement is achieved through real-time information assessment, optimized energy consumption, and secure communications and information management [12], [54].

Additionally, AI-enabled security controls in SGs employ AI techniques, such as Machine Learning (ML) algorithms, for intrusion and malware detection. This strategy is a common approach to addressing the complexity of cybersecurity and the sophistication of cyber-attacks in SGs [51]. AI-enhanced security measures in SGs are viewed as more effective than traditional signature-based and heuristic-based controls in tackling recurring security challenges [51].

Finally, drawing from the insights derived from the review, as illustrated in Table 3, and recognizing the need to identify specific areas for improvement as well as the actual implementation of AI within SGs, especially concerning AI-enhanced security and other applications discussed in this review, an analysis of documents relevant to the Swedish context was conducted. The findings are presented in the next section.

5 The Action Planning Stage: Results From Documents Analysis

A thorough documentation analysis helped us comprehend AI implementation's trends, opportunities, and challenges in practice. The documentary data (selected sources listed in Table 2) helped contextualize the research on the AI applications in smart SGs, like market dynamics and new business models, grid infrastructure development, and technology adoption. Documents were especially valuable in identifying the strategies and approaches for AI implementation in practice, adding contextual richness to the research. Also, analysis of these documents prompted more in-depth inquiry and provided insight into events or circumstances that require more attention. The document analysis was an iterative process of skimming, reading, and interpreting documents related to SGs in Sweden [33].

Finally, we used content analysis [33], [55] and thematic analysis, a form of pattern recognition that employs emergent themes as analytical categories [35] to organize information relevant to the research question. This involves focused re-reading and reviewing the selected data, where coding and category construction are conducted based on the data's characteristics to reveal pertinent themes [35]. Additionally, to maintain rigorous intra-rater reliability during single-author coding, a systematic approach centered on a detailed codebook was employed. This codebook was consistently referenced throughout the analysis, ensuring the author's coding uniformity. It facilitated close engagement with the data, allowing for iterative reflection and identifying connections between meaning units [55]. This iterative process involved ongoing adjustments, revisions, and re-coding, ultimately leading to a set of reasonable and satisfactory coding choices [55] and identifying patterns [35] that resulted in the following themes: (I) Market Dynamics and Business Models, (II) Grid Infrastructure and Development, and (III) Technology Adoption, which are presented further in this section.

5.1 Market Dynamics and Business Models

Market dynamics and business models describe how power is bought and sold in Sweden. There are various distinct power exchanges where responsible parties can purchase and sell electricity [34]. These exchanges are linked at the European level, allowing bids on one exchange to be cleared against offers on another, resulting in an integrated European power market. More so, the availability of electricity and the amount requested at any time influence electricity pricing. For instance, when there is a surplus of supply compared to demand, such as on windy days, prices tend to fall. In contrast, prices rise when demand is high, and supply is low [22], [34]. Additionally, Sweden is divided into four bidding regions for electricity prices. Supply and demand in each region affect the bidden price in its specific bidding region. Efforts to modernize the grids continue to dominate national discussion discourse. Despite efforts to modernize the Swedish electricity market, a planned transformation involving a national "data hub" did not come to fruition [56]. Swedish authority responsible for Sweden's electricity transmission (Svenska kraftnät) and the Swedish Energy Markets Inspectorate (Energimarknadsinspektionen or Ei) tried to introduce a new paradigm in 2020 through a unified data hub [56], which did not materialize. The unified data hub was meant to establish a supplier-centric model, streamline billing by consolidating distribution and consumption invoicing, and potentially promote new energy-efficient services through increased competition, transparency, and improved data access [56]. The project involved multiple stakeholders, such as electricity market actors and the government, working together to develop a platform that meets diverse needs and fosters widespread adoption. This failed project shows how engaging stakeholders with different interests, market dynamics, and emerging business models affect grid infrastructure and its development, as discussed below.

5.2 Grid Infrastructure and Development

Sweden's national grid, one of the oldest globally, faces significant infrastructure challenges [41]. Hence, many existing lines and stations are approaching the end of their operational lifespan and require modernization. Simultaneously, new lines and stations are being constructed to reinforce and expand the national grid's capacity [41]. This is done through grid infrastructure development that involves adding new lines and stations to accommodate increased wind generation, alleviate grid restrictions, and meet society's desire for a reliable electricity supply [41]. The shift in the Swedish electricity market has precipitated grid development to meet the rapid changes in the electricity market due to the increased use of renewable energy sources. Grid development is made possible through new technologies, such as battery storage, and the growing prominence of climate change concerns [34], [37], [41]. Finally, the continuous development of the grid infrastructure involves developing and adopting new technologies, which are presented below.

5.3 Technology Adoption

Technology adoption in Swedish SGs is critical to the country's transition to a more sustainable and efficient energy infrastructure [37], [41]. Sweden is noted for its progressive approach to energy and environmental legislation. Sweden has also incorporated modern technology into its energy infrastructure to improve efficiency, dependability, and sustainability. This is done by adopting emerging technologies such as AI, advanced metering infrastructure, the Internet of Things (IoT), and smart systems. Also, the rapid advancement in AI technology has prompted a growing interest in AI adoption in SGs to optimize energy distribution, estimate energy consumption, and improve grid decision-making. AI adoption in SGs is pivotal to effectively meet customer expectations and create a competitive position in the future energy market [14], [52].

However, despite the growing interest in AI applications in SGs and the considerable potential of using a big data and ML in predictive analytics, as highlighted in Svenska Kraftnat's report[22], the results of AI models remain challenging to comprehend. This leads smart grid stakeholders to favor more straightforward and transparent approaches that are easier to interpret and understand [22]. The limited transparency and interpretability of AI algorithms and the labor-intensive nature of developing machine learning workflows significantly hinder the practical implementation of AI in SGs and complicate human efforts to provide intelligent tracking and feedback. This takes humans out of the loop and makes AI adoption challenging. Hence, having human-in-the-loop during the development and implementation process requires individuals who understand how AI algorithms work to intelligently monitor changes and intermediate results over time. This will facilitate rapid iteration, quick responsive feedback, introspection and debugging, background execution, and automation [57]. Consequently, bridging the gap between research and practice requires addressing AI transparency and interpretability to enhance the efficiency and effectiveness of AI while easing its implementation in practice. We want to emphasize the following: First, improving human understanding of AI models and interpretations of AI decisions is essential. Second, AI applications in practice should allow humans to intervene when AI fails or makes biased predictions (human-in-the-loop). Third, we must adopt and implement strategies that can effectively enable the integration of AI and humans. These tactics and approaches are detailed in the following section.

6 Discussion

The energy sector fosters stakeholder collaboration to develop innovative grid resilience and sustainability solutions. This involves upgrading the national grid with new infrastructure to accommodate increased wind power generation and removing grid limitations to ensure a reliable electricity supply that meets societal demand [41]. This has led to SG digitalization and the adoption of advanced technologies like AI, enabling real-time data collection and predictive analytics [11], [13], [22], [52], [53], and shifting grid operations from reactive to proactive. Also, predictive analytics in SGs uses real-time data and historical data to predict demand, improve grid stability, and increase user engagement [13], [41], [52]; thereby improving SG's resilience, efficiency, and adaptability to changing needs and challenges.

Moreover, AI applications in such SGs as AI-enabled predictive analytics have the potential to improve power outage prediction, demand response, control and coordination, and security, thus improving smart grid resilience. However, the results and AI decisions are still complex and difficult to interpret, which stifles their practical implementation. To address this gap and enable their practical implementation, there is an urgent need to adopt strategies and approaches for the design of AI algorithms that are transparent and explainable. It also ensures the ease of integration of transparent AI for predictive analytics and improves energy generation and distribution while maintaining human oversight and building public trust. This can be achieved through the following approaches: (I) explainable AI techniques, (II) robust data management, (III) human-in-the-loop, and (IV) stakeholder engagement and collaboration.

6.1 Explainable AI Techniques

Explainable AI (XAI) techniques refer to methodologies and methods for making AI decisions more transparent and understandable to humans [13], [51], [58]. These methods are used to address the "black box" character of some AI models, particularly complicated ones like deep neural networks, which can make it challenging to interpret and understand AI results [13], [21], [51]. Explainable AI techniques are being used in the design of transparent AI models to address some of these complexities, such as transfer learning challenges, and make AI decisions transparent and interpretable [13], [21], [51], [58], [59]. Hence, SG actors should adopt explainable AI techniques to design and implement AI models in SGs for transparent and human-understandable predictive analytics.

Furthermore, implementing explainable AI strategies is decisive for addressing AI transparency and interpretability, explaining how AI works, and clarifying AI judgments for users [5], [13]. This makes it easy for AI models and AI decisions to be humanly understandable through integrating domain expertise in the training of AI models. Also, explainable AI techniques are pivotal for AI applications in SGs for predictive analytics and can potentially transform predictive analytics in SGs by moving away from "black box" models to more transparent and understandable systems [51]. Incorporating explainable AI techniques into SG development can facilitate a thorough analysis of AI requirements and feasibility studies. These studies can then effectively determine essential factors such as required data structure, data quality, necessary expert competence, ethical compliance, and, most importantly, whether AI decisions are understandable to human operators [51], [58], [59]. Lastly, developing more interpretable AI models requires carefully specifying several key elements. This includes defining the data sources, identifying the relevant features for model training, and selecting appropriate predictive models or algorithms that effectively mimic the desired behavior [51], [58], [59], thus requiring robust data management, which is discussed next.

6.2 Robust Data Management

Robust data management is a complete strategy of managing data throughout its lifecycle, ensuring that information is dependable, safe, and accessible for a variety of uses. It goes beyond simply storing data; it covers a collection of behaviors, policies, and tools that ensure data quality, accessibility, and security. Robust data management involves identifying data sources, applying extraction techniques, combining data from multiple sources into a single dataset, and preprocessing the datasets to be used [59]. Also, the increasing integration of ICT into power grids, resulting in a massive influx of data from diverse sources, has made robust data management a critical necessity for SGs, demanding effective data analysis and mining techniques to ensure high data quality. Data quality involves identifying outliers and removing errors before loading them into a data center [60] and ensuring the suitability of data for usage. Roger and Mangiameli [61] identified four properties of data quality: *correctness*, *integrity*, *consistency*, and *timeliness*. They emphasized the importance of data quality for information consumption; this is only possible through robust data management.

Moreover, Alizamini et al. [62] viewed data quality as a complex, non-structural term that requires elaboration through robust data management. Currently, significant volumes of electricity consumption data have been accumulated. Identifying hidden information from heterogeneous and inconsistent data is challenging [63]. Therefore, robust data management is necessary for creating high-quality data, which is essential for knowledge discovery and the design and deployment of interpretable and transparent AI algorithms. Also, high data quality will enhance the accuracy and transparency of electricity consumption statistics. Thus, its characteristics must be properly studied to ensure that the collected data meets user requirements [64]. This will ensure that AI algorithms trained with these data make informed decisions based on insight from electricity consumption data with high qualities. This will make it easy to thoroughly comprehend the output of AI algorithms while making it easy for human input to be integrated into an automated process or machine learning model through a human-in-the-loop system, which is discussed next.

6.3 Human-in-the-Loop Systems

Human-in-the-loop (HITL) is an approach to designing and implementing AI algorithms that incorporate human domain knowledge and expertise into the training and function of machine learning systems to automate machine learning processes [65]. This approach is pivotal in designing and implementing AI in SGs since developing ML procedures involves iterative experimentation to achieve the requisite accuracy. Thus, HITL allows one to intelligently incorporate human domain knowledge into the process to track changes and intermediate results over time [57]. Also, this allows for rapid iteration, responsive feedback, introspection, debugging, and background execution and automation [57], [65].

HITL research is becoming increasingly relevant as machine learning cannot replace human domain expertise. Thus, adopting the HITL approach in designing and implementing AI in SGs provides an opportunity to leverage more than 50 years of domain knowledge in the energy sector and improve the accuracy, transparency, and interpretability of AI algorithms in SGs. This can be done by integrating human expertise and experience to create accurate and less complex prediction models at a low cost [65]. HITL offers training data for machine learning applications and uses machine-based methodologies to complete tasks that computers may struggle with. Lastly, HITL allows humans to analyze AI algorithms and their outcomes by observing the changes that occur during their construction, diffusion, and use within social situations [21]. HITL necessitates knowledge transfer, which can be accomplished through stakeholder engagement and collaboration, which is discussed next.

6.4 Stakeholder Engagement and Collaboration

Stakeholder engagement and collaboration in AI applications in SGs is an approach of actively engaging and collaborating with stakeholders in the design and implementation of AI. This ensures that AI applications and systems are designed and implemented responsibly, ethically, and effectively, maximizing their benefits while minimizing potential risks [51], [58]. Stakeholder engagement and collaboration are pivotal throughout the design and implementation of explainable AI (XAI) systems, which is required in the design and implementation of transparent and interpretable AI in SGs for predictive analytics to allow different stakeholders to bring in diverse perspectives and needs and ensure the XAI is effective, trustworthy, and aligned with ethical principles[51], [58].

Finally, by combining these strategies and approaches, we can address the current gap between research and practice in AI applications in SGs. This is because these approaches will help stakeholders create and deploy transparent AI systems in SGs that are not only efficient but also reliable and accountable. This allows us to fully realize AI's promise and create a more efficient, reliable, and sustainable energy future.

7 Conclusion and Future Research

Smart grids (SGs) are a technology that offers a framework for producing, distributing, and consuming environmentally friendly, efficient, and dependable energy. SG functionalities have been improved significantly due to its integration with other emerging disruptive technologies such as AI. Our study focused on the latest literature on developing and deploying AI applications in

SGs, with a specific interest in predictive analytics. This study is part of an ongoing collaborative research practice project to create innovative and beneficial knowledge of SGs for multiple stakeholders using an action research approach. Referring to the research question "*What strategies and approaches can enhance the practical implementation of transparent AI for predictive* analytics *in smart grids to improve energy generation and distribution?*" this article presents the findings from the first two stages of the action research: diagnosis and action planning. The *diagnosis stage* involved a structured literature review that included 26 articles published after 2015 about AI applications in SGs, explicitly focusing on predictive analytics. *The action planning stage* involved a document analysis of the development of smart grid innovation in Sweden.

Based on the diagnosis stage, we deduce from the existing literature that AI applications in smart grid predictive analytics might enhance (1) power outage prediction, (2) demand response, (3) control and coordination, and (4) security enhancement. Furthermore, document analysis for the action planning stage reveals a dynamic interplay where evolving (I) market dynamics and business models influence (II) grid infrastructure and development, ultimately driving (III) technology adoption like AI. However, despite these huge potentials, AI applications in SGs remain largely in the research phase because AI adds another layer of opacity. For the action planning stage, we then discuss how it can be delineated, answering the research question regarding the strategies and approaches required to ease the practical implementation of AI in SGs. We discuss four approaches and strategies: (1) explainable AI techniques, (2) robust data management, (3) human-in-the-loop systems, and (4) stakeholder engagement and collaboration. These approaches could enhance the practical implementation of transparent AI in SGs. More so, transparent AI offers superior stability, reliability, and efficiency over traditional grids. It addresses many challenges in SGs and traditional grids, enhances performance, and reduces human intervention in managing energy flow. Furthermore, the study concludes that implementing transparent AI for AI-driven predictive analytics in SGs might optimize decision-making, diagnose faults, and enhance grid stability. This is essential for addressing energy consumption challenges, especially if approached from societal and behavior-oriented perspectives. Our proposed strategies and approaches offer the foundation upon which the current challenge of AI interpretability in SGs can be solved, thereby increasing AI efficiency and trustworthiness. Our diagnosis stage examines what has been done so far in the context of AI applications in SGs and highlights the necessity of making AI algorithms in SGs transparent. Our action planning stage shows that with the recent advancements in AI and the increasing amount of data in SGs, the predictive analytic technique in AI offers robust tools for optimizing SGs and increasing complexity and requires the right approach for their practical implementation.

The study contributes to the discussion on AI-enabled predictive analytic functions in SGs. It demonstrates that AI adoption requires the right strategies to uncover unforeseen elements of algorithmic systems, such as AI interpretability concerns, which have great potential to enhance AI applications in SGs. Nevertheless, the study is limited, and further work is needed to complete the remaining stages based on Susman and Evered's [27] action research. The remaining stages are (3) *action-taking* (implementing the solution), (4) *evaluation* (assessing the results), and (5) *learning* (reflecting on lessons learned). The full benefit of AI applications in SGs can be achieved if a study explicitly includes algorithms in ethnographic research to uncover unforeseen elements of algorithmic systems not addressed in the study. Hence, future studies can go a step further using our proposed strategies and explore methodologies for algorithmic ethnography [21] in SGs. Many practical issues regarding AI implementation in SGs, such as lack of transparency and interpretability, must be addressed based on empirical data. Therefore, future studies could explore these issues. However, a significant conclusion from this study is that more research with concrete empirical examples of how to adopt and deploy AI and especially predictive analytics in SG using our strategies proposed in this study is needed. Doing this kind of research focusing on AI interpretability and predictive analytics models within SGs would benefit the development of smart grids.

References

[1] B. K. Bose, “Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems – Some Example Applications,” *IEEE XPLORE, Proceedings of the IEEE*, vol. 105, no. 11, pp. 2262–2273, 2017. Available: https://doi.org/10.1109/JPROC.2017.2756596

[2] S. Dhara, A. K. Shrivastav, and P. K. Sadhu, “Smart grid modernization: Opportunities and challenges,” *Electric Grid Modernization*, 2022. Available: https://doi.org/10.5772/intechopen.97892

[3] M. C. Falvo, L. Martirano, D. Sbordone, and E. Bocci, “Technologies for smart grids: A brief review,” *the 12th International Conference on Environment and Electrical Engineering*, Wroclaw, Poland, pp. 369–375, 2013. Available: https://doi.org/10.1109/EEEIC.2013.6549544

[4] M. M. H. Sifat *et al.*, “Towards electric digital twin grid: Technology and framework review,” *Energy and AI*, vol. 11, 2023. Available: https://doi.org/10.1016/j.egyai.2022.100213

[5] S. Zhongtuo *et al.*, “Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions,” *Applied Energy*, vol. 278, 2020. Available: https://doi.org/10.1016/j.apenergy.2020.115733

[6] P. Boopathy *et al.*, “Deep learning for intelligent demand response and smart grids: A comprehensive survey,” *Computer Science Review*, vol. 51, 2024. Available: https://doi.org/10.1016/j.cosrev.2024.100617

[7] J. Wang, M. K. Lim, C. Wang, and M.-L. Tseng, “The evolution of the Internet of Things (IoT) over the past 20 years,” *Computers & Industrial Engineering*, vol. 155, 2021. Available: https://doi.org/10.1016/j.cie.2021.107174

[8] A. A. Khan, A. A. Laghari, M. Rashid, A. R. Javed, and T. R. Gadekallu, “Artificial intelligence and blockchain technology for secure smart grid and power distribution Automation: A State-of-the-Art Review,” *Sustainable Energy Technologies and Assessments*, vol. 57, 2023. Available: https://doi.org/10.1016/j.seta.2023.103282

[9] O. A. Omitaomu and H. Niu, “Artificial Intelligence Techniques in Smart Grid: A Survey,” *Smart Cities*, vol. 4, no. 2, pp. 548–568, 2021. Available: https://doi.org/10.3390/smartcities4020029

[10] G. W. Arnold, “Challenges and Opportunities in Smart Grid: A Position Article,” *Proceedings of the IEEE*, vol. 99, no. 6, pp. 922-927, 2011. Available: https://doi.org/10.1109/JPROC.2011.2125930

[11] E. A. Bhuiyan, M. Z. Hossain, S. M. Muyeen, S. R. Fahim, S. K. Sarker, and S. K. Das, “Towards next generation virtual power plant: Technology review and frameworks,” *Renewable and Sustainable Energy Reviews*, vol. 150, 2021. Available: https://doi.org/10.1016/j.rser.2021.111358

[12] M. Khalid, “Energy 4.0: AI-enabled digital transformation for sustainable power networks,” *Computers & Industrial Engineering*, vol. 193, 2024. Available: https://doi.org/10.1016/j.cie.2024.110253

[13] T. Kindong, B. Johansson, and V. Paulsson, “A systematic literature review of AI-enabled predictive analytics in smart grids,” *Joint Proceedings of the BIR 2024 Workshops and Doctoral Consortium co-located with 23rd International Conference on Perspectives in Business Informatics Research (BIR 2024)*, Ceur-ws.org, vol. 3804, pp. 16–30, 2024.

[14] D. Barth, B. Cohen-Boulakia, and W. Ehounou, “Distributed Reinforcement Learning for the Management of a Smart Grid Interconnecting Independent Prosumers,” *Energies*, vol. 15, no. 4, 2022. Available: https://doi.org/10.3390/en15041440

[15] C. Lazaro and M. Rizzi, “Predictive analytics and governance: a new sociotechnical imaginary for uncertain futures,” *International Journal of Law in Context*, vol. 19, no. 1, pp. 70–90, 2023. Available: https://doi.org/10.1017/S1744552322000477

[16] F. Li and Y. Du, “From AlphaGo to Power System AI : What Engineers Can Learn from Solving the Most Complex Board Game,” *IEEE Power Energy Mag*, vol. 16, no. 2, pp. 76–84, 2018. Available: https://doi.org/10.1109/MPE.2017.2779554

[17] H. Cao, D. Zhang, and S. Yi, “Real-Time Machine Learning-based fault Detection, Classification, and locating in large scale solar Energy-Based Systems: Digital twin simulation,” *Solar Energy*, vol. 251, pp. 77–85, 2023. Available: https://doi.org/10.1016/j.solener.2022.12.042

[18] J. R. Vázquez-Canteli and Z. Nagy, “Reinforcement learning for demand response: A review of algorithms and modeling techniques,” *Applied Energy*, vol. 235, pp. 1072–1089, 2019. Available: https://doi.org/10.1016/j.apenergy.2018.11.002

[19] K. Fatima, H. Shareef, F. B. Costa, A. A. Bajwa, and L. A. Wong, "Machine learning for power outage prediction during hurricanes: An extensive review," *Engineering Applications of Artificial Intelligence*, vol. 133, 2024. Available: https://doi.org/10.1016/j.engappai.2024.108056

[20] F. A. Rahman, A. Varuttamaseni, M. Kintner-Meyer, and J. C. Lee, "Application of fault tree analysis for customer reliability assessment of a distribution power system," *Reliability Engineering & System Safety,* vol. 111, pp. 76–85, 2013. Available: https://doi.org/10.1016/j.ress.2012.10.011

[21] A. Christin, "The ethnographer and the algorithm: beyond the black box," *Theory and Society*, vol. 49, pp. 897–918, 2020. Available: https://doi.org/10.1007/s11186-020-09411-3

[22] Svenska kraftnät, Report on Reduction of Gross Electricity consumption during peak hours in Sweden for December 2022. 2023.

[23] L. Feng, Y. Zhou, Q. Luo, and Y. Wei, "Complex-valued artificial hummingbird algorithm for global optimization and short-term wind speed prediction," *Expert Systems with Applications,* vol. 246, 2024. Available: https://doi.org/10.1016/j.eswa.2024.123160

[24] M. W. Ahmad, J. Reynolds, and Y. Rezgui, "Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees," *Journal of Cleaner Production,* vol. 203, pp. 810–821, 2018. Available: https://doi.org/10.1016/j.jclepro.2018.08.207

[25] B. Latour, *Pandora's hope: Essays on the reality of science studies*. Harvard University Press, 1999a.

[26] M. Faheem *et al.*, "Smart grid communication and information technologies in the perspective of Industry 4.0: Opportunities and challenges," *Computer Science Review,* vol. 30, pp. 1–30, 2018. Available: https://doi.org/10.1016/j.cosrev.2018.08.001

[27] G. I. Susman and R. D. Evered, "An assessment of the scientific merits of action research," *Studi Organizzativi,* no. 2022/2, 2023. Available: https://doi.org/10.3280/SO2022-002006

[28] A. Nakakawa *et al.*, "Process for Leveraging Enterprise Architecture in Information Systems Strategic Planning: A Case of Developing a Strategy and Master Plan for a National Integrated Health Laboratory Information Management System in Uganda," *Complex Systems Informatics and Modeling Quarterly,* no. 40, pp. 58–93, 2024. Available: https://doi.org/10.7250/csimq.2024-40.03

[29] N. Jahan, S. Naveed, M. Zeshan, and M. A. Tahir, "How to Conduct a Systematic Review: A Narrative Literature Review," *Cureus,* vol. 8, no. 11, pp. 864–872, 2016. Available: https://doi.org/10.7759/cureus.864

[30] A. P. Siddaway, A. M. Wood, and L. V. Hedges, "How to do a systematic review: a best practice guide for conducting and reporting narrative reviews, meta-analyses, and meta-syntheses," *Annual Review of Psychology,* vol. 70, pp. 747–770, 2019. Available: https://doi.org/10.1146/annurev-psych-010418-102803

[31] J. Webster and R. T. Watson, "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS Quarterly,* vol. 26, no. 2, pp. xiii-xxiii, 2002.

[32] L. Mathiassen, "Collaborative practice research," *Information Technology & People,* vol. 15, no. 4, pp. 321–345, 2002. Available: https://doi.org/10.1108/09593840210453115

[33] G. A. Bowen, "Document Analysis as a Qualitative Research Method," *Qualitative Research Journal,* vol. 9, no. 2, pp. 27–40, 2009. Available: https://doi.org/10.3316/QRJ0902027

[34] Svenska kraftnät, National Grid: Operations and Electricity Markets. 2024.

[35] V. Clarke and V. Braun, "Thematic Analysis," *The Journal of Positive Psychology*, vol. 12, no. 3, pp. 297–298, 2016. Available: https://doi.org/10.1080/17439760.2016.1262613

[36] Y. T. Chae, R. Horesh, Y. Hwang, and Y. M. Lee "Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings," *Energy and Buildings,* vol. 111, pp. 184–194, 2016. Available: https://doi.org/10.1016/j.enbuild.2015.11.045

[37] Tekniska Verken. Sells support services to Svenska kraftnät. Available: https://www.tekniskaverken.se/om-oss/innovation/. https://www.tekniskaverken.se/om-oss/innovation/. Accessed on January 2025.

[38] S. You *et al.*, "A Review on Artificial Intelligence for Grid Stability Assessment," *2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm),* pp. 1–6, 2020. Available: https://doi.org/10.1109/SmartGridComm47815.2020.9302990

[39] S. Idima, C. E. Nwatu, E. M. Adim, and I. J. Okwesa, "Predictive analytics for aging U.S. electrical infrastructure: Leveraging machine learning to enhance grid resilience and reliability," *World Journal of Advanced Research and Reviews*, vol. 19, no. 2, pp. 1595–1622, 2023. Available: https://doi.org/10.30574/wjarr.2023.19.2.1723

[40] S. Sankarananth, M. Karthiga, E. Suganya, S. Sountharrajan, and D. P. Bavirisetti, “AI-enabled metaheuristic optimization for predictive management of renewable energy production in smart grids,” *Energy Reports,* vol. 10, pp. 1299–1312, 2023. Available: https://doi.org/10.1016/j.egyr.2023.08.005

[41] Svenska kraftnät, Grid development. 2024.

[42] T. Kindong, “AI applications in SG for reliability, security, and stability,” *Joint Proceedings of the BIR 2024 Workshops and Doctoral Consortium co-located with 23rd International Conference on Perspectives in Business Informatics Research (BIR 2024),* Ceur-ws.org, vol. 3804, pp. 267–278, 2024.

[43] H. Shi, M. Xu, and R. Li, “Deep Learning for Household Load Forecasting – A Novel Pooling Deep RNN,” *IEEE Transactions on Smart Grid,* vol. 9, no. 5, pp. 5271–5280, 2018. Available: https://doi.org/10.1109/TSG.2017.2686012

[44] Q. Zhou, S. Natarajan, Y. Simmhan, and V. Prasanna, “Semantic Information Modeling for Emerging Applications in Smart Grid,” *2012 Ninth International Conference on Information Technology – New Generations*, Las Vegas, NV, USA, pp. 775–782, 2012. Available: https://doi.org/10.1109/ITNG.2012.150

[45] M. A. Khan, A. M. Saleh, M. Waseem, and I. A. Sajjad, “Artificial intelligence enabled demand response: Prospects and challenges in smart grid environment,” *IEEE Access,* vol. 11, pp. 1477–1505, 2022. Available: https://doi.org/10.1109/ACCESS.2022.3231444

[46] M. W. Ahmad, M. Mourshed, and Y. Rezgui, “Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption,” *Energy and Buildings,* vol. 147, pp. 77–89, 2017. Available: https://doi.org/10.1016/j.enbuild.2017.04.038

[47] H. Ma, H. Zhang, D. Tian, D. Yue, and G. P. Hancke, “Optimal demand response based dynamic pricing strategy via Multi-Agent Federated Twin Delayed Deep Deterministic policy gradient algorithm,” *Engineering Applications of Artificial Intelligence,* vol. 133, 2024. Available: https://doi.org/10.1016/j.engappai.2024.108012

[48] J. Kampars, J. Grabis, V. Pavlovs, G. Soloveja, and T. Stālmans, “Predictive and optimisation models for AI driven electricity balancing platform,” *IEEE 65th International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS),* 2024, pp. 1–6. Available: https://doi.org/10.1109/ITMS64072.2024.10741949

[49] S. Pandya, “Predictive Analytics in Smart Grids: Leveraging Machine Learning for Renewable Energy Sources,” *International Journal of Current Engineering and Technology,* vol. 11, no. 6, pp. 677–683, 2021. Available: https://doi.org/10.14741/ijcet/v.11.6.12

[50] P. C. Marques and P. A. Oliveira, “Artificial intelligence technologies applied to smart grids and management,” *Preprints,* 2024. Available: https://doi.org/10.20944/preprints202406.1248.v1

[51] A. Yayla, L. Haghnegahdar, and E. Dincelli, “Explainable Artificial Intelligence for Smart Grid Intrusion Detection Systems,” *IT Professional*, vol. 24, no. 5, pp. 18–24, 2022. Available: https://doi.org/10.1109/MITP.2022.3163731

[52] O. Babayomi, Z. Zhang, T. Dragicevic, J. Hu, and J. Rodriguez, “Smart grid evolution: Predictive control of distributed energy resources – A review,” *International Journal of Electrical Power & Energy Systems,* vol. 147, 2023. Available: https://doi.org/10.1016/j.ijepes.2022.108812

[53] R. J. Bessa *et al.*, “Data Economy for Prosumers in a Smart Grid Ecosystem,” *e-Energy ’18: Proceedings of the Ninth International Conference on Future Energy Systems*, pp. 622–630, 2018. Available: https://doi.org/10.1145/3208903.3210282

[54] M. Sarhan, S. Layeghy, M. Gallagher, and M. Portmann, “From zero-shot machine learning to zero-day attack detection,” *International Journal of Information Security,* vol. 22, pp. 947–959, 2023. Available: https://doi.org/10.1007/s10207-023-00676-0

[55] C. Erlingsson and P. Brysiewicz, “A hands-on guide to doing content analysis,” *African Journal of Emergency Medicine,* vol. 7, no. 3, pp. 93–99, 2017. Available: https://doi.org/10.1016/j.afjem.2017.08.001

[56] Svenska kraftnät, Data hub project on hold. 2024.

[57] D. Xin, L. Ma, J. Liu, S. Macke, S. Song, and A. Parameswaran, “Accelerating human-in-the-loop machine learning: Challenges and opportunities,” *Proceedings of the second workshop on data management for end-to-end machine learning*, 2018, pp. 1–4. Available: https://doi.org/10.1145/3209889.3209897

[58] K. Sandkuhl, “Putting AI into Context – Method Support for the Introduction of Artificial Intelligence into Organizations,” *2019 IEEE 21st Conference on Business Informatics (CBI),* vol. 1, pp. 157–164, 2019. Available: https://doi.org/10.1109/CBI.2019.00025

[59] A. Kumarasinghe and M. Kirikova, “Requirements Template for Analytics Projects,” *Complex Systems Informatics and Modeling Quarterly*, no. 39, pp. 65–85, 2024. Available: https://doi.org/10.7250/csimq.2024-39.04

[60] W. Chen, K. Zhoua, S. Yanga, and C. Wu, “Data quality of electricity consumption data in a smart grid environment,” *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 98–105, 2016. Available: https://doi.org/10.1016/j.rser.2016.10.054

[61] R. Blake and P. Mangiameli, “The effects and interactions of data quality and problem complexity on classification,” *Journal of Data and Information Quality (JDIQ)*, vol. 2, no. 2, pp. 1–28, 2011. Available: https://doi.org/10.1145/1891879.1891881

[62] F. G. Alizamini, M. M. Pedram, M. Alishahi, and K. Badie, “Data quality improvement using fuzzy association rules,” *2010 International conference on electronics and information engineering*, vol. 1, pp. 468–472, 2010. Available: https://doi.org/10.1109/ICEIE.2010.5559676

[63] K. Moslehi and R. Kumar, “A reliability perspective of the smart grid,” *IEEE Transactions on Smart Grid*, vol. 1, no. 1, pp. 57–64, 2010. Available: https://doi.org/10.1109/TSG.2010.2046346

[64] C. Cappiello, C. Francalanci, and B. Pernici, “Data quality assessment from the user's perspective,” *IQIS’04: Proceedings of the 2004 international workshop on Information quality in information systems*, pp. 68–73, 2004. Available: https://doi.org/10.1145/1012453.1012465

[65] X. Wu, L. Xiao, Y. Sun, J. Zhang, T. Ma, and L. He, “A survey of human-in-the-loop for machine learning,” *Future Generation Computer Systems*, vol. 135, pp. 364–381, 2022. Available: https://doi.org/10.1016/j.future.2022.05.014