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Review article

Digital twin role for sustainable and resilient renewable power plants: A systematic literature review

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ABSTRACT

Transitioning to sustainable and resilient energy generation presents challenges in optimizing resource and storage utilization, reducing operational costs, and addressing environmental impacts within renewable energy power plants. The shift away from fossil fuels in the energy sector requires innovative solutions to enhance sustainability and resilience. This study aims to explore the role of Digital Twin (DT) technology – a digital replica of a physical object or process with bidirectional communication – in promoting sustainability within power plants, an area that remains underexplored. Using a Sytematic Literature Review (SLR) of 61 peer-reviewed papers, this research examines six key categories of DT application: predictive analysis, performance optimization, risk assessment, model evaluation, process traceability, and human–machine interaction. The findings indicate that DT holds significant potential to improve power plant sustainability by enabling cost reductions, optimizing energy usage, and minimizing environmental impact through waste reduction and carbon emission management. This study underscores DT's importance in supporting the energy sector's transition towards sustainable practices and enhancing the resilience of renewable energy systems.

Contents

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Introduction

A substantial increase has been noted in daily electricity usage over the past 20 years. According to Raimi et al. [1], energy consumption is projected to increase by 50% globally by 2050, with the majority of existing energy power plants relying on fossil fuels, which contribute to Green House Gases (GHG) emissions. Due to the earth's finite resources, there is a significant shift in the energy sector towards sustainable energy. This shift involves organizations improving their energy management, increasing the use of renewable energy, reducing operational costs, and minimizing the environmental impact [2]. As part of this ongoing transition, power industries are implementing reforms to enhance their operations, with the goal of improving overall efficiency. These reforms include measures such as enhancing energy conversion rates and adopting advanced technologies like smart grids to optimize operational and maintenance practices. The aim of these reforms is to counteract the detrimental environmental consequences of fossil fuel usage, including air pollution and the exacerbation of climate change. Despite operational efforts to enhance the efficiency of the energy mix, improvements remain marginal due to the incremental nature of these solutions [3].

According to Zitney [4], emerging digital solutions such as the DT demonstrate potential for accelerating the transformation process and improving operational flexibility in the energy sector. DTs, which consist of a physical system, a virtual model, and a connecting data network, leverage computational resources to optimize the performance of their real-world counterparts [5]. Over the past two decades, DT technology has been deployed across a diverse range of applications industries including real-time monitoring [6], manufacturing [7], smart cities [8], healthcare [9], human–robot interaction [10]. For instance, Warke et al. [11] discuss DT's role in smart manufacturing, emphasizing real-time monitoring and shop floor optimization, while Carvalho and da Silva [12] conducted a systematic review highlighting environmental sustainability concerns in DT systems, including issues of fidelity, energy control, and material selection. However, despite DT's demonstrated versatility, its integration within the energy sector remains limited.

Recent studies have increasingly investigated the role of DT technology in energy power plants, with a focus on enhancing operational efficiency, predictive maintenance, and system optimization. Do Amaral et al. [13] identified DT's capabilities in managing energy generation, storage, and distribution, emphasizing its potential to improve efficiency across these processes. However, challenges in scalability and practical implementation have limited its broader application in diverse energy environments. Heluany and Gkioulos et al. [14] demonstrated DT's utility for fault diagnosis and distribution management in energy systems, yet indicated gaps in stakeholder integration and security measures within DT frameworks. Similarly, Ardebili et al. [15] reviewed DT's application for anomaly detection and smart energy system management but identified feasibility issues, including high implementation costs and data management complexities due to Internet of Things (IoT) integration. Other reviews, such as those by [16–21], underscore DT's potential for energy efficiency and carbon reduction but highlight a lack of frameworks capable of supporting long-term, sustainable outcomes within energy sectors. Additionally, [8,22], explored the challenges of integrating DTs with conventional electric grids, while Sifat et al. [23] propose a framework to address complexity in grid operations through DT. Although these studies contribute frameworks for DT application, they lack comprehensive validation and often show biases due to limited database scope. Shah et al. [24] further identified major challenges, such as data acquisition, plant modeling, and taxonomy development for DT applications in energy, emphasizing the need for IoT and Artificial Intelligence (AI) integration to enhance DT's applicability and scalability across power plants.

While these reviews establish DT's transformative potential in energy management, the majority of studies remain theoretical, with limited exploration of DT's practical application and its role in comprehensive sustainability, particularly in terms of resilience and environmental impact. Previous research predominantly addresses isolated DT functionalities, such as predictive maintenance or efficiency improvements, rather than a holistic assessment that encompasses economic, environmental, and social dimensions. This gap highlights the necessity for a systematic evaluation of DT's role in supporting sustainable, resilient renewable energy systems.

In response, this study conducts a SLR to categorize DT technology into six decision-support dimensions: performance optimization, predictive analysis, risk assessment, model evaluation, process traceability, and HMI. By mapping these categories to sustainability objectives, this research provides insights into DT's practical benefits, including cost reduction, GHG emissions mitigation, and enhanced operational resilience. Furthermore, this study examines the emerging role of AI and Machine Learning (ML) in enhancing DT capabilities, with a focus on how these advancements can support sustainability objectives in renewable energy power plants during the transition to cleaner energy sources.

Research Objectives:

To address the challenges and opportunities presented by DT technology in the renewable energy sector, this study undertakes a SLR to explore the scope and impact of DTs on sustainability and resilience in renewable power plants. Specifically, the objectives of this study are designed to address the following two research questions: (1) *How can DT contribute to the sustainability and resilience of renewable energy power plants?* This question evaluates the role of DT technology in supporting sustainable operations, reducing environmental impacts, and enhancing the resilience of renewable energy power plants. It involves analyzing how DT functionalities, such as real-time monitoring, predictive maintenance, and performance optimization, align with sustainability goals. and (2) *To what extent can current research and developments address the gaps and limitations in implementing of sustainable and resilience energy power plants using DT?*. This question reviews existing studies to identify underexplored areas and challenges in DT implementation, offering insights for future research. It highlights current limitations in DT applications, particularly regarding practical scalability, operational efficiency, and the evolving technological needs of the renewable energy sector.

The rest of this paper is organized as follows:

Section "RERs and sustainability": provides an overview of RERs, discussing their importance in sustainable development. Key economic, environmental, and social dimensions are explored, highlighting RERs potential to reduce GHG and enhance energy accessibility.

Section "DT and energy power plant": explores DT technology in energy power plants, highlighting its components, applications, and role in optimizing operations across energy sectors.

Section "Methodology": outlines the SLR methodology and presents a DT taxonomy, categorizing applications across physical, digital, and service spaces. This taxonomy serves as a foundation for analyzing DT's impact on energy sector sustainability and resilience.

Section "Systematic literature outcome": presents the insights of our SLR on the deployment of DT technology across diverse sectors, emphasizing its role as a solution to provide sustainability and enhance resilience in energy power plants.

Section "Discussion": discusses challenges in DT adoption, such as data interoperability and real-time synchronization, and suggests future directions for AI integration and improved data flows. It also discuss potential future research directions and limitation of the study.

Section "Conclusion": concludes with an emphasis on DT's potential to support sustainable energy transitions, recommending interdisciplinary efforts to enhance DT's impact on energy resilience and carbon reduction.

RERs and sustainability

RERs are energy sources that can be continually replenished and provide a constant and limitless supply of energy. These sources such as solar, wind, bioenergy, geothermal, hydropower, and ocean energy are capable of powering various applications including transportation, households, and urban heating [25]. The comparison of the energy sources share (in percentage) in global energy production is shown in Fig. 1.

Sustainable energy refers to a sufficient measure of energy management undertaken by organizations to reduce energy usage, increase the use of RERs, reduce operational costs, decrease the environmental impact of energy use, and positively impact society [26]. This definition includes the key components of affordability, accessibility, replenishable, safety for the environment, and long-term availability [27]. The environmental aspect of sustainability is often justified through the concept by considering renewable energy share, optimized natural resource usage, and climate or air quality indicators for carbon footprint and GHG emission reduction [28]. The economic aspect of sustainability includes efficiency, productivity, and export growth of sustainable energy at cost-competitive with traditional fossil fuels [29], that must be affordable for individuals, businesses, and governments [30], generated and used efficiently and effectively, and able to scale to meet the growing energy needs of a population or economy [31]. The social aspect of sustainability is often intertwined with the concepts of energy security, and equitable access, irrespective of geographic location or socioeconomic status [32]. Rather than fossil fuel, RERs are aligning with sustainable development more than ever before because fossil fuel are limited, and harmful for environment [33]. A comparison of renewable and conventional energy systems is presented in Table 1. These RERs cause minimal environmental harm due to their distributed and low-intensity nature. Additionally, as these sources capitalize on natural environments, their potential supply effectively outpaces the finite nature of conventional energy. They embody the definition of sustainable energy management, leading to reduced energy usage and operational costs while minimizing environmental impacts [26].

Despite their potential, the intermittency and unpredictability of some RERs, such as wind and solar, due to variable weather conditions, present significant challenges [34]. These include the technological disparities encountered in power-heavy industries and long-haul transport sectors [35], management of variable supply [36], and integration of clean technologies [37]. Initial costs and expenses for energy storage systems are substantial and introduce an element of unpredictability [38]. Therefore, there is a need to design strategies and optimization methods for effective planning and control of power generation and distribution within renewable energy systems [39]. According to Shaari et al. [40], predictive analytics and optimization techniques like Particle Swarm Optimization (PSO) [41] and Genetic Algorithm (GA) [42], have been extensively used to manage the fluctuating production associated with RERs. Through demand response programs and predictive control mechanisms, energy systems can adapt to the supply conditions, making energy generation and distribution within renewable energy systems more efficient and reliable [43].

Sustainability dimension for RERs

Sustained growth in global electricity demand and major reliance on fossil fuels have given rise to environmental, geopolitical, and economic challenges. As a result, transitioning to RERs is key to confronting these challenges and fostering sustainable energy systems.

To ensure a successful energy transition, it is essential to understand the key contributing factors to the sustainability and resilience of energy power plants [45]. This knowledge is critical in developing strategies to promote sustainable practices, optimize resource use, and improve overall power system performance. Table A1 in Appendix A compiles various scholarly papers to provide an in-depth examination of the economic, environmental, and social dimensions of RERs. The table offers a holistic perspective to assessing sustainability in energy systems ensuring the alignment of economic prosperity, environmental protection, and social equity.

After a thorough analysis of the sustainability and resilience dimensions found in Table A1 in Appendix A, we have pinpointed essential dimensions critical to the sustainability and resilience of energy power plants. These crucial dimensions, listed in Table 2, can guide decision-making and strategy formulation, paving the way for a successful energy transition and equipping power plants to adapt to changing conditions and maintain operational efficiency.

The LCOE serves as a critical metric for comparing different energy sources, providing a comprehensive evaluation of costs over the entire life-time of a energy power plant [50,51]. Notably, advancements in technology have narrowed the cost gap between thermal and renewable power generation [52]. It is calculated as the average net present cost of generating electric power, considering both fixed and variable costs [46]. This LCOE used for evaluating the economic viability of a energy power plant, as it provides a comprehensive cost analysis that takes into account various expenses associated with electricity production. By examining the total cost of electricity production, stakeholders can gain valuable insights into the profitability of a energy power plant and make informed decisions about its future operation.

Social aspect, in respect to sustainability, influenced by energy affordability, creates divergent experiences around the globe [53]. Advanced economies enjoy straightforward access to clean and affordable energy, promoting general well-being and economic growth, alternatively, in resource-poor settings, the population often combats challenges related to energy utilization [54]. Resources like wood and dung are routinely burned for energy, leading to health implications from indoor pollution. It underscores the critical importance of equity in energy access and affordability in driving social sustainability.

The concept of diversification involves adopting multiple energy sources to enhance energy security, reduce environmental impact, and improve the reliability of the energy system [55]. The objective of diversification is to ensure the sustainability and stability of energy supply during the transition period, mitigate the impacts of an energy crisis, and support innovations in the energy industry [56].

Energy security, which is largely contingent on the diversification of energy sources, can be compromised due to over-reliance on a single type of energy source or excessive imports [57]. The measurement of diversity in energy sources can be effectively gauged through the utilization of several reputable indices, and among these the SWI, a reputable diversity measurement by Jansen et al. [48], which evaluates the

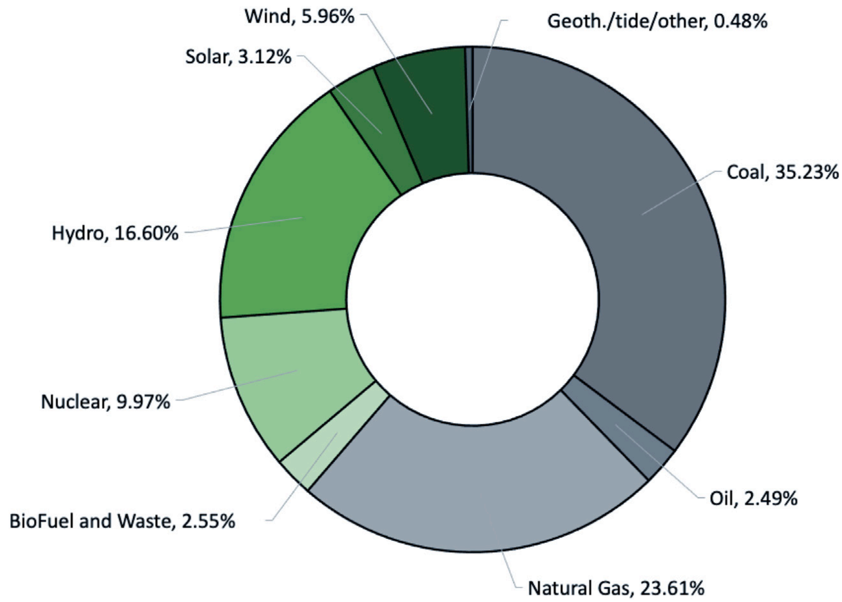

Fig. 1. Comparison of the energy sources as percentages of the share in global energy production.

Table 1
Comparison of renewable and conventional energy systems [44].

Factors	Renewable energy supplies	Conventional energy supplies
Examples	Wind, Solar, Biomass, Tidal, Hydropower	Coal, oil, gas, radioactive ore
Source	Natural environment	Concentrated stock
Initial average intensity	Low intensity, dispersed: $\leq 300\ \mathrm{W/m^2}$	Released at $\geq 100\ \mathrm{kW/m^2}$
Lifetime of supply	Infinite	Finite
Cost at source	Free	Increasingly expensive
Equipment capital cost per kW capacity	Expensive, commonly = $1,000	Moderate, perhaps $500 without emissions control, yet $1,000 with emissions reduction
Scale	Small-scale often economic	Increased scale often improves supply costs; large-scale frequently favored.
Dependence	Self-sufficient systems encouraged	Systems dependent upon outside inputs
Pollution and environmental damage	Usually little environmental harm, especially at moderate scale	Environmental pollution common, especially of air and water.

Table 2
Key sustainability and resilience dimensions for energy power plant transition to renewable energy.

Dimensions	Sub-dimension	Description	Citation
Economical	Levelized Cost of Energy (LCOE)	Capital cost	[46]
		Operational and maintenance cost	
		Fuel cost	
		Discount rate	
		Energy generated (capacity utilization of energy power plant)	
	Energy Conversion Efficiency	Efficiency of energy conversion including fossil fuel efficiency for electricity generation, efficiency of oil refining and losses occurring during electricity transmission	[47]
	Diversification	The index mostly used to measure diversity is the Shannon-Wiener Index (SWI): $H = -\sum_i p_i \ln p_i$, where H represents Shannon-Wiener Index, p_i representing the share of fuel i in the energy mix or the market share of supplier i, and $\sum_i$ indicates the calculation is applied across all fuels or supplies in the system. The higher the value of H, the more diverse the system is.	[48]
Social	Accessibility	Share of households (or population) without electricity or commercial energy, or heavily dependent on non-commercial energy	[49]
Environmental	GHG	Measurement of CO_2 during electricity generation, GHG emissions from energy production and use per capita and per unit of Gross Domestic Production (GDP)	[49]

level of diversification by weighing the number of energy sources and their proportional representation. As the proportion of RERs increases in the energy mix, the SWI rises, reflecting improved energy security. In the context of resilience, diversified energy sourcing plays a crucial role, enabling a system, community, or society to adapt to potential hazards and maintain acceptable functioning and structure [58].

Diversification, when measured effectively, provides a buffer against energy supply disruptions, guiding power generators towards a more sustainable future. Resource diversification is vital in complex energy systems like energy power plants, strengthening their sustainability [59]. Moreover, such strategies within shared resources lead to optimal operational efficiency and significant cost savings.

DT and energy power plant

According to Grieves and Vickers [60], the purpose of DT technology is to create a virtual model that replicates the real system in order to simulate, predict, and optimize the system functions using bidirectional communication. It provides a dynamic mirror of a physical system that allows for real-time analysis, monitoring and decision making [61]. By doing so, organizations can better understand how their systems are performing, identify potential issues before they become problems, test new ideas, and optimize operations for better efficiency and performance. .

With the rapid advancements in technology, the digital space has evolved from simple visual and technical representations to encompass a range of complex operations such as modeling, testing, and optimization [62]. The DT houses the actual product's properties, state, and behavior within its models and data, offering a prediction of the object's operational environment. Moving beyond the traditional three dimensions, Tao et al. [63] introduced a five-dimensional DT model:

1. Physical entity, an actual phenomenon in a physical product.
2. Virtual entity, is a set of digital models representing the physical entity.
3. The data model, consists of data from the physical and virtual entity, data from services, and domain knowledge.
4. Bidirectional connections between the physical entity, virtual entity, data model, and service space.
5. Services space, includes services for the physical and virtual entity, including optimization, assessment, prediction, and validation.

The DT model, as illustrated in Fig. 2, is characterized by seamless and autonomous interactions among its five dimensions. These dimensions are readily accessible and designed to ensure efficient utilization. According to [64,65], the services, which listed as the final dimension, offers a simplified user experience by providing comprehensive analysis across all stages, regardless of the users' technical proficiency. This dimension is crucial in ensuring the optimal performance of the DT, as it facilitates the effective utilization of all other defined dimensions. The DT can be customized to accommodate various factors, such as resources, data, modeling, and product life-cycle. As a result, the DT, with its integral dimensions, represents a dynamic and complex concept throughout its lifespan. These five crucial dimensions of the DT promote a dynamic and potentially complex concept throughout its life cycle.

Utilizing advancements in communication and information technology, the process of digitalization is transforming industrial value chains under the framework of Industry 4.0 [66]. DT technology, a cornerstone of this evolution, acts as a catalyst for highly efficient, adaptable, and automated production systems [63,67]. The potential of DT extends beyond industrial applications, finding significant relevance in energy management, where it enhances operational efficiency and sustainability. According to Lu et al. [67], DTs are crucial in energy

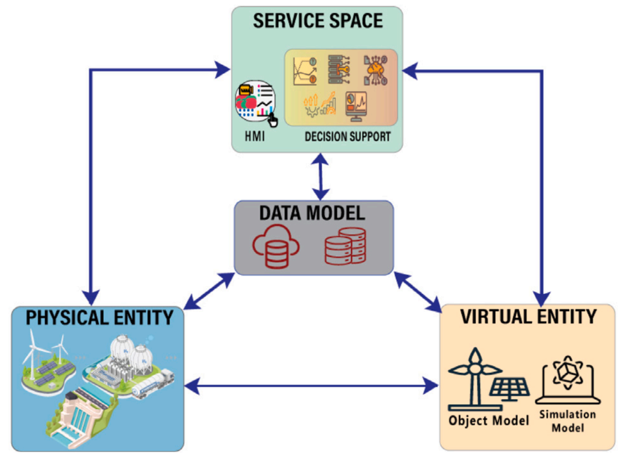

Fig. 2. Structure of a DT five-dimensional model [64,65].

plant operations, enabling real-time monitoring, predictive maintenance, and operational simulations that optimize plant efficiency and reduce environmental impacts.

Despite the promising advancements, there remains limited coverage in the literature on DT applications specifically tailored to energy systems, as highlighted in [3]. This study compiles and categorizes these applications in Table 3, providing an overview of DT implementations across various energy domains, detailing the purpose and associated limitations. This summary aids in understanding DT's evolving role in the energy sector, highlighting areas needing further research and refinement.

In nuclear power, DTs facilitate predictive analytics for service life and decommissioning, enhancing safety and cost efficiency in complex operations [68]. Within thermal power plants, DT applications focus on real-time performance monitoring and system optimization, specifically in steam turbine control stages, employing hybrid modeling to improve operational efficiency and potentially reduce coal consumption [18,67,69]. In renewable energy contexts, such as offshore wind energy, DTs provide remote monitoring and predictive maintenance, minimizing downtime and optimizing output, though limitations arise from data availability in remote environments and varying weather conditions [70,71]. In hydroelectric systems, DTs enhance operational sustainability by detecting current fluctuations in synchronous machine generators, helping prevent damage and reduce maintenance costs [72,73]. In the case of Photovoltaic (PV) panel-level power converters, DTs are effectively used for real-time fault detection [74]. Emerging studies underscore DT's role in microgrid energy management. For instance, DTs combined with IoT technologies facilitate resilient microgrid operations through ML models, which enable real-time adjustments, optimal scheduling, and load balancing to maintain sustainable energy distribution even during extreme weather or grid disruptions [75]. Similarly, smart city planning employs DT to simulate renewable energy infrastructure placements, assess demand, emissions, and costs, and promote community-friendly installations, underscoring DT's potential in sustainable urban development despite constraints related to budget and real-time adaptability [76].

In advancing net-zero urban energy systems, DT models address renewable energy variability by optimizing storage solutions within smart grids, balancing loads to reduce dependence on non-renewable sources and enhance resilience under fluctuating supply conditions [77]. In integrated multi-energy systems, proposed DT model coordinate thermal and electrical energy, improving efficiency and reducing costs through real-time demand response and intensive simulations [78]. Furthermore, DTs are being integrated with Electric Vehicle (EV) dynamics and blockchain technology to enhance secure energy management

Table 3
Summary table of existing implementations of DT in energy power plants.

Application area	Purpose of DT used	Limitation	Citation
Nuclear Power Industry	To predict service life and model decommissioning processes, both of which have safety and cost implications.	No data handling and management	[68]
Thermal power plant (330 MW steam turbines and 1000 MW ultra supercritical steam turbine)	To enhance accuracy in real-time performance monitoring and optimization in steam turbine control stage systems.	Unable to obtain all relevant internal geometric data.	[80]
Thermal power plant (320 MWe coal-fired thermal power plant unit)	To implement two optimization solutions to potentially reduce electricity coal consumption by up to 3.5 g/kWh, results in significant cost savings.	Relies on accurate data. Limiting generalizability, insights not universally applicable.	[69]
Thermal Power Plant (660 MW ultra-supercritical double reheat power plant)	To perform accurate simulation, system optimization, and integration of renewable resources of in-service energy power plant, which demonstrates remarkable validation with an average simulation error rate of 0.79% over the full working range.	Limited in obtaining key characteristic parameters.	[18]
Renewable Energy (power converters in offshore wind turbines)	To predict the remaining useful life of the power converter to optimize Operation & Management	Limited applicability.	[73]
Renewable Energy (three-phase synchronous machine generator of 310MVA, 56 poles, 13.8kV)	To prove that under-excitation and over-excitation modes increased the generator's current magnitude by at least 11% and 20%, respectively, resulting in reducing downtime and costly damages.	Considers few variables affecting the hydro generator's operation.	[72]
Renewable Energy (PV panel-level power converter prototype)	To simulate real-time and field conditions across a variety of faults. The approach could quickly detect and precisely identify various types of faults, including incipient ones, due to the difference between estimated and measured outputs.	The proposed paper focuses on fault detection, not remediation strategies.	[74]
Urban Smart City Energy Landscape	To model and simulate renewable energy landscape design, integrating IoT for data-driven decisions for emission reduction.	Synchronization with industry 4.0 automation needed.	[70]
Microgrid Energy Management	To enhancing resilience and flexibility in microgrids by employing a ML techniques for optimal scheduling under normal and resilient scenarios. Incorporates simulation and IoT monitoring for real-time adjustments to demand response programs and landscape design in renewable energy integration.	Limited in scalability across larger networks due to specific microgrid-focused algorithms.	[75]
Offshore Wind energy	Remote monitoring and predictive maintenance for minimizing downtime and maximizing output.	Limited data availability for remote turbine conditions and limiting applicability in unpredictable weather conditions.	[71]
Smart City Planning with Renewable Energy	To optimize urban renewable energy infrastructure placement through DT, assessing energy demand, emissions, and costs for community-friendly smart city planning.	Real-time adaptation is limited; budget constraints impact large-scale deployment.	[76]
Net-Zero Smart Cities with Renewable Energy Uncertainty	To optimize storage solutions for better load balancing and reduced reliance on non-renewable sources.	High variability in renewable sources challenges storage predictions.	[77]
Microgrid with Multi-Energy Carrier Model	To manage thermal and electrical energy within microgrids using a Multi-Agent System-enabled DT for real-time demand response and efficiency.	Extensive computation required and limited real-world application data.	[78]
Microgrid with EV Integration	To enhance secure energy management in smart cities by integrating blockchain with DT for resilient EV-grid interactions and cybersecurity.	Complexity in managing EV data and blockchain transactions with renewable supply.	[79]

within microgrids, supporting sustainable EV-grid interactions through enhanced cybersecurity and adaptive energy allocation [79].

However, these applications face several limitations. Key challenges include managing vast data flows, ensuring reliable internal geometrical data, achieving consistent accuracy in real-time data, and limited generalizability across varied energy systems. Additionally, constraints exist in obtaining essential operational parameters, and some applications focus narrowly on fault detection without comprehensive remediation strategies. Addressing these limitations will require robust data management and more extensive fault remediation frameworks, as well as the development of scalable DT models adaptable to diverse energy infrastructures and conditions.

While DT technology offers transformative potential for enhancing the efficiency and sustainability of energy power plants, ongoing advancements in AI and ML can further enrich DT applications, enabling continuous system improvements and robust decision-making frameworks. Continued research aimed at overcoming current limitations will allow DTs to play an increasingly integral role in transitioning to RERs, making energy systems more adaptable, efficient, and environmentally sustainable.

While there have been notable progress in the implementation of DTs in energy power plants, there are also areas that require improvement, particularly in terms of data management and the development of comprehensive strategies for fault remediation. It is essential to gain a comprehensive understanding of the current state of DT applications, their potential benefits, and the challenges associated with utilization of them in renewable energy power plants.

Methodology

A SLR is a rigorous and meticulous approach for collecting, examining, and synthesizing relevant studies from a specific research area or topic [81]. Unlike conventional narrative reviews, SLRs follow a structured protocol that is both transparent and scientifically grounded, resulting in comprehensive documentation of the reviewer's methodologies, choices, and findings [82]. Using the SLR approach by Yavari [83], papers were collected relating to DT technology as a solution across various sectors. A systematic process was employed to identify, screen, and implement the eligibility of papers using the

Table 4
Annual distribution of papers by publisher for related work Analysis.

Year	MDPI	Elsevier	IEEE	ACM	Springer	Total/year
2022	73	190	189	7	140	599
2021	82	198	319	10	141	750
2020	36	106	153	7	95	397
2019	8	46	82	2	52	190
2018	1	16	27	0	15	59
2017	0	9	8	1	3	21
Total Papers	200	565	778	27	446	**2016**

Preferred reporting items for systematic review and meta-analysis protocols (PRISMA) technique [84] (see Fig. 3 for details) in order to gain a comprehensive understanding of the existing knowledge on the subject. Only papers written in English were included in the review.

To conduct a comprehensive search for articles, the Publish or Perish software (www.harzing.com/resources/publish-or-perish), access on 07 September 2022, was employed to examine the Google Scholar (https://scholar.google.com) database for publications published between 2017 and 2022. Five prominent publishers, including Institute of Electrical and Electronics Engineering (IEEE) (www.ieee.org), Multidisciplinary Digital Publishing Institute (MDPI) (www.mdpi.com/), Association for Computing Machinery (ACM) (www.acm.org), Springer (www.springer.com), and Elsevier (www.elsevier.com) were investigated. Initially, an extensive set of search terms, including 'digital twin,' 'digital twins,' and 'digital twinning,' was utilized. These terms were combined with multiple aspects of sustainability and resilience in energy systems, resulting in a comprehensive query as follows: "('digital twin OR digital twins OR digital twinning') AND ('sustainability' OR 'economical sustainability' OR 'environmental sustainability' OR 'social sustainability') AND ('resilience') AND ('energy system' OR 'energy power plant' OR 'renewable energy sources' OR 'renewable energy plant')".

The search produced 200 articles from MDPI, 778 from IEEE, 565 from Elsevier, 446 from Springer, and 27 from ACM (refer to Table 4). These articles were imported into the EndNote library (https://endnote.com/, where 41 duplicate entries and 3 records not published in English were identified and removed, resulting in a total of 1972 articles being compiled for initial review. After screening the titles and abstracts, 280 articles (by title n=111, by abstract n=169) and 5 inaccessible articles were excluded, leaving a total of 1687 articles. The remaining articles were assessed for relevance based on predetermined criteria (outlined in Table 5), leading to the exclusion of 425 review and 10 conceptual articles. The 1252 articles that passed the initial screening underwent a thorough quality assessment, during which articles with zero citations (n=628) and those outside the top 10% of citation percentile for their publication year (n=563) using the equation defined in Eq. (1) (extends from [83]) were eliminated.

$$\mu_j = \frac{p \times (n_j + 1)}{100} \tag{1}$$

where:

- μ_j is the percentile rank for the year j,
- p is the percentile, and
- n_j is the total number of papers published by all five publishers in one year (i.e., j).

After conducting a rigorous selection process, a total of 61 articles were chosen for in-depth analysis in this systematic review. Each of the selected articles was thoroughly examined to gather data on the application of DTs, with a particular focus on instances that promoted sustainability or enhanced system resilience, regardless of whether these were the primary objectives of the publications. To ensure the validity and reliability of the review, two of the authors independently assessed each article's eligibility based on the predefined inclusion criteria. In cases where disagreements arose regarding eligibility, discussions were held to reach a consensus, and, when necessary, a third author was consulted to arbitrate and finalize the decision. This multi-step validation process was implemented to minimize selection bias and enhance the credibility of the review.

Review taxonomy

In this paper a distinct taxonomy is constructed, based on definition of DT by Grieves and Vickers [60], to thoroughly analyze and evaluate the 61 selected papers. The taxonomy extends beyond the original definition to emphasize the physical space, virtual space, and service space in the concept of DT, as well as their interconnections. This taxonomy offers a novel perspective for examining and comprehending the diverse approaches utilized by authors in implementing DT in their respective papers.

Three distinct spaces are encompassed within the DT taxonomy, as depicted in Fig. 4. Physical space delineates the tangible elements of the system that exist in the real world. Digital space encompasses data transformation and utilization, which are critical functions of the system. Lastly, the Service space highlights the interactions with users and aids in decision-making. Collectively, these spaces offer a holistic view of the operation and user engagement within the DT system. The subsequent sections delve into the specifics of each space.

Physical space

Physical space discusses physical entities like vehicles, components, products, systems, models, and artefacts. The commonalities in these entities lie in their connection with the physical world. While this list of terms all refers to man-made entities, the interest of DT has grown in the DT of humans [87], farms [88], and agriculture [89]. The physical space consists of assets, people, and processes. An asset is defined as sensors, actuators, and equipment (machinery) used in the physical world to sense, act and perform different actions and tasks. People in the physical world are human beings. For example, the implementation of a DT as discussed in [90], employs a scenario where Augmented Reality (AR) is used to create a real-time simulation of a worker or engineer operating a torch machine, providing safety measures by calculating a safe distance from the machine. Process in the physical world is a series of events to produce a result, such as designing, packing, or manufacturing a product in a factory.

Digital space

In the field of DT, the concept of digital space has been formalized by various scholars, including Glaessgen and Starge [91], Tao et al. [92], and Karakra et al. [93]. Digital space is a virtual representation of a physical entity that is used to collect data, run simulations, and investigate performance issues to generate valuable insights. These insights can then be applied back to the original physical entity. The digital space is divided into two categories including data management and data processing.

Data management includes data collection, storage, and modeling, while data processing encompasses fusion, analysis, and simulation. Data collection in the DT involves gathering information from the physical environment, such as sensor data from equipment, materials, processes, and workers. According to ISO 23247-3 [94], physical entity related data can be categorized into two categories including static information concerning the physical entity (e.g., identification, characteristics, schedule) and dynamic states (e.g., status, location, relationship) [95]. International Business Machines Corporation (IBM) defines data storage as magnetic, optical, or mechanical media that

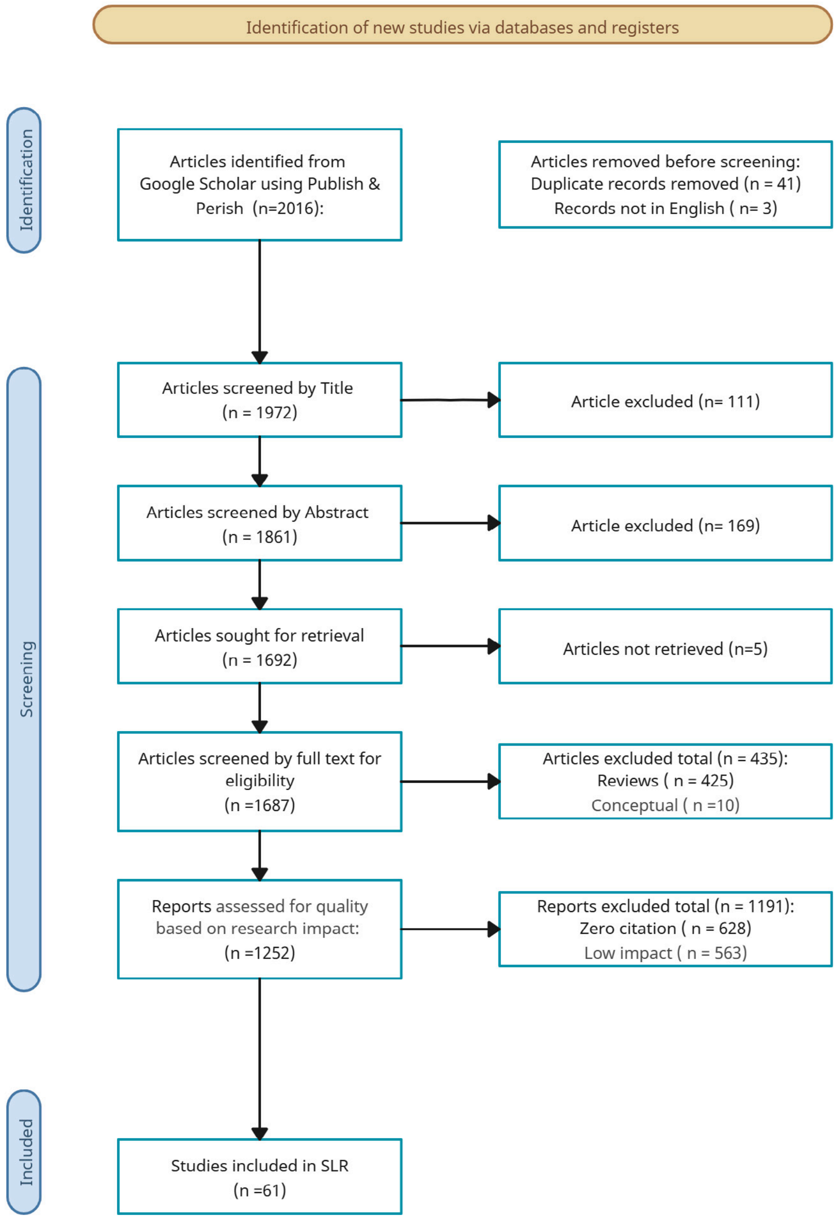

Fig. 3. Flow diagram [85] of the literature selection process and criteria applied in different steps of the process [86].

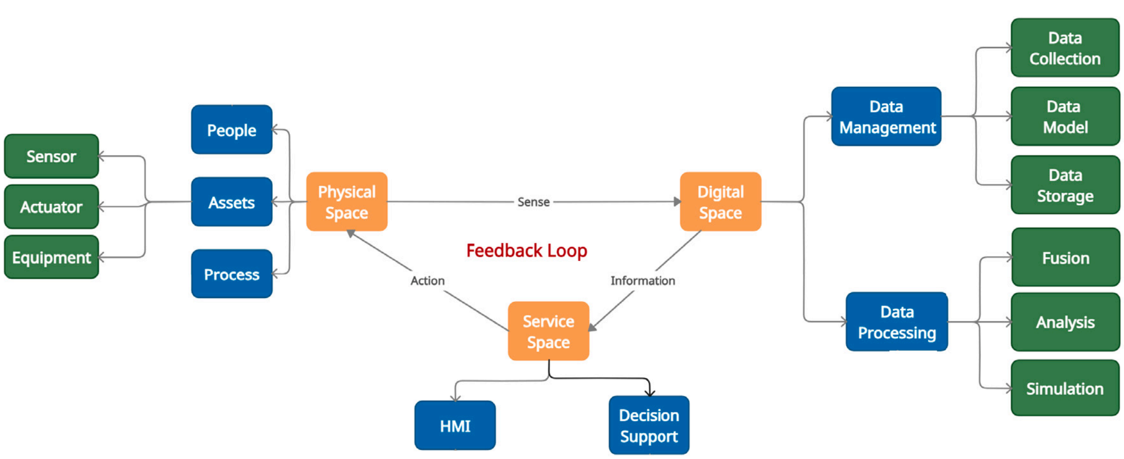

Fig. 4. Taxonomy of a DT, encompassing physical, digital, and service space.

Table 5
Inclusion and exclusion criteria.

Inclusion Criteria:
• Articles focus on the concept of the DT technology as a solution framework in case studies or real-world applications across various sectors. • Original research presenting empirical data and primary studies. • Published in peer-reviewed journals from 2017 to 2022. • Accessible full-text articles written in English, as articles in other languages were considered out of scope for this review.
Exclusion Criteria: • Articles that discuss DT technology in a purely theoretical manner without any original empirical data or evidence of practical application. • Secondary studies such as literature reviews, opinion papers, editorials, and other forms of meta-analyses. • Non-peer-reviewed materials, including conference proceedings, book chapters, unpublished theses, and position papers. • Studies focusing on unrelated applications of DT technology outside the context of solving specific problems in various sectors.

records and preserves digital information for ongoing or future operations [96]. Data modeling for a DT, as described in [97], is defined as the practice of structuring and defining data elements using specific syntax and semantics, allowing for the organization, communication, and storage of information in a standardized, machine-readable format. These structured data representations facilitate interoperability and data exchange between different systems and applications which is crucial for facilitating the processing and analysis of the diverse data collected.

In data processing, statistical analysis, ML, and data mining techniques are utilized to uncover hidden patterns within large datasets, which can be unearthed through techniques such as association rule mining, clustering, and anomaly detection [98]. Data fusion involves the integration of data from multiple sources to create enhanced, precise, and reliable insights, improving comprehensiveness and accuracy [99]. This process can take place at various levels, such as sensor level, feature level, decision level, and multi-modal level. Additionally, data processing simulation replicates a real-world process, system, or phenomenon within a digital environment, where models are used to observe system dynamics, predict outcomes, assess performance, or test various strategies without interfering with the original system [63].

Service space

The DT service space leverages digital information to direct actions in the physical world. Transformed and analyzed data is conveyed in a comprehensible and actionable form, allowing for seamless implementation in decision-making processes. The DT service space comprises two sub-categories, HMI and decision support, which both rely on these insights.

HMI, is the interface that enables interaction between a human and a machine or computerized system. It comprises hardware and software components that allow the operator to manage system processes, review data, and input information [100]. Key attributes of HMI at this layer include accessibility, intuitiveness, and usability, ensuring effective control and understanding of insights by the users.

Decision support refers to the use of analytical models, and data analysis to help organizations and individuals make informed decisions based on an understanding of their possible practical and theoretical outcomes [92]. The goal of decision support is to produce actionable insights that improve the quality of decision-making. Visualization allows for the representation of data in visual formats such as graphs and maps, enabling easier comprehension and interpretation. It is particularly useful in pattern and trend identification, as well as for communicating insights.

Systematic literature outcome

The insights of our SLR on the deployment of DT technology across diverse sectors and its potential as a solution towards sustainable and resilience energy power plants are presented in this section. First, a taxonomy, described in Section d, is developed to analyze and investigate the literature as per three main spaces including physical, digital, and service spaces. Then, the role of DT in the context of the sustainability and resilience of energy power plants is investigated.

Analyzing outcomes with DT taxonomy perspective

In this section, the literature was investigated using the DT taxonomy outlined in Section "Methodology". A comprehensive analysis of the 61 selected papers is presented in Table B1 of Appendix B.

Upon reviewing the papers on physical space (as shown in Table 6), only 53 out of 61 incorporated assets like sensors and actuators to validate their proposed DT models. The remaining 8 papers relied solely on historical data, excluding real-time data collection for experimental purposes. Furthermore, the papers gave low emphasis on people and process, with only 11 and 14 papers incorporating these aspects, respectively.

Of the 61 papers reviewed, 36 discuss data collection through sensors in both physical and digital spaces. As shown in Table 6, only 16 papers address the data model for collected data from the physical space. These papers stress the importance of modeling heterogeneous data in a uniform format, with specific techniques mentioned in their experiments before storing them. Meanwhile, data storage techniques were addressed in only 18 papers. For example, [101] utilizes Structured Query Language (SQL), while [91] employs text files for data storage. However, these techniques may not be suitable for large-scale systems. Additionally, a total of 53 papers have employed AI and ML techniques, such as Principal Component Analysis (PCA) [102], Long Short-Term Memory (LSTM) [103], Convolutional Neural Networks (CNN) [104], Support Vector Machine (SVM) [105] are commonly used algorithms in DT frameworks for tasks such as data analysis, monitoring, prediction, and decision-making. Among these, 29 papers utilize simulation techniques. However, the area of data fusion is often overlooked, with only 12 papers addressing this issue. Data fusion is crucial for generating compatible data formats that can be processed collectively.

The Table 6 indicates that in service space 51 out of 61 examined papers implemented the DT across various fields for decision-making, including fault and risk assessment, performance optimization, predictive analysis, process traceability, and optimal model evaluation in production and manufacturing [69], automation and robotic [90], energy power system [106],healthcare [9].

In contrast, HMI integrates immersive reality technologies, such as AR and Virtual Reality (VR), found sparse representation in the selected papers, with only 8 of these using such technology to augment user interaction, planning, and design experiences. Despite the enhancement of safety and user involvement, HMI remains largely unexplored.

Table 6
Distribution of DT implementation within a constructed taxonomy including physical space (i.e., assets, people, and process), digital space (i.e., data management and data processing), and service space (i.e., decision support and HMI).

DT spaces			No. of papers
Physical Space	Assets		53
	People		11
	Process		14
Digital Space	Data Management	Data Collection	36
		Data Model	16
		Data Storage	18
	Data Processing	Fusion	12
		Analysis	53
		Simulation	29
Service Space	Decision Support		51
	HMI		8
Bidirectional Data Transmission			17

Although bidirectional data transmission has been mentioned in only 17 out of 61 papers, it remains an essential aspect for real-time synchronization between the physical and digital space. Further research in this area could lead to more efficient management of complex physical spaces through the incorporation of actuation support, which enables reactions in the physical space based on the virtual space output. Enhancing these features could result in a more seamless exchange of data between the two environments, ultimately improving the capabilities of DT technology.

Role of DT for energy power plant sustainability and resilience

This section presents a comprehensive analysis of selected papers, highlighting the various DT decision support categories that may be potentially relevant to contributes towards sustainability and resilience of energy power plants. Reviewing the included papers shows that decision support categories of DTs implemented in various application domain can be broadly classified into six categories: predictive analysis, performance optimization, risk and fault assessment, optimal model evaluation, process traceability and HMI. Table 7 summarize the potential of DT technology in leveraging these decision support categories for power plant sustainability and resilience, which is further elaborated on in the following sections (detailed analysis are provided in Appendix C Table C1).

Predictive analysis

Predictive maintenance technology offers a range of benefits including cost reduction, aiding regulatory compliance, improving safety, and mitigating the issues of old infrastructure. A stream of the literature focuses on predictive analysis with innovative approaches aimed at minimizing downtime and enhancing operational efficiency across a diverse range of domains [127]. From predicting the RUL of critical machinery to foreseeing anomalies that could lead to system failures, these predictive models play a pivotal role in optimizing performance and reducing operational costs [128]. Moreover, they are not limited to one specific sector, the industry is seeing continuous development in predictive maintenance techniques, especially by utilizing the IoT and advanced data analytics.

The four selected papers in Table 7 highlight the significant impact of specific predictive maintenance models in minimizing downtime, enhancing operational efficiency, and reducing costs by predicting resource consumption and facilitating demand forecasting. For example, Priyanka et al. [101] proposed a machinery prognostic model that improved operation and maintenance by predicting the RUL of oil pipelines based on abnormal pressure fluctuations. Similarly, Hosamo et al. [106] developed a predictive maintenance model for an Air Handling Unit (AHU) using an Artificial Neural Netwrok (ANN) [129] and SVM [105] to detect anomalies and estimate the RUL of the AHU. Additionally, Yang et al. [107] implemented a hybrid ML model to predict the degradation of transmission units, while Park et al. [110] employed heuristic rule planning in a production process to optimize resource use and anticipate abnormalities. These proactive maintenance models help in maintenance planning by enable optimized scheduling and reduce energy costs by minimizing downtime.

By leveraging predictive analytics, organizations can gain meaningful information into resource utilization patterns and make informed decisions to enhance operational efficiency. This proactive approach aids in cost optimization by effectively managing resource allocation based on accurate predictions of future workloads [130]. As shown in Table 7 predictive analytic minimize costs through resource consumption optimization, as [112–114] used predictive models for demand forecasting and resource consumption optimization, as well as improving system health forecasting. These analytical models help in reducing waste, cutting costs, scheduling effective resource management and preventative maintenance. Overall, the papers in the literature show how predictive analysis can enhance efficiency and reduce operational costs in sectors such as energy. However, there is still potential for further research to uncover more applications in energy power plants.

Performance optimization

Performance optimization is important in various industries to improve the efficiency and effectiveness of systems. It can benefit the entire industry by expanding the design space and heuristic knowledge base while maintaining sustainability [131]. By maximizing output while minimizing resource utilization, organizations can achieve cost savings, increase revenue, improve customer satisfaction, and gain a competitive advantage [132]. Literature suggests that performance optimization is closely related to sustainability, as it can improve development plans, scheduling, cost reduction, and pollution reduction [133]. Additionally, Deng et al. [134] highlights the need for a comprehensive evaluation of power system performance from a sustainability perspective. This argument is supported by Sunder Raj [135] to discuss the shift towards fleet-wide performance monitoring and optimization in energy power plants for maximum economic benefits.

Reducing downtime, increasing operational and energy efficiency, optimizing resource allocation, reducing waste, and cutting costs are some of the benefits of performance optimization, as shown in Table 7. In robotic and automation application, Li et al. [90] implements a DT framework using Reinforcement Learning (RL) [136] enabled motion planning algorithm to enhance productivity and reduce downtime in handling operation and maintenance cost. The concept of defect detection is another important aspect to consider in the multifaceted field of performance optimization. [117,118] utilize a thorough analysis of various performance attributes of a system to increase the accuracy of detecting defects, which is central to achieving sustainability objectives. By minimizing maintenance, operational costs, and energy consumption, this strategy can potentially reduce costs and improve overall efficiency.

Table 7
Summary of the evidence regarding the implementation of DT decision support categories for enhancing the sustainability and efficiency of energy power plant operations.

Decision support category	Key benefits	Key aspects	Primary contribution	Secondary contribution
Predictive Analysis	Minimizing Downtime and Enhancing Operational Efficiency	Achieved through Remaining Useful Life (RUL), Proactive Maintenance, and Utilizing Health State Prognostics	[101,106–108]	[109–111]
	Cost Reduction	Achieved through Demand Forecasting and Resource Consumption, Time Sensitive Traffic Prediction, and System Health Forecasting	[112–114]	[115,116]
Performance	Downtime Reduction and Enhancing Operational Efficiency	Achieved through Robust Process Management, and Enhancing Fault Diagnosis	[69,90,110,117,118]	[101,102,104,106, 108]
	Resource Allocation and Energy Efficiency	Achieved through Efficient Task Distribution, Real-Time Data Analysis, Reducing Transit and Waiting Time, and Target Association Modeling	[119–122]	[112,123]
	Real-Time Traceability, Reduced Waste, and Lower Costs	Achieved through Predictive Maintenance and System Optimization Strategies, and Real-Time Synchronization and Control Flexibility	[124]	[98,107]
Risk and Fault	Operational Sustainability	Achieved through proactive maintenance and advanced damage detection	[115,123]	[69]
	Performance Enhancement & Cost Reduction	Achieved through real-time status monitoring and Strategic Optimization Model for Mechanical Component Durability	[109,111]	[113]
Optimal Model Evaluation	Maximum Operational Efficiency and Cost Savings	Achieved through optimal Resource Selection and Diversified Selection Strategy in shared resources	[98,125]	
Process Traceability	Advancing Energy Efficiency and Operational Performance	Achieved through Real-Time Process Traceability for Enhanced Quality and Data Management in Complex Production Processes	[104,116]	
HMI	Enhanced Human Safety and Continuous Productivity	Achieved through Visualization of Data and Operations via Smart Mixed-Reality and Utilizing Human–Robot Interaction	[102,126]	

Manufacturing plants have benefited from a system proposed in [110], which focuses on strategic planning and real-time alerts for abnormal situations. This approach has been effective in reducing operational costs and quickly responding to changes or abnormalities. Additionally, [69] employees a two-phase approach to fault diagnosis prioritizes early detection and precision throughout the product life cycle, minimizing downtime and operational costs. Studies also suggest that optimizing resource allocation with DT technology can improve energy conversion efficiency. The study by Negri et al. [120], founds that implementing optimal scheduling and real-time data analysis can help reduce operation costs during high-demand periods. Overall, these papers emphasize the importance of optimizing processes and resource allocation to achieve sustainability objectives and improve efficiency in various industries.

The utilization of algorithms for resource allocation can lead to substantial improvements in production. This has been demonstrated by research conducted in [121,122] show that advanced algorithms can optimize data tasks, streamline planning processes, and enhance overall productivity. By optimizing resource allocation, these methods can also reduce energy waste and improve operational efficiency. According to Guo et al. [124], real-time digital synchronization and flexible controls in assembly systems can lead to substantial energy savings and streamlined workflows. This is achieved by eliminating unnecessary setups, reducing waiting times, and optimizing resource allocation, resulting in substantial cost savings and increased operational efficiency across various manufacturing processes.

To enhance operational efficiency and decrease energy consumption and waste, deploying advanced techniques like algorithms, precise fault detection methods, and innovative digital technologies holds immense promise. These techniques not only improve productivity but also minimize downtime and operational expenses. Further investigation into their application across diverse industry settings and varying production conditions would aid in unlocking their full potential. Adapting to the continually changing industrial landscape, particularly in the context of energy power plants, is essential for achieving a future of enhanced productivity and sustainability. This study aims to explore how implementing digital technologies can lead to these improvements and shape the future of the energy sector.

Risk and fault assessment

The effective maintenance of system reliability and sustainability can be achieved through fault diagnosis and risk assessment techniques. Fault diagnosis plays a crucial role in the early identification of system anomalies, which dramatically reduces downtime and enhances machine lifespan and operational performance. In support of this concept, the study by Karve et al. [111] elaborates on the use of a Bayesian estimation algorithm (defined detailed in [137] for predictive maintenance strategies developed to ensure the uninterrupted operation of mechanical systems. Similarly, [109] focused on real-time status monitoring and finite element analysis to prevent excessive physical damage, such as wear and aging in equipment, thus increasing the longevity and reliability of operation. On the other hand, risk assessment plays a pivotal role in predicting potential dangers and allowing proactive intervention. For instance, Xia et al. [123] proposed a deep transfer learning [138] based method, which is applied for the early detection of operational faults and plays a key role in risk mitigation and aligns with sustainable operational goals. In addition, [115] uses Quadratic Discriminant Analysis (QDA) [139] method to underline the vital importance of risk management for the necessity of advanced damage detection techniques in infrastructure systems from a sustainability standpoint. It is crucial to note that fault diagnosis and risk assessment serve different purposes, though both are critical for effective system management. Specifically, fault diagnosis is concerned with identifying existing anomalies, while risk assessment focuses on anticipating potential problems. These strategies lead to optimal resource usage, reducing maintenance and operational costs, and enhancing overall system performance in energy power plants are characterized by their intricate systems, which require early fault detection and risk prediction to prevent operational downtime and improve overall performance. The integration of RERs necessitates the utilization of such techniques to identify potential issues and predict risks associated with new technologies, thereby facilitating a smoother transition. By preventing faults and mitigating the risks associated with this transition, energy power plants can not only enhance their operational efficiency but also ensure long-term sustainability and resilience.

Optimal model evaluation

Optimal model evaluation within the context of DTs involves more than just evaluating current system performance. It is a comprehensive approach that aims to improve efficiency, sustainability, and adaptability to changing demands and fluctuating weather conditions affecting energy production [131]. Unlike basic performance assessments that focus on functionality, optimal model evaluation delves deeper and develops strategies for dynamic adaptation, thereby enhancing system reliability and accuracy under various circumstances [140].

An DT framework proposed by Mi et al. [125] emphasizes accuracy and reliability of predictive maintenance task with the aim of optimized operational efficiency. This framework also provides a mechanism for assessing resources and guiding their optimal selection under varying parameters, allowing for an agile response to fluctuating energy market conditions. This approach prioritizes achieving the optimal state of operations, surpassing simple performance evaluation to ensure reduced costs and carbon emissions. This concept is supported by Wang et al. [98], which proposes a DT-driven service model for seamless monitoring and control of shared manufacturing resources. This model prioritizes factors such as cost, time, and provider trustworthiness during the allocation process, and allows for the selection of the most suitable resource from a range of options. This diversified strategy guides decision-making from an efficiency, cost-effectiveness, environmental impact, and reliability perspective. Such optimal model evaluation enables organizations to enhance operational efficiency, maintain the sustainability of their operations using diversify resource allocation by implementing DT models.

Process traceability

Process traceability as enacted by DT technology provides a service distinct and separate from operations themselves. This service enables real-time surveillance within intricate manufacturing and production workflows, consequently allowing in-depth comprehension of operational processes, expedited in-process modifications, and strategic improvements leading to superior product quality [141]. The unique role of process traceability is exemplified in the work by Liu et al. [104], who proposed a biomimicry [142] based traceability framework. This framework compiles and analyses real-time data on geometry, behavior, and process to enhance comprehension of ongoing procedures, enabling immediate tuning and alterations that improve overall product quality. The key here is the utilization of collected data to adjust processes in real-time, rather than just carrying out operations without continual optimization.

Similarly, Zhuang et al. [116] also offered a traceability approach distinctively made for enhancing quality control, troubleshooting, and process optimization. Through real-time monitoring at each stage of production, they can enable effective problem-solving and process enhancement, which go beyond mere execution of operations, but leverage data for continuous optimization.

In summary, process traceability is not just about the execution of operations but involves real-time, data-driven tracking and improvement of processes for optimized operational performance and energy efficiency. It is an ongoing evaluative method to refine operations rather than a static process of operation execution.

HMI

The use of DT technology in HMI highlights the importance of understanding the dynamics and dependencies involved in collaborations [143]. This knowledge can improve collaboration efficiency and optimize task assignment and workload distribution between humans and robots [10]. According to Table 7, [126] developed a model using DT and HMI to enhance safety and productivity in robotics and automation. The integration of smart mixed-reality glasses offers a cutting-edge platform for optimized human–machine collaboration. Similarly, [102] implemented an HMI system integrated with DT, which replicates the processes of skilled human users to guide robots and novice users, improving operational efficiency and productivity.

Although the focus of these papers is not on energy power plant operations, the implications of these HMI strategies, made possible by digital technology, for the sustainability and resilience of energy power plants are significant. Incorporating these HMI strategies into energy power plant operations can improve safety, minimize downtime, and enhance operational efficiency, which are crucial aspects for the sustainability and resilience of energy power plants. By combining DT technology with cutting-edge HMI techniques, it is possible to enhance system efficiency and resilience, ultimately making a significant contribution to the development of sustainable and resilient energy power systems.

Discussion

This review provides a comprehensive overview of how DTtechnology can support sustainability and resilience in renewable energy power plants. By analyzing 61 studies, with a specific focus on 27 that directly address our research objectives, this SLR categorizes DT functionalities into six primary decision support categories outlined in our taxonomy (see Table 7): performance optimization, predictive analysis, risk and fault assessment, optimal model evaluation, process traceability, and HMI. The implementation of these DT decision support categories play a pivotal role in achieving economic objectives by enabling cost reduction, enhancing operational efficiency, and ensuring optimal resource allocation, and for achieving environmental objectives by promoting operational sustainability and contributing to GHG emission reduction. We elaborate on these outcomes in more detail below; followed by the limitation, challenges and future directions.

Fig. 5 demonstrates the connections between identified DT decision support categories (on the right) and the dimensions of sustainability and resilience in energy power plants (on the left). The Fig. 5 differentiates between primary (illustrated with solid lines) and secondary (illustrated with dotted lines) contributions based on the prevalence and significance of DT functionalities within each sustainability dimension. Primary contributions represent core areas where DT technologies have a direct, robust impact, whereas secondary contributions indicate complementary or supporting roles where DT functions have an indirect effect. The categorization into primary and secondary contributions reflects common trends observed within the literature, where certain studies address multiple decision support functions. For example, Wei et al. [109] developed a DT framework focused on fault and risk assessment aspects, bringing its contribution to predictive analytics, hence showing the overlap of DT functions. This dual focus is either on risk management or predictive maintenance for operational efficiency in the identification and mitigation of possible issues that support economic resilience and sustainability goals. Similarly, Patel [144] propose the DT model for a Computer Numerical Control (CNC) machine tool, including real-time status monitoring and predictive analytics for improving longevity. It reduces not only downtime but also resource use and hence helps attain economic and environmental sustainability goals. Further detail is provided in Appendix C Table C1. The thematic overlap observed in these studies suggests that DT functionalities are often interconnected, with certain categories like performance optimization and predictive analysis frequently complementing each other. Such overlaps are illustrated in Fig. 5 as lines connecting multiple sustainability dimensions, showing how a single DT functionality can contribute to multiple areas of sustainability and resilience.

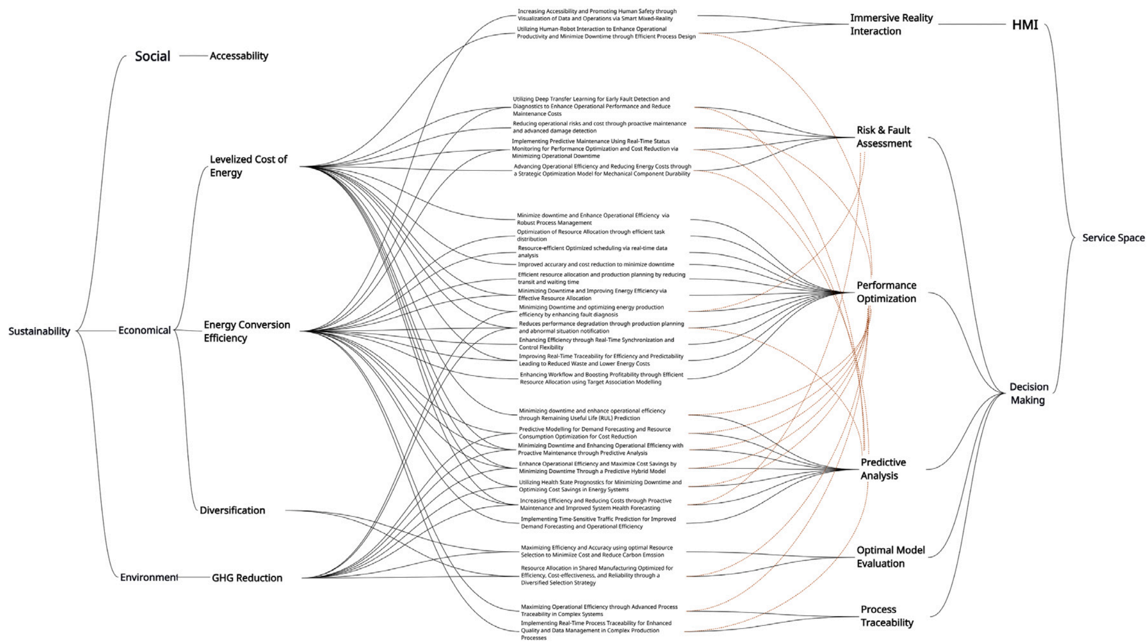

Fig. 5. Mapping DT frameworks in literature, highlighting their potential to contribute to the sustainability of renewable energy power plants across social, economic, and environmental dimensions, with a focus on the service space of DT technology.

Economic sustainability: DT role in cost reduction and resource optimization

Economic sustainability is essential for renewable energy power plants as they transition from fossil fuels to RERs. DT technology enhances economic resilience through proactive strategies like demand forecasting, resource consumption analysis, system health forecasting, and predictive maintenance, all of which contribute to cost reduction and efficient resource utilization. Below, we summarize key insights from Table C1 in Appendix C regarding how these decision support categories contribute to economic sustainability.

By utilizing predictive analysis frameworks, as seen in studies [101, 107], DT systems provide real-time insights into the health of power plant components, allowing for proactive maintenance and minimizing downtime. These frameworks use predictive modeling to forecast critical maintenance needs, which prevents unplanned interruptions. In a power plant setting, applying predictive analysis helps avoid costly emergency repairs and extends the lifespan of equipment, directly supporting economic sustainability by reducing unexpected expenditures and improving asset longevity. Similarly, performance optimization frameworks, highlighted in the literature (e.g., Wang et al. [98]), help streamline operations by dynamically allocating resources based on real-time data. In power plants, this type of optimization ensures that equipment is used efficiently, reducing energy waste and operational costs. By aligning with economic metrics like the LCOE, these frameworks enhance economic sustainability by lowering production costs, ultimately contributing to more affordable renewable energy generation. In addition, risk and fault assessment frameworks enable early detection of potential issues, allowing for timely interventions that significantly reduce maintenance expenses. For example, the proactive fault identification approach used in [109] minimizes downtimes, which is crucial in high-stakes power generation environments where even brief interruptions can be costly. In the context of renewable energy, this risk mitigation reduces the need for expensive reactive maintenance, contributing to stable operations and improving the plant's overall economic resilience.

Optimal model evaluation, is one of the key DT decision support category that has the potential within the economic dimension, to contribute to the sustainability of energy power plants using diversification factor. The proposed optimal model evaluation frameworks in the literature in [98,125] offer effective solutions to achieve cost optimization and GHG emission reduction through accurate and reliable predictive maintenance tasks. These model evaluation frameworks maximize efficiency and accuracy by selecting optimal resources, rapidly responding to changing energy markets, and sustaining operations under uncertain conditions. In shared manufacturing contexts, the optimal model evaluation use a credit-aware approach in [145] for resource allocation, ensuring a robust and efficient selection strategy from a diverse pool of resources. This diversified selection strategy considers various parameters like cost-effectiveness, efficiency, reliability, and environmental impact for higher adaptability in resource utilization. By leveraging optimal model evaluation, DT technology used in energy power plants can allocate resources more efficiently, leading to sustainability and resilience during the transition to RERs. This approach also enhances operational efficiency and cost-effectiveness through strategic shared resource management.

Together, these DT decision support categories enable a multi-faceted approach to achieving economic sustainability in renewable energy power plants. Through predictive analysis, performance optimization, risk assessment, optimal model evaluation, DT technology supports cost-effective, adaptable, and resource-efficient operations. Each of these categories plays a distinct role in reducing costs, improving resource allocation, and reinforcing economic resilience, facilitating an economically sustainable transition to renewable energy. For detailed descriptions of each framework, please refer to Appendix C, Table C1, which provides a comprehensive overview of the decision support categories and their contributions to economic sustainability.

Environmental sustainability: DT's role in emission reduction

The Fig. 5 highlights that several decision support categories within DT technology–such as performance optimization, predictive analysis, and optimal model evaluation–are crucial for enhancing environmental sustainability. These DT frameworks contribute to environmental goals by improving operational efficiency, reducing resource consumption, and lowering GHG emissions. With capabilities to monitor real-time data and optimize energy usage, DT technology aligns directly with environmental objectives, supporting renewable energy systems as they transition away from carbon-intensive operations.

Performance optimization and predictive analysis are DT decision support categories that drive environmental sustainability by managing resources more effectively and minimizing energy waste. In manufacturing contexts, studies like those by Meraghni et al. [108] have shown that DT applications can reduce energy consumption by optimizing operations and decreasing inefficiencies. When applied to renewable energy plants, performance optimization ensures efficient energy use, indirectly contributing to GHG reduction goals by curtailing unnecessary resource usage. This functionality supports an environmentally sustainable operation by conserving energy, reducing material waste, and aligning renewable power plant operations with broader sustainability objectives.

Risk assessment and optimal model evaluation contribute further by ensuring that resources are allocated efficiently and waste is minimized. DT models that assess risks and optimize resource management enable precise maintenance scheduling, which reduces repair frequency and extends equipment lifespan, conserving both materials and energy. In renewable power plants, optimal model evaluation can strategically allocate resources to limit their environmental impact, thus reducing the carbon footprint through effective resource management and maintenance planning. While these strategies may not directly target GHG emissions reduction, they indirectly support environmental objectives by minimizing waste and promoting cost-effective, energy-efficient resource deployment. Additionally, DT frameworks offer ecological adaptability by using real-time monitoring and predictive analytics to allow renewable energy plants to remain resilient under dynamic environmental conditions. The adaptability of DT technology enables systems to respond effectively to fluctuations in energy demand, preventing overproduction and waste. This approach aligns operations with real-time needs, ensuring sustainable resource management that benefits both the environment and the economic viability of renewable energy systems.

Although the primary focus of DT frameworks may not always be environmental sustainability, their ability to facilitate multifaceted resource selection and rapid adaptability to unpredictable energy trends allows them to support sustained operations even under uncertain demand conditions. By reducing machine downtime, optimizing maintenance, and using diversified resources, DT technology aids energy power plants in achieving greater decision-making accuracy and operational resilience. This adaptability not only contributes to cost reductions but also lowers carbon emissions, reinforcing DT's role in supporting an ecologically sustainable transition to RERs.

Together, these DT decision support categories foster cleaner, more efficient operations by reducing emissions, conserving resources, and enhancing adaptability. Each category plays a distinct role in environmental sustainability, from decreasing energy consumption and material waste to aligning renewable energy practices with sustainable goals.

Social sustainability: Accessibility, affordability and safety

As indicated in Fig. 5, DT frameworks are not directly connected to social sustainability in terms of explicit focus areas. However, based on the frameworks outlined in Appendix C, Table C1, it is clear that DT systems can contribute to social sustainability indirectly by enhancing accessibility, affordability, and safety within renewable energy systems. Cost reductions achieved through DT-supported performance optimization and predictive maintenance make renewable energy more economically accessible to broader communities. Below, we discuss how specific DT decision support categories have the potential to promote social sustainability.

Performance optimization and predictive maintenance frameworks increase operational efficiency and reduce downtime, creating cost savings that can make renewable energy production more affordable. By lowering operational costs, DT systems help reduce energy prices, which expands access to clean energy, especially for underserved or remote communities. These cost savings align with the principles of energy justice, promoting equitable access to renewable energy and supporting a more inclusive energy landscape where diverse communities benefit from cleaner energy sources. HMI frameworks within DT systems contribute significantly to social sustainability by enhancing safety and ensuring seamless interactions between operators and complex digital systems. Tools like immersive reality interfaces enable operators to interact with real-time data safely, reducing the likelihood of errors and minimizing operational delays. In renewable energy power plants, these HMI capabilities not only improve worker safety but also protect surrounding communities from potential hazards. By prioritizing safety and reliability in operations, DT frameworks offer a socially responsible approach to energy production that safeguards both personnel and nearby residents.

Additionally, environmentally sustainable operations promoted by DT frameworks indirectly enhance public welfare by reducing emissions and supporting better air quality and health standards. As DT technology helps decrease GHG emissions and environmental impact, it contributes to healthier communities, particularly those located near renewable energy installations. This indirect contribution to social sustainability aligns with broader objectives of public well-being, fostering cleaner environments, and improving the quality of life for communities close to RERs.

In summary, DT technology, though not explicitly focused on social sustainability, supports this dimension by making renewable energy more accessible, affordable, and safe. By promoting equitable access to clean energy, enhancing safety, and contributing to community health, DT frameworks indirectly advance the social dimension of sustainability within the renewable energy sector.

Limitations of this study

This study encompasses a SLR utilizing Google Scholar as the primary search engine to access an array of high-impact, peer-reviewed journals including those published by MDPI, IEEE, Elsevier, Springer, and ACM, covering the years 2017–2022. The study did not include additional literature sources, such as Web of Science, Scopus, technical journals, and non-peer-reviewed articles, which might provide a more comprehensive view of this emergent topic. However, the chosen publishers are known for their high-quality, peer-reviewed articles, enabling the authors to select the most impact-ful papers and prioritize the quality of the content over the breadth. This review aims to elucidate the ways in which DT technology can enhance sustainability in the energy sector by improving operational efficiency and decision-making processes in energy power plants. It is important to note that this study has limitations in scope and does not account for the full range of potentially relevant studies. Future research could address these gaps and provide a more comprehensive evaluation of the relationship between DTs and sustainable practices in energy infrastructure.

Challenges and future directions

DT technology faces a multitude of challenges that are similar to those found within data analytics, the IoTs, and the Industrial Internet of Things (IIOT) as mentioned in [8]. In addition, various researchers have brought to the forefront additional challenges, such as the need for clear standardization protocol [18], difficulty of accurate sustainability data collection [146] and dealing with data interoperability. According to Sleiti et al. [3] data management and analysis stand out as pressing challenges in utilizing DTs, especially when it comes to reflecting and forecasting the performance of physical power plant systems within their virtual counterparts. This problem is not unique to the energy sector; it is a common thread spanning diverse domains from aerospace to healthcare. However, within the context of renewable energy, these issues become especially salient due to the inherent sustainability goals. The primary challenge at hand is effectively managing a substantial amount of various and continual data streams, which encompass production to consumption metrics. Doing so is essential for creating and maintaining an accurate digital representation for decision-making and process enhancement [3]. A particular emphasis is needed on the precision of data concerning power plant sustainability, where the consequences of inaccuracies can have far-reaching impacts on environmental and economic outcomes. Advanced analytics and algorithms—such as those referenced in [147–149] are essential tools that enable us to sift through complex datasets effectively. By adopting these tried and tested methods from other applications, we can achieve not only insightful analysis but also build precise predictive models that can inform more sustainable practices within power plants, ultimately leading to more efficient and greener energy production.

Maintaining rigorous data collection standards is a complex task that is further complicated by the difficulty of accurately capturing sustainability data, as evidenced by Yavari et al. [146]. Given the complexity of renewable energy systems, disparities in measurement protocols, and fluctuating environmental conditions that can impact energy production, the collection of precise data is paramount. The drive for real-time data that encompasses the full spectrum of resource inputs, energy outputs, and environmental effects is essential for developing a reliable DT. This digital counterpart is crucial for enhancing operational practices and accurately predicting system behavior under various scenarios. Consequently, there is a need for a rigorous effort to enhance the reliability of data collection, standardize measurement protocols, and utilize advanced sensor and time-sensitive data analysis as demonstrated in [150]. At the same time, the challenge of merging various data vectors into a unified model within the DT – while safeguarding data precision and relevance – remains a prime objective for ongoing research endeavors.

Interoperability, which refers to the ability of different systems to work together in a coordinated manner, poses a notable challenge for implementing DTs [151]. As these virtual models need to communicate with a range of systems and components, developing standardized data formats and interfaces becomes a critical task. This standardization aids in the seamless integration of systems, allowing the full benefits of DT technology to be realized. Advancing collaboration across various sectors will depend on this ability to securely and efficiently manage and share data. Therefore, tackling interoperability is crucial for unlocking the transformative impact DTs promise in power plants.

It is crucial to make a concerted effort in future research to enhance DTs for renewable power plants. This requires addressing the major obstacles of big data analysis, interoperability, data precision, and standardization. To overcome these challenges, it is necessary to develop advanced analytical methods for processing and interpreting the vast amounts of data generated by renewable energy operations. This will enable the extraction of valuable insights for predictive maintenance and real-time optimization. Additionally, seamless interoperability among diverse systems must be achieved to ensure cohesive and efficient DT functionality. Efforts to enhance data precision through the implementation of robust collection standards and granular analytics are also essential to accurately reflect the dynamic nature of RERs in the DT environment. Furthermore, the establishment of comprehensive standardization protocols will be vital to ensure the universal application and effectiveness of DTs across the sector. Overcoming these challenges is critical to unlocking the potential of DTs to create more resilient, efficient, and sustainable renewable energy infrastructures.

Conclusion

This study has highlighted the vital role that DT technology can play in advancing sustainability and resilience in renewable energy power plants, answering two core research questions. Through a comprehensive review of 61 studies, this paper identified six primary decision support areas–performance optimization, predictive analysis, risk and fault assessment, optimal model evaluation, process traceability, and HMI–within DT frameworks. These DT capabilities address the economic, environmental, and social dimensions of sustainability, driving improvements in energy efficiency, reducing costs, and optimizing resource use.

In response to the first research question – How can DT contribute to the sustainability and resilience of renewable energy power plants? – the findings highlight DT's ability to support proactive management through tools like demand forecasting and system health monitoring. These functions help renewable power plants reduce downtime, minimize energy waste, and indirectly lower GHG emissions. The capacity for energy diversification and enhanced system resilience reinforces DT's role in both economic and environmental sustainability.

Addressing the second research question – To what extent can current research and developments address gaps and limitations in implementing sustainable and resilient energy power plants using DT? – the review reveals that while DT frameworks are highly effective in supporting economic and environmental objectives, their potential for promoting social sustainability, such as through improved accessibility, safety, and affordability, is an emerging area. Integrating ML and AI into DT frameworks promises further advancements, enabling refined predictive maintenance, enhanced resource allocation, and optimized energy management as the renewable energy sector evolves.

These findings offer important implications for both theory and practice. Theoretically, this study expands sustainability frameworks by demonstrating DT's capacity to integrate economic, environmental, and social objectives, aligning with resilience theory through DT's adaptability in dynamic conditions. Practically, DT frameworks present actionable tools for renewable energy plants, enhancing cost-efficiency and enabling the energy sector to progress towards more accessible and sustainable solutions. As DT applications continue to evolve, they are positioned to become foundational for addressing future challenges in renewable energy. However, it is important to note that many applications of DT's in the energy sector are still in the early stages. A comprehensive, multidisciplinary approach will be necessary to fully unlock the potential of DT's, ensuring they integrate economic, environmental, and social factors to achieve sustainability and resilience in energy power plants.

CRediT authorship contribution statement

Waqar Ali Khan: Writing – original draft, Visualization, Methodology, Conceptualization. **Ashkan Pakseresht:** Writing – review & editing, Supervision, Conceptualization. **Caslon Chua:** Writing – review & editing, Supervision, Conceptualization. **Ali Yavari:** Writing – review & editing, Supervision, Conceptualization, Methodology, Funding acquisition.

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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Supplementary data

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Data availability

No data was used for the research described in the article.

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