The New Power Couple: Artificial Intelligence and Renewable Energy

Gabriele Mauro
Université Libre de Bruxelles

Achieving net-zero emissions is one of the most challenging goals of our time, requiring large-scale integration of renewable energy (RE) into national energy supply chains. This demands new competencies for firms to preserve their competitive advantages in rapidly evolving market environments, often called dynamic capabilities. A promising technology for integrating, scaling, and diffusing renewable energy within energy supply chains is artificial intelligence. However, the literature on AI-renewable energy supply chains is still in its early stages and often lacks broader theoretical development or managerial insights. In response, we introduce a theoretical framework to identify and develop AI-based dynamic capabilities in renewable energy supply chains through a case study approach. Supply chain predictability and optimization, key components of sensing and seizing capabilities, are crucial for developing effective renewable energy supply chains. Our study provides valuable insights also for practitioners aiming to establish AI-driven renewable energy supply chains.

Keywords: artificial intelligence, renewable energy, dynamic capabilities

INTRODUCTION

The increasing atmospheric CO2 levels drive many nations to pursue a 100% renewable energy target by 2050, aiming for carbon neutrality to mitigate climate change (Liu et al., 2022; Hannan et al., 2021). In addition to environmental pressures, geopolitical risks and volatile gas prices are prompting major fossil fuel importers like the European Union, Japan, and China to ramp up their investments in renewable energy. The potential of RE lies in its ability to eliminate harmful emissions (e.g., SO2, CO2, and particulate matter) and virtually create a low-cost energy environment for manufacturing (Ahmad et al., 2021; Liu et al., 2022). However, for RE to dominate the energy market, its production and distribution must be stable and competitive to effectively integrate this volatile, yet affordable, energy source into national energy supply chains. Renewable energy supply chains require rethinking energy infrastructure and the long-term competitive advantages of companies and countries. Artificial intelligence plays a fundamental role in renewable supply chains by autonomously adapting, learning, and generalizing knowledge from new data sources and situations to make frequent decisions, identify new patterns, and solve daily problems with limited human supervision (Liu et al., 2022; Hoffreumon et al., 2024). Renewable energy supply chains and AI have emerged as an important new industrial paradigm. AI can help manage RE variability and unpredictability, reduce trading, production, and maintenance costs, stabilize renewable energy supply chains, and effectively integrate prosumers into power networks (Liu et al., 2022; Zhang et al., 2022; Gawusu et al., 2021).

It is of fundamental importance to understand how firms can leverage AI as a "dynamic capability," beyond its mere role as a "disruptive technology." Dynamic capabilities, or competences, enable firms to effectively exploit resources and maintain a competitive advantage in rapidly changing markets (Teece et al., 1997; Vanpoucke et al., 2014). As the renewable energy sector undergoes profound transformations through consumer market, regulatory, and technological shifts, together called the "twin transition" to refer to digitization and sustainability, there is a need for research on how firms prioritize and develop AI-based dynamic capabilities to enhance renewable energy integration in energy supply chains (Liu et al., 2022; Zhang et al., 2022). This study focuses on how AI-driven capabilities can strengthen renewable energy supply chains. Despite a growing body of engineering and computer science literature and several practical examples (Liu et al., 2022; Ahmad et al., 2021; Hannan et al., 2021), the overall literature on AI and renewable energy supply chains lacks theoretical saturation, and two important gaps remain.

First, while managing AI-based capabilities is essential for developing AI-driven renewable energy supply chains, we lack knowledge on which AI-based dynamic capabilities are prioritized by firms, which AI capabilities specifically support renewable energy supply chains, and how these AI-based dynamic capabilities are developed (Craighead et al., 2016; Pournader et al., 2021). AI encompasses a set of technologies that offer several capabilities for firms seeking to integrate renewable energy sources into their supply chains. For instance, AI can optimize operational costs (Allal et al., 2024; Hannan et al., 2021), flexibility of renewable energy power plants (Liu et al., 2022; Hannan et al., 2021); and it can facilitate a distributed marketplace of prosumers, enabling bi-directional energy flows in the market (Zhang et al., 2022). Despite these important benefits, there remains uncertainty about which AI-based dynamic capabilities most effectively support renewable energy supply chains and the saliency of relationships between these capabilities (Ellström et al., 2022). Understanding these relationships could significantly aid in the development of artificial intelligence-based dynamic capabilities for renewable energy supply chains.

Second, there is currently a lack of guidance and tools to assist firms in making informed decisions about how to effectively deploy AI for a renewable energy and zero-emission economy. Without this RE-AI guidance, efforts to integrate cost-effective renewable energy sources into national energy markets become challenging, fragmented, uncoordinated, and ultimately slow. The diffusion and scaling of renewable energy can significantly benefit from clear guidance on AI-based dynamic capabilities within the renewable energy sector.

To fill these gaps, our research addresses two research questions: What AI-based dynamic capabilities support renewable energy supply chains? And what is their importance in facilitating effective renewable energy integration within these supply chains? To answer these two questions, we present a theoretical framework for understanding AI-based dynamic capabilities in renewable energy supply chains which combines industry experience and real-life cases of renewable energy in distribution and transmission through dynamic capabilities as intra-organizational theory. This approach allows us to theoretically systematize our empirical knowledge on AI technological drivers in enabling renewable energy supply chains (Liu et al., 2022; Gawusu et al., 2021), establishing a link between sustainability and digitalization (the previously mentioned “twin transition”) that is of growing importance in the AI-based renewable energy studies. We derive our conceptual framework from a multiple case study using empirical analysis of secondary data sources, such as press releases, websites, and industry reports (Eisenhardt and Graebner, 2007). Our AI application cases are selected based on their full implementation within renewable energy supply chains, focusing on an empirical analysis of published industry case studies, with third-party triangulation and full public disclosure (primarily linked to reports published in compliance with CORDIS requirements).

While engineering and computer science research have made substantial contributions to the design and implementation of physical AI infrastructure in renewable energy (Zhang et al., 2022; Ahmad et al., 2021), our study contributes to the literature on renewable energy supply chains and artificial intelligence showing the relevance of the dynamic capability theory as lens. By effectively connecting two previously disjointed fields of research, namely the dynamic capabilities view (Teece et al., 1997) and AI-driven renewable energy supply chains, this study shows the importance of developing AI-based dynamic capabilities for effective renewable energy supply chain strategies. Although the potentials of renewable energy supply chains are increasingly evident in the business practice and academic literature, how to develop and scale these potentials through AI has not been discussed in the literature. Our case analysis shows that AI is a versatile technology that facilitates renewable energy integration into existing energy supply chains. The potential of renewable energy supply chains largely depends on enhanced forecasting and optimization. We also highlight several critical contingencies for developing AI-based capabilities in renewable energy supply chains. Our work offers theoretical implications for the dynamic capabilities' theory as well as important managerial insights.

This paper is organized as follows: the next section presents a review of the literature on renewable energy supply chains, AI, and dynamic capabilities. We then describe the research design and methodology and provide the research findings. We conclude by discussing practical and theorical contributions and implications, highlighting the study's limitations and suggesting avenues for future research.

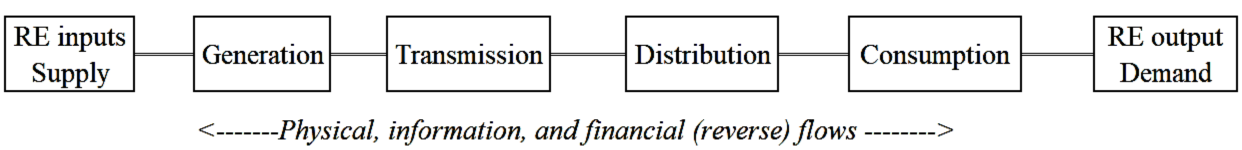
LITERATURE BACKGROUND

Renewable Energy Supply Chains

Renewable energy supply chains are integral components of green supply chains, as sustainable systems cannot exist without incorporating renewable energy sources (Gawusu et al., 2021). These supply chains play a critical role in climate change mitigation, aligning with the United Nations Framework Convention on Climate Change (UNFCCC) goals, including those outlined in COP 21. The transition away from fossil fuels, adopting renewable energy, managing energy price volatility, and improving energy access are key aims of virtually all green supply chains (Gawusu et al., 2021). Figure 1 illustrates the five domains of renewable energy supply chains, highlighting the critical bi-directional flows that characterize them. According to Aslani et al. (2013), renewable energy supply chains encompass supply, generation, transmission, distribution, and demand, covering all phases from energy transformation to consumption. These supply chains involve multiple sub-chains, characterized by upstream and downstream transformation and distribution nodes, each with distinct stakeholders, technologies, and operations.

Unlike discrete manufacturing supply chains, where physical flows dominate, and information and financial flows support, renewable energy supply chains elevate information flows. Physical flows encompass the tangible processes of production, transmission, and distribution. In the case of renewable energy, these physical flows are entirely standardized and increasingly IT-led. By contrast, information flows that cover the collection, transfer, exchange, and analysis of supply chain data (Vanpoucke et al., 2009) precede and predict physical flows, determining the necessary actions due to wind and solar power's intermittent and discontinuous nature. Moreover, unlike conventional energy supply chains, information and physical flows in renewable energy supply chains are increasingly bi-directional (Gawusu et al., 2021). Consequently, information technology emerges as a key enabler for effective renewable energy supply chain management, ensuring the optimization and stability of these systems.

FIGURE 1
RENEWABLE ENERGY SUPPLY CHAIN DOMAINS AND BI-DIRECTIONAL FLOWS (MODIFIED FROM ASLANI ET AL., 2013)



Due to their cleanliness and inexhaustibility, wind, solar, geothermal, biomass, tidal, and hydropower are the most common renewable energy sources. Among them, wind and solar are prevalent in national energy mixes and share important characteristics. Both are intermittent, random, and chaotic, distinguishing them from other renewable energy sources (Allal et al., 2024; Hannan et al., 2021). These properties generate unique challenges—with significant cost implications—for their integration into electricity supply chains. Table 1 presents key barriers and drivers of renewable energy supply chains, focusing on wind and solar.

Supplier integration, customer collaboration, innovation, distributed energy systems, and regulations are often discussed regarding renewable energy drivers and barriers (Gawusu et al., 2021). Renewable energy's intermittent availability and intensity lead to voltage and frequency fluctuations, resulting in asynchronization between energy production and consumption (Liu et al., 2022; Gawusu et al., 2021). Consequently, energy storage equipment and grid management become necessary for two main purposes: first, to balance supply and demand during periods of low or zero production; and second, to smooth sudden “peaks and valleys”—the increases or decreases in voltage and frequency linked to wind and solar energy production.

Additional challenges, such as excess production, electricity reactivity, outages, overloaded energy transformers, frequent switching of electrical equipment, and the forecasting and scheduling of production and load management, contribute to increased costs associated with renewable energy. All these barriers hinder the implementation and diffusion of renewable energy and raise supply chain and operating costs relative to non-renewable energy sources.

Unlike fossil fuels, the marginal cost of renewable energy production is low and is not influenced by commodity price volatility or input scarcity. While installation and infrastructure costs can be high upfront, the maintenance costs of solar and wind farms are generally lower than those of thermoelectric plants once they are operational. Pressure from customers to utilize renewable energy sources, consumer collaboration opportunities, and rising consumer demand are also cited as significant drivers of renewable energy. Collaboration with customers allows for information and resource sharing, risk reduction, and distribution of benefits. It also enhances innovation and sustainability performance in renewable energy supply chains. The diffusion of renewable energy enables firms to learn and accumulate sustainable knowledge, evolving toward more sustainable practices. Innovation is a key element of green supply chains.

Wind and solar farms are often location-specific, thriving in areas with necessary geophysical characteristics (Liu et al., 2022; Allal et al., 2024). The deployment of decentralized energy sources and the evolution toward prosumers have led to the introduction of trading and crediting instruments in the virtual grid to facilitate reverse flows on a distributed wholesale level. This, in turn, allows prosumers to trade with the grid.

Finally, several policymaking initiatives have been enacted by governments to promote the diffusion of solar and wind electricity. Regulatory compliance, codes of practice, proactive actions to pre-regulation, and self-regulation are also strong motivators for renewable energy supply chains.

TABLE 1
CLASSIFICATION OF DRIVERS AND BARRIERS OF WIND AND SOLAR ENERGY

Category	Drivers	References
Low-cost production	Low marginal cost of RE Grid parity of renewables	Engelken et al. (2016) Gawusu et al. (2021)
Supply chain collaboration	Decarbonization of energy business models Tranformation towards prosumers, demand by customers	Engelken et al. (2016) Gawusu et al. (2021)
Innovation and sustainability **Stakeholder expectations**	Adaptation towards new regulatory enviornments; customes demand greater share of RE	Engelken et al. (2016) Gawusu et al. (2021)

Category	Barriers	References
Lack of resource mobilization	Storage costs, upfront investments, development cycles, lack of investor interest	Engelken et al. (2016); Gawusu et al. (2021); Allal et al. (2024)
Supply chain integration	Uncertain timing and challenges of RE production; randomness of intensity, scheduling and inventory management	Engelken et al. (2016); Gawusu et al. (2021)
Distributed marketplace	Geographical dispersion of suppliers (1) grid capacity (2) Availability of real-time location, condition and intensity of RE (3)	Eleftheriadis and Anagnostopoulou (2015) Gawusu et al. (2021)

Artificial Intelligence in Renewable Energy Supply Chains

AI applications can be divided into three categories: technologies that sense various forms of data (such as speech, vision, and natural language processing), technologies that learn from data (machine learning), and technologies used for decision-making (including expert systems, planning, simulation, modelling, scheduling, and optimization) (Pournader et al., 2021). AI can handle extensive and nonlinear data processing and analysis, extract insights from patterns, predict outcomes, identify market opportunities, adapt to changing conditions, enhance risk management, improve customer engagement, and make decisions based on real-time data (Hendricksen, 2023; Liu et al., 2022; Zhang et al., 2022). While AI finds application in all renewable energy supply chain domains represented in Figure 1, we focus specifically on renewable energy production, transmission, and distribution segments (i.e., renewable energy production and grid management), and exclude consumption and energy inventory management (e.g., battery optimization) due to their limited diffusion and scale in these latter areas. We examine AI applications in supply and demand forecasting, generation, and grid management.

TABLE 2
APPLICATIONS IN WIND AND SOLAR SUPPLY CHAINS OF AI TOOLS AND METHODS

AI Tool/Method	Applications in Wind and Solar Energy
Machine Learning	Predictive maintenance, wind strength forecasting, turbine performance analysis; energy yield forecasting, panel performance optimization
Natural Language Processing (NLP)	Analyzing maintenance logs, regulatory documents, customer service automation
Speech Recognition	Voice-activated control for wind/solar farm maintenance and operation systems
Vision Recognition	Drone inspections of turbine blades for defects and wear; Identifies dirt, shading, or damage on solar panels via drone or camera inspections
Expert Systems	Troubleshooting and diagnosis of wind turbine or solar system faults, offering recommendations
Planning and Scheduling	Scheduling turbine/solar maintenance, wind/solar farm operation strategies based on weather data
Optimization	Turbine positioning, maximizing energy output from wind patterns; Optimal panel placement and angle for maximum solar exposure
Simulation and Modelling	Simulating wind farm performance under different wind conditions; Modeling solar farm performance based on varying weather conditions

In renewable energy production, AI reduces operational costs associated with design, installation, maintenance, and performance evaluation. AI applications use large quantities of data (geographical, meteorological, demographic) to optimize plant location, size, layout, and component selection, thereby minimizing plant life-cycle costs, fixed costs, and optimizing overall supply profiles. AI-optimized designs can generate efficiency gains of up to 30%, due to AI's ability to improve equipment sizing and energy yield by up to 20% (Arrieta et al., 2020). AI-led drones equipped with computer vision technology perform inspections, site evaluations, land monitoring, and early maintenance warnings, leading to cost savings of up to $100 000 per megawatt installed by reducing labour and equipment expenses (Melnikov et al., 2018). Real-time data from sensors can ensure effective equipment installation and maximize system performance by design. Automated AI design processes can reduce project timelines and labour costs by up to 40% (Melnikov et al., 2018). AI can analyse real-time operational data and forecast potential issues, enabling predictive maintenance activities that maintain optimal system efficiency and reliability. AI-enabled proactive maintenance can save up to $30 000 per megawatt, thanks to decreased downtime and overall maintenance expenses (Kelko et al., 2022). Beyond predictive maintenance, AI-powered real-time monitoring and adaptive controls can reduce energy operation costs by optimizing the tilt angles of solar panels or the pitch of wind turbine blades to capture more renewable energy, and by storing excess energy during peak production for release during periods of low production. AI-powered optimization models also assist in integrating renewable energy production with stability, voltage control, and frequency requirements of the grid, offering long-term benefits for the durability and dependability of energy infrastructure. Overall, AI can lead to a cumulative performance improvement of up to 40% over the life of renewable energy production plants, with cost savings of up to $200 000 per megawatt installed (Kelko et al., 2022), depending on the specific renewable technology.

Forecasting RE supply and demand is key to stabilizing and reducing the operational costs of RE transmission and distribution and improving source dispatching. Accurate predictions are crucial for market operators and energy traders to make informed decisions regarding energy pricing, scheduling, and market participation (Sweeney et al., 2020). AI allows excellent forecasting RE production and consumption across multiple geographical, dispersed sites, different time zones, under different probabilistic and hybrid scenarios (Sweeney et al., 2020; Ahmad et al., 2020). Large volume of weather data, historical generation trends, real-time and remote sensors can predict "ramp events", that is sudden changes in RE production, to facilitate smooth integration of RE in energy networks (Nelson et al., 2020; Avtar et al., 2019). AI-powered load models and real-time data analytics can predict future electricity consumption patterns, enable accurate load predictions and improve peak demand-side management outcomes at the grid level (Boza and Evgeniou, 2021; Stanelyte et al., 2022).

AI, coupled with other technologies, can monitor RE flows in real-time, predict outages, and automatically balance bi-directional exchange of physical and information flows within various nodes of grids (consumption, distribution, production) and stabilise distribution grids (Ahmad et al., 2021; Abdulsalam et al., 2023). By analysing sensor data across the grid, AI optimises smoothing supply fluctuations, reducing grid imbalances, or voltage variations. AI-powered supervisory control and data acquisition systems, phasor measurement units, and other monitoring techniques allow real-time decision-making and more efficient grid operations. AI help optimise sizing, placement, of energy storage to balance supply and demand, enhance grid stability, optimize load profiles, reduce peak demand (Jordehi, 2019; Tang and Wang, 2019; Hafeez et al., 2020). AI can improve the efficiency of controlling distributed energy sources, generators, flexible loads, and storage systems. AI is used for fault detection, predictive maintenance, and optimizing grid operations through real-time and predictive large datasets for economic dispatch, energy management, and optimal power flows (Abdulsalam et al., 2023; Hasan et al., 2023). Due to the diffusion of distributed energy resources (and prosumer models), AI is increasingly being looked at to improve grid resilience, integrate fluctuating renewable energy generation, and balance demand and supply real-time. AI is effectively applied to optimize overall costs of demand response strategies, energy consumptions, smoothing peaks during high demand or supply variability.

TABLE 3
APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN THE PRODUCTION AND DISTRIBUTION OF RENEWABLE ENERGY SUPPLY CHAINS

Supply Chain Domain	Area of AI Application	Description
Production	Predictive Maintenance	AI analyzes data from sensors on wind turbines and solar panels to predict equipment failures, thus enabling proactive maintenance and reducing downtime costs
	Energy Forecasting	AI can forecast energy production based on weather, geographical data, historical generation patterns to optimize integration in energy grid
	Resource Assessment	AI processes satellite imagery and on-ground data to evaluate potential sites for wind farms and solar
	Performance Optimization	AI enhances the efficiency of energy production optimizing the orientation of solar panels and turbine blades based on real-time weather conditions
	Automated Control Systems	AI-driven systems can optimize operations of renewable energy systems to maximize output based on real-time data
Distribution and Transmission	Grid Management	AI optimizes the distribution and transmission of energy, predicting, and balancing demand and supply to stabilise the grid
	Demand Response Optimization	AI analyzes consumption patterns to optimize demand response strategies, managing peak loads and reducing strain on the grid
	Energy Trading	AI eases real-time energy trading by predicting price movements and optimizing RE trading strategies
	Integration of Distributed Energy Resources (DER)	AI improves grid flexibility and resilience integrating multiple DERs, such as residential solar or battery storage

Theoretical Background: Dynamic Capabilities in Sustainable Supply Chains

The dynamic capabilities theory explains how firms use capabilities to integrate, exploit, and reconfigure resources to maintain or create competitive advantages in evolving market conditions. Broadly, capabilities refer to competences or routines that enable firms to perform business tasks and activities in a way that supports their competitiveness. Teece (2007) categorizes capabilities into two types: foundational (or "static") capabilities, which may lead to short-term competitive advantages and economic performance improvements, and "dynamic" capabilities, which ensure long-term, sustainable firms' competitiveness by reconfiguring existing operational practices (Teece and Linden, 2017; Vanpoucke et al., 2014). Dynamic capabilities are particularly important during market disruptions, technological diffusion, or intense competition, as they enable firms to respond effectively to such environments, fostering sustainable competitive advantage and superior economic performance (Teece et al., 1997). More generally, dynamic capabilities involve learnable routines and strategic activities that allow firms to adapt, innovate, and create new knowledge, products, or processes, thereby preserving a long-term competitive advantage. These capabilities are repeatable and ingrained, allowing firms to adjust structurally to changes in product offerings, processes, and market demand (Winter, 2003; Vanpoucke et al., 2014).

According to Teece et al. (1997), dynamic capabilities involve three core activities: sensing (identifying market opportunities and threats by accessing new information), seizing (making strategic decisions based on identified opportunities while managing risks), and reconfiguring (reorganizing assets to enhance capabilities and promote organizational learning). Adaptive learning and reconfigurations are fundamental mechanisms for developing and evolving dynamic capabilities through repetition, correcting errors, empirical testing, and integrating new data into ordinary routines (Teece et al., 1997). Furthermore, sensing, seizing, and reconfiguring capabilities are sequentially linked and developed according to the dynamic capabilities' theory. Artificial intelligence can provide firms with unique dynamic capabilities, and strong

AI-based dynamic capabilities can stimulate operational process redesign and alignment with external environments.

Dynamic capabilities theory is increasingly applied in supply chain literature as it represents a flexible theoretical paradigm for understanding critical new phenomena especially in contexts of technological transitions (Teece et al., 1997). Discussions of dynamic capabilities in the context of AI are also becoming more common. In this research, we examine AI-based dynamic capabilities in renewable energy supply chains by analysing company cases, relying on Beske (2012) and Gruchmann and Seuring (2018) taxonomy of sustainable supply chain management dynamic capabilities. Beske (2012) and Gruchmann and Seuring (2018) identify specific types of sub-capabilities relevant to the three main dynamic capabilities identified by Teece et al. (1997). A summary of the dynamic capabilities used in the coding schemes to examine sensing, seizing, and reconfiguring capabilities in the selected cases is presented in Table 4 (see next section).

TABLE 4
DYNAMIC CAPABILITIES IN SUSTIANBLE SUPPLY CHAINS

Dynamic capabilities	Definitions	References
Knowledge assessment	Acquisition and evaluation of new and current information by supply chain members	Beske (2012); Gruchmann and Seuring (2018)
Reflexive SC control	Evaluation of supply chain functionality, monitoring internal and external operations, supporting decision-making and planning	Beske (2012); Gruchmann and Seuring (2018)
Partner development	Collaboration with supply chain partners to fulfill their responsibilities and deploy external resources, adapt toward a more sustainable supply chain configuration	Beske (2012)
Co-evolution	More efficient cooperations among supply chain members, tranferring efficient processes and systems from one business domain to another	Beske (2012)
Reconceptualization	Routines enabling the long-term strategic reorientation and change of the SC business models members	Beske (2012); Gruchmann and Seuring (2018)
Distribution	Integration of distributed resources in the supply-chain enabling new business models and sustainable practices	Gruchmann and Seuring (2018)

METHODOLOGY

Our research adopts a multiple-case study approach appropriate for theory building (Voss, 2010). We theorise on AI applications in renewable energy supply chains to extend our understanding of how AI-based capabilities are developed in the selected cases drawing from dynamic capabilities theory and empirical evidence on AI applications. Our unit of analysis is implemented AI applications in the renewable energy supply chain. We compare the four case applications through dynamic capabilities lenses, identifying and comparing applications to obtain further elaborations of the AI-based renewable energy supply chains.

In line with the research scope to examine AI applications, we select AI application cases from the population of existing AI-applications within the renewable energy sector from the Community Research and Development Information Service (CORDIS), a structured public repository of the European Commission's Research and Innovation community platform. We sample four case applications in line with Eisenhardt's (1989) suggestion of four to ten cases. All the cases belong to the European energy transmission and distribution industry since the matching renewable energy supply and demand takes place at grid level. EU governments and companies make large adaptations to accommodate the increasing share of renewable energy sources in energy mix. Table 5 presents the sampled application-cases from CORDIS, and the relative data supports.

We employ secondary data collection to improve the robustness and reliability of theory development and the source for case study research (Eisenhardt and Graebner, 2007). Prior studies have conducted case study research on secondary data sources collecting reliable and high reputation data. We collect multiple authoritative third-party sources to mitigate researcher bias, such as public reports and websites, scientific journal articles, professional newspapers (see Table 5 for details). The triangulation between various secondary data sources helps construct validity and improve reliability. The collected data of each case are saved in separate documents. Qualitative analysis clustering dynamic capabilities is based on theory. The data within each case is analysed deductively in the first stage, cross-case patterns are investigated through dynamic capabilities lenses in a second stage with a more inductive approach, following Eisenhardt's (1989) suggestion of conducting a two-step analysis. The coding analysis employed coding rules that maintain an exploratory angle for new insights emergent from the data. The level of each renewable energy supply chain practice and AI dynamic capability is rated high, medium, or low, based on the intensity of codes.

Within-Case Analysis

Case 1 – OPENAI

The project is coordinated by Amper S&C IOT SL and focused on expanding smart grid functionalities and energy efficiency services. XGBoost selection algorithms, discrete wavelet transform-based denoising schemes and SARIMAX statistical forecasting are used for the prediction of electricity consumption combining external sources such as weather data, sensor data, socio-economic data. This improved the demand forecasts based on real-world data improves the energy efficiency and demand management, and ultimately reduced energy waste. Blockchain is added to allow the development of decentralised markets promoting adoption of sustainable renewable energy used and reduction of energy costs.

Case 2 – ADAPT

The ADAPT project focuses on enhancing decision support for customers, RE generators and aggregators involved in negotiations within wholesale electricity markets and smart grids transactions. ADAPT proposes solutions to accommodate emerging players like RE generators since traditional wholesale and energy trading don't adequately support new players and optimise their transactions. A multi-agent decision support system composed of planning and negotiation components identifies lucrative RE opportunities in the market. A machine learning optimises actual energy transactions based on market volumes, prices, and competitors' negotiation profiles.

Case 3 – ADMS

ADMS aims to address critical challenges faced by the optimization of ROI by Distribution System Operators in optimizing Return on Investment linked to grid instabilities generated by RES. By continuously monitoring supply chain dynamic, the project aims to use MAC's low-cost supply chain monitoring and Gridhound's data-driven Advanced Distribution Automation system increase both grid capacity, reduce outage duration, and improve supply chain stability with TRL9 operational product standards.

Case 4 – I-ENERGY

The I-NERGY project developed an open modular framework, AI4 Energy, for AI-on-Demand in the energy sector, leveraging advanced technologies like AI, IoT, semantics, and data analytics. It facilitates cross-sector analytic tools for smart energy management, seamless data exchange while adhering to regulatory principles. The project evolved and scaled up AI-as-a-Service Energy Analytics Applications to optimize EPES value chains, especially for SMEs and non-tech industries. The project's objectives focus on reinforcing the AI-on-demand platform's service layer and expanding its usage through new user domains and experiments.

TABLE 5
CASE CHARACTERISTICS, DESCRIPTION, AND SOURCES

Case Application	Description	Sources
OPENAI	OPENAI uses a variety of AI techniques for the analysis and prediction of energy-related data and to manage energy supply and demand	CORDIS reports, scientific literature
ADAPT	Multi-agent decision support system for smart grid and electricity market negotiations. A portfolio optimization model identifies optimal negotiation opportunities, while a machine learning techniques selects negotiation strategy based on contextual factors	CORDIS reports, peer-reviewed articles, conference proceedings, book chapters
ADMS	ADMS enhances network stability and capacity via continuous monitoring, leveraging MAC's sensors and Gridhound's ADA system	CORDIS reports, scientific literature, websites
I-NERGY	I-NERGY develops AI-based tools for smart energy management, optimizing EPES value chains and promoting seamless data exchange thorugh a energy-specific AI framework	CORDIS reports, scientific literature, websites

Cross-Case Analysis

Sensing Capabilities

Knowledge assessment covers the acquisition and evaluation of new or current information by the supply chain partners. In contrast, reflexive control refers to the dynamic assessment of supply chain functionality via monitoring routines of internal and external operations that support strategic decision-making (Beske, 2012). Three cases selected (OPENAI, ADMS, I-ENERGY) show a significant potential of AI for acquiring real-time and multi-source data, in the forecasting and RE integration. ADMS utilizes smart machine-learning Network Management System NMS, such as micro–Phasor Measurement Units and LV/MV Network Monitor products, to sense the dynamic state of electricity supply chains (voltage, phase angles), enabling continuous situational awareness for DSOs and provide predictive analysis of grid behaviour. I-NERGY identifies AI-based analytics from several distributed intelligent collaborative nodes employing energy and non-energy related data from TSO, DSO and aggregators, off-the-grid domain data (simulated, open data, weather). Although not explicitly mentioned, ADAPT’s decision support system likely utilizes data from market prices, RE production forecasts, and opponent negotiation profiles, thus demonstrating sensing capabilities in acquiring crucial information for decision-making for players in electricity markets.

Seizing Capabilities

Partner development capabilities refer to empowering supply chain members (customers, upstream providers) to pursue shared sustainability goals via collaboration and knowledge evaluation, while co-evolution capabilities foster supply chain partners’ performance via improved communication, trust, and relationships (Beske, 2012). Seizing is linked to optimizing market trading, upscaling, and RE diffusion with customers in the four cases. ADAPT's multi-agent DSS aids negotiation processes in grids and markets through ML, integrating AI to optimize negotiation outcomes. OPENAI exploits trading opportunities through optimization algorithms for decision-making in smart grids and energy markets. OPENAI empowers customers to distinguish RE in the market, reducing intermediation costs and increasing transparency to foster greater RE adoption. Through AI-based monitoring, ADMS increases grid capacity, reduces integration costs, and minimizes supply chain outages and customer losses. It integrates ANN into existing DSO grid management to predict supply chain behaviour, optimize operations, reduce emissions, facilitate adoption, and manage RE.

Reconfiguration Capabilities

Reconceptualization refers to the long-term, strategic transformation of supply chain-wide business models, thereby improving the focal firm competitive position (Beske, 2012). Distribution refers to the integration of geographically distributed supply chain resources, which enables the design of new business models and implementation of additional sustainable practices. All four cases mention AI solutions for enhancing grid capacity, managing reverse flows, and enabling the participation of new small-scale players. I-NERGY offers AI analytics and an interconnection layer, ML models, and AI energy analytics applications to optimize AI on-demand service, boost the deployment of AI-based solutions and services, and enable a larger user community to reap economic benefits. Through developing a decentralized, transparent energy trading marketplace, OPENAI aims to reconfigure traditional energy market infrastructures, optimizing operating costs and energy prices. ADAPT aims to reconfigure traditional market models by enabling the participation of emerging players, such as RE generators and small-sized consumers, in wholesale electricity markets through AI-driven decision support solutions, addressing the divergent evolution of smart grids and electricity markets.

TABLE 6
IDENTIFIED DYNAMIC CAPABILITIES AND RELATED ROUTINES

Case company	OPENAI	ADAPT	ADMS	I-NERGY
Knowledgement assessment				
Forcasting RE supply and demand	High	High	High	Medium
Reflexive supply chain control				
Supply chain integration	High	High	High	Medium
Partner development				
Supply chain collaboration	Low	High	High	High
Co-evolution				
Low cost production	High	Medium	High	High
Reconceptualization				
Innovation and sustainability	Low	Low	Medium	Low
Distribution capabilities				
Distributed marketplace	High	High	Low	High

DISCUSSION

Overall, our research results highlight AI's potential to address renewable energy supply chain dimensions of forecasting, low-cost production, and collaboration (Gawusu et al., 2021). Surprisingly, AI possesses less applicability in innovation and sustainability, perhaps due to the still limited diffusion of prosumer models. We summarize our cross-case findings and propose propositions for future empirical and theoretical advancements.

Forecasting and low-cost production are the two major categories identified in this research. The potential to improve predictability stems from how AI collects, processes, and predicts future changes based on real-time data (Pournader et al., 2021). All analyzed cases demonstrate that predictability has reached a significant level of maturity, both on the supply and demand sides, consistent with the literature (Zhang et al., 2022). AI enables the reduction of operational costs, energy trade costs, and optimization of scheduling and planning, somewhat contrasting with the main internal cost benefits highlighted in the literature (Liu et al., 2022). ADMS supply chain sensors and analytics help reduce grid inertia, improving supply chain stability and predictability, while reducing customer losses and outages. OPENAI reduces operating costs and energy prices by eliminating transaction costs and intermediaries through AI and blockchain. Hence, our first proposition is:

Proposition #1: *AI-enabled information processing improves predictability of renewable energy demand and supply and reduces renewable energy distribution costs.*

Closely linked with predictability is the critical aspect of RE integration. Consistent with prior research, our findings demonstrate the important role of information technology in enhancing supplier integration. ADMS facilitates improvements in supply chain flow stability and predictability, bolstering capacity demand measurement and enhancing RE energy quality. This advancement enables greater integration of RE sources into the grid, thereby augmenting grid capacity for RE integration. Furthermore, ADAPT plays a pivotal role in enabling the participation of emerging players, such as RE generators and small-scale consumers, in wholesale electricity markets through AI-driven decision-support solutions. This strategic approach addresses the evolving landscape of smart grids and electricity markets. Consequently, our second proposition is:

Proposition #2*: Forecasting improves integration of renewable energy production and facilitates sensing capabilities.*

Data sharing drives supply chain collaboration, a prevalent theme across most cases, notably highlighted in OPENAI. These findings align with literature on AI and sustainable operations (Gawusu et al., 2021). AI, along with complementary technologies, effectively addresses reliability and scalability—key factors for collaboration—as evidenced in cases like OPENAI and I-NERGY. Furthermore, AI enables renewable energy differentiation within supply chains, facilitates sharing of advanced solutions with customers, and supports the co-development of technological paradigms. Literature emphasizes AI's role in managing renewable energy-related information to foster collaboration (Zhang et al., 2021; Jha et al., 2022). I-NERGY, for instance, provides AI analytics and an interconnection layer that optimizes on-demand AI platform services for TSOs, DSOs, and aggregators, thereby amplifying the deployment of AI-based solutions across renewable energy supply chains. Collaboration in these cases yields new services and streamlines operations among partners for enhanced efficiency. Hence, our third proposition is:

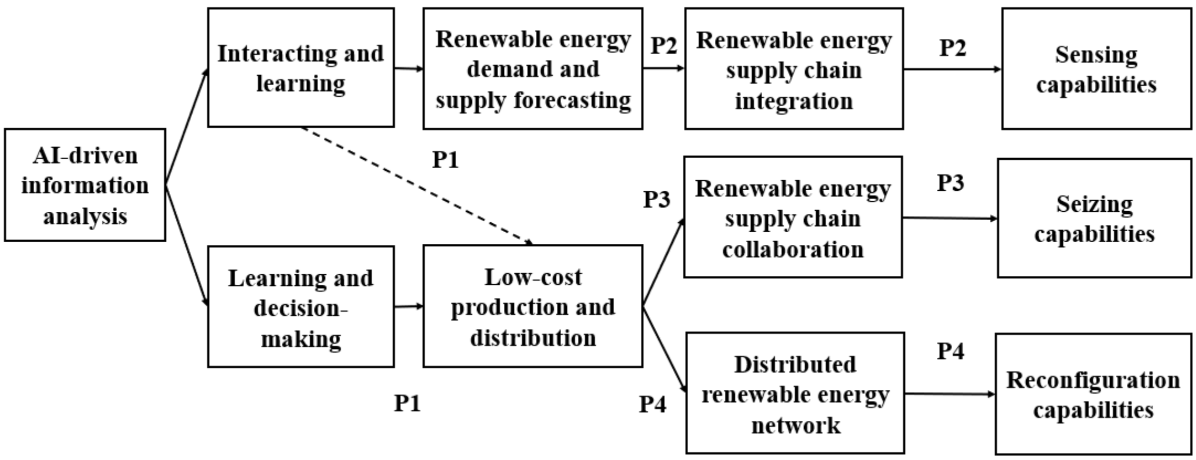
Proposition #3: *Low-cost production and distribution improve renewable energy supply chain collaboration and improve seizing capabilities.*

Based on the findings, distributed renewable energy supply chains emerge as a prominent domain for AI application. Encouraging suppliers and partners to adopt renewable energy through AI plays a pivotal role in this context. AI's role in facilitating renewable energy participation, particularly in terms of reverse flow management and prosumers, has been emphasized (Liu et al., 2021). This study corroborates the increasing presence of prosumers and highlights the importance of incentivizing users and corporate partners to participate in AI-driven renewable energy supply chain initiatives. Advanced Distribution Management Systems (ADMS), by significantly enhancing renewable energy integration and predictability, have notably improved supply chain electricity quality as the share of renewable energy connections grows. The utilization of AI and blockchain by OPENAI has further enabled active participation, establishing a discernible distributed supply chain of prosumers engaged in renewable energy exchange. Additionally, this study demonstrates AI's effectiveness in streamlining core processes of reverse flow management, including phase synchronization. Addressing the geographical dispersion of supply chain partners remains an important consideration for future research. Currently, only ADMS explicitly addresses the regulatory compliance requirements for Distribution System Operators (DSOs) during the net-zero transition. The lack of strong links between AI and innovation in other cases suggests a need for further exploration. Therefore, our fourth proposition is:

Proposition #4: *Low-cost production and distribution enhance distributed RE supply chains and improve reconfiguration capabilities.*

Building on these propositions, we propose the theoretical framework shown in Figure 2.

FIGURE 2
THEORICAL FRAMEWORK OF AI-BASED DYNAMIC CAPABILITIES FOR RENEWABLE ENERGY SUPPLY CHAINS



Implications for Theory

This research offers important theoretical contributions to the dynamic capability theory and the emerging field of renewable energy supply chains management. We identify the dynamic capabilities derived from AI applications that facilitate the pursuit of competitive advantages based on renewable energy sources. We elaborate further on these theoretical contributions below.

First, a recurrent criticism of dynamic capability theory is its lack of transferable managerial applications from a theoretical perspective (Schilke et al., 2018). However, our study highlights significant practical applications of dynamic capability theory, demonstrating how the energy sector can develop capabilities through AI to achieve operational improvements from otherwise unpredictable, unstable, and complex renewable energy sources (such as wind and solar). Our research identifies the most important dynamic capabilities and sub-capabilities that can guide energy companies as they navigate the challenges of net-zero and digital transitions. Therefore, this study offers practical managerial insights that strengthen the applicability of dynamic capability theory in the renewable energy sector.

Second, AI research is predominantly driven by engineering and computer science (Zhang et al., 2022; Liu et al., 2021), with limited focus on supply chain management (Pournader et al., 2021; Hendriksen, 2023). Highlighting the need for theories to offer context-specific conceptualizations, our research provides theory-driven contributions applicable to the renewable energy supply chains empirical setting (Craighead et al., 2016). We demonstrate how AI enables energy firms to enhance their operational performance by equipping them with dynamic capabilities to sense, seize, and reconfigure opportunities presented by renewable energy sources. This research advances the conceptualization of dynamic capabilities within the renewable energy supply chain context. It empirically supports the adaptability of dynamic capability theory for examining AI applications in supply chains (Pournader et al., 2021). Therefore, our study shows that dynamic capabilities can be conceptualized, transferred, and examined even in new, complex technological environments, such as those created by the increasing adoption of intermittent renewable energy sources and artificial intelligence in the energy sector.

Third, there is ongoing debate in the literature regarding how firms develop capabilities for competitive advantage. While some scholars suggest that capabilities are developed sequentially and hierarchically (i.e., higher-order capabilities cannot be developed before lower-order ones), others propose that capabilities are developed and exploited simultaneously in non-linear patterns. Dynamic capabilities are typically thought to follow a hierarchical and sequential process of sensing, seizing, and reconfiguration (Khan et al., 2021).

Our study does find evidence of clustering of dynamic capabilities at the lower levels, that is at sensing and seizing (see Table 6). Still, we also find evidence that AI-based dynamic capabilities (and related technologies) can also work synergistically and complementarily, allowing simultaneous exploitations of opportunities rather than being sequential and hierarchical in their development and exploitation. This is shown by the fact that sensing and reconfiguring capabilities manifest and develop jointly, affecting one another in our research. While we recognize that this "jump" of seizing capabilities could be linked to the specific characteristics of energy production and the energy market, we do not find sufficient support to claim that dynamic capabilities do not follow linear, hierarchical developmental pathways. Greater evidence to generalize these simultaneous sensing-reconfiguring capabilities is necessary beyond the renewable energy sector. A case-by-case (or industry-specific, ad-hoc) approach may be necessary to advance dynamic capability development theory and to untangle these complex patterns.

Finally, we find that AI can significantly enhance reconfiguring capabilities, enabling the case applications to introduce new products, services, and production processes, and to reach previously untapped market segments. Our research expands our understanding of the inter- and intra-firm factors that influence the development of dynamic capabilities. Developing a distributed marketplace of small-scale renewable energy consumers and producers (reconfiguration-distributed marketplace) strongly depends on renewable energy learning and predictability (sensing-supply and demand forecasting), both of which can be enhanced via AI. This study reveals a distinct association: renewable energy supply chains in distributed energy markets depend on learning and forecasting, both of which derive from the simultaneous exploitation of multiple technologies, including blockchain and the Internet of Things. Companies adopting AI must prioritize aspects of renewable energy demand and supply forecasting, leveraging real-time and prospective data on renewable energy production at the supply chain level. To this end, developing an infrastructure of real-time sensors and off-grid data sources is imperative for enhancing grid capacity management ahead of actual renewable energy production, addressing the supply chain's demand and supply sides (Liu et al., 2021). In summary, our research shows that AI applications in the renewable energy supply chain depend on several contingencies that are specific to this context.

Implications For Practice

While many energy firms invest in uncoordinated and sometimes piecemeal AI initiatives as part of renewable energy-centred business models, few are aware of how to develop the AI-based dynamic capabilities needed to manage renewable energy sources effectively. Embracing more sustainable and more digital business models simultaneously presents several technological, competitive, and environmental challenges. This research offers a model for managers aiming to achieve the dual goals of decoupling from fossil fuels and scaling up disruptive technologies like AI. We provide key insights for renewable energy practitioners with implications for developing AI-based dynamic capabilities in renewable energy supply chains. The cases presented in this research serve as a guide for AI rollout phases.

First, AI applications can significantly optimize costs across renewable energy supply chains, encompassing production, distribution, consumption, and trading. Improved predictability and learning in renewable energy production through AI can reduce grid balancing costs by enabling better scheduling and planning (Zhang et al., 2022). Enhanced efficiency also lowers renewable energy integration costs, creating opportunities for benefits-sharing among supply chain partners (Hannan et al., 2021). However, AI adoption remains costly due to legacy system constraints, implementation challenges, and transition expenses (Gawusu et al., 2021). Advanced Distribution Management Systems (ADMS) and similar tools illustrate AI's potential to reduce renewable energy-related costs, though post-implementation expenses require further examination and scrutiny. Projects like I-NERGY suggest that maximum benefits may be realized when AI is integrated with technologies such as IoT and blockchain. While ADMS may provide cost-effective monitoring, large-scale deployment can raise costs related to computational power, data storage, and processing (Ahamad et al., 2021). Managers should prepare for potential cost escalations associated with AI-driven renewable energy supply chains, prioritizing improvements in computational efficiency and data management. Given AI's complexity, firms with low digital maturity should work to enhance their digital capabilities before AI implementation (Hendricksen, 2023), although renewable energy integration may occur earlier. With limited empirical evidence available, companies must carefully assess AI's potential impact on renewable energy supply chains.

From a renewable energy perspective, we demonstrate that firms can develop AI-based dynamic capabilities by first prioritizing sensing—arguably the most critical capability—before advancing to the more complex capabilities of seizing and reconfiguring. A capability-building approach that emphasizes sensing capabilities as a foundation for implementing renewable energy supply chains, before progressing to seizing and reconfiguring, may thus be more effective. Sensing sub-capabilities, such as renewable energy demand and supply forecasting and supply chain network integration, are essential for managing fluctuations among renewable energy producers. Without these, it would be technically impossible to synchronize the flows of renewable energy within the distribution and transmission network. In all case applications, sensing is achieved through establishing a network of sensors that integrate various sources of real-time information (e.g., season, socio-demographics, solar irradiance, wind strengths).

This research highlights the importance of AI-based dynamic capabilities for fostering collaboration and upgrading partnerships within renewable energy supply chains, both at the production and consumption stages. Our findings suggest that managers should engage in technological and developmental partnerships with renewable energy producers and consumers to facilitate effective distribution and transmission of renewable energy across the grid. Information flows at both consumption and production points help reduce uncertainty, while introducing new renewable energy technologies—such as batteries, transformers, and distributed sensors—lowers competitive barriers and enables bi-directional flows between consumers and producers. Collaboration can thus serve as a foundation for advancing distributed marketplaces.

CONCLUSIONS, FUTURE RESEARCH, AND LIMITATIONS

This study demonstrates that AI is a valid tool for enhancing the integration of renewable energy in energy supply chains, as there are unsuccessful cases of firms applying artificial intelligence to renewable energy supply chains without AI-driven dynamic capabilities. The main goal of this research is to develop a conceptual framework of AI-driven dynamic capabilities to design a renewable energy supply chain in the context of increasing diffusion of renewable energy. We find that sensing dynamic capabilities are the most relevant enablers of renewable energy supply chains. Yet, while AI-based dynamic capabilities of sensing, seizing, and reconfiguring are essential to developing a renewable energy supply chain, they do not necessarily appear to build sequentially but broadly sustain and complement one another simultaneously. Consequently, energy companies will benefit from developing AI-based dynamic capabilities beyond sensing to integrate renewable energy in their business models. Priority should be given to the most salient dynamic capabilities we identify in this study, without ignoring the less salient ones, since we find evidence of non-linear rather than sequential development of AI-based dynamic capabilities. Finally, agility and adaptability in developing AI-based dynamic capabilities are important, as these can overlap to a considerable extent.

This research has limitations, which we outline in four key areas below. First, the study lacks evidence of AI failures, focusing primarily on successful implementations or pilot cases. Although scholars note that AI implementation can be complex, there is limited information on the challenges of adopting AI for managing renewable energy. Further research is needed to investigate the operational and technical difficulties of integrating AI into existing electricity production and consumption processes. Second, the study is limited in sample size to four case applications of AI, presenting an opportunity for future research to conduct a more in-depth examination, including stakeholders from production, consumption, and distribution in renewable energy supply chains. Third, our study identifies the main AI-based dynamic capabilities for renewable energy integration and the relevant sub-capabilities for each. We recognize that our list may not be exhaustive and that other AI-related factors may have been overlooked. Lastly, the study highlights the frequent combined use of AI, IoT, and blockchain technologies. Future research should explore the integration of IoT and, more critically, blockchain technology to better understand the drivers and overcome barriers in renewable energy supply chains. Our study is conducted among AI applications in the renewable energy sector within the European Union. The findings might differ in countries with greater or lesser AI maturity than the EU. Future research could validate our findings through case studies in other countries and gather further evidence on the overlaps among dynamic capabilities.

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