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Artificial intelligence and robotics in the hydrogen lifecycle: A systematic review

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ABSTRACT

Hydrogen lifecycle, encompassing production, storage, and transportation, is crucial in the global transition to clean energy. Integrating artificial intelligence (AI) and robotics into hydrogen lifecycle offers promising solutions to enhance efficiency, safety, and scalability. This paper presents a comprehensive review of the current advancements published over the past two decades (2005–2025), analyzing AI and robotics applications across hydrogen production, storage, and transportation. We systematically examine the role of AI in optimizing hydrogen production processes, improving the safety and efficiency of storage systems, and enhancing transportation logistics through real-time monitoring and route optimization. Additionally, the paper explores the use of robotics to handle complex tasks in hazardous environments within the hydrogen lifecycle. We identify key challenges and gaps in the literature and propose future research directions to fully leverage AI and robotics across hydrogen technologies. This review serves as a foundation for researchers and practitioners seeking to advance the integration of AI and robotics in the hydrogen economy.

1. Introduction

As the world confronts the escalating challenges of climate change and the depletion of fossil fuel resources, the transition to sustainable energy systems has become a global priority [1]. Within this transition, hydrogen has emerged as a pivotal player due to its potential to serve as a clean, versatile, and efficient energy carrier [2,3], offering the potential to decarbonize multiple sectors that are difficult to electrify, such as heavy industry, aviation, and maritime transport. Hydrogen's environmental benefits are significant; its combustion emits only water vapor, making it a key contributor to efforts aimed at reducing greenhouse gas emissions and achieving international carbon neutrality targets [4–9]. Hydrogen can be produced from various renewable sources, such as wind, solar, and biomass.

Hydrogen can be produced via multiple methods, with electrolysis (using renewable electricity) and steam methane reforming (SMR) being the most prominent [10]. While SMR is a mature and cost-effective technology, its carbon intensity necessitates integration with carbon capture and storage (CCS) to align with global decarbonization goals [11]. Electrolysis offers a cleaner alternative but remains constrained by high energy consumption and economic challenges [12]. In addition to these technical barriers, the slow pace of technological advancements in large-scale hydrogen production, especially for green hydrogen, presents further challenges to commercial viability [13] as it is highly reactive and difficult to store and transport [14]. High-pressure storage systems and cryogenic technologies introduce significant safety concerns, particularly in large-scale applications. Additionally, developing a hydrogen infrastructure that includes pipelines, distribution networks, and refueling stations is critical but remains underdeveloped, rendering it inadequate to meet the anticipated future demand [15,16]. Achieving cost parity with existing fossil-fuel infrastructure requires substantial investments and policy support, particularly in developing hydrogen refueling stations and long-distance pipelines [17].

Governments and industries worldwide are investing heavily in hydrogen technologies, recognizing their capacity to decarbonize sectors that are difficult to electrify, such as heavy industry, aviation, and maritime transport [13]. The European Union, Japan, and several other countries have announced ambitious hydrogen strategies, aiming to

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integrate hydrogen into their energy systems at scale by 2030 and beyond [17–19]. However, achieving these ambitions requires overcoming substantial technical and economic barriers, particularly those related to production efficiency, storage safety, and distribution costs. Furthermore, significant variations in regional policies, government support, and public perception may affect the global pace and scale of hydrogen adoption. Public acceptance of hydrogen technologies and emerging AI and robotics applications is critical for their successful adoption [20].

Recent advancements in artificial intelligence (AI) and robotics offer promising solutions to many such challenges. AI-driven systems have demonstrated their potential to optimize hydrogen production processes by enhancing efficiency and reducing energy consumption through real-time monitoring and predictive maintenance [21]. Meanwhile, robots can be deployed in dangerous or complex environments, such as hydrogen pipelines and electrolysis systems, to perform tasks otherwise classed as hazardous for humans [22]. These technologies collectively promise to improve hydrogen infrastructure by enhancing safety, reliability, and operational efficiency [23,24]. However, the large-scale deployment of AI and robotics in hydrogen systems is still in its early stages, with significant technological readiness gaps and regulatory challenges that must be addressed before these solutions can be widely adopted [12]. Public concerns regarding hydrogen safety and AI's role in critical infrastructure management could also hinder acceptance. Addressing these concerns through public education and robust safety standards will ensure broad societal acceptance of these technologies [25].

AI and robotics applications in hydrogen technologies have gained increasing attention, with comprehensive reviews highlighting key advancements and persistent challenges across hydrogen production, storage, and transportation (see Table 1). These studies emphasize the integration of AI-driven optimization algorithms, machine learning (ML)-based predictive modeling, and digital twin technologies to enhance hydrogen infrastructure efficiency and safety. One central area of advancement is the application of AI to optimize hydrogen production processes. A recent review of renewable energy-integrated AI techniques for hydrogen production [26] highlights the role of ML and optimization algorithms in improving electrolysis efficiency and reducing costs by adapting to intermittent renewable energy sources. AI-driven catalyst design, mainly through neural network-based models, has also played a crucial role in reducing the dependence on rare and expensive materials. However, these approaches face challenges in scalability and validation due to the limited availability of experimental datasets, emphasizing the need for industrial-scale AI validation frameworks.

AI applications in hydrogen safety have also seen significant progress. For example [23], have demonstrated using artificial neural networks, computer vision, and sensor fusion techniques to improve real-time monitoring and hazard prediction in hydrogen production and storage facilities. AI-powered leak detection systems have significantly reduced false alarms and enhanced response times, making hydrogen storage and refueling infrastructure safer. However, ensuring AI model robustness across varying environmental conditions remains a key challenge, as hydrogen facilities operate in diverse and unpredictable settings. Material discovery and electrocatalyst optimization for hydrogen energy transformation have also benefited from ML advancements [37]. High-throughput ML approaches now facilitate the rapid screening of catalysts for hydrogen evolution and oxygen reduction reactions, integrating density functional theory data to accelerate experimental validation. However, training AI models on incomplete datasets remains challenging, impacting the scalability of AI-driven material discovery for commercial applications. Similarly, ML models have been employed in solid-state hydrogen storage systems to predict hydrogen adsorption properties in magnesium- and titanium-based materials, reducing the need for extensive experimental testing [38]. Despite these advancements, data standardization and model interpretability remain critical barriers, requiring further research to improve AI-driven material performance predictions.

Table 1
Recent review papers on the hydrogen value chain.

Reference	Scope	Is Robotics application in hydrogen lifecycle considered?	Is AI application in hydrogen lifecycle considered?
[27]	Analyzed the use of machine learning in hydrogen energy systems, focusing on production, storage, and practical applications, while linking machine learning solutions to the challenges encountered.	No	Yes
[28]	Discussed development in hydrogen value chain for the Middle East region by focusing on the feedstock, production techniques, storage choices, delivery routes, and end-user applications	No	No
[29]	Studied the European region's green hydrogen supply chain risk factors	Very briefly	No
[30]	Reviewed hydrogen tank designs focusing on spherical tanks	No	No
[31]	Studied the hydrogen value chain identifying both the present challenges and recent advances	No	No
[32]	Studied the technical and economic factors for the viability and competitiveness of two competing large-scale renewable hydrogen value chains via ammonia and liquid hydrogen	No	No
[33]	Conducted a techno-economic review of hydrogen energy systems consisting of power-to-power, power-to-gas, hydrogen refueling and stationary fuel cells	No	No
[34]	Studied the green hydrogen value chain in meeting the objectives stated in the 2030 Agenda	No	No
[35]	Reviewed optimization models for hydrogen supply chains and production	No	No
[36]	Performed strengths, weaknesses, opportunities, and threats (SWOT) analysis to the clean hydrogen value chain in different sectors to determine Japan's clean hydrogen value chain	No	No
This work	**Systematically reviewed the role of AI and robotics within the hydrogen lifecycle, from production to storage and transport.**	**Yes**	**Yes**

Beyond production and storage, AI-enabled energy management systems are gaining traction, particularly in hydrogen-powered microgrids. A recent study on Artificial Intelligence of Things (AIoT) frameworks for hydrogen energy systems [39] demonstrated how AIoT can be combined to enhance real-time decision-making and predictive maintenance across hydrogen production, distribution, and storage. Similarly, ML-driven smart energy management systems [40] have optimized hydrogen-based islanded microgrids, dynamically adjusting energy flow between hydrogen production and consumption based on real-time demand. These technologies underscore the potential of AI in decentralized hydrogen energy systems, though integration challenges persist, particularly in autonomous microgrid operations. The emergence of digital twin technology has also provided a transformative approach to hydrogen safety, operations, and predictive maintenance. A recent study on digital twin-based hydrogen refueling station safety models [41] demonstrated how convolutional neural networks (CNNs) combined with real-time 3D simulations can accurately predict safety risks, improving station reliability and operational efficiency. Similarly, digital twin integration is used for hydrogen leakage modeling [42]. has advanced scenario-based risk assessment, combining virtual experiments and AI-driven simulations to enhance safety in hydrogen transport and storage facilities. However, these AI-enhanced digital twins face challenges in data standardization, limiting their scalability for large-scale hydrogen applications.

While some studies have explored the potential of AI to enhance energy efficiency and safety in hydrogen systems [43], comprehensive research that examines the role of both AI and robotics throughout the entire hydrogen value chain remains sparse. This includes cost-benefit analyses, considering the upfront investment and long-term operational savings [3,14]. Previous research highlights AI's contributions to hydrogen production and storage optimization but fails to address how AI could work with robotics to automate operational tasks and mitigate safety risks. Similarly, while valuable insights are provided into the material challenges of hydrogen storage, the role of robotics in enhancing the safety and efficiency of these storage systems is generally overlooked. This omission is critical, as combining AI's predictive capabilities with robotics' operational precision can significantly mitigate the risks associated with hydrogen's highly reactive nature and its storage under extreme conditions [44]. Qureshi et al. [45] emphasize hydrogen's commercial potential but do not engage with the technological barriers, such as the high upfront investment costs associated with AI and robotics deployment [12]. This indicates a gap in the literature where the potential of AI and robotics to tackle economic and technical constraints jointly remains largely unexplored [46]. identified that there is an existing literature that recognizes the potential of hydrogen energy as an alternative to replace fossil fuels [47], but there is a shortage of comprehensive studies analyzing the recent evolution of hydrogen fuel technologies [46]. contributed to this research agenda, offering new insights to better understand the technological trajectories of hydrogen fuel, as well as a first mapping of the leading countries in developing new technologies in this field.

Despite these advancements, several fundamental challenges remain across AI and robotics applications in the hydrogen lifecycle. Data challenges persist, as many AI models lack high-quality, standardized datasets for hydrogen production, storage, and safety applications [23,37,38], and the limited availability of large-scale experimental datasets further hinder safety and material optimization efforts [48,49]. Scalability concerns also arise, as AI-driven hydrogen optimization models often perform well in small-scale demonstrations but struggle when applied to industrial-scale operations [38,48]. Additionally, integration bottlenecks remain a significant hurdle, as the full convergence of AI, robotics, and AIoT in hydrogen infrastructure is still largely conceptual, with limited real-world deployment [39,40]. A significant issue in AI adoption is model interpretability, as many widely used models, such as neural networks and CNNs, lack transparency, making their application in critical hydrogen energy systems more challenging [38,42]. There are still gaps in robotics applications, especially in hydrogen handling, transport automation, and infrastructure maintenance, even with the successful implementation of digital twins and automated inspection systems in hydrogen pipelines and storage. Tackling these issues is vital for progressing AI and robotics in hydrogen technologies and ensuring their efficient integration into industrial applications.

This review identifies critical gaps in the integration of AI and robotics across the hydrogen lifecycle and presents potential solutions to address these challenges. The analysis contributes to a deeper understanding of how AI and robotics enhance hydrogen production, storage, and transportation. The key contributions of this review include:

- Comprehensive analysis of the role of AI and robotics in hydrogen production, storage, and transport, with a focus on the current applications, challenges, and potential solutions.
- Exploration of AI-driven optimization techniques for hydrogen production, focusing on efficiency improvements and cost reduction through predictive analytics.
- Discussion on the potential of AI-based predictive maintenance to improve transportation logistics and support the development of hydrogen infrastructure.

This paper is divided into five sections. Section 2 outlines the research questions and the methodology for the systematic literature review. Section 3 provides an overview of trends in publications related to AI and robotics in the hydrogen lifecycle. Section 4 discusses the results of the literature review on hydrogen production, storage, and transportation, along with their respective challenges and opportunities. Section 5 summarizes and concludes the paper.

2. Methodology

This section details the methodology employed in this review, including the search strategy, selection criteria, and data extraction processes. A combination of systematic review protocols and traditional literature review methods was applied to ensure a thorough analysis of empirical studies while maintaining a broad understanding of key themes in the field. The study is guided by two research questions: (i) What is the current role of AI and robotics in the production, storage, and transportation of hydrogen fuel? (ii) What are the barriers and potential solutions to the further integration of AI and robotics technologies in the hydrogen lifecycle?

A structured approach was followed to ensure the collection of relevant literature while maintaining integrity and reproducibility. The literature search was conducted in widely recognized academic databases, including Scopus and IEEE Xplore. The search strategy was designed to systematically capture relevant studies examining AI and robotics applications in the hydrogen lifecycle. A combination of keywords and Boolean operators (AND, OR, NOT) ensured a comprehensive yet targeted search. The search focused on hydrogen fuel production, storage, and transportation while selecting studies incorporating AI, machine learning, and robotics. The specific search query was: "Hydrogen fuel*" AND "Production*" OR "Storage*" OR "Transport*" OR "Adoption*" AND "Technology*" OR "AI*" OR "Artificial Intelligence*" OR "Machine Learning*" OR "Algorithm*" OR "Robot*". The study included research articles from the past 20 years to maintain relevance and accuracy. The timeframe was chosen because, before 2005, only a few studies addressed AI and robotics in the hydrogen lifecycle. Selecting papers from 2005 to 2025 ensures that the review remains up-to-date and reflects the most recent advancements.

Fig. 1 illustrates the methodological framework used in this study. The process begins with identifying research questions, which focus on the role of AI and robotics in hydrogen production, storage, and transportation, as well as barriers to their integration. The next step involves searching for relevant studies in academic databases. Scopus provided 5916 papers, while IEEE Xplore contributed 991 papers, resulting in an initial dataset of 6907 studies. The study selection was conducted in multiple stages using Python Pandas library [50]. The first filter excluded studies outside the 2005–2025 timeframe and removed duplicate papers. A keyword-based filtering approach was then applied,

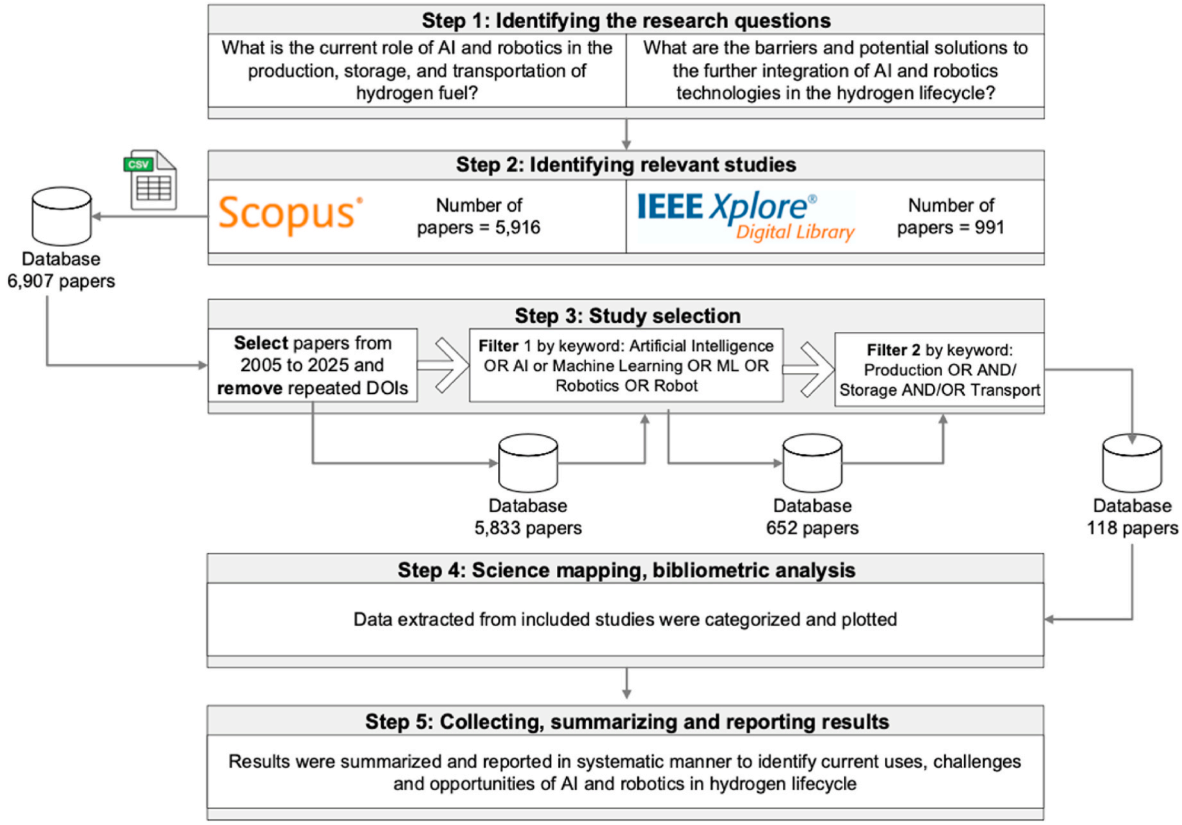

Fig. 1. Systematic review methodology for identifying, selecting, and analyzing relevant studies on AI and robotics in the hydrogen lifecycle. The process includes defining research questions, searching academic databases, filtering studies based on relevance, conducting bibliometric analysis, and synthesizing findings.

and papers that specifically discussed AI, robotics, and automation in the context of hydrogen technologies were selected. Additional filtering was performed to categorize studies based on their relevance to hydrogen production, storage, and transportation. The selection process reduced the dataset to 6907 papers, which was further refined to 652 papers. After applying additional relevance filters, 118 highly relevant papers were identified for detailed analysis. Following the selection process, bibliometric analysis was performed to categorize and visualize the distribution of studies using Python matplotlib [51] and plotly [52] libraries. Data extracted from the selected papers were organized based on their focus on the hydrogen lifecycle. The final stage involved summarizing and synthesizing findings in a structured manner. Key trends and challenges were highlighted to provide a comprehensive understanding of AI and robotics applications in hydrogen technologies. The analysis identified research gaps and potential future directions that could enhance the adoption of AI-driven solutions in the hydrogen lifecycle.

3. Overview of research trends

The extracted data are synthesized using a thematic analysis approach. Key themes and patterns across the selected studies are identified, allowing for the comparison of findings across different segments of the hydrogen lifecycle (production, storage, and transportation) and the integration of AI and robotics. Studies are clustered into thematic categories, enabling this review to systematically address the research questions and to ensure both depth and breadth in the analysis. The analysis specifically focused on synthesizing findings related to the role of AI and robotics in the hydrogen lifecycle, identifying common barriers to the integration of these technologies (such as cost, technological readiness, and regulatory constraints), and highlighting potential solutions, technological advancements, and areas requiring further research.

Fig. 2 illustrates the growth in research publications related to AI and robotics in hydrogen technologies from 2005 to 2025. The data indicate a slow and steady increase in publications until 2017, followed by a sharp rise from 2018 onward, aligning with increasing global efforts toward hydrogen energy development. The total number of publications on AI and robotics in hydrogen surged from 16 in 2018 to 291 in 2024, reflecting the growing recognition of AI-driven solutions in hydrogen technologies. The subset of studies specifically focused on the hydrogen lifecycle (production, storage, or transport) also shows a rising trend, albeit at a lower volume, reaching a peak of 44 studies in 2024. This surge reflects a confluence of global factors, including the growing recognition of hydrogen's potential as a clean energy vector and the integration of advanced technologies like AI and robotics in addressing its production, storage, and transportation challenges. The sharp increase in research following the 2018 EU Renewable Energy Directive underscores how policy-driven initiatives can accelerate scientific inquiry and technological advancements. The International Energy Agency's 2019 G20 report on the future of hydrogen catalyzed international attention and investment, driving research in this field.

The distribution of publication types in research on AI and robotics in the hydrogen lifecycle is depicted in Fig. 3. Results reveal that journal articles (41.5%) constitute the largest proportion of studies, indicating a strong emphasis on peer-reviewed, high-impact research. Conference papers (37.9%) follow closely, reflecting the fast-paced nature of technological advancements in AI and robotics, where early findings are frequently presented at conferences before complete journal publication. Review articles (11.1%) account for a smaller but significant share, highlighting efforts to synthesize existing knowledge and identify research gaps. Other publication types (5.5%), including white papers, IEEE magazines, technical notes or technical reports, and book chapters (4.0%), which typically provide broader conceptual discussions,

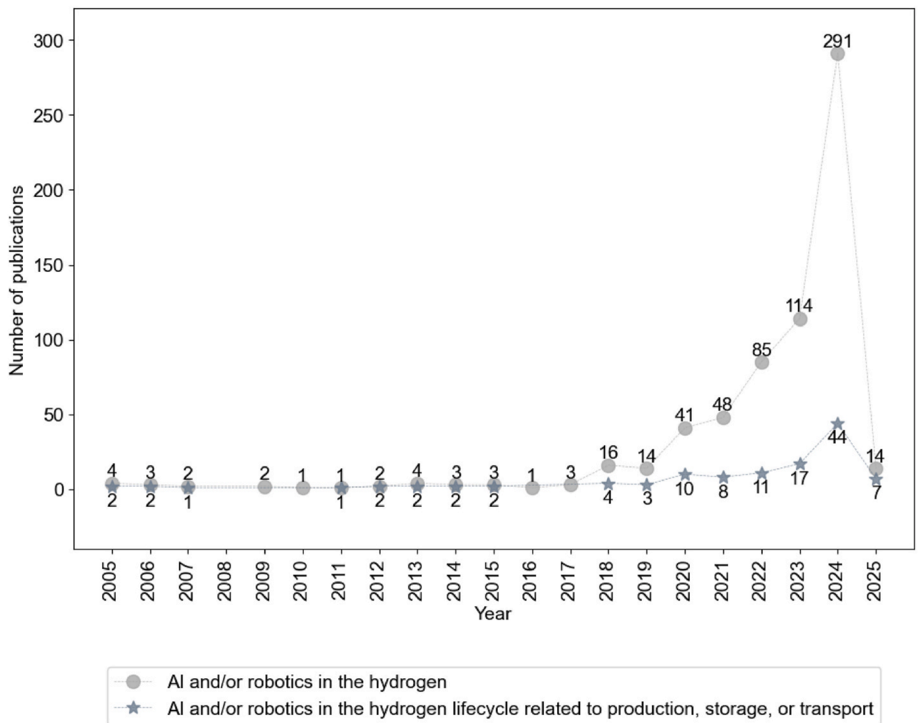

Fig. 2. Article number on robotics and AI in hydrogen lifecycle from 2005 to 2025 in Scopus and IEEE Xplore after filters.

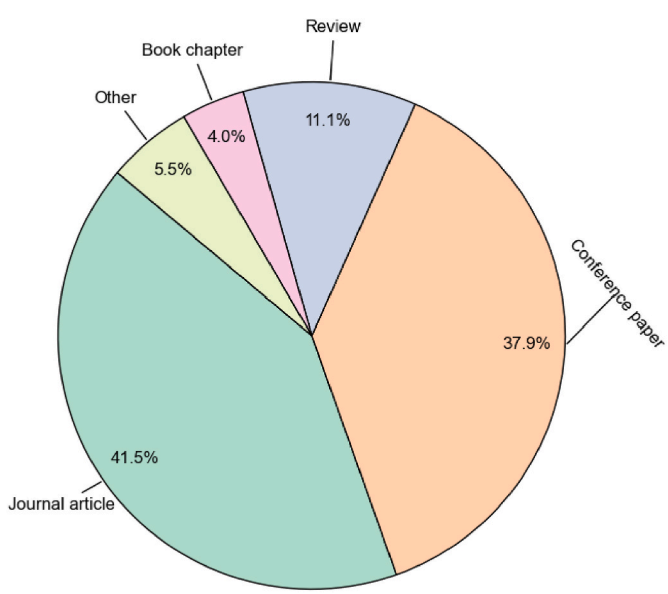

Fig. 3. Distribution of publication types in research on AI and robotics in the hydrogen lifecycle.

represent a minor portion of the literature. This distribution suggests that while foundational and applied research dominates the field, there is still room for more systematic reviews and interdisciplinary book contributions to consolidate findings and guide future research directions.

Fig. 4 illustrates the distribution of the top 25 most used keywords in research on AI and robotics in the hydrogen lifecycle (excluding 'hydrogen'). The analysis of the most frequently used keywords in AI and robotics research within the hydrogen lifecycle highlights a strong focus on machine learning (28.0%) and artificial intelligence (7.0%), underscoring the growing reliance on AI-driven techniques for optimizing hydrogen-related processes. The prominence of fuel cells (6.3%) and hydrogen fuel cells (5.6%) indicates a significant research emphasis on hydrogen's role as an energy carrier, particularly in fuel cell technologies. The presence of renewable energy (4.9%), sustainability (4.2%), and green hydrogen (2.8%) suggests a parallel focus on integrating hydrogen production with clean energy sources to enhance efficiency and reduce environmental impact.

For hydrogen storage, keywords such as hydrogen storage (3.5%) and optimization (2.1%) point to ongoing research in AI-driven safety monitoring, predictive maintenance, and advanced storage materials. The appearance of autonomous vehicles (2.8%) and autonomous underwater vehicles (2.1%) suggests that robotics and automation are being explored to facilitate hydrogen distribution and logistics, particularly in transportation and storage infrastructure maintenance. Furthermore, the presence of deep learning (2.1%) and genetic algorithms (2.1%) reflects the increasing adoption of advanced AI methodologies to enhance predictive modeling, process control, and system efficiency.

While technical advancements are well represented, the relatively lower frequency of terms such as sustainable development (2.1%) and renewable energies (2.1%) indicates that broader discussions on policy frameworks, economic feasibility, and long-term sustainability remain less emphasized. These insights set the stage for a deeper exploration of the applications, challenges, and potential solutions for AI and robotics in hydrogen production, storage, and transportation, discussed in the following sections.

In terms of geographical distribution of research on AI and robotics in the hydrogen lifecycle, Fig. 5 shows that China is the dominant contributor, accounting for 17.6% of total publications. The United States follows with 12.9%, reflecting its continued commitment to technological advancements in hydrogen energy. India ranks third with 8.5%, demonstrating its growing investment in renewable energy and emerging AI applications. Several European and East Asian countries also play a significant role in the field. Germany (4.7%), Italy (4.2%), and the United Kingdom (4.1%) contribute substantially, aligning with their strong hydrogen policies and AI-driven energy research. Canada (3.4%), South Korea (2.8%), and Australia (2.5%) also exhibit notable

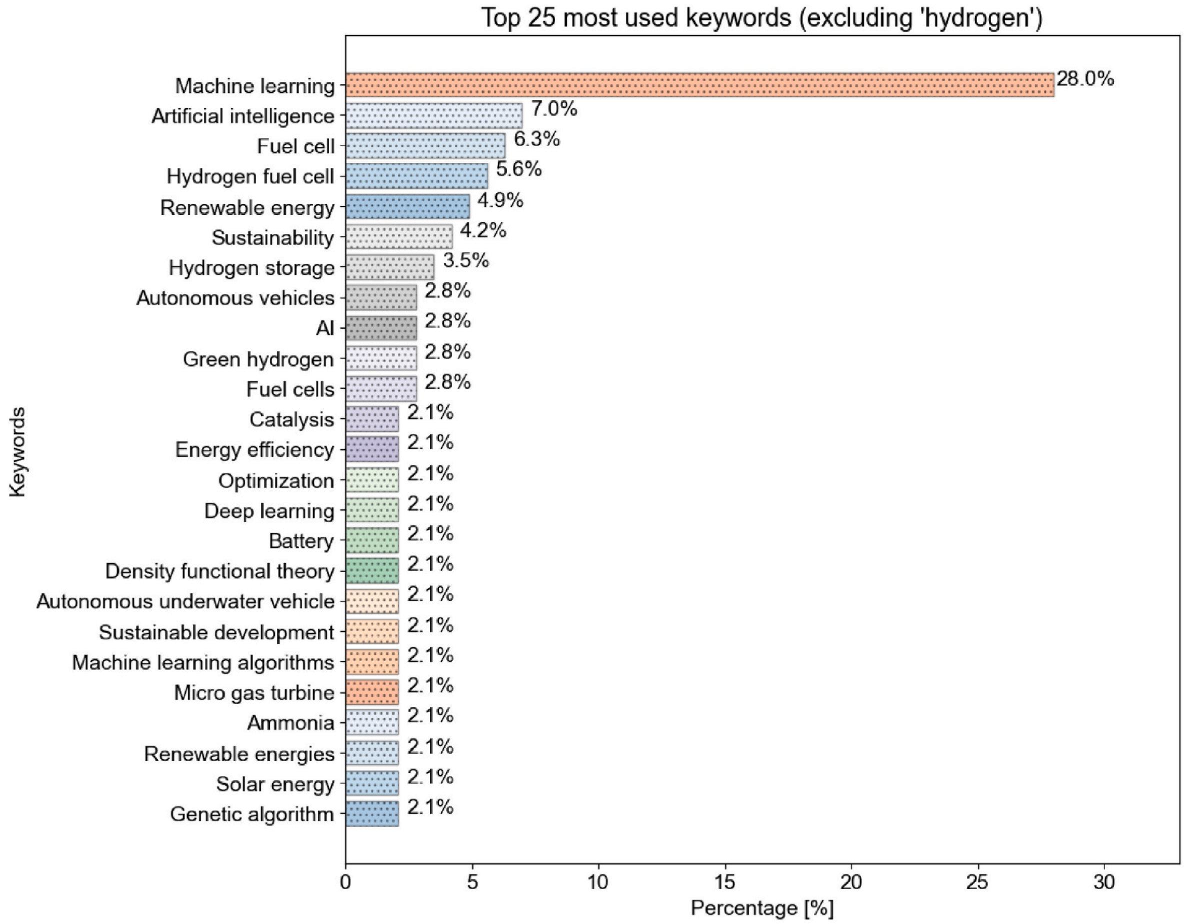

Fig. 4. Distribution of the top 25 most used keywords in research on AI and robotics in the hydrogen lifecycle (excluding 'hydrogen'). The prevalence of terms such as 'machine learning' and 'artificial intelligence' highlights the growing role of AI-driven optimization, while keywords related to fuel cells, sustainability, and storage reflect key technological and environmental priorities across hydrogen production, storage, and transportation.

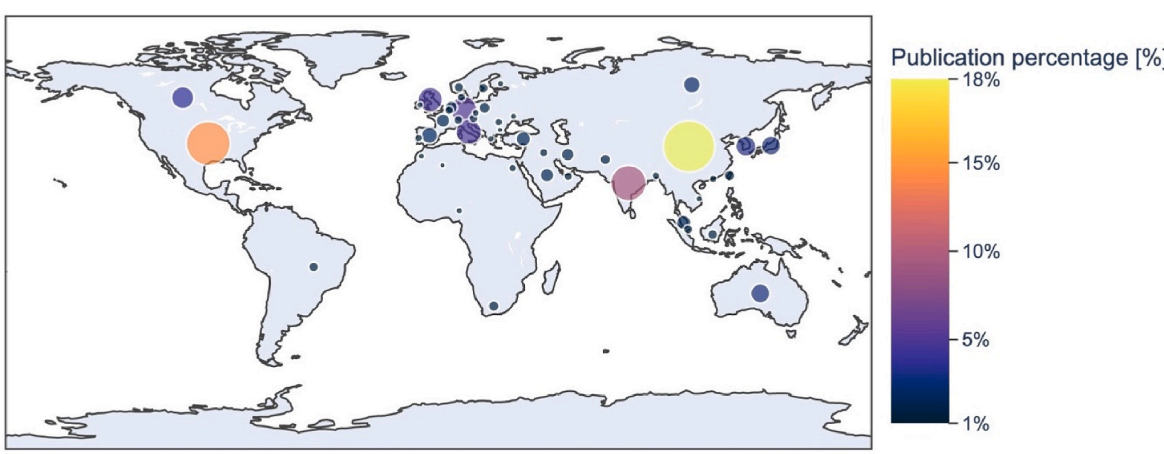

Fig. 5. Geographical distribution of research on AI and robotics in the hydrogen lifecycle.

research efforts, particularly in hydrogen production and storage. Beyond these leading nations, contributions are observed from a diverse range of countries, including Japan (2.5%), Russia (2.0%), Spain (1.8%), and Turkey (1.5%), indicating a globalized interest in AI and robotics applications within hydrogen technologies. Middle Eastern and Southeast Asian nations, such as Saudi Arabia (1.3%), Iran (1.1%), Malaysia (1.5%), and Indonesia (0.74%), have also made contributions, particularly in hydrogen storage and industrial automation. While research efforts span multiple regions, China and the United States remain dominant, with a significant gap between them and other contributors. The relatively low representation from South America and Africa, aside from Brazil (0.7%) and South Africa (0.81%), suggests a disparity in research funding, policy incentives, and industrial engagement in hydrogen AI technologies. Addressing these gaps through international collaboration and technology transfer could enhance the global development and deployment of AI and robotics in the hydrogen economy.

The impact of increased government funding, particularly in the application of AI and robotics, has been profound. Fig. 6 illustrates the year-on-year growth of The European Commission (ERC)-funded AI projects as a percentage of total ERC-funded projects from 2007 to 2021 taken from European Research Council Executive Agency [53]. Initially, AI-related projects constituted a relatively small share, remaining below 5% until 2013. However, from 2014 onwards, a noticeable upward trend emerged, reflecting an increasing prioritization of AI research within European funding schemes. This acceleration aligns with the broader global shift toward artificial intelligence as a transformative technology, driven by advancements in machine learning, robotics, and data-driven decision-making. The sharp rise after 2016 can be attributed to initiatives under Horizon 2020, which actively promoted AI and digital transformation projects. By 2021, AI projects accounted for nearly 15% of all ERC-funded research, highlighting the growing role of AI in addressing scientific and societal challenges. This trend suggests a continued focus on AI within Horizon Europe, reinforcing the importance of sustained investment in AI research and its applications across various domains, including hydrogen energy, automation, and industrial robotics.

According to the International Federation of Robotics [55], global investment in robotics research and development varies significantly across countries, with each nation allocating substantial budgets to advance industrial automation, artificial intelligence, and autonomous systems. China has focused on integrating robotics into key industries, investing approximately 45.2 million USD in 2023 and 44.5 million USD in 2024 for its National Key R&D Plan on Intelligent Robots. This aligns with China's broader strategy to dominate the global humanoid robot market and enhance industrial automation. Similarly, Japan has prioritized robotics in its Moonshot Research and Development Program, allocating 334 million USD over five years (2020–2025) and providing an additional 660 million USD in 2023 alone. Korea has also established long-term strategies, committing 163 million USD in 2023 for the Intelligent Robot Action Plan and an additional 128 million USD in 2024 for its 4th Basic Plan on Intelligent Robots. The European Union continues to be a leader in AI and robotics through Horizon Europe, with 183.5 million USD dedicated to robotics-related projects between 2023 and 2025. Meanwhile, Germany has committed 69.12 million USD annually until 2026 under its High-Tech Strategy 2025, reinforcing its position as the largest robotics market in Europe.

The United States leads in robotics funding, particularly in defense and space applications. The Department of Defense (DoD) allocated 10.3 billion USD for autonomy and robotics technologies in FY23 and requested 10.2 billion USD for FY24, reflecting the growing role of unmanned systems in military operations. The National Science Foundation (NSF) also supports robotics research, investing 53.8 million USD in 2023 and 69.9 million USD in 2024 under the Intelligent Robotics and Autonomous Systems (IRAS) R&D programs. Additionally, NASA's Artemis lunar exploration program received a total budget of 53 billion USD for 2020–2025, including 10.67 billion USD in 2023 alone. The United Kingdom's funding is more modest in comparison, with approximately 28.8 million USD allocated to robotics programs in 2023 and 2024, supporting initiatives like Made Smarter Innovation and Transforming Food Production. These investments reflect a global recognition of robotics as a transformative technology, with increasing applications in automation, energy systems, and AI-driven industrial operations.

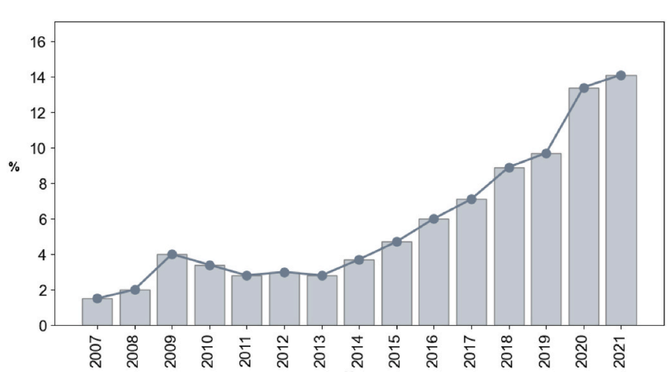

Fig. 6. Yearly evolution of ERC-funded AI projects as a percentage of total ERC-funded projects (2007–2021), reproduced from the European Research Council Executive Agency [53].

4. Results and discussions

This section discusses the integration of AI and robotics across the hydrogen lifecycle, focusing on their applications in production, storage, and transport. The results are discussed in terms of the benefits that these technologies bring to optimizing processes, enhancing operational safety, and enabling real-time decision-making. Additionally, the challenges associated with scaling AI and robotics in industrial hydrogen systems and integrating them with existing infrastructure are analyzed. Table 2 summarizes the key applications, challenges, and potential solutions for AI and robotics in hydrogen production, storage, and transport to provide a comprehensive overview of the current landscape.

4.1. Hydrogen fuel production

4.1.1. Current uses of AI and robotics in hydrogen production

Generative models, such as generative adversarial networks (GANs), have been increasingly employed for the design of advanced materials used in hydrogen production, such as high-efficiency membranes for gas separation. A significant breakthrough in AI-driven materials design for hydrogen production has been achieved through the GLIDER framework, a deep generative artificial intelligence model developed by Niu et al. [74]. This deep generative AI model integrates generative AI, data-driven modeling, and collective intelligence, enabling the efficient optimization of Pt-carbon-ionomer nanostructures for fuel cell electrodes while remaining adaptable to other electrochemical energy devices. The approach addresses key challenges in catalyst layer design, reducing high synthesis costs and improving nanostructure-performance relationships. These models enable the creation of novel materials with optimized properties that are critical for enhancing the efficiency of hydrogen production processes.

Similarly, utilizing deep learning algorithms, AI-driven process control has been transformative in optimizing complex production processes like SMR. The integration of deep learning algorithms into AI-driven process control has been transformative in optimizing complex hydrogen production processes. For instance, Lee et al. [58] developed a deep neural network (DNN) trained on over 485,000 real-world operational datasets to optimize SMR performance, achieving an exceptional accuracy of $R^2 = 0.9987$. Their results demonstrated a thermal efficiency of 85.6%, surpassing previous benchmarks. The model's capability to conduct over 20,000 case studies per second makes it highly suitable for real-time process monitoring and optimization, allowing operators to dynamically adjust conditions and enhance efficiency [75]. A multi-objective optimization approach was applied to SMR to balance thermal efficiency and CO_2 emissions by Hong et al. [54], using particle swarm optimization (PSO) and multi-objective PSO (MOPSO) (see Fig. 7). In the single-objective optimization, a higher PSA recovery rate (84%) improved hydrogen production but required additional natural gas (NG) combustion, increasing CO_2 emissions. Conversely, optimizing for lower CO_2 emissions (577.9 t/y) reduced NG input but sacrificed thermal efficiency (77.5%). The MOPSO algorithm identified Pareto-optimal solutions, allowing decision-makers to select trade-offs suited to operational priorities. A hybrid DNN model trained on pilot plant and process simulation data further improved prediction accuracy ($R^2 = 0.94$), enabling soft sensing of unmeasured variables. The study suggests that optimizing SMR processes through AI-driven modeling can

Table 2
Summary of AI and robotics applications, challenges, and solutions in the hydrogen lifecycle.

Category	Current applications	Challenges	Potential solutions	Application examples
Hydrogen production	**Electrocatalyst design:** ML applies high-throughput datasets and simulations like density functional theory for material development, accelerating hydrogen evolution reaction research. **Electrolysis optimization**: ML-driven electrolysis optimization enhances efficiency and reduces costs by analyzing operational parameters in green hydrogen production. **SMR optimization**: Employing AI and machine learning to optimize the SMR process, minimizing energy consumption and maximizing yield. **Predictive maintenance**: Using AI-driven predictive algorithms and robotics to minimize downtime in production facilities	**Scalability**: Limited datasets and scalability for industrial applications. **Integration with existing production infrastructure**: Ensuring compatibility between AI-driven systems and legacy production infrastructure. **Energy efficiency**: Developing algorithms to optimize energy consumption while maintaining hydrogen purity and yield. **Safety compliance**: Implementing AI and robotics in compliance with safety standards for handling high-pressure systems and hazardous materials.	**Adaptive algorithms**: Implementing adaptive learning algorithms to continuously optimize energy efficiency in electrolysis and SMR. **Collaborative human–robot interaction**: Developing systems for safe and efficient human–robot collaboration in maintenance tasks	[26] [49] [37] [56] [54] [57] [58] [59] [23] [60] [61] [62]
Hydrogen storage	**Pressure-based storage management**: Implementing robotics to manage high-pressure storage tanks, ensuring safety and efficiency. **Cryogenic storage automation**: Applying robotics to handle cryogenic storage procedures, ensuring precision and safety. **Leak detection and prevention**: Utilizing AI algorithms and sensors for real-time leak detection and automated response. **Material property**: AI contributes to solid-state hydrogen storage optimization, focusing on material property prediction for systems like Mg-based compounds and solid-state hydrogen storage materials. **Digital twins:** They simulate and manage storage system vulnerabilities, providing real-time monitoring of conditions like temperature and pressure.	**Material compatibility**: Ensuring that robotic materials and sensors withstand high-pressure hydrogen storage conditions. **Scalability**: Managing complexities in scaling AI-driven robotic solutions to industrial levels. **Energy efficiency**: Managing energy consumption in cryogenic storage using AI and robotics.	**Energy-efficient designs**: Implementing algorithms and robotic designs to minimize energy consumption in cryogenic storage. **Dynamic optimization**: Utilizing AI for dynamic optimization and condition forecasting to enhance storage solutions.	[41] [63] [48] [39] [64] [59] [65] [66] [38]
Hydrogen transport	**Hydrogen fuel transportation**: Utilizing AI for route optimization and predictive maintenance in transportation, including pipelines and trucking. **Intelligent distribution networks**: Designing AI algorithms for real-time monitoring and control of hydrogen distribution networks. **Intelligent pipeline monitoring**: AI contributes to hydrogen transport through real-time monitoring and prediction of leaks in hydrogen refueling stations via digital twins, achieving high accuracy using CNNs. Computer Fluid Dynamics (CFD)-ML hybrid models for leak dispersion and safety analysis reduce computational burdens.	**Reliability in diverse conditions**: Ensuring consistent performance of route optimization in various conditions, including weather. **Intermodal coordination**: Coordinating between different transport modes (pipelines, trucks, ships) with complex AI-driven logistics solutions. **Robotics integration**: Robotics in transportation lacks coverage, aside from conceptual references to AIoT frameworks for infrastructure optimization. Robotics integration into this domain is mainly conceptual, focusing on inspection or visualization through digital twins	**Dynamic supply chain optimization**: Implementing AI for dynamic optimization and forecasting to strengthen supply chain resilience. **Integrated multimodal systems**: Applying AI to seamlessly coordinate different modes of transport.	[67] [41] [68] [69] [70] [71] [72] [73]

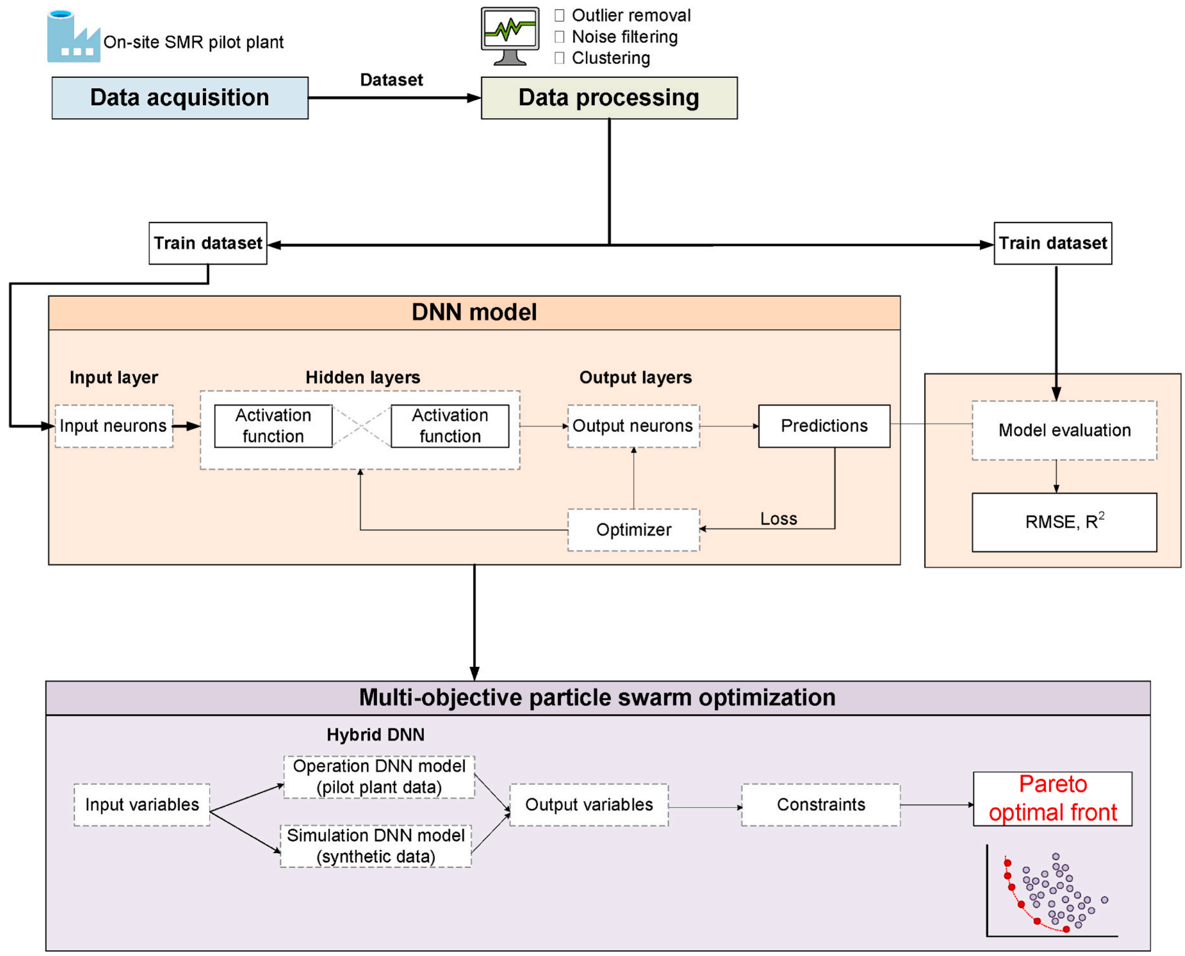

Fig. 7. DNN and MOPSO framework for optimizing hydrogen production in SMR, adapted from Hong et al. [54]. The process involves data acquisition from an on-site SMR pilot plant, data processing, and training a DNN model to predict system performance. A hybrid DNN, integrating both pilot plant and simulation data, refines predictions for multi-objective optimization. The MOPSO algorithm identifies Pareto-optimal solutions balancing thermal efficiency and CO_2 emissions, providing decision-makers with trade-off solutions for process optimization.

significantly lower emissions while maintaining efficient hydrogen production. This bridges the gap toward low-carbon hydrogen technologies until green hydrogen becomes fully commercialized.

Beyond process optimization, ML-based soft sensors have been developed to enhance real-time monitoring and fault detection in hydrogen production. Nkulikiyinka et al. [76] introduced a random forest (RF) and artificial neural network (ANN)-based soft sensor for monitoring sorption-enhanced SMR. Both models exhibited high accuracy ($R^2 > 98\%$), with RF outperforming ANN in predictive reliability. These soft sensors serve as backup systems when hardware sensors fail or require maintenance, ensuring uninterrupted monitoring. Additionally, they facilitate real-time quality control, reducing the reliance on intermittent laboratory analysis, which is often time-consuming and lacks real-time responsiveness. Predictive maintenance technologies that leverage robotics and AI are being used to anticipate equipment failures and perform safe repairs. This integration significantly enhances operational safety and reduces downtime by allowing for proactive maintenance rather than reactive repairs [77]. Integrating AI-driven material discovery techniques with existing deep learning-based process control could further enhance the overall optimization and scalability of hydrogen production systems. Despite these advancements, AI and robotics in hydrogen production face critical challenges that must be addressed to ensure widespread adoption and industrial feasibility.

4.1.2. Challenges of employing AI and robotics in hydrogen production

Traditionally, hydrogen production processes (mostly fossil-fuel based hydrogen production technologies e.g. grey, and more recently, blue hydrogen) have been mostly flow-sheeted, modelled and optimized by means of specialist advanced software such as Aspen Suite, and gPROMS. Despite the high level of accuracy and relative practicality of the employment of these conventional methods in process optimization and control, these methods could be significantly computationally demanding while may require the developer/user to have an in-depth knowledge of the process and the modelling techniques to be able to both interpret the data and fine-tune the process when needed. In addition to the process optimization and control, ML techniques have been equally used in the identification of suitable adsorbents and catalysts used in grey and blue hydrogen production processes.

With the global commitment to achieving net-zero carbon emissions by 2050 (both nationally in the UK and internationally), there is a continued reliance on fossil-fuel-based hydrogen production during the transition to fully renewable energy sources. As a result, there has been a significant increase in plans for the construction of blue hydrogen plants across the UK, expected to be developed over the coming decades until 2050. These facilities are mandated to capture at least 95% of the CO_2 emissions generated during the production process, ensuring compliance with low-carbon transition strategies while bridging the gap toward a renewable hydrogen economy. Unlike grey hydrogen, blue hydrogen is referred to hydrogen produced using fossil fuels as feedstock (i.e. grey hydrogen); while capturing the co-generated CO_2 by-product (for each kg of hydrogen, 8–12 kg of CO_2 is generated when using fossil fuels as feedstock). As a result, a significant number of datasets have been generated for blue hydrogen production plants which would be vital to fully understand the behavior of such plants under both steady-state (i.e. normal continuous operation) and unsteady-state conditions (e.g. start-up and shut-down, and also, under variable load/demand). These datasets, whether generated via optimization of process models, or, gathered on pilot-scale units, could facilitate the generation of ML-based models. These models, when effectively implemented, could help to reduce the time necessary to understand and respond to a variation in the operating conditions of the plant, and also, to predict the impact of such variations. This becomes even more crucial when dealing with a highly non-linear process in nature, such as hydrogen production plants.

The basics, as well as the applications of ML techniques and black-box models, including ANN, recurrent neural network (RNN), long-short term memory (LSTM), CNNs, modular neural network, deep learning (DL) and autoencoders in grey and blue hydrogen production processes, has been comprehensively reviewed by Masoudi Soltani et al [75] and Davies et al.[78]. More recently, Babamohammadi et al. [79] investigated the application of full factorial designs to probe into the potential interactions between various operational parameters in blue hydrogen production processes. One of the key challenges of the existing ML models is the lack of adequate datasets based on commercial-scale plants. This affects the reliability of such models and limits their applications in real-world scenarios. Additionally, although ML models can significantly enhance the overall speed and computational demands, they suffer from offering interpretable outputs. This would be beneficial to plant operators; however, these models could fail to paint a clear picture of the underlying issues. To address this, recently, physics-informed neural networks (PINNs) have been introduced in which biases are fed into the learning process. This approach enables the learning process to pinpoint physically interpretable solutions to the problem at hand. This is especially important if ML models are to be deployed in the start-up and/or shutdown of the plant, where safety and accurate control are of paramount importance.

One of the key challenges associated with commercial hydrogen production plants is the potentially intermittent nature of the production load. This could be dictated by the variable feedstock flow rate, such as natural gas (i.e. in case of SMR) and/or other fossil fuels (i.e. collectively referred to as grey hydrogen). Such intermittencies (i.e. disruptions) directly impact the instantaneous energy demands, and hence, the operating variables such as temperature, pressure, flow rates and etc. Also, such fluctuations induce a transitional unsteady-state phase of operation similar to startup/shutdown scenarios. Salah et al. [80] developed and employed a structured neural network as a surrogate platform for dynamic modelling of a biomass steam reformer, where the data was collated from a 200 kW_{th} pilot plant. The importance of real-time control under non-linear and dynamically changing conditions is also important when applying ML techniques to inherently unsteady-state (or pseudo steady-state) processes such as pressure and temperature swing adsorption (TSA and PSA, respectively). PSA is a key unit operation in both grey and blue hydrogen production plants in which hydrogen is purified to high concentration before storage. Within the literature ML has been mostly applied to the overall process at hand; however, there have been studies where such algorithms have been used to optimize individual process units. With regards to PSA/TSA units, the highly dynamic nature of these processes, makes the development of a detailed first-principles model and its application in the real-time operation of the plant (e.g. digital twins) highly challenging and time-consuming [81]. The advantages of the employment of ML techniques in the optimization of PSA units have been reported in Subraveti et al. [82]. The authors have noted that their approach offers approximately a tenfold reduction in computational demands while still offering the same level of performance as that of the detailed physics-based models.

4.1.3. Potential solutions for employing AI and robotics in hydrogen production

To overcome these challenges, hybrid AI models that integrate physics-based principles with data-driven ML offer a robust solution for improving advanced control in hydrogen production. These models enhance transparency and reliability in process optimization by combining traditional process knowledge with AI. For example, PINNs integrate physical process knowledge into machine learning models, improving prediction accuracy and interpretability. PINNs have demonstrated significant potential in optimizing start-up and shutdown sequences in hydrogen plants, where accurate control is essential for safety and efficiency. This approach allows for more accurate predictions and better decision-making by ensuring that AI recommendations align with established scientific principles [83]. Swarm intelligence algorithms, such as PSO and Ant Colony Optimization (ACO), provide a powerful method for balancing multiple objectives in hydrogen production, including efficiency, cost, and environmental impact. These algorithms simulate decentralized systems to achieve optimal trade-offs between conflicting goals, thereby enhancing overall production performance.

The adoption of digital twins, i.e., virtual replicas of physical hydrogen production systems, enables advanced simulations and real-time optimization. Integrating AI allows these digital twins to conduct virtual tests on different operational strategies and predict potential problems prior to physical execution. This method minimizes the need for expensive trials and improves decision-making by offering comprehensive insights into system performance [21]. However, while these solutions offer significant advancements, their implementation requires overcoming challenges related to data integration, model validation, and system scalability. Ensuring effective integration into existing production systems will be critical for maximizing the benefits of AI and robotics in hydrogen production. The use of hybrid AI models, swarm intelligence, and intelligent digital twins presents promising solutions to optimize hydrogen production processes. These approaches address key challenges and offer substantial improvements in control, optimization, and decision making.

4.2. Hydrogen fuel storage

4.2.1. Current uses of AI and robotics for hydrogen storage

The integration of robotics and AI into hydrogen storage systems has the potential to transform the industry by enhancing precision, safety, and efficiency. Nanomaterial-enhanced sensing technologies represent a significant advancement in monitoring hydrogen storage conditions. Researchers have achieved precise real-time monitoring of critical parameters such as hydrogen purity, pressure, and temperature by utilizing sensors embedded within nanomaterials combined with AI algorithms. This approach allows for the early detection of deviations from optimal storage conditions, which is crucial for maintaining the integrity and safety of storage systems. ML for structural integrity analysis is another key area where AI is making a substantial impact. AI algorithms can analyze data from high-pressure hydrogen storage tanks to predict material fatigue and failure. This capability is critical for preventing catastrophic failures in storage tanks subjected to extreme conditions. ML models help extend the lifespan of storage tanks and enhance operational safety by predicting potential issues before they occur [84,85]. Zhou et al. [38] provide a comprehensive review of the applications of ML in solid-state hydrogen storage materials, particularly in addressing key challenges such as low hydrogen storage capacity and unfavorable de-/hydrogenation conditions. The study highlights various ML techniques, including high-throughput composition-performance scanning for Ti-based hydrogen storage materials, as well as predictive modeling for rare-earth, magnesium-based, and complex hydrides. The authors emphasize the importance of dataset quality, feature selection, and the balance between model accuracy and interpretability. By leveraging ML-driven approaches, researchers can accelerate the discovery of next-generation hydrogen storage materials with improved efficiency, durability, and operational safety, thereby advancing the development of sustainable energy storage solutions.

Fig. 8 illustrates the fundamental ML workflow for materials discovery in hydrogen storage science, encompassing dataset establishment, feature engineering, model training, and performance evaluation. The first step involves defining key research objectives, such as optimizing phase structures, enhancing hydrogen absorption and desorption kinetics, and improving overall storage capacity. Subsequently, high-quality dataset curation and preprocessing are essential to ensure accurate and reliable model training. This includes selecting relevant feature descriptors that characterize solid-state hydrogen storage materials. Proper feature engineering enhances the model's ability to identify patterns and predict material performance, ultimately accelerating the discovery of advanced hydrogen storage solutions.

One of the most critical challenges in hydrogen storage is identifying materials with high hydrogen storage capacity (HSC), low desorption temperature, and long-term stability. Traditional material discovery relies on trial-and-error experiments, which are time-consuming and resource-intensive. Recent studies demonstrate how ML accelerates this process by predicting material properties and optimizing hydrogen storage conditions. For instance, Athul et al. [63] employed ML algorithms to identify stable intermetallic compounds for hydrogen storage, utilizing databases such as the U.S. Department of Energy Hydrogen Storage Materials Database and the Open Quantum Materials Database. Their study generated 349,772 hypothetical intermetallic compounds, of which 8568 were identified as stable. The random forest algorithm emerged as the most accurate ML model, demonstrating its potential in predicting enthalpy of formation, equilibrium pressure, and HSC. These insights reduce the time required for material discovery and improve the accuracy of storage performance predictions. Similarly, Li et al. (2025) explored the integration of ML in chemical looping hydrogen production and storage systems, showing that ANNs and Extra Trees models achieved high prediction accuracy ($R^2 = 0.96$ for hydrogen yield and $R^2 = 0.94$ for purity). Their interpretability algorithm identified reaction temperature and fuel gas composition as the most influential factors in

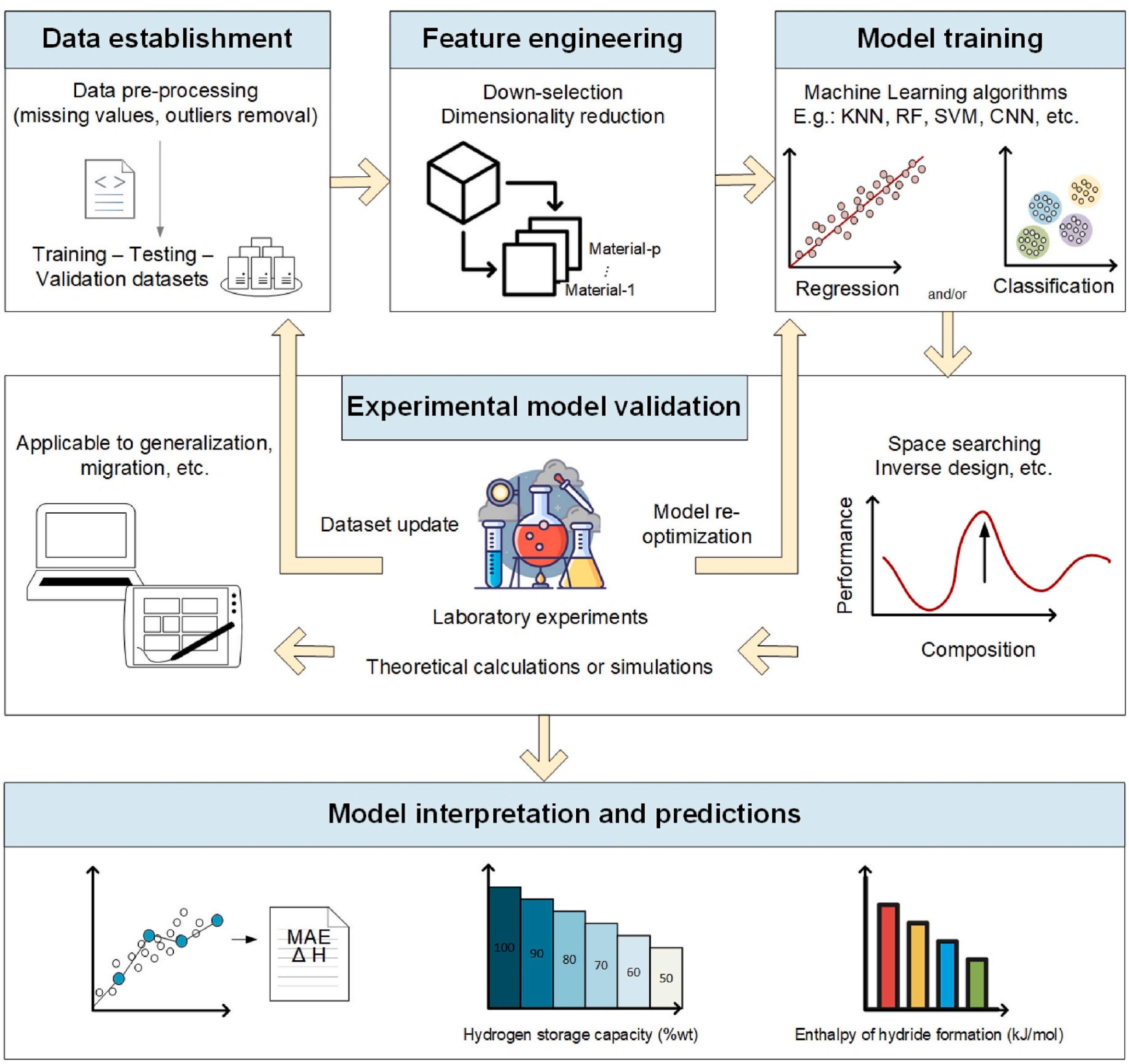

Fig. 8. Machine learning framework for material screening and selection in hydrogen storage, based on Zhou et al. [38]. The process begins with data establishment, including pre-processing to handle missing values and dataset partitioning. Feature engineering then reduces dimensionality and selects relevant material properties. Model training utilizes machine learning algorithms such as K-nearest neighbors (KNN), RF, support vector machine (SVM), and CNN for regression and classification tasks. Experimental model validation integrates laboratory experiments, theoretical calculations, and iterative model refinement. Finally, model interpretation and predictions provide insights into hydrogen storage capacity and enthalpy of formation, aiding in material optimization and discovery.

hydrogen storage efficiency, providing a data-driven approach to system optimization. AI-driven nanomaterial-based hydrogen sensing further enhances real-time storage monitoring. Huang et al. [48] reviewed the application of AI in Mg-based hydrogen storage, emphasizing how ML-assisted microstructure modification and composition regulation improve hydrogen adsorption/desorption rates. These approaches optimize storage conditions dynamically, ensuring long-term material performance stability.

Robotics has also become a transformative force in hydrogen fuel production by significantly enhancing precision, efficiency, and safety in manufacturing processes. A key application is in assembling Proton Exchange Membrane Fuel Cell (PEMFC) stacks. Robots are particularly valuable for handling the precise and sensitive tasks required in assembling PEMFC stacks, which involve thin components and are often exposed to corrosive acids. These conditions make manual assembly challenging and hazardous [86]. Robotic systems improve both the efficiency and safety of PEMFC production. They reduce the risk of errors and ensure consistent quality by performing tasks with high precision, thereby addressing the limitations and safety concerns associated with manual assembly. This advancement underscores the critical role of robotics in optimizing hydrogen fuel production processes and enhancing overall operational effectiveness [87].

Robotics has transformed the production of PEMFC stacks, significantly improving efficiency, safety, and precision. Gurau et al. [88] demonstrate the effectiveness of robotic assembly in PEMFC production by introducing a robot end-effector with a passive compliance system. This innovation compensates for the robot's limitations in accuracy and flexibility, leading to enhanced assembly productivity and the ability to handle larger-scale fuel cell stacks. Similarly, a previous study showcased an automated assembly process for PEMFC stacks, where robots equipped with advanced end-effectors handle various components with high precision. The design of these components, including alignment pins and positioning holes, ensures accurate assembly within a tolerance of 0.02 inches, thereby preventing accidental overlaps that could lead to gas leaks during operation. he integration of robotics enhances the precision of PEMFC assembly and adds an extra layer of safety to hydrogen production. Given the extensive range of flammable concentrations and the low ignition energy associated with hydrogen, the integration of robotics presents significant advantages in maintaining stringent safety protocols and operating within hazardous environments [65]. Robotics effectively mitigates the risks involved in handling hydrogen by automating intricate and perilous tasks, thereby facilitating safer production practices.

The industrial application of robotics in hydrogen production is gaining momentum, with pioneering companies leading the charge. Greenlight Innovation offers a fully integrated robotic fuel cell assembly system, which includes cell and stack assembly, inspection, liquid dispensing, and welding systems [89]. This comprehensive automation enhances precision and efficiency throughout the production process. Similarly, Comau, a global leader in industrial automation, collaborates with international clients to automate the production of fuel cells and electrolyzers. This automation is expected to reduce operating costs by up to 20% and improve product quality by increasing precision and minimizing the need for cleanroom security measures. The shift from manual to automated manufacturing environments aims to scale up production volumes and make zero-emission power generation more accessible and affordable. The application of robotics in hydrogen fuel production offers substantial improvements in efficiency, safety, and cost-effectiveness. The advancements in robotic technology streamline the assembly process and address critical safety concerns, positioning robotics as a key enabler in the transition towards a sustainable energy future.

4.2.2. Challenges of employing AI and robotics for hydrogen storage

Despite significant advancements, several challenges hinder the widespread adoption of AI and robotics in hydrogen storage. Data limitations remain a major obstacle, as many AI models are trained on small-scale, pilot plant datasets that may not generalize well to commercial-scale storage systems. Ensuring model interpretability is another critical issue, as many ML algorithms function as black-box systems, making it difficult for engineers to trust and refine AI-driven decisions. For example, achieving precise robotic handling at cryogenic temperatures, typically below -150 °C, presents significant challenges due to the extreme conditions. These low temperatures cause materials to become fragile, lubricants to freeze, and electronic systems to malfunction, all of which decrease the reliability and precision of robotic operations. Robots must be constructed with specialized materials and components to resist these harsh conditions, and their sensors and actuators must be meticulously calibrated for accuracy.

Developing intelligent control systems for these environments demands advanced AI algorithms capable of real-time adjustments, continuous monitoring, and predictive maintenance to prevent failures, such as reinforcement learning (RL), and CNNs. However, incorporating these techniques in cryogenic environments presents additional complexities. While RL could help to optimize robotic movements, it faces challenges due to the high risks of trial-and-error learning, which could lead to equipment damage. CNNs need large, high-quality datasets to analyze in real-time. Obtaining such data in cryogenic conditions can be challenging due to potential sensor malfunctions adding to the noise. Each technique demands significant computational resources, and ensuring energy efficiency in extreme conditions adds to the overall challenge.

One of the primary challenges in hydrogen storage monitoring is integrating AI with existing hydrogen storage infrastructure [90], which often involves legacy systems that may need to be more easily compatible with modern AI technologies. Implementing AI-driven solutions requires substantial upgrades to hardware and software and significant investment in time and resources, which can be a barrier to widespread adoption. Another challenge lies in ensuring the reliability and accuracy of AI algorithms in the highly specialized and critical environment of hydrogen storage. AI systems must be capable of making precise predictions and decisions in real time, but the quality and availability of data often hinder them. Data can be sparse, noisy, or incomplete in hydrogen storage environments, making it difficult for AI models to learn effectively and make accurate predictions [66]. Finally, there are concerns about the security and ethical implications of using AI in hydrogen storage. AI systems can be vulnerable to cyber-attacks, potentially leading to catastrophic failures in hydrogen storage facilities [91]. Ensuring robust cybersecurity measures and developing ethical guidelines for using AI in this context are essential to mitigate these risks.

4.2.3. Potential solutions for employing AI and robotics for hydrogen storage

Addressing these challenges requires innovative solutions centered around advanced AI algorithms, robotic adaptability, and sustainable AI practices. Next-generation robotics designed for safe human interaction in hydrogen storage environments can enhance precision and safety. These systems must feature advanced sensors and AI algorithms for real-time adjustments and collision avoidance. However, challenges include ensuring reliable human-robot collaboration and maintaining safety in dynamic conditions. AI algorithms capable of adaptive control in extreme pressures and temperatures are crucial for hydrogen storage. These algorithms need to manage real-time changes and predict maintenance needs; however, they face difficulties due to the harsh conditions and the complexity of the interactions within the storage systems (e.g. [77,92]).

Adaptive AI algorithms represent another promising solution, as these algorithms can dynamically respond to real-time data variations, manage sudden shifts in storage conditions, and accurately predict maintenance requirements. Techniques such as RL, when carefully controlled and guided by simulated environments, can optimize robotic movements without endangering sensitive equipment. A particularly compelling approach is developing PINNs. They significantly improve interpretability, prediction accuracy, and reliability by embedding established physical knowledge within AI algorithms, which is particularly critical in safety-sensitive storage operations. This hybrid model combines the benefits of traditional physical modeling with the flexibility and efficiency of modern AI, delivering reliable and actionable insights.

Finally, the concept of "Green AI" addresses concerns related to AI's energy-intensive computational requirements. Green AI focuses on developing energy-efficient algorithms that require less computational power and data. This approach aims to reduce the environmental impact of AI systems. Implementing Green AI involves balancing efficiency with performance, ensuring that models remain accurate while minimizing resource use [93]. Each solution presents benefits and challenges; for example, intelligent robotics must ensure safe human interaction, adaptive control algorithms need to perform reliably under extreme conditions, and Green AI aims to optimize efficiency. Addressing these challenges is key to advancing AI and robotics in hydrogen storage for long-term system reliability and sustainability.

4.3. Hydrogen fuel transport

4.3.1. Geographical infrastructure

Geographical infrastructure is pivotal in shaping the efficiency, cost, and environmental impact of hydrogen fuel transport. In the Middle East, the prevailing use of SMR for hydrogen production highlights a trade-off between efficiency and environmental impact. SMR is favored for its cost-effectiveness and high efficiency compared to electrolysis, but it generates significant CO_2 emissions and poses safety risks [28]. This reliance on carbon-intensive menkthods underscores the need for alternative production strategies that mitigate environmental impacts while meeting future hydrogen demands. Conversely, China has made notable advancements in hydrogen refueling infrastructure, particularly in urban areas with high population densities. Concentrating hydrogen refueling stations in these cities effectively reduces refueling distances, enhancing the convenience for fuel-cell vehicle users [94]. However, while this strategy improves user experience, it raises questions about the scalability and cost-effectiveness of such concentrated infrastructure in less densely populated areas.

International supply chains present additional complexities. A comparative analysis reveals that, while e-hydrogen production in Morocco and Chile may eventually be more cost-effective than in Germany and Finland, high transportation costs diminish these advantages [95]. This disparity suggests a potential shift towards more localized production to offset transportation expenses, which could foster regional job creation, enhance energy security, and generate additional tax revenue. In Turkey, the design of a hydrogen supply chain network reflects a strategic move towards decentralized systems that balance cost, CO_2 emissions, and safety risks [96]. This approach is indicative of a broader trend towards optimizing supply chains to address specific regional challenges; yet it highlights the ongoing need to reconcile efficiency with environmental and safety considerations. Last, Rasool et al. [97] introduce a probabilistic decision analysis cycle methodology to evaluate renewable energy supply chain pathways for hydrogen. This methodology underscores the complexity of decision-making due to multiple factors. It highlights how technology and carrier options might shift based on criteria such as the levelized cost of hydrogen or energy. It emphasizes the need for adaptive strategies that can respond to evolving conditions and technological advancements. Geographical infrastructure is crucial in determining the success of hydrogen supply chains, influencing cost, efficiency, and environmental impact. While advancements are being made, challenges remain, including high transportation and production costs, CO_2 emissions, and safety risks. To facilitate the broader adoption of hydrogen, it is essential to develop strategies that address these challenges. This includes enhancing local production capabilities, advancing renewable production technologies, and increasing public awareness and acceptance.

4.3.2. Current uses of robotics and AI for hydrogen transport

AI has significantly improved hydrogen leak detection by enhancing accuracy and reducing response time compared to conventional sensor-based methods. Traditional techniques rely on fixed sensor networks, which can be affected by environmental factors such as temperature and humidity, leading to false positives and negatives. Moreover, manual inspections remain time-consuming and hazardous. AI-driven approaches address these limitations by integrating deep learning and advanced sensor placement optimization techniques. For instance, in a study by Zhao et al. [73], deep residual networks and k-nearest dynamic programming models were applied to hydrogen leakage localization in underground garages, achieving precise leak source identification. Another AI-based approach employs transfer learning and multimodal sensor fusion to improve hydrogen leak detection and localization. Bi et al. [68] developed a hybrid model combining data denoising and deep learning to enhance leak location prediction accuracy. Additionally, Yang et al. [71] proposed a wavelet denoising-based hybrid model for hydrogen leakage detection, achieving 99.14% accuracy in predicting leak locations and 97.42% in determining leak intensity.

Despite these advancements in hydrogen leak detection, the role of robotics in hydrogen transportation remains an underexplored research area. While robotics has been successfully integrated into hydrogen storage and refueling stations for monitoring and safety, there is limited research on how robotic systems could enhance hydrogen leak detection and infrastructure maintenance during transportation. The absence of studies focusing on autonomous robotic systems for pipeline inspection, real-time hydrogen leakage monitoring, and transport vehicle safety highlights a critical research gap. Investigating the integration of mobile robotic platforms, such as drones or ground-based autonomous systems, with AI-driven leak detection could offer transformative solutions. Developing adaptive robotic inspection strategies that operate under different environmental conditions and transportation modes could significantly improve safety and efficiency in hydrogen logistics. This gap underscores the need for interdisciplinary research combining AI, robotics, and hydrogen transport engineering to enhance real-time monitoring and safety in hydrogen distribution networks.

4.3.3. Challenges of employing AI and robotics in hydrogen transport

Ensuring the reliability of AI for hydrogen transport is a significant challenge. Route optimization algorithms must perform well under varying conditions and unexpected events. The capability of AI systems to handle future conditions is crucial to prevent disruptions in hydrogen supply chains. These systems must be adaptable and resilient, using advanced predictive analytics and real-time data to ensure a consistent and reliable supply. For example, extreme weather conditions such as heavy snowfall, rain, or heat waves can significantly impact road conditions and, consequently, the effectiveness of AI-driven route optimization [98]. These systems must be able to quickly adapt to such changes to avoid delays in hydrogen delivery. Urban areas often experience fluctuating traffic conditions, with rush hours, accidents, and construction work creating unpredictable traffic flows. AI route optimization algorithms need to account for these variables in real-time, requiring sophisticated machine learning models capable of processing large amounts of data quickly and accurately [99].

ML algorithms are essential for analyzing vast amounts of historical data to identify patterns and predict future conditions. Techniques like reinforcement learning can help AI systems learn optimal routing strategies over time by interacting with the environment [100] Deep reinforcement learning-based routing schemes have advantages such as autonomous training, strong adaptability, and reduced need for manual data labelling, making them stand out among many machine learning approaches. Convolutional neural networks can process real-time traffic camera feeds to assess road conditions [101]. However, these schemes often rely on fixed neural network structures like feedforward or recurrent networks, limiting their generalization ability and making it challenging to adapt to dynamic changes in network topology [102].

Maintaining data integrity in real-time distributed monitoring systems for hydrogen pipelines poses significant challenges [103]. These systems rely on numerous sensors across vast networks, continuously collecting data on critical parameters like pressure and flow rates. Sensor malfunctions, environmental interferences, and transmission errors can compromise data quality [104]. Accurate timing and data synchronization across distributed monitoring systems are also crucial to avoid misinterpretations. AI algorithms must address this challenge to prevent false alarms or missed detections [105]. Additionally, the vulnerability of these systems to cyber-attacks requires robust AI-based security measures, which can be challenging to implement, especially in remote areas [106].

Inconsistent collaboration between various transportation modes, such as road, rail, and shipping, can result in significant inefficiencies in the hydrogen transport network. One of the primary challenges in this context is ensuring the quality and consistency of data used by AI models to optimize logistics across these different modes. Good quality data is essential for the effective operation of AI systems. Yet, data heterogeneity and inconsistencies between datasets from different transportation sectors can lead to suboptimal decision-making and coordination failures. For instance, proprietary datasets built from scratch for specific tasks may not align with datasets from other studies, leading to gaps in coordination. This issue is combined with the need for more standardized datasets in the transportation sector, which impedes AI systems from integrating and fully optimizing operations across different modes of transport [107]. AI-driven systems must deal with the uncertainty and limited nature of data in real-time operations, particularly in scenarios involving rare events such as accidents or critical system failures. Techniques such as transfer learning and using digital twins for generating synthetic data can help AI models perform more effectively even with limited or imperfect data (Pan &Yang,2009). By improving data quality and integration, AI can enhance the coordination between different transportation modes, thereby reducing inefficiencies and improving the overall reliability of hydrogen transport.

4.3.4. *Potential solutions for employing AI and robotics in hydrogen transport*

To address these challenges, techniques such as transfer learning and digital twins offer potential solutions. Transfer learning allows AI models to adapt to new data with limited additional training, while digital twins can generate synthetic data to supplement real-world observations [108]. However, these approaches introduce their own complexities and require further development to effectively enhance data integration and improve the reliability of hydrogen transport networks. Effective AI integration across multiple transportation modes in hydrogen transport requires overcoming significant data quality and standardization challenges. Addressing these issues through advanced techniques like transfer learning and digital twins is essential for improving coordination and efficiency in hydrogen logistics.

AI-driven management within smart energy grids can significantly enhance hydrogen transportation. By integrating hydrogen transport with smart grids, AI systems can optimize distribution, monitor energy flows, and improve overall efficiency. This integration supports real-time adjustments and better alignment with energy demands, promoting a more flexible and responsive hydrogen transport network. Developing machine learning models for real-time anomaly detection is crucial for maintaining safety and operational integrity in hydrogen transport. AI algorithms can detect anomalies such as leaks, unauthorized access, and equipment malfunctions. Implementing advanced models ensures timely identification and mitigation of potential issues, thus preventing accidents and system failures. Ensuring seamless synchronization across different transportation modes (pipeline, road, maritime) is essential for efficient hydrogen logistics. AI algorithms can facilitate real-time decision making and coordination between these modes. Techniques for forecasting future conditions and optimizing logistics based on real-time data can enhance the reliability and efficiency of hydrogen transport systems. AI and robotics offer transformative solutions for hydrogen transport, including smart grid integration, real-time anomaly detection, and multi-modal synchronization. Addressing these areas with advanced AI technologies can enhance efficiency, safety, and operational effectiveness in hydrogen transportation.

5. Conclusions

This review systematically analyzed the role of AI and robotics in hydrogen production, storage, and transportation, identifying both advancements and challenges. AI-driven optimization in hydrogen production has improved electrolysis efficiency, enhanced catalyst discovery, and enabled predictive maintenance in steam methane reforming (SMR) plants. In hydrogen storage, AI-enhanced leak detection, real-time monitoring, and nanomaterials discovery have contributed to improving storage safety and efficiency. In hydrogen transport, AI-powered route optimization, autonomous robotics, and digital twins have enhanced pipeline monitoring, leak detection, and distribution logistics.

The systematic review methodology used in this study involved a structured literature search across Scopus and IEEE Xplore, filtering 6907 studies down to 118 highly relevant research papers. A combination of bibliometric analysis, thematic clustering, and empirical synthesis was employed to identify key trends, challenges, and solutions in AI and robotics applications within the hydrogen lifecycle. This approach provided a comprehensive assessment of existing research and highlighted areas requiring further development. Despite these advancements, several key actions are needed to accelerate AI and robotics deployment in hydrogen infrastructure:

- Develop large-scale, standardized hydrogen data repositories to improve AI model training and validation across production, storage, and transport.
- Enhance AI model interpretability using physics-informed neural networks (PINNs) to bridge the gap between machine learning predictions and established hydrogen system principles.
- Strengthen cybersecurity frameworks to protect AI-driven hydrogen systems from cyber threats, particularly in pipeline monitoring and storage facilities.
- To improve automation and safety, advance robotics for extreme environments, including cryogenic hydrogen storage and high-pressure containment.
- Expand digital twin applications for real-time hydrogen system management, predictive maintenance, and operational optimization.

Integrating AI and robotics into hydrogen infrastructure is essential for achieving the global transition to clean energy. Still, its success depends on overcoming these technological, economic, and regulatory barriers. Future research should focus on scaling AI-driven hydrogen production, developing autonomous robotic systems for hydrogen storage and transport, and ensuring real-world validation of AI models. An intensive effort from policymakers, industry stakeholders, and researchers is required to unlock the full potential of AI and robotics in hydrogen systems, ensuring a more efficient, safe, and scalable hydrogen economy.

CRediT authorship contribution statement

Paulina Quintanilla: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation. **Ayman Elhalwagy:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Lijia Duan:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Salman Masoudi Soltani:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation. **Chun Sing Lai:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pantea Foroudi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Md Nazmul Huda:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monomita Nandy:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability statement

No data has been generated in this work.

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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Abbreviations

ACO: Ant colony optimization
AI: Artificial intelligence
AIoT: Artificial intelligence of things
ANN: Artificial neural network
CFD: Computational fluid dynamics
CNN: Convolutional neural network
CCS: Carbon capture and storage
DL: Deep learning
DNN: Deep neural network
ERC: European research council
HSC: Hydrogen storage capacity
KNN: K-nearest neighbors
LSTM: Long–short term memory network
ML: Machine learning
MOPSO: Multi-objective particle swarm optimization
NG: Natural gas
PEMFC: Proton exchange membrane fuel cell
PINN: Physics-informed neural networks
PSA: Pressure swing adsorption
PSO: Particle swarm optimization
RF: Random forest
RL: Reinforcement learning