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Shaping the future of sustainable energy through AI-enabled circular economy policies

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A B S T R A C T

The energy sector is enduring a momentous transformation with new technological advancements and increasing demand leading to innovative pathways. Artificial intelligence (AI) is emerging as a critical driver of the change, offering new ways to optimize energy systems operations, control, automation, etc. Developing a competitive policy framework aligned with circular economy practices to adapt to the trends of the rapid revolution is crucial, shaping the future of energy and leading the sector in a sustainable, equitable, and impartial direction. This study aims to propose an AI-driven policy framework that aligns with the circular economy business model to address the transformation trend in the development of energy policies through a multidisciplinary approach. The study identifies key trends, various approaches, and evaluates the potential of AI in addressing the challenges. The AI-driven policy paradigm outlines a comprehensive framework and roadmap to harness the potential of AI through a forward-looking policy framework that considers the rapidly changing landscape and the essence of the circular economy. The proposed novel framework provides a roadmap for researchers, governments, and other stakeholders to navigate the future of energy and unlock the potential of AI for a sustainable energy future.

1. Introduction

Integrating artificial intelligence (AI) in policy making and implementation offers a complex and multifaceted challenge, requiring considering multiple interrelated factors and dimensions (Chawla et al., 2022). Energy policies play a crucial role in shaping energy flow to achieve specific goals, e.g., energy conservation, renewable energy integration, and carbon emission reduction that can target different phases including generation, transmission, distribution, and end-user; use market-based mechanisms, such as carbon pricing or renewable energy portfolio standards, or rely on subsidies and regulations to incentivize certain behaviors. The implementation phase is supported by utility and industry initiatives (Zhang et al., 2022), e.g., smart grid technologies and advanced metering infrastructure, which improve the efficiency and reliability of the energy system. Government policies also incentivize community and individual actions in building retrofits and energy-efficient transitions. They can contribute to achieving energy conservation and efficiency goals aligning with the sustainable development goals (SDGs) (Singh et al., 2021). Government regulations and subsidies, e.g., energy conservation standards and renewable energy tax credits, are significant in driving innovation and supporting the development of new energy technologies through energy research and development (Yang et al., 2019). Additionally, energy policy coordination and international cooperation can be used to achieve shared goals and support the implementation of policies at national and international levels.

In this context, many literatures explore energy policy within techno-economic and circular economy scenarios using AI and other automation technologies. Valle-Cruz et al. (2020) analyzed the public policy cycle in the age of AI, developing a new framework called the dynamic public policy-cycle. This study examined the impact of AI on the public policy cycle, using a systematic analysis of 49 references from AI and public policy literature. This study found that AI applications in public administration can improve decision-making, forecasting, and citizen services, but also bring about risks such as algorithmic discrimination and opacity, and recommended future research to understand the challenges posed by AI in public policy, including ethical and moral issues, workforce substitution, and transparency. Chawla et al. (2022) studied AI deployment in India, which has a majority share in the IT industry, facing energy sector strain due to not fully leveraging AI in the

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energy sector. This study analyzed the role of AI and information management in India's energy transition and highlighted challenges and barriers. It also reported limited incentives for AI in the energy sector, calling for adaptive action from policymakers towards AI integration, meanwhile, the energy sector transition and big data access call for a comprehensive AI policy. Li and Xu (2022) reported that the world's rapid economic growth since the Industrial Revolution had been driven by natural resource extraction, with global material usage tripling to 96 billion metric tons from 1970 to 2019. The challenge of balancing finite resources and low-carbon demands with material modernization demands is significant, and “circular economy” that prioritizes minimizing, reusing, recycling, and recovering materials is a solution for global economic sustainability. However, current recycling covers only 9% of global material demand, highlighting a gap in science, policy, and technology that needs to be addressed.

Safarzadeh and Rasti-Barzoki (2019) proposed a novel pricing model for a sustainable supply chain consisting of an energy supplier and efficient manufacturer based on a rebound effect energy efficiency of improvement in the production process and proposes a multi-stage model with a tax deduction and subsidy scenarios as alternative energy policies. The study found that tax deductions are more effective than subsidy schemes, but subsidies provide better conditions for the government to control energy consumption. Sotiriou and Zachariadis (2021) proposed a multi-objective optimization framework to provide decision-makers in the European Union (EU) with insights into the trade-offs between stronger decarbonization goals and higher costs. The study found that the maximum achievable reduction for the EU Effort Sharing sectors corresponds to a 35% target, which can be achieved with net social benefits. However, implementing a specific policy mix approach requires investments and public expenditures to accomplish this goal. Sitepu et al. (2019) proposed a new approach to support the formulation of sustainable replanting policies in the Indonesian natural rubber supply network by considering trade-offs between economic, social, and environmental factors. The approach uses composite indicators and computer simulations to find optimal replanting policies for different scenarios.

Zhu et al. (2021) supposed government incentive policies approach and residential choices in China's solar photovoltaic (PV) market using a Stackelberg game model. This study suggested that government subsidies are gradually no longer needed for smaller-capacity PV investments when only economic benefits are considered. The role of government subsidies in the PV market has transitioned from encouraging residents to invest in solar PV equipment to promoting investment in larger-capacity PV equipment. Optimal subsidies, tailored to specific regions, can effectively influence resident choices. In contrast, a unified subsidy policy has limited effectiveness. York et al. (2018) used a systematic approach model to evaluate the national-level dairy policy of 23 countries to identify international trends of the sector and its impact on greenhouse gas emission reduction policy. Jafari et al. (2022) investigated the impact of government subsidies and tax reductions on the energy efficiency and profitability of hydrogen fuel cell vehicles in a supply chain. Game-theoretic frameworks are applied to make equilibrium decisions. It is found that the demand for hydrogen fuel cell cars and the members' profits increase as the efficiency increases. Results indicate that increasing efficiency and reducing manufacturer taxes boost demand and profitability. However, subsidies alone do not affect equilibrium prices.

Runge and Zmeureanu (2019) reviewed the application of artificial neural networks (ANNs) for forecasting energy consumption in buildings. The results showed that ANNs are frequently used and demonstrate high accuracy and reliability compared to traditional methods. The majority of the ANN models were found to be black-box based and employed a feed-forward neural network with manually-determined hyperparameters. The performance of the ANN models was reported between 0.001% and 36.5% mean absolute percent error (MAPE) for single-step ahead forecasting and 1.04%–42.31% MAPE for multi-step ahead forecasting. Entezari et al. (2023) studied the optimization of energy systems to meet increasing demand while preserving resources. Still, computer-aided decision-making using AI and machine learning, with its ability to mimic human decision-making and learning processes, holds great potential and has become increasingly imperative in the energy sector.

Ko et al. (2017) proposed using a rough set approach to analyze the financial ratios of distressed companies applied to the solar energy industry in Taiwan, China from 2009 to 2014. The study used hypothetical approximations to maximize decision accuracy and certainty. Jiang and Zhao (2022) proposed a new method for detecting micro-crack anomalies in PV module cells. The network utilizes attention mechanisms to focus on critical features of the cell images, improving accuracy and efficiency in anomaly detection. The performance of the proposed network is evaluated and compared to other state-of-the-art methods, with results demonstrating its effectiveness in detecting micro-cracks with high accuracy. It is claimed that this method significantly improved the reliability and longevity of PV module cells by ensuring effective deployment.

Zeng et al. (2022) reported a lack of attention in the regulation of recovered materials and toxic substances, combined with international challenges, hinders the effectiveness of the circular economy. Kaya (2022) studied lithium-ion battery recycling technologies focusing on the challenges of lithium (Li) extraction processes due to its presence in seawater and Earth's crust at 20–70 mg/L, mostly in granite rocks, with new clay sources like hectorite being rare. The total global Li resource is estimated at 55–99 Mt, with Bolivia having 21 Mt, Argentina 19.3 Mt, Chile 9.6 Mt, USA 7.9 Mt, and Australia 6.4 Mt. Lithium minerals, including spodumene, petalite, lepidolite, zinnwaldite, amblygonite, montebrasite, eucryptite, triphylite, jadarite, and hectorite, contain between 1% and 9.7% lithium oxide. Brine deposits have 66% of total Li reserves, while solid mineral deposits are found in igneous and sedimentary rocks, but have higher extraction costs and environmental impact that requires an in-depth consideration in terms of circular economy practices.

Many research studies on data science, AI, machine learning, and deep learning methods and tools have been conducted across various sectors and applications (Busari & Lim, 2021; Daradkeh et al., 2022; Entezari et al., 2023; Pai & Chen, 2009; Shi et al., 2022; Steinwandter et al., 2019; Tebenkov & Prokhorov, 2021), and some real-world examples have also been discussed.

The data collection process for various policy approaches presented in this study is based on thoroughly examining the literature across multiple domains. A comprehensive search was conducted in the famous article depository database, especially Elsevier, IEEE, and MDPI; focusing on research and review articles that preferred the energy, circular economy, and AI subjects areas. Resources are selected from different perspectives, combining several domains to provide a multifaceted perspective.

Energy policy encompasses the legal, regulatory, and strategic measures and actions undertaken by policy stakeholders to manage and optimize energy generation, transmission, and consumption. This ensures energy security, promotes sustainable development, and fosters innovation and efficiency within the energy sector (Danish et al., 2020; Wohlfarth et al., 2020). These policies aim to propose a solution paradigm that addresses various scenarios through analytical and pragmatic approaches. The structure of this study is as follows: Section 2 provides a snapshot of global energy and possible decarbonization scenarios. Sections 3 and 4 discuss policy paradigms and approaches, respectively, which are followed by proposed roadmaps and innovative energy policy development tools and techniques in Sections 5 and 6. In Section 7, an attempt is made to integrate sustainability requirements within energy policies. Finally, Section 8 offers integrated frameworks for contemporary policy through multidimensional analysis of interdisciplinary domains, including approaches to enhance efficiency, optimization of resources, circular economy, and more.

2. A snapshot of the global energy and decarbonization scenarios

According to the Global Energy Perspective - 2022 (Tryggestad et al., 2022), the global energy landscape is encountering a significant transformation, with an anticipated shift towards electricity and hydrogen as the primary energy sources. By 2035, the share of electricity and hydrogen in final energy consumption is expected to reach 32%, and it will even reach 50% by 2050. Despite population growth, energy consumption is only expected to grow by 14% due to advancements in energy efficiency. Electrification plays a crucial role in driving energy efficiency in key sectors, such as buildings, transportation, and industry, leading to an expected doubling of the part of electricity in final energy consumption, from 20% to 40% by 2050. The uptake of hydrogen is also expected to offset the consumption of fossil fuels. The power demand is expected to triple by 2050, owing to the rise in electrification and living standards. The demand for appliances and space cooling in buildings will lead to ~60% electrification in 2050, compared to ~30% today (Tryggestad et al., 2022). Green hydrogen production is the main driver behind the increase in power demand, accounting for 42% growth between 2035 and 2050. Renewable energy sources are anticipated to become the new baseload, making up 50% of the power mix by 2030, and 85% by 2050. The cost competitiveness of solar and wind power is expected to increase globally. Thermal generation is expected to support grid stability, with load factors declining from 40% to 28% by 2050. Flexible assets such as hydrogen electrolyzers, batteries, and gas plants are essential for grid stability and decarbonization. Green hydrogen is expected to play a critical role as a storage mechanism for power production and will account for 28% of power demand by 2050. In the event of challenges in implementing renewable energy solutions, alternative low-carbon technologies like carbon capture, utilization, and storage (CCUS), nuclear energy, and long-duration energy storage can help reach emission targets.

The same analysis (Tryggestad et al., 2022) reported that global emissions remain far from meeting the 1.5 °C pathway, even with all countries meeting their current commitments. Local knock-on effects and regional differences can result in significantly higher temperature increases. The “Achieved Commitments” scenario shows expected emissions in 2050 to be 30% lower than in the “Further Acceleration” scenario, reflecting a quicker shift to renewable power generation and the adoption of lower-carbon technologies. However, all scenarios still result in emissions far from the 1.5 °C pathway. The median of expected global temperature increases is 1.7–2.4 °C by 2100, with a 50% chance of exceeding the global average and more substantial gains in specific regions.

A quick outlook on the energy and climate change crisis highlights the need for a policy documentation procedure. However, the volume of information and data available from various sources is much more extensive. It requires using different statistical and mathematical approaches to gather relevant data. The importance of energy and climate data and scenario-based and case-by-case analyses of these datasets cannot be overstated, but it reported limitations for successful policy development, e.g., for Qinghai province in China, energy policy development, scenario simulation, and policy analysis were faced with the limitations due to data availability and systematicness of energy and economy (Yang et al., 2013). Therefore, examining past and future scenarios is paramount in developing energy policies. It provides a comprehensive understanding of the energy sector and its evolving trends, thereby enabling effective policymaking. This analysis can assess the efficacy of current policies and suggest necessary adjustments, plan for future challenges and opportunities, evaluate the impact of different policy options, and foster collaboration among stakeholders (Al-Masri et al., 2019). By conducting scenario analysis, decision-makers can make informed choices that lead to a more sustainable and efficient energy future.

3. Policy paradigm

A paradigm serves as the foundation of science that provides a point of reference for theories that can be utilized to solve practical issues (Brunner, 2006). Additionally, it can offer instruments and techniques that can be measured and evaluated following scientific principles intertwined with the idea of paradigm shift and scientific revolution in a philosophical context (Orman, 2016). A paradigm design encompasses theories, studies, methods, and benchmarks to form a consistent and balanced set of ideas based on specific indicators and underlying data/information within its structure. A policy paradigm typically includes objectives, policy instruments, implementation, monitoring, evaluation, stakeholder engagement, adaptiveness, and transparency. These components work together to define the goals of the policy, choose practical tools to achieve those goals, establish procedures for implementation, regularly monitor the policy's performance, engage stakeholders, and be adaptable to changing circumstances. A competitive approach demonstrates with transparency, clear information about goals, design, outcomes, and consistency with other relevant policies and initiatives.

Developing a viable energy policy is a complex endeavor that requires a transdisciplinary approach, which requires a paradigm to give a roadmap of an exhaustive evaluation of multidimensional inputs and facilitate the formation of a sustainable future. The proposed paradigm results from multiple scenarios backed by theories and practices, retrieved from inclusive literature in various perspectives, and sorted, analyzed, scenarioized, and visualized in Fig. 1 (Ahmad et al., 2015, 2021; Chan, 2020; Mulholland et al., 2017; Project Management Institute, 2021; Pyka et al., 2022; Suzuki et al., 2016; Zhao et al., 2022). These scenarios are classified into 5 categories with interplay criteria. Scenario (1) focuses on energy system resilience and access, while Scenario (2) prioritizes data management and privacy. Scenario (3) emphasizes environmental sustainability and circular economy, and Scenario (4) explores governance and decision-making processes. Lastly, Scenario (5) ensures energy transition toward a neutral carbon society. These scenarios are grouped based on their relevance to the policy paradigm goals, providing a comprehensive approach to policy development and assessment (Table 1).

The scenarios are classified based on their relevance to achieving the goals of sustainable energy and policy development, as identified by the weighting method (Danish, Senjyu, Zaheb, et al., 2019). The criteria based on Fig. 1 are grouped to prioritize renewable energy exploitation, improving multiple efficiencies, and implementing the circular economy. The proposed scenarios can be adjusted based on localized needs. The analysis results contribute to policy development and decision-making, aligning with the requirements set forth by the AI setup.

Weighting adjustments are used to reduce the bias of estimations that can cause nonresponse and noncoverage (Kalton &

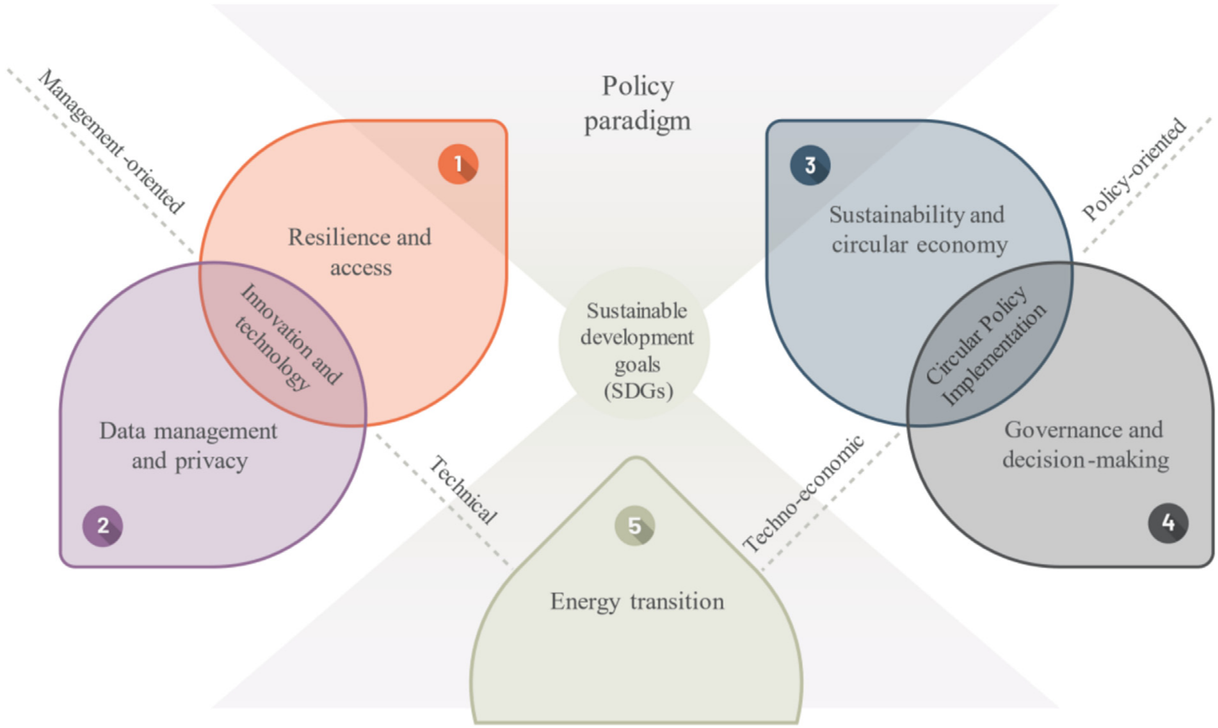

Fig. 1. Analysis of energy policy high-level structural scenarios based on functional domain approaches within the energy policy paradigm.

Table 1
A scenario-oriented policy development analysis involving distinguishing the importance of individual components in formulating energy policy, both on a scenario-based and component-based level, for the entire process.

Components / Scenarios	Circular economy	Data accessibility	Data management	Data privacy	Data security	Decision-making	Digitalization	Energy efficiency	Energy storage	Equity	Gases Emission	Incentives	Innovation	Governance	Participation	Renewable energy	Resilience	Smart grid	Stakeholder engagement	Sustainability	Regulations	Scenario Number	Tentative Weight	Importance
Energy Transition																						1		
Data Management and Privacy																						2		
Sustainability and Circular																						3		
Governance and Decision Making																						4		
Resilience and Access																						5		
Component Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	The darker to lighter shades indicate higher to lower importance, respectively.		
Tentative Weight																								
Importance																								

Flores-Cervantes, 2003). Assigning weights to non-quantitative measures, priority is given to the pairwise comparison based on magnitude scaling, the ideal-point methods (Kok & Lootsma, 1985), and analytic hierarchy process methods (Redfoot et al., 2022) by determining weights based on the relative importance of the policy components in each scenario, with the assistance of expert judgment and the Delphi approach (Rose, 2017; Van Schoubroeck et al., 2019) (Table 1).

These scenarios are interrelated and overlap in some cases, e.g., in Scenario 3, the criteria for innovation and regulation are also relevant to energy transition and data management, highlighting the need for a comprehensive and integrated approach to policy development. Also, assessing qualitative scenarios using quantitative measures is difficult due to the subjective nature of qualitative data and the limitations of proxies used to quantify, which sometimes cannot accurately represent the bipartite degree of the attribute (Chen, 2019). It can lead to inaccuracies and biases in results, making interpretation challenging (Lowhorn, 2007). It is essential to use appropriate methods and interpret results cautiously to ensure validity and robustness. Therefore, the analyzed scenarios are quantified to the nearest approximation to meet the proposed policy objectives. These scenarios can be adapted and customized based on specific needs and priorities.

4. Policy development approaches

This section endeavors to furnish a comprehensive and systematic examination of the energy policies development approaches in the era of the AI revolution. The main argument of this section is that integrating AI-based tools, techniques, and algorithms, such as machine learning algorithms, is essential for contemporary energy policies to meet the techno-economic and environmental sustainability constraints (Chawla et al., 2022). This section explores the various facets of policy development approaches, ranging from the early planning stages to advanced decision-making using AI-based tools and methods. Providing a concrete foundation and applying algorithms for data analysis in policy formulation can result in a nuanced understanding of energy policy formulation through a systematic and interdisciplinary analysis. Additionally, the section delves into the role of AI in policy formulation, examining its potential advantages, e.g., increased efficiency and efficacy, as well as the challenges it presents, such as data privacy and security. Drawing on literature and expert judgment, this section sheds light on how AI can effectively integrate into the policy development process and its potential impact on modern, responsive policy development approaches. Ultimately, this section aims to provide a comprehensive and holistic view of modern, responsive policy development approaches and their relationship with the AI revolution, considering the need to balance economic and environmental considerations in investment decisions.

Developing policies, such as energy policies, is a complex and multifaceted process that requires a thorough understanding of the factors that impact their formulation and implementation. A variety of approaches can be used to inform policy development, and the choice of approach will depend on the specific context and goals of the policy. Therefore, it is essential to note that it can be challenging to generalize policy formulation within a single framework. To provide a clear and comprehensive understanding of the most commonly used approaches in policy development, Table 2 outlines each approach's key characteristics and applications. These approaches are mainly retrieved, adapted, and selected from 26 potential ideas from Sala et al. (2015), who provided a competitive and exhaustive reference for sustainability assessment. This information is intended to serve as a valuable resource for policymakers and researchers undertaking policy development's nuances and making informed decisions.

Despite their shared objective of evaluating and analyzing energy policies, the various policy approaches within each category employ distinct methodologies and techniques. As a result, certain approaches may be more suitable for specific situations than others. For instance, when assessing the economic ramifications of

Table 2
Selected approaches for adapting to energy policy development and implementation assessment (Raza et al., 2022; Sala et al., 2015; Tolentino-Zondervan et al., 2021; Wei et al., 2022).

Policy approach	Function and application
Quantitative approach	Utilizes quantitative data and statistical techniques, quantifying the costs, benefits, and distributional effects of different energy policy options.
Qualitative approach	Employs non-quantitative data and methods such as interviews and observation, comprehending stakeholders' subjective experiences and perceptions.
Interdisciplinary approach	Integrates disciplines such as economics, engineering, and social science, offering a holistic understanding of the impacts of energy policies.
Systems approach	Analyzes energy policies as part of a larger system and investigates the interactions and feedback between different components, realizing the effects of energy policies on other sectors of the economy and society.
Comparative/analysis-orientated approach	Compares different energy policies in varied contexts to identify similarities, differences, and best practices, identifying the most effective policies for different situations.
Theoretical approach	Utilizes theories from various disciplines such as political science, sociology, and psychology, underlying mechanisms that drive energy policies and their impacts.
Empirical approach	Based on data collected from real-world observations or experiments, offers a detailed understanding of how energy policies are implemented and their actual impact.
Participatory approach	Involves various stakeholders in the policymaking process and allows them to participate in the analysis of energy policies, ensuring that policies take into account the perspectives and needs of different stakeholders.
Risk assessment approach	Evaluates the risk associated with energy policies by taking into account the likelihood and severity of different potential impacts, mitigating potential negative impacts of energy policies.
Life-cycle approach	Analyzes energy policies' environmental, economic, and social impacts over their entire life-cycle, recognizing the most sustainable energy policies.
Normative approach	Evaluates energy policies based on pre-established criteria and norms such as ethical principles, human rights, and environmental standards, ensuring energy policies are consistent with broader societal values.
Scenario-based approach	Uses different hypothetical scenarios to analyze the potential future effects of energy policies, testing different assumptions, and evaluating energy policies' robustness in different conditions.
Behavioral approach	Examines the psychological, social, and economic factors that influence individuals' and organizations' behavior concerning energy policies, comprehending how people and organizations respond to energy policies, and identifying opportunities for behavior change.
Spatial approach	Analyzes energy policies about geographic space and location, evaluating the spatial distribution of energy policies and their effects on different regions and communities.
Technical approach	Focusing on the technical aspects of energy policies, such as the design and implementation of technology and infrastructure, recommends the most efficient and effective ways to implement energy policies.
Historical approach	Examines energy policies' historical evolution and context, managing how policies have developed over time, and identifying trends and patterns.
International/Cross-national approach	Examines similarities, differences, and best practices across countries and regions in energy policies.
Institutional approach	Approaches legal frameworks and regulations that govern energy policies and how they are enforced.
Dynamic approach	Studies the evolution of energy policies and interactions between different factors over time.
Value-based approach	Evaluates energy policies against societal values such as social justice, environmental protection, and economic development.

a policy, a quantitative approach may be more fitting, whereas a qualitative approach may be more appropriate for comprehending the subjective perceptions of stakeholders.

5. Roadmap for modern energy policies formulation

Energy systems require a balanced supply and demand in a world with more encouraging ways to consume electricity with constrained climate change but more significant variability in green energy supply. Utilizing computational intelligence tools and techniques is compulsory for ensuring sustainable and efficient energy systems and maintaining reliability and performance in the face of growing demands. These tools must be flexible and adaptable within competitive markets and diverse political contexts while adhering to ethical guidelines and codes of conduct.

5.1. Policy building blocks and classifications

Categorizing energy policy methodologies, plans, tools, techniques, and approaches presents a significant challenge. It is contingent upon a nation's demands and priorities in light of future perspectives, budgetary constraints, and many other factors. Conducting thorough examination considering the primary agenda for an energy development plan and policy has been segmented into eight distinct domains, which include.

- Energy conservation and efficiency measures
- Promotion and integration of renewable energy technologies
- Reduction and mitigation of carbon emissions
- Deregulation and restructuring of energy markets
- Management of energy data and information
- Promotion of electric vehicles and infrastructure development
- Research and development in the energy sector
- Coordination and international cooperation in energy policy

To effectively integrate these eight categories with the utilization of AI, a comprehensive research roadmap for energy policy development should encompass the top 20 critical policy components, which may differ depending on the specific policy objectives. Table 3 presents a comprehensive examination of various machine learning techniques and their respective scenario-specific applications, providing a clear set of guidelines for selection and implementation. This information enables interdisciplinary researchers to smoothly identify the most appropriate machine learning methods for their specific energy research and development projects. It eliminates the need for extensive literature reviews and provides a streamlined roadmap for utilizing the right strategies, tools, and techniques.

Energy efficiency and demand management programs aim to reduce energy consumption through various measures such as building retrofits, appliance standards, and education; utility

Table 3
Linking machine learning techniques and their scenario-based representation to energy policy development and implementation.

No.	Energy policy building block	Supposed code	AI and machine learning method/ technique (Omitaomu & Niu, 2021)	Application scenario	Reference
1	Energy efficiency and demand management programs	EEDM	Neural networks, decision trees, regression analysis, computer vision and natural language processing, time series analysis, and clustering.	AI-based building energy management systems, AI-powered smart appliances, and machine learning algorithms for demand forecasting and load management.	Krarti (2019)
2	Renewable energy portfolio standards	RPS	Neural networks, decision trees, and support vector machines.	Machine learning-based forecasting and optimization of renewable energy generation and integration into the grid.	Liao et al. (2019)
3	Net metering policies	NM	Neural networks and decision trees.	Machine learning-based prediction and optimization of distributed energy resources, such as PV systems, etc.	(Gabr et al., 2020; Huang et al., 2020)
4	Feed-in tariffs	FIT	Neural networks, decision trees, and support vector machines.	AI-powered prediction and optimization of renewable energy generation, such as wind and solar power, to optimize feed-in tariffs.	(Gabr et al., 2020; Mormann, 2021)
5	Carbon pricing mechanisms	CPM	Neural networks, decision trees, linear regression, and random forest.	AI-based carbon footprint tracking and forecasting, machine learning-based prediction, and optimization of carbon emissions reduction.	Cao et al. (2017)
6	Energy market deregulation and restructuring	EMD	Neural networks, decision trees, linear regression, and support vector machines.	Machine learning-based market forecasting and optimization, AI-based price prediction and optimization in deregulated markets.	(Cao et al., 2017; Lin et al., 2022; Tong et al., 2019)
7	Energy conservation standards	ECS	Neural networks, decision trees, and regression analysis (linear).	AI-based energy management systems and machine learning algorithms for energy systems simulation and optimization.	Inoue and Matsumoto (2019)
8	AI integration robustness in energy codes and standards	AIEC	Interdisciplinary tools and techniques.	The ways to provide AI-friendly codes and standards to welcome techno-economic integration of AI at various levels of the system.	(Arcelay et al., 2021; Castrillón-Mendoza et al., 2020; Sabory et al., 2021)
9	Renewable energy tax credits and incentives	RETI	Linear regression, decision trees, and neural networks.	Machine learning-based prediction and optimization of renewable energy project costs and benefits.	Majeed et al. (2022)

Table 3 (*continued*)

No.	Energy policy building block	Supposed code	AI and machine learning method/ technique (Omitaomu & Niu, 2021)	Application scenario	Reference
10	Smart and automation technologies and advanced metering infrastructure	SATM	Neural networks, decision trees, computer vision, deep learning, and linear regression.	Machine learning-based prediction and optimization of grid operations, AI-based fault detection and diagnosis in power systems, and machine learning-based demand response management.	Omitaomu and Niu (2021)
11	Energy storage systems and technologies	ESST	Neural networks and decision trees.	Machine learning-based prediction and optimization of energy storage systems, AI-based battery management systems.	Cao et al. (2017)
12	Electric vehicle deployment and charging infrastructure	EVCI		Machine learning-based prediction and optimization of electric vehicle charging patterns and infrastructure needs.	
13	Carbon capture and storage	CCS		Machine learning-based prediction and optimization of carbon capture and storage systems, AI-based process control and monitoring.	Gładysz et al. (2022)
14	Energy data analytics and modeling	EDA	Neural networks, decision trees, computer vision and natural language processing, sentiment analysis, and text classification.	Machine learning-based prediction and optimization of energy systems, AI-based data visualization and analysis, and natural language processing for text-based energy data.	Omitaomu and Niu (2021)
15	Energy system benchmarking and reporting	EB	Linear regression, decision trees, computer vision, and natural language processing.	Machine learning-based building energy performance prediction and optimization, AI-based energy benchmarking and reporting systems.	(Guo et al., 2023; Hu, 2022)
16	Energy-efficient transportation planning and programs	ETP	Neural networks, decision trees, computer vision, and deep learning.	Machine learning-based prediction and optimization of transportation demand and energy consumption, AI-based traffic management systems.	Guo et al. (2023)
17	Energy education and outreach	EE	Natural language processing and dialogue management, sentiment analysis, and text classification.	AI-based chatbots for energy education and natural language processing for text-based energy education materials.	Middleton (2018)
18	Energy research and development	ERD	Neural networks, decision trees, evolutionary algorithms, particle swarm optimization, convolutional neural networks, and generative models.	Machine learning-based modeling and simulation of energy systems, AI-based optimization of energy technologies, deep learning-based material design and discovery.	(Gu et al., 2020; Pandey et al., 2022)
19	Energy market design and regulation	EMD	Various supervised and unsupervised machine learning methods.	Machine learning-based prediction and optimization of market dynamics, AI-based market surveillance, fraud and thief detection.	
20	International cooperation on energy and climate policy	ICEC	Neural networks, decision trees, sentiment analysis, and text classification.	Machine learning-based prediction and optimization of global energy and climate scenarios, AI-based natural language processing for international agreements and frameworks.	

companies offer financial incentives to customers who invest in building retrofits, e.g., upgrading the old appliances and systems at residential to big commercial and industrial facilities to improve its energy efficiency. The adoption and enforcement of stringent energy efficiency codes for new residential and commercial buildings reported a 12.7 TWh/a reduction in final annual energy consumption for the Arab region (Krarti, 2019).

Renewable energy portfolio standards aim to combat climate change by setting a minimum requirement for the percentage of energy that must come from renewable sources. Governments mandate that a certain portion of their energy must be produced from green resources by a specific timeline. It can diversify the energy mix and increase clean energy resource utilization. For example, the proposed Renewable Portfolio Standard for 2030 is projected to reduce carbon emissions by 56.33 million tons in China, as reported by Liao et al. (2019).

Net metering policies allow customers who generate renewable electricity to sell excess energy back to the grid, e.g., homeowners with a rooftop PV system can feed back to the utility company at the retail electricity rate, providing incentives for individuals and businesses to invest in distributed generation. For example, Egypt started incentivizing small-scale PV systems in 2013 with a successful net metering policy offering $0.04/kW·h sell price in September 2017 (Gabr et al., 2020).

Feed-in tariffs offer fixed prices for renewable energy generation to encourage investment, e.g., governments implementing a policy that provides long-term contracts and fixed prices for renewable energy producers, reducing financial risks and providing a stable income for clean energy production. Achieving ambitious targets like proposals to produce 45% of the nation's electricity from solar energy by 2050 requires significant government support, e.g., encouraging investment in the residential PV system with 40% of the initial investment cost incentive (Gabr et al., 2020; Mormann, 2021).

Carbon pricing mechanisms put a cost on carbon emissions to incentivize emission reductions, introducing a carbon tax or a cap-and-trade system, which provides a financial incentive for businesses and individuals to reduce their greenhouse gas emissions, promoting a reduction in their carbon footprint. The ideal level of carbon caps and low-carbon subsidies depends on various factors such as the carbon trading price, the amount of initial carbon emissions, the extent of environmental damage, and consumer perception of the need for carbon emission reduction (Cao et al., 2017).

Energy market deregulation and restructuring aim to increase its competition and efficiency, opening up the electricity market to competition among generators, allowing customers to choose their electricity supplier, promoting competition in the energy market, and encouraging efficiency. Carbon emissions trading, or cap and trade, operates assuming that market demand is influenced by price, competition, and the cost of environmental damage (Lin et al., 2022). The government sets a limit, or a cap, on emissions, and businesses adjust their pricing accordingly, reducing market demand (Cao et al., 2017). The effectiveness of this approach is influenced by factors such as the cost of environmental damage and competition within the market.

Energy conservation standards for appliances and buildings set energy performance requirements for products and buildings by implementing regulations that set energy efficiency standards for household appliances. The study (Inoue & Matsumoto, 2019) reported that monthly electricity usage of air conditioners in Japan decreased from 35.20 kW h in 1999 to 27.78 kW h in 2004, resulting in a 21.1% saving, intensively due to a 67.8% increase in efficiency. Despite these improvements, the average monthly electricity usage per household decreased from 68.29 to 62.50 kW h. This suggests that much of the energy savings were achieved by implementing the Top Runner Program, which aimed to set efficiency standards for major home appliance upgrades.

AI integration in energy systems codes and standards establishes minimum energy system robustness requirements for new and planned infrastructures, imposing residential, commercial, industrial, agriculture, etc. sectors codes and standards that require to meet a certain level of energy automation, efficiency, safety, and reliability as determined by a recognized rating system such as Leadership in Energy and Environmental Design (LEED or Energy Star), promoting energy efficiency in new constructions and reducing energy consumption using different machine learning approaches. A study by Sabory et al. (2021) reported on the potential for reducing energy consumption in buildings in Afghanistan, where the building sector accounts for 93% of total energy demand. The average electrical energy consumption in a residential facility is 1856 kW h per year, with the largest consumption being for lighting (18%), refrigeration (17%), and cooking (11%). At the industrial level, ISO Standard 50001 helps industries implement systems and processes to improve energy efficiency and consumption (Castrillón-Mendoza et al., 2020). In light of the digital evolution and AI intervention in the energy sector, a shift towards attracting and acquiring talented human resources is expected, which will impact the future skill requirements of jobs in the sector (Arcelay et al., 2021).

Renewable energy tax credits and incentives support renewable energy development, offering tax breaks, grants, or other financial support to help reduce the costs of renewable energy projects and promote clean energy development. Promoting energy investment schemes encourages the world to transition from coal to green resources. Policymakers play a crucial role in this shift by providing permits, tax credits, grants, and direct investment in emerging clean energy sources such as carbon capture and storage (CCS), advanced storage systems, hydrogen, geothermal energy, and offshore wind (Majeed et al., 2022). This will help ensure decarbonization efforts and support a sustainable energy future.

Smart grid technologies and advanced metering infrastructure improve the efficiency and reliability of the power grid by implementing advanced meters, sensors, and communication systems that can help optimize the flow of electricity, improve the integration of renewable energy, and enhance the reliability of the grid with high compatibility of AI. The future of AI in smart grids involves integration with cloud computing, fog computing, transfer learning, and consumer behavior prediction to create a complete, self-learning, responsive, adaptive, and cost-effective system. Integration with cloud computing enhances security and robustness, while fog computing provides on-demand resources for computing (Omitaomu & Niu, 2021). Transfer learning reduces the need for training data, and consumer behavior prediction helps with demand-side management and demand response tasks to create a more efficient and effective power system.

Energy storage systems and technologies, such as batteries, thermal storage, and pumped hydro storage, can help balance supply and demand on the grid, promoting energy reliability and security.

Electric vehicle deployment and charging infrastructure support the adoption of electric vehicles, building charging stations, offering financial incentives for the purchase of electric vehicles, and setting standards for electric vehicle charging, promoting the adoption and use of electric vehicles. The USA has invested $2.4 billion in loans for electric vehicle companies and $2 billion for constructing 30 factories producing batteries and other clean energy vehicles, demonstrating its commitment to the transition to sustainable transportation (Cao et al., 2017).

CCS captures carbon dioxide (CO_2) emissions from power plants or industrial processes, and store them underground by installing carbon capture technology at a coal-fired power plant. Biomass combustion with CO_2 capture and storage is vital to reducing global warming below 2 °C with net-zero CO_2 emissions through photosynthesis (Gładysz et al., 2022). Adding CCS to a bioenergy power plant results in a negative CO_2 balance and reduced emissions. Direct air CO_2 capture is another option for removing CO_2 from the atmosphere and distributed carbon sources through industrial processes.

Energy data analytics and modeling use data to inform energy policy and decision-making in terms of datasets, utilizing advanced modeling, simulation, and data visualization techniques to analyze and interpret energy data. The transition from traditional power systems to smart grids has exposed more uncertainties and challenges due to the complex environment and outdated infrastructure. The high volume of data with high variability in smart grids in terms of data-driven modeling is a challenge to be handled, improving the robustness, adaptiveness, and online processing of AI algorithms in the context of smart grids (Omitaomu & Niu, 2021).

Energy benchmarking and reporting measure and compare systems operation performance, behavior, and organizations. Transparency in energy performance data reporting and benchmarking is crucial for bridging the gap between simulated building performance and actual energy use, and evaluating the efficacy of sustainable design rating systems like LEED certification (Hu, 2022). The process of energy performance benchmarking involves calculating a benchmark that considers important factors such as ambient conditions and then comparing the actual performance of a system to the benchmark using an energy performance index (EPI) (Guo et al., 2023).

Energy-efficient transportation planning and programs promote energy-efficient modes of transportation, e.g., providing incentives for public transit, bike-sharing, and electric vehicles, as well as transportation demand management strategies, promoting energy-efficient transportation options and reducing the carbon footprint of transportation. Transportation contributes significantly to global CO_2 emissions (37%), and electric vehicles (EVs) can emerge as a cleaner alternative to traditional internal combustion engine vehicles; with 16.5 million EVs on the roads worldwide by 2021, their deployment has seen fast growth in the past decade (Guo et al., 2023).

Energy education and outreach inform the public about energy conservation and renewable energy, e.g., by offering workshops, educational resources, and public awareness campaigns to educate individuals and communities on ways to conserve energy and use renewable energy sources, promoting energy conservation and renewable energy awareness. The promotion of sustainability through education and awareness-raising can create a robust and informed workforce offering training and education in sustainability-related fields for professionals, developing curricula on sustainability for students, and using a variety of communication strategies to raise awareness and provide tools for people of all ages to implement and share best practices (Middleton, 2018).

Energy research and development (R&D) supports the development of new energy technologies by funding a research project to develop a new type of energy storage technology, supporting the advancement of new energy technologies, and driving innovation by integrating AI with energy systems. Empirical evidence suggests that R&D has a positive relationship with financial development, and increasing R&D expenditures can lead to growth in economic development (Gu et al., 2020). Expanding R&D activities can lead to more innovation and the promotion of technological innovation and quality human capital, which can enhance financial development.

Energy market design and regulation ensure fair competition and efficient functioning of energy markets, implementing regulations on market participants, rules for transmission and distribution, and oversight of market operations to promote fair competition and prevent market manipulation, ensuring the efficient functioning of energy markets. The relationship between institutions and markets of the financial system in the Group of Seven (G7) economies, with the available data from 1990 to 2017, presents that financial development is linked with R&D; if financial markets share the risk, increasing energy prices can hinder financial markets' expansions (Gu et al., 2020).

International cooperation on energy and climate policy helps to coordinate efforts to address global energy and climate challenges. International efforts to transfer technology for sustainable development in developing countries have been ineffective, while it is the primary agreement of international cooperation on climate change and sustainable energy, which encompasses exchanging knowledge, experience, and equipment among various stakeholders, including governments, international organizations, private entities, financial institutions, NGOs, and educational institutions (Pandey et al., 2022). Technology transfer aims to facilitate the understanding, utilization, and replication of technology, including the capacity to choose, adapt, and integrate it with local technologies.

This study endeavors to generalize a roadmap of essential components of energy sector policies, analyzing them from various perspectives. However, the limitation is that some of the policy components presented in this classification may be mutually exclusive, while others may exhibit overlap and fall under multiple categories. It mainly depends on the policy objectives and the means of achieving them. The proposed generalization approach, in the context of being abstractive-multidimensional, offers a novel approach in terms of classification. Tables 4 and 5 provide a comprehensive overview of the segmentation of energy policy and their interlink in terms of building blocks and illustrate how the energy policy segments are distributed within the implementation process, energy flow, and market analysis.

5.2. Application of AI in energy policies formulation

AI has a long history dating back to the creation of the first computer "Electronic Numerical Integrator and Computer (ENIAC)" in 1946 (Kubassova et al., 2021). Alan Turing explored the concept of computing machinery and intelligence in the early 1950s (Turing, 2009). The flourishing period of AI from 1957 to 1974 saw advancements in computer development and machine learning algorithms. After 1980, ambitious investments, technological advancements (such as machine learning, deep learning, and quantum computing), and inspiration from young generations have driven the development of AI into a future technology (Anyoha, 2017). For example, Japan's Fifth Generation Computer Project budgeted 400 million US dollars from 1982 to 1990 for AI research and development (Odagiri et al., 1997).

Table 4
Segmenting energy policy based on the building blocks.

Policy Segments / Policy Building Blocks	EED	RPS	NM	FIT	CPM	EMD	ECS	AIEC	RETI	SAT	ESST	EVCI	CCS	EDA	EB	ETP	EE	ERD	EMD	ICEC
Energy conservation and efficiency measures	✓					✓	✓	✓		✓					✓	✓	✓			
Renewable energy promotion and integration		✓	✓	✓					✓		✓	✓	✓					✓		
Carbon emission reduction and mitigation measures					✓								✓	✓						✓
Energy market design and regulation						✓													✓	✓
Energy data and information management														✓	✓					
Electric vehicle promotion and infrastructure												✓								
Energy research and development																		✓		
Energy policy coordination and international																			✓	✓

Table 5
Distributing energy policy segments within the implementation, energy flow process, and market analysis.

Analysis	Breakdown \ Policy Segments	EEDM	RPS	NM	FIT	CPM	EMD	ECS	AIEC	RETI	SATM	ESST	EVCI	CCS	EDA	EB	ETP	EE	ERD	EMD	ICEC
Implementation	Government policies and regulations	✓	✓			✓	✓	✓	✓	✓			✓	✓	✓	✓	✓		✓	✓	✓
	Utility and industry initiatives			✓	✓						✓	✓						✓			
	Community and individual actions	✓		✓														✓			
Energy Flow	Generation				✓					✓		✓	✓	✓					✓		
	Transmission and distribution										✓	✓	✓								
	End-use and demand management	✓		✓			✓	✓	✓							✓	✓	✓			
Market	Market-based mechanisms		✓		✓	✓															✓
	Government regulations and subsidies	✓		✓			✓	✓	✓	✓			✓	✓	✓	✓	✓		✓	✓	

Integrating AI in energy policy development offers many merits, providing a new perspective on optimizing energy usage and reducing costs. However, there are also barriers to implementation, such as a lack of expertise and data privacy concerns. Despite these challenges, there are currently many opportunities to utilize AI in areas such as demand forecasting, grid optimization, and building energy management. As AI continues to evolve, it can be expected to witness even more innovative solutions and trends in energy policies, such as integrating AI into renewable energy systems and developing smart cities. Incorporating AI in energy policy development is a promising step toward a more sustainable and energy-efficient future.

The utilization of AI and machine learning is prevalent in controlling, monitoring, and optimizing energy systems. Out of the numerous studies conducted in this field, some are highlighted for their specific applications, such as economic load dispatch (Bellizio et al., 2018), voltage stability and regulation (Dobbe, Sondermeijer, et al., 2020; Zienkiewicz et al., 2018), system fault identification restoration (Ardakanian et al., 2019; Brahma et al., 2017), planning and forecasting (Sun et al., 2018; Zhao & Guan, 2016), network observability (Deka et al., 2018; Liao et al., 2019), frequency regulation and stability (Ernst et al., 2004; Glavic et al., 2017; Karagiannopoulos, Dobbe, et al., 2019), system storage and power management (Karagiannopoulos, Aristidou, & Hug, 2019; Xiong et al., 2018), demand-side management (Lesage-Landry & Taylor, 2018; Lu & Hong, 2019), electricity theft control (Duan et al., 2018; Jokar et al., 2016), and unit commitment and power management (Zhao & Guan, 2016).

AI and machine learning have the potential to support and enhance many aspects of energy policy, such as increasing energy efficiency, improving the integration of renewable energy, reducing greenhouse gas emissions, and optimizing the functioning of energy markets. However, implementing AI and machine learning in energy policy requires careful consideration of ethical, legal, and social implications and addressing data security and transparency concerns. Dobbe, Hidalgo-Gonzalez, et al. (2020) reported that the application of AI and machine learning in power systems is crucial for advanced monitoring, control, operation, and integration of large-scale renewable energy sources, handling uncertainty and instability, adapting to changing conditions, and managing new aspects of smart grids, while also incorporating these new methods into existing infrastructure and practices through the use of flexible and optimized machine learning approaches.

Incorporating machine learning methods in energy policies requires data-driven models based on accurate and appropriate datasets. Therefore, broken-down policy processes and milestones facilitate achieving low hierarchy manageable portions to analyses and generate adequate data-driven-friendly datasets. Therefore, at this point, energy policies are sorted into six categories based on policy objectives. A classification of policy segments based on goals through an in-depth literature analysis is conducted. This classification includes supervised, unsupervised, reinforcement, deep learning, and natural language processing methods (Omitaomu & Niu, 2021). Additionally, the level of automation, energy system stages, the scale of implementation, type of energy, and type of energy policy are also considered. These classifications provide different perspectives on the integration and application of methods, tools, and techniques, allowing for identifying strengths, weaknesses, potential synergies, and areas for further research and development. Fig. 2 can contribute to considering broader and deeper perspectives, uncovering hidden policy aspects that may be overlooked. This will be achieved by breaking down policy components and exploring their interlinked concepts from various angles to align with the policy objectives.

AI and machine learning methods can be applied in a variety of applications across energy systems, which can be categorized by their preference of focus or decision-making preference based on their automation level, energy type, energy policy type, application type, technique type, and so on. Supervised learning methods are mainly used for energy management, demand, and market forecasting, while unsupervised learning methods can be used for fault detection and diagnosis in power systems and electric thief recognition. Reinforcement learning methods are used for grid operations optimization, and demand response management and deep learning methods are helpful for material design and discovery and automatic compliance checking. Techniques such as optimization algorithms, predictive modeling, artificial neural networks, and decision trees can be integrated with energy systems operation and control.

6. Innovative energy policy tools and techniques in the era of AI

This section explores the various policy and management tools and techniques (Danish et al., 2019; Hettiarachchi & Kshourad,

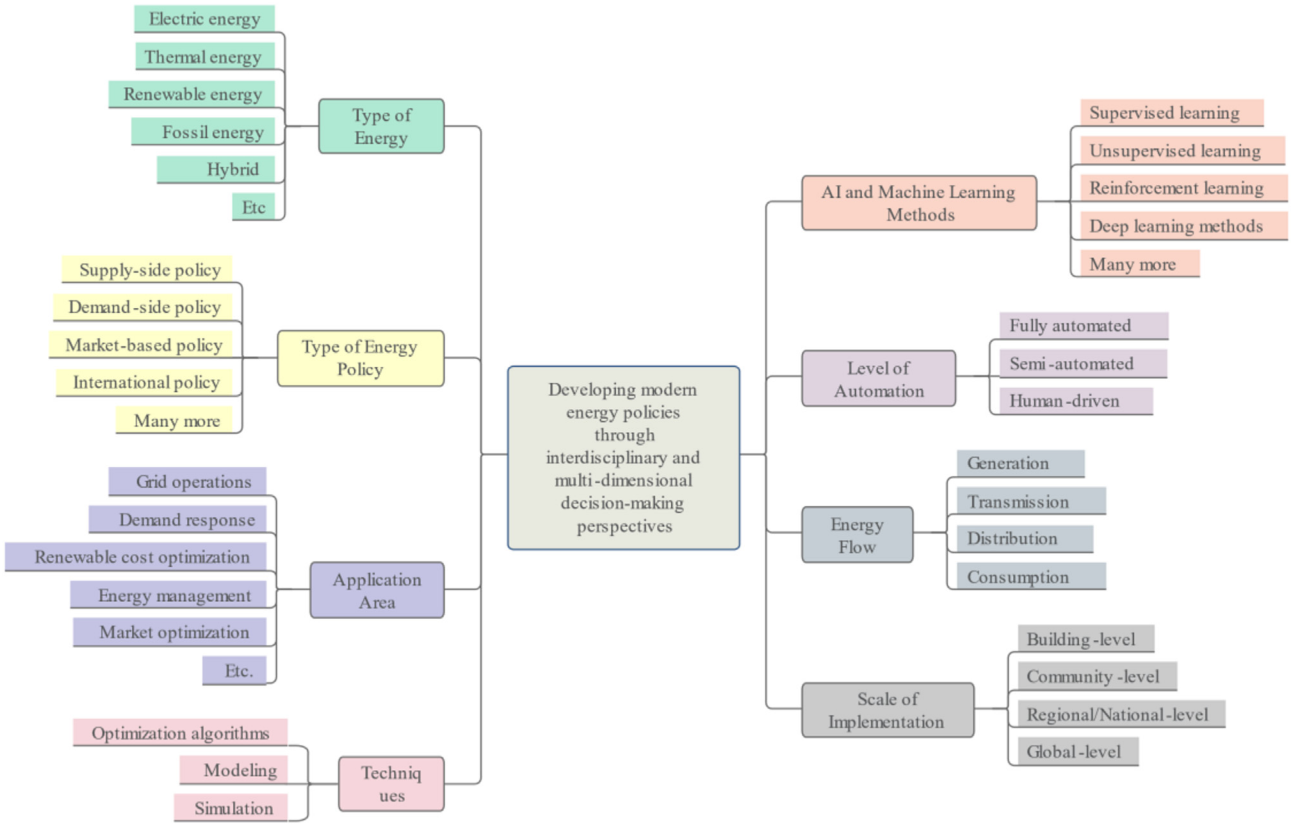

Fig. 2. Developing modern energy policies through interdisciplinary and multidimensional decision-making perspectives.

2019; Pavitt, 1972) that can be employed to develop and implement energy policies in the age of the AI revolution. The discussion encompasses a wide range of policy instruments, including regulatory, incentive-based, and market-based mechanisms (Shams et al., 2021). It examines each approach's advantages, limitations, and suitability to specific policy objectives and contexts (Danish et al., 2020), as well as the potential of AI-based indices, indicators, tools, and methods to enhance their effectiveness. This section provides examples of how these tools and techniques have been used in practice and highlights the best practices for their implementation (Danish, Senjyu, Funabashia, et al., 2019). In conclusion, this section aims to provide a comprehensive understanding of modern energy policy tools and techniques and their potential to effectively address the challenges of energy transition in the era of AI (Omitaomu & Niu, 2021).

The energy sector is witnessing significant transformation with increasing AI and data science adoption through various methods and applications. Their effectiveness depends on the specific application and case. The proposed classification of methods is based on their usage frequency and efficacy for specific functional domains to hint at their proper and efficient deployment. For instance, supervised learning is effective in consumers' energy management systems, forecasting demand and market trends, while unsupervised learning methods are suitable for fault detection and improper electricity consumption recognition in power systems. Reinforcement learning can optimize grid operations and demand response management. Deep learning is useful in material design and automatic compliance checking, which are discussed in detail in the following sections. Aligning appropriate methods, tools, and techniques within a well-understanding of a policy's purpose will ensure policy development and implementation effectiveness, leading to achieving desired outcomes within the scope of a policy, as shown in Fig. 3.

6.1. Aligning modeling with AI requirements

Three purposes for modeling an energy system are reported: prediction/forecasting, exploring, and backcasting. Prediction/forecasting involves extrapolating trends from historical data, and is suitable for analyzing medium to long-term impacts of actions (Beeck, 1999; Neshat et al., 2014). Exploring involves scenario analysis, where a limited number of scenarios are compared with a reference scenario, with assumptions made for economic growth and technological progress. Backcasting determines the conditions of a desired future and defines steps to attain it. It is useful for complex problems that require major change and is a planning methodology under uncertain circumstances.

Data-driven models are based on historical data, using machine learning algorithms to identify patterns and relationships in the data (Busari & Lim, 2021; Daradkeh et al., 2022; Entezari et al., 2023; Pai & Chen, 2009; Shi et al., 2022; Steinwandter et al., 2019; Tebenkov & Prokhorov, 2021). These models can make predictions or decisions based on new input data without prior knowledge of the system's physical properties or dynamics, whereas system parameter-based models require such prior knowledge. These models are based on mathematical equations describing the system's behavior and need accurate data for the system's parameters. Data-driven models are suggested when the underlying physical processes are complex and non-linear. At the same time, parameter-based models are evaluated against the

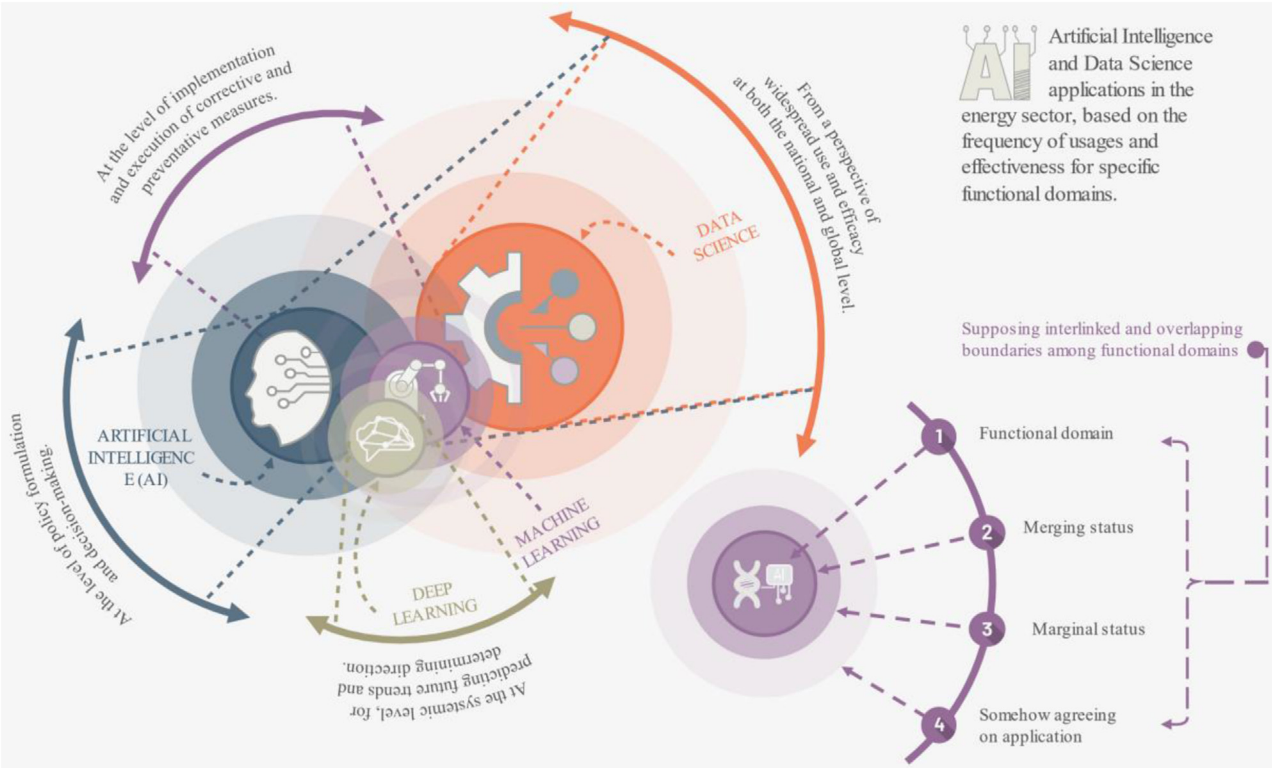

Fig. 3. The efficacy of AI and data science (methods) in the energy sector in the context of the frequency of their usage and effectiveness for specific functional domains.

system's behavior observation of accurate modeling using mathematical equations.

Data-driven models demonstrate with several advantages as follows.

- The task to automatically learn and identify patterns and relationships within the data may be challenging or impossible for human analysts to detect manually.
- The potential for high accuracy when trained on big data and representative datasets.
- The capability to improve over time as new data becomes available.

However, data-driven models also have some limitations, including.

- Susceptibility to overfitting when trained on small or biased sets of data.
- The choice of a suitable algorithm for addressing a problem seems to be minimally affected by concerns related to the quality and representativeness of the data used during the training process.
- The potential difficulty in interpretation can impede understanding of how the model makes its predictions or decisions.

Digital technologies such as data analytics, machine learning, the Internet of Things, digital platforms and more require sophisticated software and hardware applications supporting automated decision-making and enhancing security and resilience. The energy systems, particularly power systems, are facing challenges in transitioning to AI-enabled models, including the need for advanced information technologies, efficient new energy technologies, market-based price signals, mitigating network congestion, avoiding the negative impacts of “inc-dec gaming”, implementing a sequential market structure, and incentivizing system-beneficial investments in renewable technologies (Novirdoust et al., 2021).

Diversely, literature (Bansal et al., 2022; Barlas et al., 2015; Busari & Lim, 2021; Danish et al., 2015; Hameed et al., 2021; Jiang & Zhao, 2022; Ko et al., 2017; Kosana et al., 2022; Kotu & Deshpande, 2019; Lin et al., 2022; Omitaomu & Niu, 2021; Pai & Chen, 2009; Pujahari & Sisodia, 2020; Rajendran & Sundarraj, 2021; Shi et al., 2022; Stefano & Michèle, 2022; Steinwandter et al., 2019; Sulaimany & Mafakheri, 2023; Tarmanini et al., 2022; Westreich et al., 2010; Yadranjiaghdam et al., 2016; Zeng, Qiu, & Sun, 2022) discussed and classified data science, AI, machine learning, and deep learning from various perspectives and viewpoints (Fig. 4), which can lead to a generalization that overlooks the overlapping and interconnectivity of some methods and tools as follows.

- Classification: naive Bayes, support vector machines (SVM), decision trees, neural networks, induction rules, *k*-nearest neighbors
- Regression: linear and logistic regression, polynomial regression, classification and regression trees (CART)
- Association analysis: *A* priori algorithm, equivalence class transformation (ECLAT) algorithm, FP-growth algorithm
- Clustering: *k*-means, density-based spatial clustering of applications with noise (DBSCAN), hierarchical clustering, XRF spectral based sorting (SBS)
- Anomaly detection: isolation forest, distance-based, density-based, LOF (local outlier facto), one-class SVM, *Z*-score
- Recommendation engines: collaborative filtering, content-based filtering, hybrid recommendation

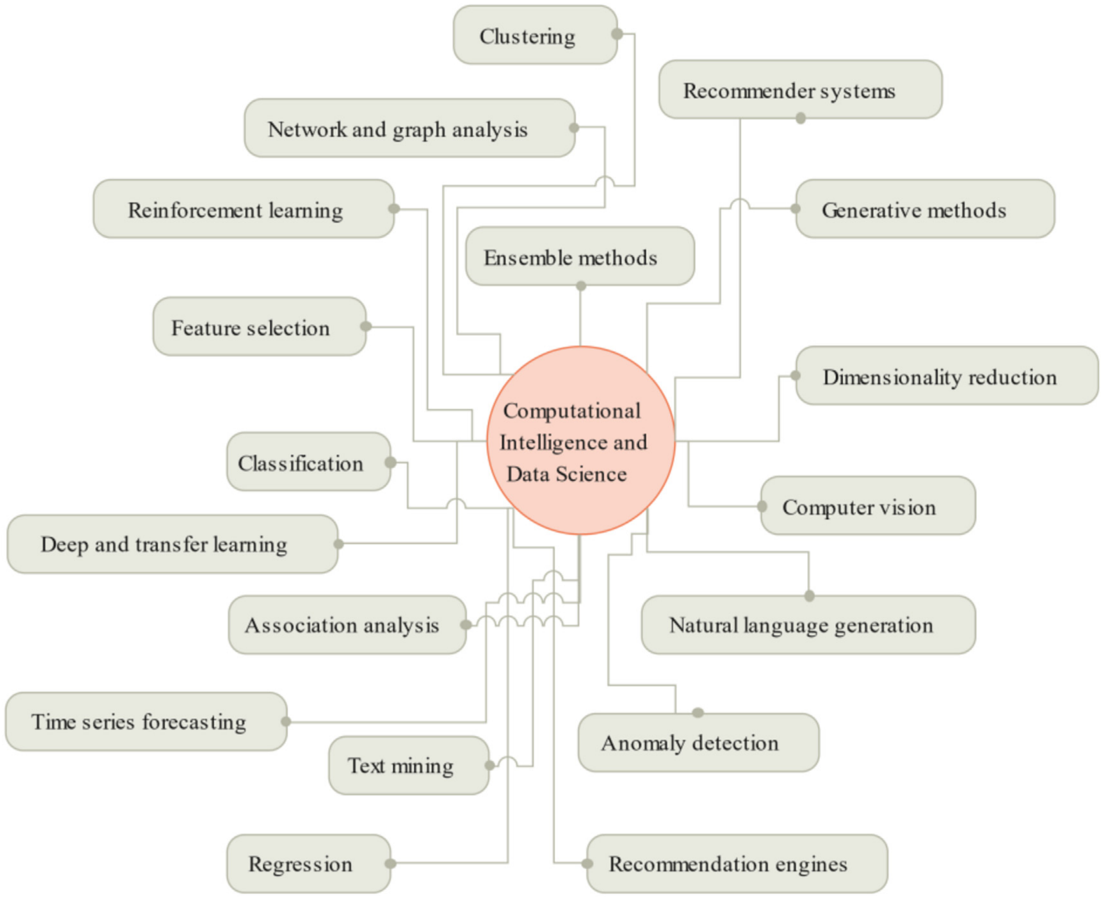

Fig. 4. Computational intelligence and data science main tasks and performances.

- Feature selection: recursive feature elimination, Lasso regression, random forest
- Time series forecasting: autoregression (AR), mean absolute percentage error (MAPE), moving average (MA), exponential smoothing, auto regressive integrated moving average (ARIMA)
- Deep and transfer learning: convolutional neural networks (CNNs), recurrent neural ntworks (RNNs), generative adversarial networks (GANs)
- Text mining: natural language processing (NLP), term frequency-inverse document frequency (TF-IDF), sentiment analysis
- Computer vision: image classification, object detection, segmentation
- Natural language generation: generative pretrained transformer 3 (GPT-3), OpenAI, embeddings from language models (ELMo), OpenAI Gym
- Dimensionality reduction: principal component analysis (PCA), singular value decomposition (SVD), linear discriminant analysis (LDA)
- Ensemble methods: random forest, gradient boosting, AdaBoost
- Reinforcement learning: *Q*-learning, state-action-reward-state-action (SARSA), deep *Q*-networks (DQN)
- Generative methods: variational autoencoders (VAE), generative adversarial networks (GAN), Boltzmann machines
- Network and graph analysis: centrality measures, community detection, link prediction, PageRank, community detection
- Recommender systems: matrix factorization, neighborhood-based collaborative filtering, deep learning-based recommender systems.

6.2. Tools and techniques

Some common tools and techniques can be used in energy policy development and implementation to promote energy efficiency, increase the share of renewable energy, reduce greenhouse gas emissions, and improve the overall functioning of energy markets. However, the specific policies and programs will depend on the policy and context. For example, the A-B-C-D method, a methodology congruent with the backcasting approach, is advocated for strategic planning and the management of policy development (de Oliveira Musse et al., 2018). It comprises four distinct phases: awareness and visioning, baseline mapping, creative solutions, and decisions on priorities (Soria-Lara & Banister, 2018). This approach is versatile, can be applied across many domains, and is continually refined in terms of terminology and application (Park et al., 2016). The backcasting approach assesses decisions and actions to determine if they propel entities toward the predetermined targets. It is bolstered by other tools and techniques, which leads to new scenarios and principles, thus ensuring the success of the planning process. Based on these methods, it conducted various futuristic planning for 2035 and 2090 (Hines et al., 2019). The most applied tools and techniques are retrieved and selected from a long list of approaches in Table 6.

Among the tools and techniques mentioned in Table 6, backcasting is elaborated (Fig. 5), which is a drastic approach that can be adopted for energy policy development to enable policymakers to envision a desirable carbon-neutral future and look backward to adjust preventive and corrective actions if needed to achieve the strategic goals of the policy objectives.

Table 6
Proposed machine learning and AI approaches, methods, tools, and techniques for applying to energy systems.

No.	Method	Machine learning and AI tools and techniques
1	Quantitative approach	Surveys, experiments, statistical analysis (e.g., regression, ANOVA), mathematical modeling (e.g., simulation, optimization), etc.
2	Qualitative approach	Interviews, focus groups, ethnography, case studies, content analysis, grounded theory, etc.
3	Interdisciplinary approach	Collaboration and communication among experts from different fields, integrating different perspectives and methods, etc.
4	Systems approach	Systematic thinking, system dynamics, causal loop diagrams, stock and flow diagrams, input–output analysis, system mapping, etc.
5	Comparative approach	Case-control studies, cross-case analysis, process tracing, most similar systems design, most different systems design, within-case analysis, cross-cultural analysis, etc.
6	Theoretical approach	Literature review, conceptual analysis, formal modeling, hypothesis testing, theoretical sampling, theory development, deduction and induction, etc.
7	Empirical approach	Observation, experimentation, field studies, case studies, survey research, statistical analysis, archival research, secondary data analysis, etc.
8	Participatory approach	Community engagement, co-creation, co-design, action research, participatory design, stakeholder engagement, citizen science, user-centered design, etc.
9	Risk assessment approach	Hazard identification, exposure assessment, risk characterization, risk management, decision analysis, cost–benefit analysis, probabilistic risk assessment, risk communication, etc.
10	Life-cycle approach	Life-cycle assessment, life-cycle costing, material flow analysis, input–output analysis, process analysis, environmental impact assessment, etc.
11	Normative approach	Ethical analysis, value assessment, moral reasoning, stakeholder analysis, multi-criteria decision analysis, social impact assessment, etc.
12	Scenario-based approach	Scenario planning, backcasting, strategic foresight, futures studies, scenario building, scenario analysis, scenario workshops, etc.
13	Behavioral approach	Psychology, cognitive science, behavioral economics, experimental methods, field studies, survey research, self-report measures, physiological measures, etc.
14	Spatial approach	GIS, spatial statistics, spatial econometrics, spatial epidemiology, spatial optimization, spatial autocorrelation, spatial data mining, spatial analysis, etc.
15	Technical approach	Engineering, computer science, information technology, data analysis, machine learning, AI, programming, simulation, etc.
16	Historical approach	Archival research, oral history, historiography, historical document analysis, historical comparative analysis, historical case studies, etc.
17	International/Cross-national approach	Cross-cultural research, cross-national surveys, comparative case studies, cross-national statistical analysis, global data analysis, multi-level analysis, etc.
18	Institutional approach	Institutional analysis, institutional theory, organizational analysis, institutional ethnography, case studies, historical analysis, discourse analysis, etc.
19	Dynamic approach	System dynamics, agent-based modeling, computational modeling, simulation, dynamic optimization, time-series analysis, panel data analysis, etc.
20	Value-based approach	Value engineering, value management, value analysis, value mapping, value stream analysis, value-based design, value-based decision making, stakeholder value analysis, etc.

6.3. Criteria for assessing an energy policy

As a benchmark for evaluating the competitiveness of an energy policy that aligns with sustainability criteria and the requirements for AI integration, a tangible energy policy reflects the following keywords throughout its development and implementation: data management, data privacy, data security, data accessibility, sustainability, resilience, emission, equity, access, participation, governance, decision making, stakeholder engagement, regulation, incentives, innovation, digitalization, smart grid, energy efficiency, renewable energy, and energy storage (International Energy Agency, 2021; New York Power Authority, 2021). These primary baselines are essential in ensuring that the energy policy is comprehensive, inclusive, and promotes energy transition.

7. Sustainability rollout within environmental constraints

The 2030 Agenda for SDGs constitutes a comprehensive representation of the challenges facing humanity and the planet, encompassing 17 primary goals and 169 sub-targets, which the United Nations General Assembly unanimously ratified in September 2015 (Rosati & Faria, 2019). The International Energy Agency (IEA) (Birol, 2022) estimates that fossil fuels will take up 5% of the total energy supply by 2050. The emissions reduction goal of 90% by 2050 can be achieved by the end-user sectors deploying hydrogen and hydrogen-based fuels and CO_2 capture technologies.

8. Circular economy exigency

This section synthesizes a circular economic model that aims to increase techno-economic efficiencies, conserve/recover resources, mitigate pollution by enhancing renewable technologies, eliminate market and political incompetency, and engage demand-side stakeholders at various levels to maintain long-term sustainable services. Harmonization and compatibility of policies are needed to transform to a circular model successfully, but economic, environmental, and social challenges persist (Zeng, Ogunseitan, et al., 2022).

The essence of the circular economy concept in the energy policies development process is to move away from the traditional linear model of take–make–dispose (materially, institutionally, financially, etc.) to an integrated-closed-loop system in which resources are kept not only in use for as long as possible, but also to use for multipurpose and levels at the same time for reducing and repurposing objective (Danish, Senjyu, Zaheb, et al., 2019; Li & Xu, 2022; Velvizhi et al., 2020). This approach contributes to environmental challenges and climate change by mitigating resource depletion, increasing efficiencies and stakeholders' shared benefits, etc., while creating business opportunities and ensuring socio-economic benefits. More objectively, to figure out new business model approaches and services, prioritizing sustainability, and offering more resilient and adaptive energy systems.

The exigency and application scenarios of circular economy in energy policy harmonizing with AI deployment are explored in five traditional categories (Fig. 6) (Danish, Senjyu, Zaheb, et al., 2019; Kaya, 2022; Khajuria et al., 2022; Laghari et al., 2013; Velvizhi et al., 2020), followed by the proposed emerging roadmap in Figs. 7 and 8.

- Promoting energy efficiency: Uplifting energy-efficient technologies and practices to reduce energy demand and boost environmental economics.

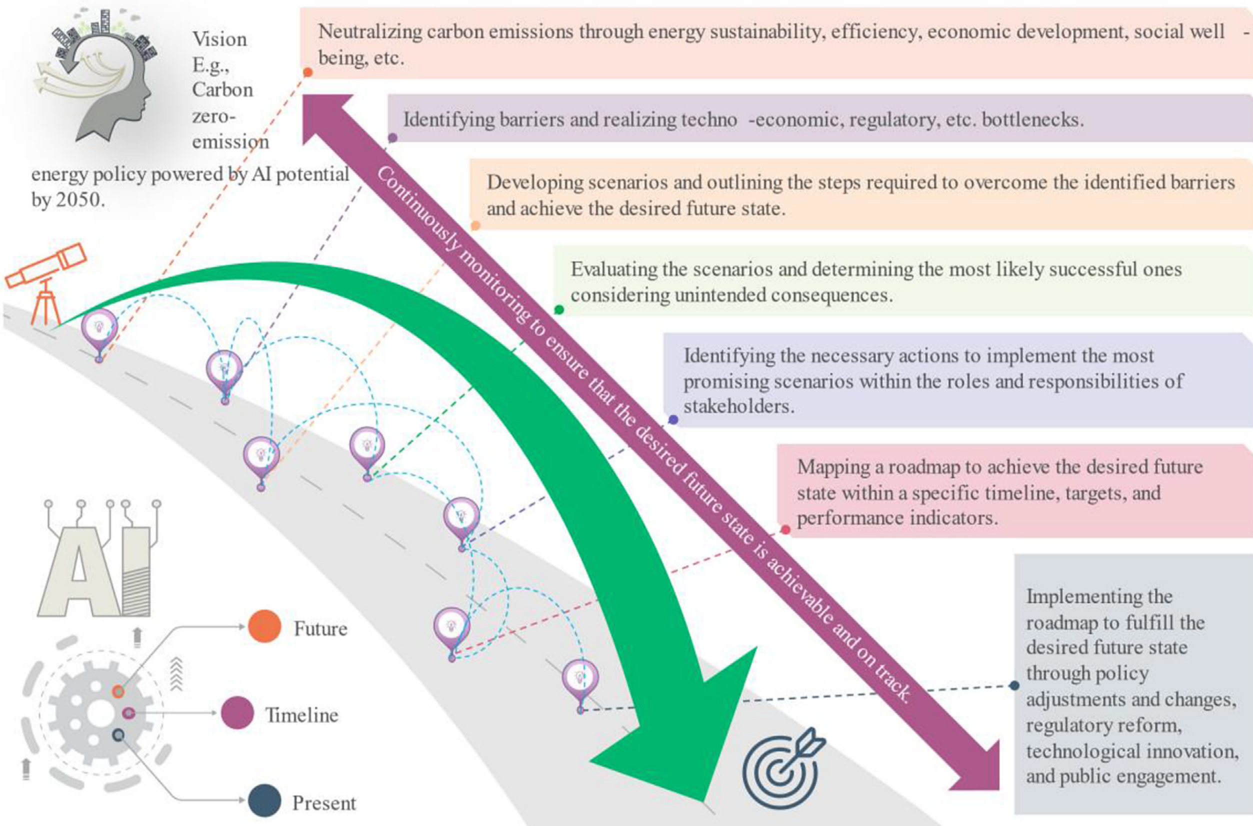

Fig. 5. Proposed framework of backcasting in energy policy development and implementation processes, enabling policymakers to envision a desirable carbon-neutral future within energy sustainability.

- Supporting renewable energy technologies: Supporting the development and use of renewable energy sources such as solar, wind, and hydropower can reduce the reliance on finite energy resources.
- Incentivizing triple-R (reduce, reuse, and recycle) of energy resources: Policies that incentivize reduction, recycling, and reuse of energy resources, e.g., batteries, PV panels, etc., to reduce waste and conserve resources.
- Fostering collaboration between energy and other sectors: Collaboration between the energy sector and other sectors to optimize demands and supplies of technologies and resources in line with the circular economy requirements by creating closed-loop systems.
- Implementing economic incentives and R&D: Inspiring the circular economy in energy systems through economic incentives by deploying decent AI and machine learning technologies with instant use services and promotions of subsidies, tax breaks, etc., to motivate businesses and individuals to adopt more sustainable practices (Rizos & Bryhn, 2022). Investing in research, and developing new technologies and practices that support the circular economy in energy systems to advance the transition towards a more sustainable future.

Promoting circular economy in the energy sector involves several measures to reduce energy demand and boost environmental economics. One of the ways is by uplifting energy-efficient technologies and practices. This can significantly reduce energy demand while ensuring that the environment is protected. Furthermore, supporting the development and use of renewable energy sources such as solar, wind, and hydropower can help reduce the dependence on finite energy resources, ensuring that they are used sustainably. In general, a circular economy in the energy sector is critical to achieving sustainable development goals.

The commonly used methodologies in developing energy models include econometrics, macroeconomics, economic equilibrium, optimization, simulation, backcasting, multi-criteria, and hybrid (Beeck, 1999; Neshat et al., 2014). Econometrics uses statistical methods to predict short or medium-term future based on past market behavior and requires large amounts of data and stable economic behavior. Macroeconomics analyzes energy–economy interactions and energy demand analysis from a neo-Keynesian perspective. Economic equilibrium models simulate long-term growth paths, but the underlying approach is unclear. Optimization models are used to optimize energy investment decisions, while simulation models present a simplified operation of an energy system. Backcasting is used to construct desired future visions, and multi-criteria methodology includes various criteria in the analysis. The hybrid methodology consists of two or more methodologies (Neshat et al., 2014).

In general, circular economy aims to reduce waste and maximize resource efficiency in various ways within the energy sector, including the use of renewable energy sources, implementation of

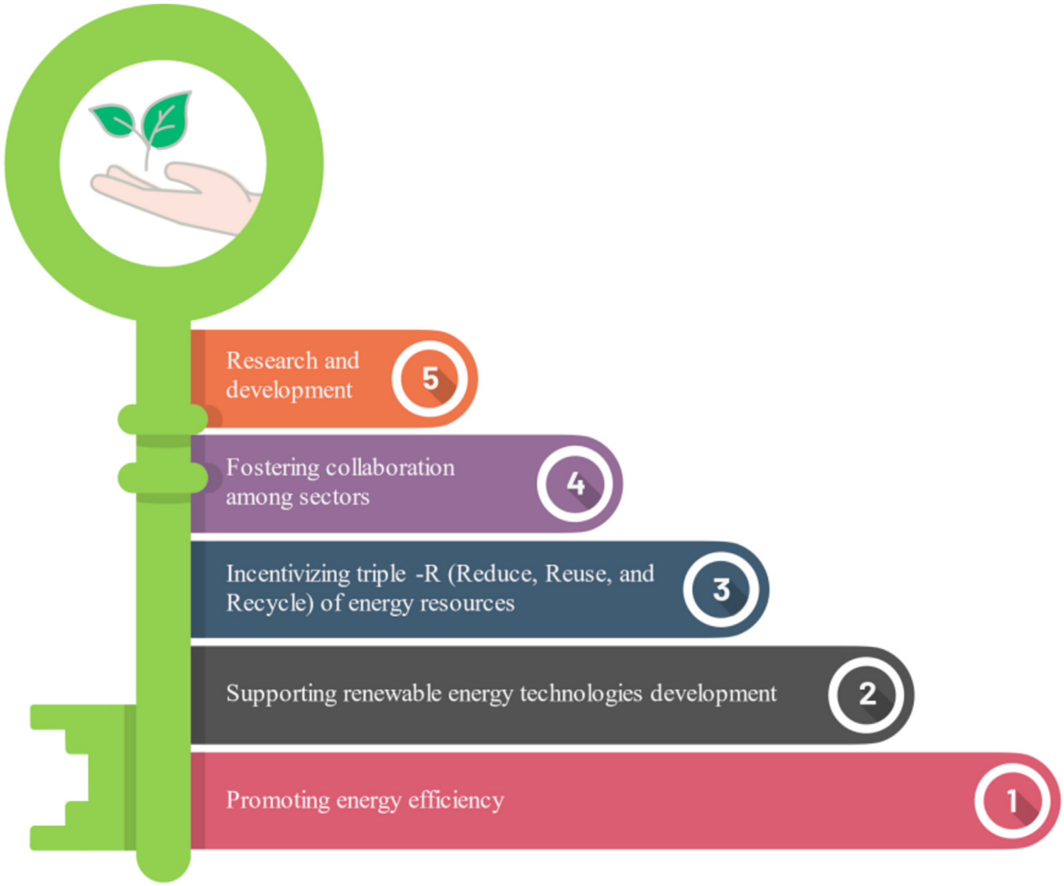

Fig. 6. The exigency and application scenarios of the circular economy for energy policy development.

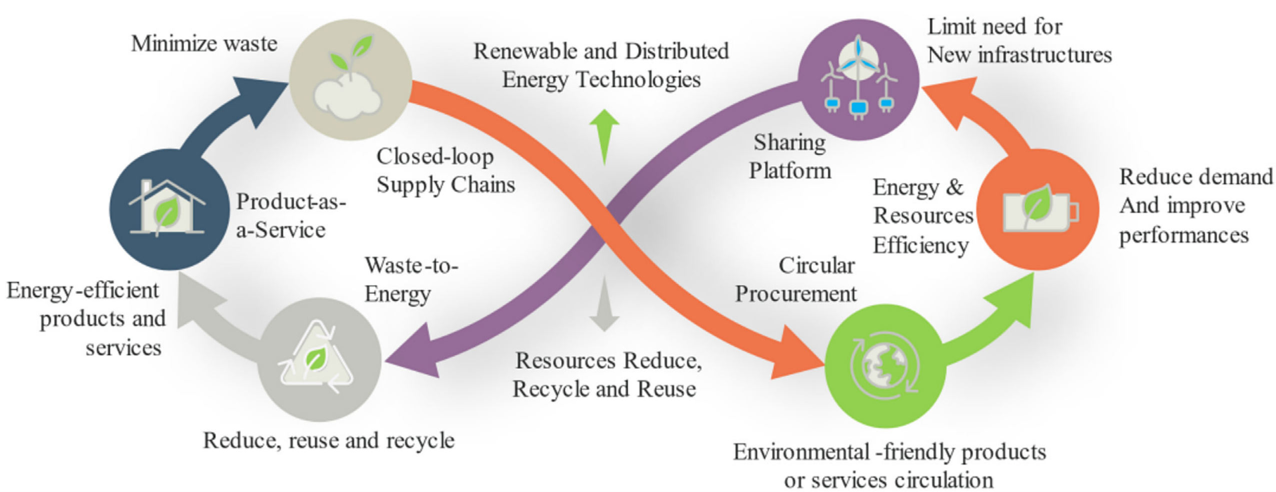

Fig. 7. The proposed framework of circular business model applied in energy systems.

energy efficiency measures, development of smart grid and microgrids, promotion of battery reuse and recycling, and utilization of waste biomass and solid waste to generate energy. Other strategies involve circular heat, carbon capture, energy generation from waste, sustainable supply chains, and circular business models (Fig. 7). Circular business models, such as product-as-a-service, sharing platforms, waste-to-energy, closed-loop supply chains, circular procurement, and energy efficiency services can be implemented to promote the reuse and recycling of materials and energy options. Decentralized energy systems can increase energy resilience and reduce system losses. Interdisciplinary approaches of strategies (Fig. 8) can reduce waste, promote sustainability, and create new revenue streams from waste materials that otherwise will be sent to landfills.

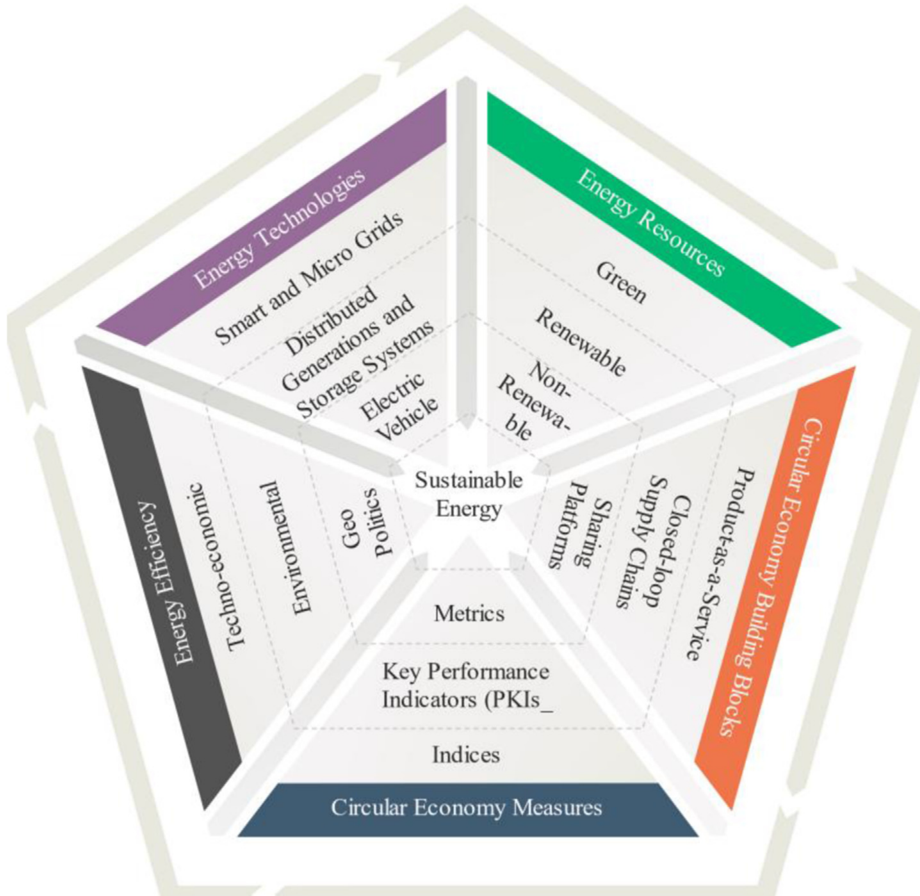

Fig. 8. Big picture of harmonizing energy resources and technologies integration across multiple efficiency requirements based on circular economy business models.

9. Conclusion and the way forward

This study underscores the crucial role of AI in shaping the future of the energy sector, offering innovative solutions to optimize energy systems operations, control, and automation as a critical driver of the energy sector's transformation. The proposed AI-driven policy frameworks and roadmaps aligned with the circular economy business model present competitive and forward-looking approaches to modern energy policy development and implementation. This multidisciplinary approach considers the rapidly changing landscape of the energy sector. It provides a roadmap for researchers, governments, and other stakeholders to address the challenges and unlock the potential of AI for a sustainable, equitable, and impartial energy future.

This study emphasizes the significance of harnessing the potential of AI, promoting circular economy, and creating a possible future that benefits both society and the environment. The unique aspect of this study is the coordinated use of policy indicators, indices, and metrics, which categorizes, identifies, and applies various computational intelligence methods and exposes the integrated roadmaps within multidisciplinary approaches that are followed by summarizing the essential findings and recommendations for energy policy development and implementation in the AI era, with a critical assessment of the current state of energy policies and identification of gaps and opportunities. Through interdisciplinary recommendations, this study will contribute to advancing knowledge and developing effective and responsible energy policies, enabling energy sector policymakers and researchers, and providing rationales to develop a general and adequate energy policy development and implementation roadmap.

Last but not the least, this study has identified several areas for future research, including energy policy management and implementation processes, data management and governance, governance and ethical implications of AI in energy policy, environmental analysis of modern energy policies, the social impact analysis of contemporary energy policies, and international benchmarking and collaboration in the context of modern energy policies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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