

Modeling the Key Enablers for Artificial Intelligence-Driven Transformation of the Green Hydrogen Supply Chain

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ABSTRACT

Objective: The increasing complexity of green hydrogen supply chains requires the adoption of advanced digital technologies capable of enhancing operational efficiency, resilience, and sustainability. Among these technologies, Artificial Intelligence (AI) has emerged as a key enabler of intelligent decision-making, predictive analytics, and process optimization. Despite its significant potential, AI adoption in green hydrogen supply chains remains constrained by multiple technological, organizational, economic, institutional, and environmental factors. Therefore, this study aims to identify, evaluate, and analyze the causal relationships among the critical enablers influencing AI adoption in green hydrogen supply chains.

Methodology: Initially, an extensive literature review was conducted to identify the major AI adoption enablers. Subsequently, thirteen critical enablers were validated through expert consultation involving specialists in AI, hydrogen energy, renewable energy systems, and supply chain management. The DEMATEL method was then employed to examine the interdependencies, driving power, dependence relationships, and causal structure among the identified enablers based on expert judgments.

Results: The findings indicate that top management support, technological capability, digital infrastructure readiness, regulatory and policy support, and stakeholder collaboration and ecosystem integration are the primary driving enablers facilitating AI adoption. Conversely, investment and financial support, expected operational benefits, and sustainability and environmental commitment were identified as highly dependent enablers with considerable centrality, reflecting their strategic importance within the AI adoption ecosystem.

Conclusion: Unlike previous studies that primarily focused on identifying adoption factors, this research uncovers the causal relationships among the enablers and provides a structured understanding of their interactions. From a practical perspective, the findings offer valuable guidance for managers and policymakers seeking to accelerate AI implementation within GHSCs.

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Introduction

The global transition toward carbon neutrality has accelerated the search for sustainable energy carriers capable of replacing fossil fuels across industrial, transportation, and power generation sectors (Zhang et al., 2024). Among the emerging alternatives, green hydrogen has gained substantial attention as a clean and versatile energy vector produced through water electrolysis powered by renewable energy sources. Unlike conventional hydrogen production methods that rely heavily on fossil fuels and generate considerable greenhouse gas emissions, green hydrogen offers a pathway toward decarbonizing hard-to-abate sectors and supporting long-term energy security (Perna et al., 2023). Consequently, governments, energy companies, and international organizations are increasingly investing in green hydrogen projects and infrastructure to facilitate the transition toward a low-carbon economy (Sahebi, Edalatipour, et al., 2025).

Despite its significant environmental and economic potential, the development of an efficient GHSC remains a complex challenge. The green hydrogen supply chains (GHSCs) encompass multiple interconnected stages, including renewable energy generation, hydrogen production, storage, transportation, distribution, and end-use applications (Mothafar et al., 2024). Each stage generates large volumes of operational, technical, and market-related data that require real-time processing and intelligent decision-making. Furthermore, uncertainties associated with renewable energy intermittency, infrastructure limitations, demand fluctuations, and regulatory changes increase the complexity of supply chain operations (Azadnia et al., 2023). These challenges highlight the need for advanced digital technologies capable of improving visibility, coordination, forecasting accuracy, and operational efficiency across the entire supply chain (Sahebi et al., 2026).

In recent years, Artificial Intelligence (AI) has emerged as one of the most transformative technologies in modern supply chain management (Masoomi, Radman, et al., 2025). AI technologies, including machine learning, deep learning, predictive analytics, optimization algorithms, and intelligent decision-support systems, enable organizations to process large datasets, identify hidden patterns, and generate actionable insights (Dagou & Gurgun, 2024). Within the context of GHSCs, AI can contribute to demand forecasting, production planning, energy management, predictive maintenance, route optimization, risk assessment, and strategic decision-making. By enhancing operational intelligence and resource utilization, AI has the potential to significantly improve the performance, resilience, and sustainability of hydrogen supply chain networks (Ahmed et al., 2024; Sahebi et al., 2026).

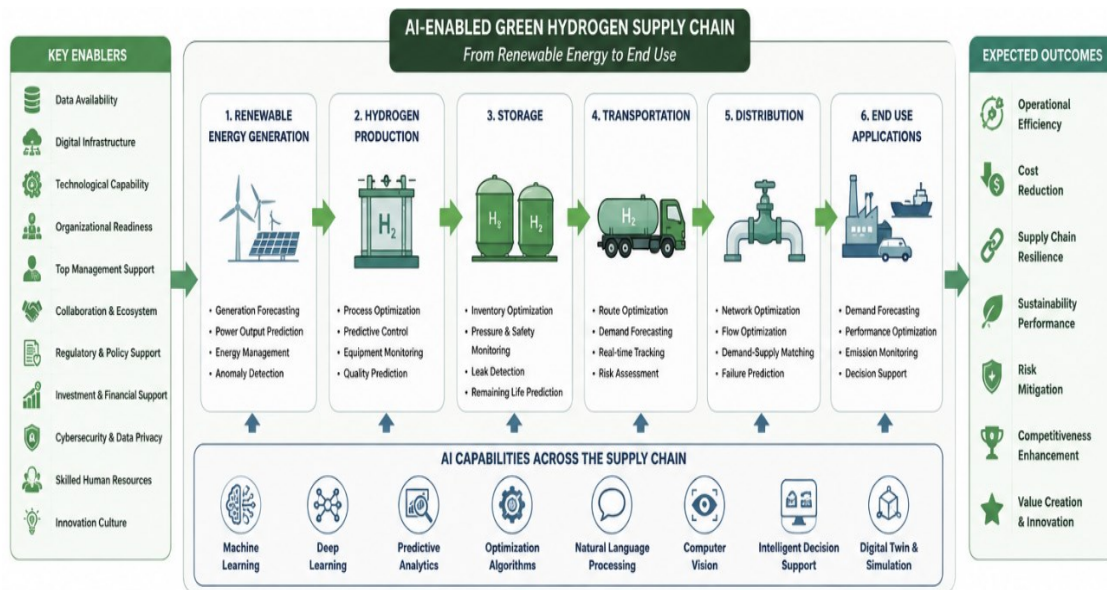


Figure 1. AI-enabled GHSC Framework

To better illustrate the role of AI across the GHSCs, Figure 1 presents a conceptual framework linking major supply chain stages with AI-enabled capabilities. Figure 1 demonstrates that artificial intelligence functions as an enabling layer that supports data-driven decision-making throughout the entire GHSCs. Through advanced analytics and intelligent automation, AI enhances operational visibility, improves resource allocation, and facilitates proactive management of supply chain activities (Gan et al., 2021). Although the benefits of AI adoption are widely recognized, organizations operating within the green hydrogen ecosystem face numerous barriers and challenges when implementing AI-driven solutions. The successful adoption of AI depends on a variety of technological, organizational, economic, and environmental factors. These factors may include data quality and availability, digital infrastructure readiness, top management support, technological expertise, investment capability, cybersecurity considerations, regulatory frameworks, stakeholder collaboration, and organizational culture. Since these factors are highly interconnected, understanding their causal relationships becomes essential for developing effective implementation strategies and maximizing the benefits of AI adoption (Ahmed et al., 2024; Sahebi et al., 2026).

The existing literature has extensively investigated AI applications in traditional supply chains, manufacturing systems, logistics operations, and renewable energy management. Similarly, several studies have examined technological adoption drivers in hydrogen energy systems and sustainable supply chains (Dagou & Gurgun, 2024; Jahin et al., 2024; W. Wang et al., 2024). However, research focusing specifically on the adoption enablers of artificial intelligence within GHSCs remains limited. More importantly, previous studies have primarily concentrated on

identifying influential factors without adequately exploring the complex cause-and-effect relationships that exist among them. This research gap restricts the ability of practitioners and policymakers to prioritize critical enablers and formulate effective strategies for AI implementation. Despite the growing body of research on AI, green hydrogen, and sustainable supply chain management, a significant research gap remains at the intersection of these fields. First, previous studies on AI in supply chains have predominantly focused on conventional manufacturing, logistics, renewable energy, and general supply chain environments, with relatively limited attention to the specific characteristics of GHSCs. The distinctive features of green hydrogen systems, including renewable energy intermittency, electrolyzer dependency, specialized storage and transportation infrastructure, demand uncertainty, and the need for coordination among multiple stakeholders, make AI adoption considerably different from its implementation in conventional supply chains. Consequently, findings derived from other supply chain contexts cannot necessarily be directly generalized to the green hydrogen domain. Second, existing studies related to green hydrogen have primarily concentrated on technical and operational issues, such as hydrogen production technologies, renewable energy integration, storage, transportation, infrastructure development, techno-economic feasibility, and supply chain optimization. Although digital technologies and AI are increasingly recognized as potential solutions for improving these processes, limited research has systematically examined what enables organizations to adopt AI across the different stages of the GHSCs. Thus, the current literature provides insufficient understanding of the organizational and technological conditions required for successful AI adoption in this emerging sector. Third, previous technology-adoption studies have generally examined individual factors such as technological readiness, organizational support, investment, regulatory conditions, or employee capabilities independently. However, AI adoption in GHSCs is a multidimensional and interconnected phenomenon, in which technological, organizational, economic, institutional, and environmental enablers can influence one another. A major limitation of the existing literature is therefore the lack of a systematic examination of the cause–effect relationships among these enablers. Identifying the most important factors alone is insufficient because decision-makers need to understand which factors act as fundamental drivers and which factors are primarily outcomes of other conditions. Finally, while several studies have applied multi-criteria decision-making approaches to energy and supply chain problems, there is limited empirical evidence regarding the use of DEMATEL to uncover the causal structure of AI adoption enablers specifically within GHSCs. This methodological gap is particularly important because DEMATEL can distinguish between cause and effect factors and reveal the direct and indirect influence relationships among interconnected enablers. Therefore, the present study addresses these gaps by developing and empirically evaluating a structured framework comprising thirteen AI adoption enablers and by applying DEMATEL to identify their relative prominence and causal relationships. In doing so, the study moves beyond simply listing potential adoption factors and

provides a causal perspective that can support more targeted managerial and policy interventions for AI-enabled GHSCs development.

To address the identified contextual, theoretical, relational, and methodological gaps, this study aims to identify and model the critical enablers of Artificial Intelligence adoption in the GHSCs. Specifically, the study seeks to determine the relative importance of these enablers and uncover their causal relationships using the DEMATEL method (Paul & Mahapatra, 2025). By distinguishing between driving and dependent enablers, the study provides a more comprehensive understanding of the mechanisms underlying AI adoption and offers actionable insights for managers, policymakers, and other stakeholders involved in the development of green hydrogen ecosystems.

Literature Background

Artificial intelligence

AI has emerged as one of the most influential technological innovations driving digital transformation across industries. AI refers to the ability of computer systems to perform tasks that traditionally require human intelligence, including learning, reasoning, problem-solving, decision-making, pattern recognition, and predictive analysis. The rapid advancement of computational power, cloud computing, big data analytics, and machine learning algorithms has significantly expanded the practical applications of AI in business and industrial environments (Ghosh et al., 2025; A. Singh et al., 2023). In recent years, organizations have increasingly adopted AI technologies to improve operational efficiency, enhance decision-making quality, and gain competitive advantages. AI encompasses a broad range of technologies, including machine learning, deep learning, neural networks, natural language processing, computer vision, expert systems, and predictive analytics (Sahebi, Edalatipour, et al., 2025). These technologies enable organizations to analyze large volumes of structured and unstructured data, identify hidden patterns, and generate actionable insights in real time.

Within supply chain management, AI has become a critical enabler of intelligent operations. Traditional supply chains often struggle with uncertainties arising from demand fluctuations, supplier disruptions, transportation delays, and market volatility. AI-powered systems can mitigate these challenges through demand forecasting, inventory optimization, predictive maintenance, risk management, and autonomous decision support (Singh et al., 2023). By transforming raw data into valuable information, AI improves supply chain visibility and responsiveness. Despite its numerous advantages, successful AI implementation remains challenging. Organizations frequently encounter obstacles related to technological readiness, data quality, infrastructure limitations, organizational culture, employee skills, cybersecurity concerns, and financial

investments. Therefore, understanding the factors that facilitate AI adoption has become a major research priority (Fraga-Lamas et al., 2021). Identifying and modeling these enablers can assist organizations in developing effective implementation strategies and maximizing the benefits derived from AI technologies.

Green hydrogen supply chain

Green hydrogen is widely regarded as a cornerstone of the future low-carbon energy system. Unlike gray or blue hydrogen (Sahebi, Masoomi, et al., 2025), green hydrogen is produced through water electrolysis powered entirely by renewable energy sources such as solar, wind, and hydropower (Suarez et al., 2023). This production process generates virtually no carbon emissions, making green hydrogen an environmentally sustainable energy carrier capable of supporting global decarbonization efforts (Wannack, 2023). The GHSCs comprise a sequence of interconnected activities extending from renewable energy generation to final consumption. The first stage involves the generation of renewable electricity, which serves as the primary energy source for electrolysis. The second stage focuses on hydrogen production through electrolyzers that separate water molecules into hydrogen and oxygen (Masoomi, Toufighi, et al., 2025). Following production, hydrogen must be stored and transported using specialized infrastructure, including storage tanks, pipelines, trailers, and shipping systems. Finally, hydrogen is distributed to industrial, transportation, power generation, and residential sectors for end-use applications. Managing the GHSC is considerably more complex than managing conventional energy supply chains. Renewable energy intermittency, high infrastructure costs, technological uncertainties, market immaturity, and regulatory challenges create significant operational risks. Furthermore, the integration of multiple stakeholders, including renewable energy producers, hydrogen manufacturers, logistics providers, regulators, and end-users requires extensive coordination and information sharing (Mothafar et al., 2024; Perna et al., 2023).

The effectiveness of the GHSC depends heavily on operational visibility, forecasting accuracy, resource optimization, and risk management. Failures at any stage can negatively impact overall system performance and economic viability. Consequently, researchers and practitioners increasingly emphasize the importance of digital technologies that can enhance transparency, resilience, and efficiency throughout the supply chain (Azadnia et al., 2023; Sens et al., 2022). As investments in hydrogen infrastructure continue to grow worldwide, improving supply chain performance has become a strategic priority. Emerging technologies such as artificial intelligence, digital twins, blockchain, and the Internet of Things are expected to play a crucial role in addressing existing challenges and accelerating the commercialization of green hydrogen systems.

AI-Enabled green hydrogen supply chain

The convergence of artificial intelligence and green hydrogen technologies has created new opportunities for enhancing supply chain performance (Tourang et al., 2026). AI-enabled GHSCs utilize advanced analytics, machine learning algorithms, and intelligent decision-support systems to optimize operations across all supply chain stages. By integrating AI capabilities into production, storage, transportation, distribution, and consumption activities, organizations can improve efficiency, reduce uncertainty, and strengthen supply chain resilience (Ahmed et al., 2024). AI applications in hydrogen production include process optimization, electrolyzer performance monitoring, energy consumption management, and predictive maintenance. Machine learning algorithms can analyze operational data and identify patterns that improve hydrogen production efficiency while reducing operational costs (Gan et al., 2021). Similarly, predictive maintenance systems can detect equipment anomalies before failures occur, minimizing downtime and maintenance expenses. In storage and transportation operations, AI contributes to route optimization, inventory management, pressure monitoring, leak detection, and safety management (Sahebi et al., 2026). Intelligent forecasting models can predict hydrogen demand patterns and facilitate efficient allocation of storage resources. Furthermore, AI supports real-time monitoring and dynamic decision-making, enabling organizations to respond rapidly to changing operational conditions. From a strategic perspective, AI enhances risk management capabilities by identifying potential disruptions and evaluating alternative response strategies (Matani, 2021). It also supports sustainability objectives through optimized resource utilization and reduced energy waste. Consequently, AI is increasingly viewed as a critical enabler for achieving economic viability and operational excellence within green hydrogen ecosystems.

However, the successful implementation of AI within GHSCs depends on multiple enabling factors. These factors span technological, organizational, economic, environmental, and institutional dimensions (Jayabal, 2025). Understanding these enablers is essential because they determine the readiness of organizations to adopt AI technologies and influence the effectiveness of implementation initiatives. Based on the synthesis of the reviewed literature, thirteen enablers were identified as particularly relevant to AI adoption in GHSCs. The selection of these enablers was guided by two complementary considerations: evidence from prior research on technology and AI adoption and the specific characteristics of GHSCs. Rather than focusing exclusively on technological factors, the present study adopts a multidimensional perspective because successful AI adoption requires the simultaneous development of technological capabilities, organizational preparedness, human competencies, financial resources, institutional support, interorganizational coordination, and sustainability orientation.

The technological dimension is represented by Data Availability and Quality (E1), Digital Infrastructure Readiness (E2), Technological Capability (E3), and Cybersecurity and Data Protection (E4). These factors are essential because AI applications depend on reliable data, adequate digital infrastructure, appropriate technological capabilities, and secure data environments. In the GHSC context, these requirements become particularly important because supply chain activities involve interconnected production, storage, transportation, and distribution processes that generate and exchange substantial amounts of operational data. The organizational and human dimensions include Top Management Support (E5), Organizational Readiness (E6), Skilled Human Resources (E7), and Innovation-Oriented Culture (E8). Previous technology-adoption research consistently emphasizes managerial commitment, organizational preparedness, employee competencies, and an organizational culture supportive of innovation as important conditions for successful digital transformation. These factors are particularly relevant to AI adoption because organizations must possess both the managerial willingness and internal capabilities required to integrate AI into existing processes.

The economic and value-related dimensions are captured through Investment and Financial Support (E9) and Expected Operational Benefits (E10). AI implementation may require considerable investment in digital infrastructure, computing resources, software, data management, employee training, and system integration. At the same time, organizations are more likely to adopt AI when they perceive tangible operational benefits, such as improved forecasting, optimization, efficiency, reliability, and decision-making. These two factors therefore capture both the resources required for adoption and the expected value generated by it. The institutional, collaborative, and sustainability dimensions are represented by Regulatory and Policy Support (E11), Stakeholder Collaboration and Ecosystem Integration (E12), and Sustainability and Environmental Commitment (E13). GHSCs involve multiple stakeholders, including energy producers, hydrogen producers, infrastructure providers, technology developers, regulators, logistics operators, and end users. Consequently, supportive policies, regulatory clarity, interorganizational collaboration, and ecosystem integration can significantly influence the conditions under which AI technologies are adopted. Moreover, because green hydrogen is closely associated with decarbonization and energy-transition objectives, sustainability and environmental commitment provide an important contextual dimension for understanding AI adoption in this sector. Taken together, these thirteen enablers provide a comprehensive representation of the technological, organizational, human, economic, operational, institutional, collaborative, and environmental conditions that may facilitate AI adoption in GHSCs. The factors were therefore retained because they are conceptually distinct, collectively relevant to the adoption process, and sufficiently broad to capture the complexity of AI-enabled GHSCs. However, the literature provides limited understanding of how these enablers influence one another. Accordingly, the present study does not treat the thirteen factors as

independent variables; instead, DEMATEL is employed to determine their relative prominence and reveal the causal relationships between driving and dependent enablers.

Table 1. Key enablers of AI adoption in the GHSC (Ahmed et al., 2024; Jayabal, 2025; Sahebi et al., 2026; L. Wang et al., 2023)

Code	Enabler	Dimension
E1	Data availability and quality	Technological
E2	Digital infrastructure readiness	Technological
E3	Technological capability	Technological
E4	Cybersecurity and data protection	Technological
E5	Top management support	Organizational
E6	Organizational readiness	Organizational
E7	Skilled human resources	Organizational
E8	Innovation-Oriented culture	Organizational
E9	Investment and financial support	Economic
E10	Expected operational benefits	Economic
E11	Regulatory and policy support	Institutional
E12	Stakeholder collaboration and ecosystem integration	Institutional
E13	Sustainability and environmental commitment	Environmental

The enablers presented in Table 1 represent the most frequently cited factors influencing AI adoption across energy and supply chain literature. Technological enablers provide the foundational capabilities required for AI implementation, whereas organizational factors determine the ability of firms to integrate AI into operational processes. Economic enablers influence investment decisions and technology acceptance, while institutional factors create supportive external conditions for adoption. Environmental commitment has also emerged as a critical driver because organizations increasingly pursue AI initiatives to achieve sustainability objectives. Since these enablers are highly interrelated, analyzing their causal relationships becomes essential for identifying the most influential factors and prioritizing managerial actions. This complexity justifies the application of the DEMATEL methodology in the present study.

Research gap and contribution

Although previous studies have investigated artificial intelligence adoption, digital transformation, sustainable supply chains, and hydrogen energy systems separately, limited research has examined AI adoption specifically within the context of GHSCs. Existing studies predominantly focus on technical applications of AI or operational aspects of hydrogen production, while insufficient attention has been given to the underlying enablers that facilitate successful AI implementation. Furthermore, the majority of prior research identifies adoption factors independently without investigating the complex causal relationships among them. As a result, decision-makers often lack a clear understanding of which enablers act as driving factors and which are primarily influenced

by others. This limitation reduces the effectiveness of strategic planning and resource allocation. To address these gaps, the present study identifies the critical enablers of AI adoption in the GHSCs and employs the DEMATEL method to model their cause–effect relationships. The study contributes to the literature by providing a comprehensive framework of AI adoption enablers, revealing their interdependencies, and distinguishing between driving and dependent factors. From a practical perspective, the findings support managers and policymakers in prioritizing strategic initiatives that accelerate AI-driven transformation and improve the sustainability, resilience, and competitiveness of GHSCs.

Materials and Methods

The research framework adopted in this study consists of six sequential stages designed to systematically identify, evaluate, and model the enablers of AI adoption in the GHSC. As illustrated in Figure 2, the process begins with problem identification and scope definition, where the importance of AI implementation within green hydrogen ecosystems is established through an extensive review of the literature and industry reports. This stage provides the theoretical foundation and clarifies the objectives and boundaries of the study. The second stage focuses on the identification of potential enablers influencing AI adoption. Relevant factors are extracted from previous studies related to artificial intelligence, digital transformation, sustainable supply chains, hydrogen energy systems, and technology adoption. Subsequently, the identified factors are refined and validated through expert consultation to ensure their relevance to the green hydrogen context. In the third stage, a panel of experts comprising academics, industry practitioners, and energy-sector specialists is selected. Their knowledge and experience are utilized to evaluate the degree of influence among the identified enablers. Data are collected using a structured pairwise comparison questionnaire based on the DEMATEL scale, allowing experts to assess the direct influence of one factor on another. The fourth stage involves the implementation of the DEMATEL methodology. Initially, the direct-relation matrix is constructed based on expert judgments. The matrix is then normalized, and the total-relation matrix is calculated to capture both direct and indirect interactions among the enablers. Subsequently, the values of D (sum of rows) and R (sum of columns) are computed for each factor. These values serve as the basis for determining the prominence and causal characteristics of the enablers.

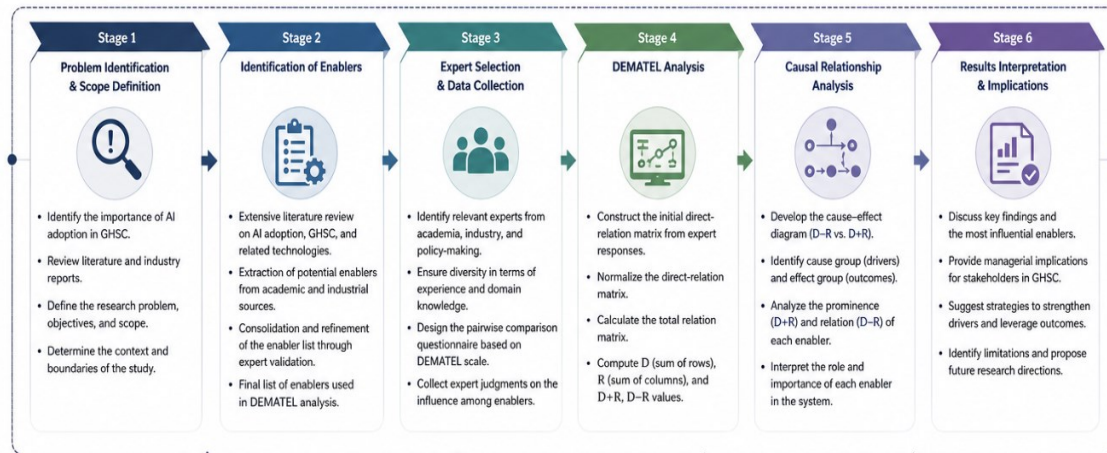


Figure 2. Research framework for modeling AI adoption enablers in the GHSC

In the fifth stage, causal relationship analysis is performed using the DEMATEL outputs. The prominence value ($D + R$) indicates the overall importance of an enabler within the system, while the relation value ($D - R$) identifies whether an enabler belongs to the cause group or the effect group. Positive values indicate driving factors that exert influence on other enablers, whereas negative values represent dependent factors that are primarily influenced by the system.

Finally, the sixth stage focuses on interpreting the findings and deriving managerial implications. The most influential enablers are identified, and their strategic significance for AI adoption within GHSCs is discussed. The results provide valuable insights for policymakers, managers, and technology providers seeking to accelerate digital transformation and improve the sustainability, resilience, and operational performance of green hydrogen ecosystems. Figure 2 therefore presents a comprehensive methodological roadmap that integrates literature-based factor identification, expert knowledge, and DEMATEL-based causal analysis to reveal the structural relationships among AI adoption enablers in the GHSCs. This systematic approach enhances the reliability of the findings and supports evidence-based decision-making in emerging hydrogen energy systems.

DEMATEL method

The DEMATEL method, initially proposed by (Gabus & Fontela, 1972), analyzes and interprets the intricate interconnections within complex systems. It is widely regarded as one of the most effective analytical techniques for uncovering cause–effect relationships among evaluation criteria. As outlined earlier, DEMATEL translates the interrelationships among factors into a comprehensive structural model, categorizing them into cause and effect groups. The final output of the DEMATEL analysis is an Influence Relation Map (IRM), which visually represents the

direction and magnitude of interdependencies among the identified variables, offering clearer insights into the system's underlying dynamics (Pathak et al., 2021; Sharma et al., 2023).

The DEMATEL methodology applied in this study involves the following systematic steps (Bhanot et al., 2017; Kao et al., 2019; Poudeh et al., 2019; C. Singh et al., 2021):

1. Construct the initial direct-relation matrix: Experts are asked to evaluate the direct influence of one factor on another using a linguistic scale, typically ranging from 0 (no influence) to 4 (very strong influence). The average of expert responses is used to construct the initial direct-relation matrix (A).
2. Normalize A: The initial matrix is normalized to ensure that the sum of the maximum row or column does not exceed 1.

$$D = \frac{A}{\max(\sum A_i, \sum A_j)} \quad (1)$$

This step produces the normalized direct-relation matrix (D).

3. Calculate the total relation matrix (T): This matrix is defined as follows, where I is the identity matrix of the same order as D . This matrix captures both direct and indirect influences among enablers.

$$T = \frac{D}{I - D} \quad (2)$$

4. Compute the prominence and relation values: For each enabler i , compute:

- $D_i = \sum_j T_{ij}$ as the sum of row i (total influence given)
- $R_j = \sum_i T_{ji}$ as the sum of column j (total influence received)

Then compute:

- Prominence ($D_i + R_j$): the total degree of interaction (importance)
- Relation ($D_i - R_j$):

If positive, the factor is a cause (net influencer)

If negative, the factor is an effect (net influenced)

5. Develop the Cause–Effect Diagram: Plot ($D + R$) on the X-axis (prominence) and ($D - R$) on the Y-axis (relation) for each factor.
 - Positive ($D + R$): cause group
 - Negative ($D - R$): effect group

This diagram helps decision-makers distinguish root enablers (drivers) from dependent enablers (outcomes), which is crucial for strategic planning.

Data collection

Data collection was conducted using a structured expert-based approach to evaluate the causal relationships among the identified enablers of AI adoption in the GHSC. Since the DEMATEL method relies on expert knowledge and judgment to determine the degree of influence among factors, the selection of knowledgeable and experienced experts was considered a critical step in ensuring the reliability and validity of the results. A purposive sampling technique was employed to identify experts with substantial academic and industrial experience in the fields of artificial intelligence, sustainable supply chain management, renewable energy systems, hydrogen technologies, and digital transformation. To ensure the quality of the collected data, the experts were required to satisfy at least one of the following criteria: (1) holding a doctoral degree in a relevant field, (2) possessing more than five years of professional experience related to AI, energy systems, or supply chain management, or (3) actively participating in research, consulting, or industrial projects associated with hydrogen technologies and digital innovation. A panel of ten experts participated in this study. The panel consisted of university professors, researchers, supply chain specialists, renewable energy consultants, and senior managers from technology-oriented organizations. The diversity of expertise helped provide a comprehensive understanding of the technological, organizational, economic, and institutional factors influencing AI adoption within the GHSCs. To collect the required data, a DEMATEL-based pairwise comparison questionnaire was developed. The questionnaire required experts to evaluate the degree of influence of each enabler on every other enabler using a five-point linguistic scale. The scale ranged from 0 to 4, where 0 represented “No Influence,” 1 represented “Low Influence,” 2 represented “Moderate Influence,” 3 represented “High Influence,” and 4 represented “Very High Influence.” This evaluation process generated the initial direct-relation matrix used in the DEMATEL analysis. To ensure the reliability and relevance of the expert judgments, a purposive expert-selection approach was adopted. Experts were selected based on predefined eligibility criteria reflecting their relevance to the research context. First, participants were required to have substantial professional or academic experience in at least one of the core domains of the study, including Artificial Intelligence and digital technologies, green hydrogen and renewable energy systems, supply chain management, or energy-sector digital transformation. Second, preference was given to experts with practical or research experience in technology adoption, digitalization, intelligent systems, hydrogen supply chains, renewable energy, or related sustainability applications. Third, participants were required to possess sufficient professional experience to critically assess the technological, organizational, economic, institutional, and sustainability-related factors influencing AI adoption. These criteria were established to ensure that the experts were not only

familiar with AI or hydrogen technologies individually but also capable of evaluating their potential integration within a complex GHSC environment.

Based on these criteria, ten experts were selected from academic and industrial backgrounds. The expert panel included specialists with complementary expertise in Artificial Intelligence, renewable energy, hydrogen energy systems, supply chain management, and digital transformation. The multidisciplinary composition of the panel was considered particularly important because AI adoption in GHSCs involves interconnected technological, managerial, financial, regulatory, human, and sustainability dimensions. Accordingly, the selected experts were considered capable of providing informed judgments regarding both the importance of the identified enablers and the causal influence relationships among them. The profile of the participating experts is presented in Table 2, including their professional position, area of expertise, and years of relevant experience. The experts had approximately 10–20 years of professional or academic experience in their respective fields. Their combined expertise provided a sufficiently broad knowledge base for evaluating the thirteen AI adoption enablers identified from the literature. Following the selection process, the experts were asked to assess the degree of influence of each enabler on the others using the five-point DEMATEL scale ranging from 0 (no influence) to 4 (very high influence).

Table 2. Demographic profile of experts

Expert code	Position	Area of expertise	Experience (years)
E1	Professor	Artificial intelligence	18
E2	Associate professor	Supply chain management	15
E3	Researcher	Hydrogen energy systems	12
E4	Professor	Renewable energy technologies	20
E5	Industry manager	Digital transformation	14
E6	Consultant	Sustainable supply chains	11
E7	Senior engineer	Hydrogen infrastructure	10
E8	Research scientist	AI applications in energy	13
E9	Operations manager	Energy supply chain	16
E10	Associate professor	Industrial engineering	17

As shown in Table 2, the expert panel possessed extensive experience and multidisciplinary knowledge relevant to the study context. The average professional experience of the participants exceeded 14 years, indicating a high level of expertise and strengthening the credibility of the collected judgments. Such diversity and experience are particularly important in DEMATEL studies, where expert evaluations directly influence the identification of causal relationships among factors.

Results

DEMATEL results

The structural interconnection diagram was developed by analyzing the relationships among the seven primary enablers using the DEMATEL approach. This method comprises four sequential phases designed to identify and interpret the complex causal relationships among the enablers. The detailed computational procedures of the DEMATEL analysis are outlined in this section, while only the aggregated, enabler-level results are presented for interpretation and discussion. Regarding identification, the primary enablers of AI in GHSC and questionnaire recovery are:

Step 1: In the first step of the DEMATEL method, expert judgments are gathered to evaluate the degree of direct influence that each enabler exerts on the others. Using a predefined linguistic scale, each expert independently assesses the pairwise relationships between all enablers. The pairwise comparison aims to capture the perceived causal effect from enabler i to enabler j . Once all responses are collected, the average score for each pair is calculated to minimize individual bias and ensure a balanced representation of the panel's opinions. The resulting average direct-relation matrix reflects the collective view of the expert group regarding the strength and direction of influences among the enablers (Masoomi et al., 2023). This matrix serves as the foundation for subsequent DEMATEL computations, including normalization, total-relation matrix derivation, and cause–effect grouping. Table 3 presents the averaged evaluations obtained from the expert panel for all enabler pairs.

Table 3. Initial relationship matrix at the enablers level

Enablers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13
E1	0.00	3.10	3.25	2.95	2.10	2.30	2.85	2.20	1.95	2.15	1.80	2.40	1.70
E2	2.95	0.00	3.40	3.10	2.65	2.45	2.90	2.35	2.25	2.10	1.95	2.55	1.85
E3	3.20	3.35	0.00	2.80	2.95	2.65	3.15	2.70	2.45	2.35	2.05	2.60	2.10
E4	2.40	2.75	2.55	0.00	2.15	1.95	2.30	1.85	1.90	1.80	2.40	2.15	1.65
E5	2.50	2.70	2.95	2.20	0.00	3.45	3.25	3.50	3.15	3.20	2.55	2.95	2.40
E6	2.20	2.40	2.55	1.95	3.35	0.00	3.10	3.20	2.75	2.85	2.20	2.65	2.15
E7	2.75	2.90	3.05	2.15	3.00	3.15	0.00	3.25	2.60	2.70	2.05	2.50	2.00
E8	2.35	2.45	2.70	1.90	3.40	3.25	3.20	0.00	2.55	2.75	2.15	2.70	2.30
E9	2.00	2.20	2.35	1.80	3.10	2.85	2.65	2.75	0.00	3.30	2.45	2.60	2.35
E10	2.05	2.10	2.25	1.75	2.95	2.80	2.50	2.65	3.20	0.00	2.30	2.40	2.60
E11	2.15	2.40	2.35	2.55	2.85	2.50	2.25	2.35	2.90	2.70	0.00	3.35	3.10
E12	2.45	2.60	2.55	2.20	3.05	2.85	2.65	2.90	2.75	2.60	3.25	0.00	2.95
E13	1.95	2.05	2.20	1.70	2.50	2.25	2.10	2.40	2.55	2.70	3.05	2.85	0.00

Step 2: To create the normalized direct-relationship matrix shown in Table 4, equations (1) and (2) were used to normalize the initial relationship matrix.

Table 4. Calculation of the normalized direct relationship matrix

Enablers	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13
E1	0.00 0	0.07 6	0.08 0	0.07 3	0.05 2	0.05 7	0.07 0	0.05 4	0.04 8	0.05 3	0.04 4	0.05 9	0.04 2
E2	0.07 3	0.00 0	0.08 4	0.07 6	0.06 5	0.06 1	0.07 1	0.05 8	0.05 5	0.05 2	0.04 8	0.06 3	0.04 6
E3	0.07 9	0.08 3	0.00 0	0.06 9	0.07 3	0.06 5	0.07 8	0.06 7	0.06 0	0.05 8	0.05 0	0.06 4	0.05 2
E4	0.05 9	0.06 8	0.06 3	0.00 0	0.05 3	0.04 8	0.05 7	0.04 6	0.04 7	0.04 4	0.05 9	0.05 3	0.04 1
E5	0.06 2	0.06 7	0.07 3	0.05 4	0.00 0	0.08 5	0.08 0	0.08 6	0.07 7	0.07 9	0.06 3	0.07 3	0.05 9
E6	0.05 4	0.05 9	0.06 3	0.04 8	0.08 2	0.00 0	0.07 6	0.07 9	0.06 8	0.07 0	0.05 4	0.06 5	0.05 3
E7	0.06 8	0.07 1	0.07 5	0.05 3	0.07 4	0.07 8	0.00 0	0.08 0	0.06 4	0.06 7	0.05 0	0.06 2	0.04 9
E8	0.05 8	0.06 0	0.06 7	0.04 7	0.08 4	0.08 0	0.07 9	0.00 0	0.06 3	0.06 8	0.05 3	0.06 7	0.05 7
E9	0.04 9	0.05 4	0.05 8	0.04 4	0.07 6	0.07 0	0.06 5	0.06 8	0.00 0	0.08 1	0.06 0	0.06 4	0.05 8
E10	0.05 0	0.05 2	0.05 6	0.04 3	0.07 3	0.06 9	0.06 2	0.06 5	0.07 9	0.00 0	0.05 7	0.05 9	0.06 4
E11	0.05 3	0.05 9	0.05 8	0.06 3	0.07 0	0.06 2	0.05 6	0.05 8	0.07 1	0.06 7	0.00 0	0.08 3	0.07 6
E12	0.06 0	0.06 4	0.06 3	0.05 4	0.07 5	0.07 0	0.06 5	0.07 1	0.06 8	0.06 4	0.08 0	0.00 0	0.07 3
E13	0.04 8	0.05 0	0.05 4	0.04 2	0.06 1	0.05 5	0.05 2	0.05 9	0.06 3	0.06 7	0.07 5	0.07 0	0.00 0

Step 3: In this step, the total-influence matrix is obtained using the normalized direct-relation matrix. This matrix incorporates both direct and indirect relationships among the indicators, providing a comprehensive representation of the extent to which each factor influences the others (see Table 5). The total influence matrix incorporates both direct and indirect relationships among the enablers of AI adoption in the GHSCs. Compared with the normalized direct-relation matrix, the values in this matrix reflect the cumulative influence transmitted through the entire system. Therefore, the matrix provides a more comprehensive representation of factor interdependencies and serves as the basis for calculating the prominence ($D + R$) and relation ($D - R$) values in the subsequent DEMATEL analysis.

Step 4: Next, the sum of each row and column in the total-influence matrix is calculated. The row sums represent the driving power of each factor (vector D), while the column sums represent

the dependence power (vector R). These values are presented in Table 6 and form the basis for the cause–effect analysis among the indicators.

Table 5. The total influence matrix

Enabler s	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13
E1	0.15 2	0.24 1	0.25 8	0.22 1	0.19 8	0.20 3	0.22 8	0.20 7	0.18 6	0.19 1	0.17 4	0.21 4	0.16 8
E2	0.23 6	0.15 8	0.27 1	0.23 4	0.21 4	0.20 8	0.23 7	0.21 6	0.20 1	0.19 6	0.18 1	0.22 3	0.17 4
E3	0.25 4	0.26 6	0.16 7	0.22 9	0.23 6	0.22 1	0.25 7	0.23 4	0.21 4	0.20 8	0.18 9	0.22 6	0.18 3
E4	0.19 4	0.21 3	0.20 5	0.14 1	0.18 2	0.17 6	0.19 6	0.18 1	0.17 2	0.16 8	0.19 1	0.18 8	0.15 9
E5	0.22 8	0.23 7	0.25 1	0.21 4	0.17 4	0.28 9	0.27 8	0.29 2	0.26 4	0.26 9	0.21 8	0.24 1	0.19 6
E6	0.21 2	0.21 9	0.23 1	0.19 8	0.27 8	0.16 6	0.26 9	0.27 6	0.24 2	0.24 7	0.20 1	0.22 3	0.18 7
E7	0.22 6	0.23 4	0.24 7	0.20 9	0.26 4	0.27 1	0.17 1	0.28 1	0.23 6	0.24 1	0.19 4	0.21 6	0.17 9
E8	0.22 1	0.22 7	0.24 1	0.20 3	0.28 3	0.27 8	0.27 4	0.16 8	0.23 1	0.24 6	0.19 9	0.22 4	0.19 1
E9	0.19 8	0.20 6	0.21 8	0.18 9	0.25 7	0.24 4	0.23 6	0.24 2	0.16 2	0.27 9	0.21 3	0.22 1	0.19 4
E10	0.19 4	0.20 1	0.21 4	0.18 4	0.24 8	0.23 9	0.22 9	0.23 6	0.27 2	0.15 9	0.20 8	0.21 4	0.20 1
E11	0.20 7	0.21 9	0.22 3	0.21 4	0.24 1	0.23 1	0.21 8	0.22 4	0.24 9	0.24 3	0.16 3	0.28 4	0.26 7
E12	0.22 3	0.23 1	0.23 6	0.20 8	0.25 8	0.24 7	0.23 6	0.25 1	0.24 4	0.23 8	0.27 9	0.16 9	0.25 1
E13	0.19 1	0.19 8	0.20 6	0.17 8	0.22 1	0.21 4	0.20 8	0.21 6	0.22 7	0.23 6	0.26 1	0.24 8	0.15 1

Step 5: The final phase of the DEMATEL analysis involves constructing the causal influence diagram, which helps decision-makers identify the most critical and influential elements within the system. The threshold value, calculated as the mean of the total relation matrix, is 0.11 at the criteria level. Only relationships whose influence values exceed this threshold are depicted in the causal influence diagram. Conversely, relationships below this threshold are considered to exert a negligible impact on other enablers. Based on the computed D+R (prominence) and D–R (net effect) values, the significant causal interconnections among the enablers are illustrated in Fig. 3, while the corresponding quantitative results are summarized in Table 6. The results indicate that Top Management Support (E5), Technological Capability (E3), Data Availability and Quality (E1), Regulatory and Policy Support (E11), and Stakeholder Collaboration (E12) belong to the cause

group, as evidenced by their positive D–R values. These factors exert substantial influence on other enablers and play a fundamental role in facilitating AI adoption within the GHSCs. Conversely, Investment and Financial Support (E9), Expected Operational Benefits (E10), and Sustainability and Environmental Commitment (E13) belong to the effect group, indicating that they are primarily influenced by other factors in the system. Among all enablers, Investment and Financial Support (E9) exhibits the highest centrality value ($D+R = 12.465$), highlighting its strategic importance despite being a dependent factor. The findings suggest that managers and policymakers should prioritize strengthening the causal enablers to accelerate AI-driven transformation across the GHSCs.

Table 6. Centrality degree and cause-effect influence relations

Code	D (Driving Power)	R (Dependence Power)	D+R (Centrality)	D–R (Cause–Effect)	Interpretation
E1	5.842	5.416	11.258	0.426	Strong driving enabler
E2	6.031	5.774	11.805	0.257	Key technological driver
E3	6.285	5.923	12.208	0.362	High-impact technological driver
E4	5.354	5.798	11.152	-0.444	Dependent technological factor
E5	6.472	5.961	12.433	0.511	Critical managerial driver
E6	6.115	5.897	12.012	0.218	Strong organizational driver
E7	6.263	6.085	12.348	0.178	Important capability driver
E8	6.084	6.213	12.297	-0.129	Balanced and supportive factor
E9	5.891	6.574	12.465	-0.683	High-centrality dependent factor
E10	5.728	6.402	12.130	-0.674	Performance-oriented dependent factor
E11	6.176	5.811	11.987	0.365	Institutional driving factor
E12	6.024	5.688	11.712	0.336	Ecosystem collaboration driver
E13	5.942	6.398	12.340	-0.456	Sustainability-oriented dependent factor

The final step of the DEMATEL analysis establishes the causal relationships among the AI enablers in GHSCs. Figure 3 presents the prominence–causal diagram derived from the DEMATEL analysis, illustrating the structural relationships among the enablers of Artificial Intelligence (AI) adoption in the GHSCs. The horizontal axis represents the prominence value ($D+R$), indicating the overall importance of each enabler within the system, while the vertical axis represents the relation value ($D–R$), distinguishing between cause and effect factors. Enablers positioned above the horizontal axis belong to the cause group and exert influence on other factors, whereas those located below the axis belong to the effect group and are primarily influenced by

other enablers. The results show that Top Management Support (E5), Technological Capability (E3), Regulatory and Policy Support (E11), and Stakeholder Collaboration (E12) are among the most influential driving factors facilitating AI adoption in the GHSCs. Conversely, Investment and Financial Support (E9), Expected Operational Benefits (E10), and Sustainability and Environmental Commitment (E13) are classified as dependent factors that reflect the outcomes of improvements in the causal enablers. Furthermore, the high prominence values associated with E9, E13, and E7 indicate their strategic importance within the overall system. These findings emphasize that strengthening the key causal enablers can create cascading positive effects throughout the supply chain and significantly enhance the successful implementation of AI technologies within green hydrogen ecosystems.

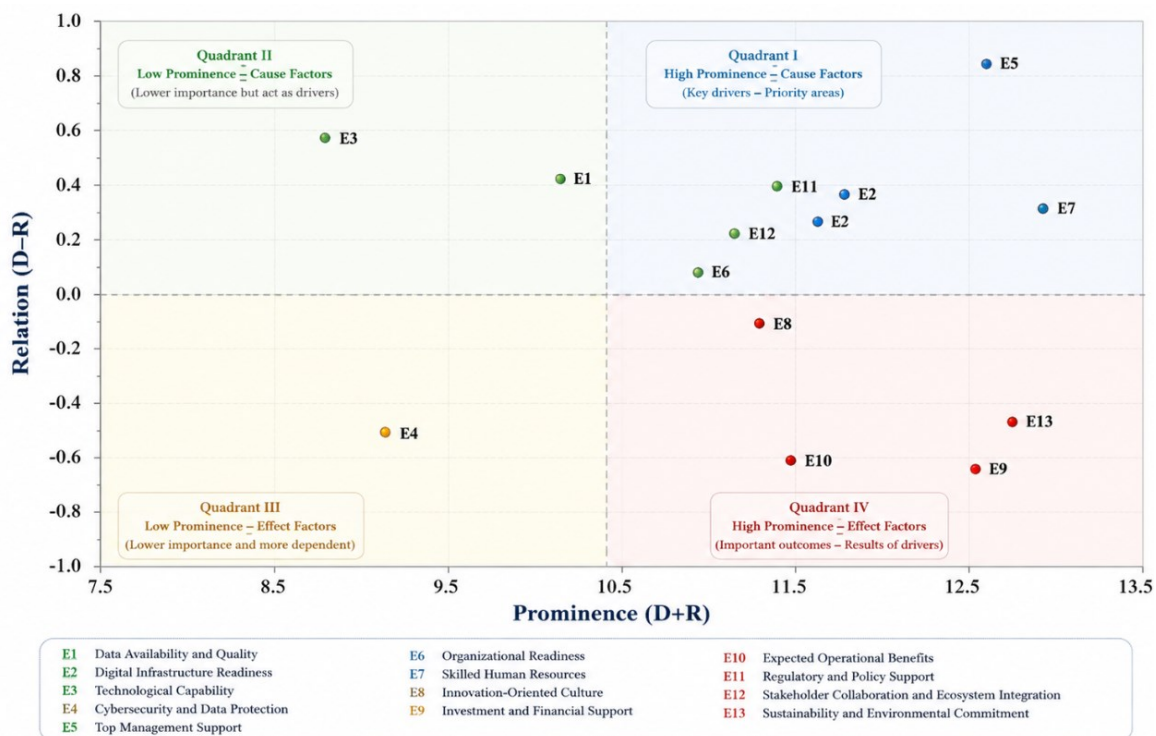


Fig 3. Causal diagram

The DEMATEL results indicate that Top Management Support (E5), Technological Capability (E3), and Digital Infrastructure Readiness (E2) occupy important positions within the causal structure of AI adoption in the GHSCs. Their positive D-R values indicate that these enablers exert greater net influence on the other factors than they receive from them. This finding is particularly important because it suggests that AI adoption in GHSCs is fundamentally dependent on the establishment of appropriate managerial, technological, and infrastructural foundations rather than solely on the perceived benefits of AI applications.

Discussion

The findings of the DEMATEL analysis provide valuable insights into the complex interactions among the enablers of Artificial Intelligence (AI) adoption within the GHSCs. The results reveal that AI implementation is not solely dependent on technological resources but is significantly influenced by managerial, organizational, and institutional factors. The cause–effect analysis demonstrates that several enablers function as driving forces that shape the overall readiness of organizations to adopt AI technologies across hydrogen supply chain operations. Top Management Support (E5) emerged as one of the strongest driving factors. This result can be explained by the strategic and resource-intensive nature of AI adoption. Implementing AI across GHSCs often requires investment in digital infrastructure, data systems, employee training, organizational restructuring, and integration with existing operational technologies. Senior managers play a central role in establishing strategic priorities, allocating financial and human resources, reducing organizational resistance, and coordinating AI initiatives across organizational functions. Moreover, GHSCs involve multiple interconnected activities, including renewable electricity integration, hydrogen production, storage, transportation, distribution, and demand management. Consequently, AI adoption cannot be effectively implemented through isolated departmental initiatives; it requires strategic commitment and coordination at the organizational level. The strong causal position of Top Management Support therefore suggests that managerial commitment can trigger improvements in several other adoption conditions, including organizational readiness, employee capabilities, innovation culture, investment decisions, and technological development.

The results further indicate that Technological Capability (E3) and Digital Infrastructure Readiness (E2) serve as major causal enablers. AI applications rely heavily on advanced digital infrastructure, data-processing capabilities, cloud platforms, and intelligent analytics systems. Since GHSCs involve large volumes of operational and technical data generated across multiple stages, technological readiness becomes a prerequisite for successful AI integration. Organizations with stronger technological capabilities are more likely to develop predictive models, optimize operational processes, and improve supply chain visibility. Another significant finding relates to the importance of Regulatory and Policy Support (E11) and Stakeholder Collaboration (E12). The green hydrogen sector remains an emerging industry characterized by evolving regulations, technological uncertainties, and infrastructure challenges. Therefore, supportive government policies, financial incentives, and industry standards play a vital role in reducing uncertainty and encouraging AI investments. Similarly, collaboration among energy producers, technology providers, logistics operators, research institutions, and policymakers facilitates knowledge sharing and accelerates innovation across the hydrogen ecosystem.

The prominence analysis highlights the strategic importance of Investment and Financial Support (E9) despite its classification as an effect factor. This suggests that financial readiness is strongly influenced by improvements in managerial commitment, technological capability, and institutional support. Organizations are more likely to attract investments and justify AI expenditures when the foundational drivers of adoption are adequately established. Financial Support (E9) is identified as a dependent enabler, as indicated by its negative D–R value. This finding deserves particular attention because previous studies on technology adoption, digital transformation, and green energy development have frequently regarded financial resources as a primary driving factor. Financial support can reduce investment barriers, facilitate the acquisition of advanced technologies and digital infrastructure, and enable organizations to develop the capabilities required for AI implementation. From this perspective, the availability of adequate financial resources is generally expected to directly facilitate technology adoption. Therefore, Financial Support should not be interpreted as unimportant; rather, its causal position suggests that its availability and effectiveness are partly shaped by other conditions within the adoption system. For example, Top Management Support can influence investment priorities and resource allocation, while Technological Capability and Digital Infrastructure Readiness determine whether financial investments can be effectively converted into functional AI applications. Similarly, Regulatory and Policy Support can influence access to public funding, investment incentives, and financial mechanisms for green hydrogen development. This finding highlights an important distinction between financial support as a critical resource and financial support as a causal driver. Likewise, Expected Operational Benefits (E10) and Sustainability and Environmental Commitment (E13) appear as outcome-oriented factors that reflect the success of broader implementation efforts. Overall, the findings demonstrate that AI adoption within the GHSCs should be viewed as a systemic transformation process rather than a purely technological initiative. Strengthening the causal enablers can generate cascading effects throughout the system and significantly improve the effectiveness of AI implementation strategies. The DEMATEL results provide several practical implications for managers, policymakers, and other stakeholders involved in the development of AI-enabled GHSCs. Importantly, the findings indicate that the thirteen enablers do not have equal causal importance. Top Management Support (E5), Technological Capability (E3), and Digital Infrastructure Readiness (E2) occupy prominent causal positions and should therefore receive priority in AI adoption strategies. The practical implications of these findings are discussed below.

Managerial implications

First, managers should treat Top Management Support as a strategic priority rather than a general organizational condition. Senior executives should establish a clear AI adoption roadmap aligned with the organization's broader green hydrogen strategy and communicate measurable objectives

for AI implementation. Management should also create dedicated budgets for AI-related investments, appoint responsible teams or managers for digital transformation, and establish cross-functional coordination mechanisms involving operations, IT, engineering, supply chain, and sustainability functions. Because top management support can influence organizational readiness, investment decisions, employee capabilities, and innovation culture, strengthening this factor can create favorable conditions for several other enablers simultaneously.

Second, organizations should systematically strengthen their Technological Capability. Managers should assess their existing technological maturity before implementing advanced AI applications and identify capability gaps in areas such as data analytics, machine learning, system integration, cloud or edge computing, and AI-enabled decision support. Investment should not be limited to purchasing AI software; organizations should also develop the internal capability required to integrate AI with existing hydrogen production, renewable energy, storage, transportation, and supply chain management systems. Partnerships with technology providers, universities, and specialized research organizations can further accelerate capability development.

Third, Digital Infrastructure Readiness should be treated as a foundational investment. Managers should prioritize reliable data platforms, communication networks, interoperable information systems, appropriate computing resources, and secure data-management architectures. Particular attention should be given to interoperability because GHSCs involve multiple interconnected activities and organizations. Developing an integrated digital infrastructure can improve data availability, facilitate real-time monitoring, support predictive analytics, and create the technical foundation required for broader AI deployment.

Fourth, managers should adopt a priority-based implementation strategy. The causal structure identified by DEMATEL suggests that organizations should not attempt to improve all thirteen enablers simultaneously with equal intensity. Instead, initial investments should focus on the major driving factors, particularly management commitment, technological capability, and digital infrastructure, followed by organizational, human, financial, collaborative, and outcome-oriented factors. This approach can improve the efficiency of resource allocation and reduce the risk of implementing AI applications without adequate organizational and technological foundations. Fifth, organizations should translate AI adoption into measurable operational objectives. Once the foundational capabilities are established, managers should evaluate AI applications according to specific GHSC requirements, such as renewable energy forecasting, hydrogen production optimization, demand forecasting, predictive maintenance, inventory management, transportation planning, and system monitoring. Linking AI initiatives to measurable operational outcomes can increase organizational commitment and provide evidence of the value generated by digital transformation.

Policy implications

The findings also provide important implications for policymakers and public institutions supporting the development of green hydrogen ecosystems. First, policymakers should prioritize digital infrastructure as part of green hydrogen development strategies. Public investment programs should not focus exclusively on physical hydrogen infrastructure such as production, storage, and transportation facilities. They should also consider the digital infrastructure required to support AI-enabled GHSCs, including high-quality data systems, connectivity, interoperability, and secure digital platforms. Second, governments should establish supportive policies for AI capability development. Financial incentives, innovation grants, technology-development programs, and public-private partnerships can reduce the barriers associated with developing AI capabilities in emerging hydrogen markets. Such policies can be particularly valuable for organizations that lack the financial and technical resources required to develop advanced AI systems independently.

Third, regulatory institutions should provide greater clarity regarding the use of AI and data within hydrogen supply chains. Clear guidelines concerning data governance, cybersecurity, data sharing, system interoperability, and responsible AI use can reduce uncertainty and encourage organizations to invest in digital technologies. Regulatory frameworks should simultaneously protect sensitive operational data and facilitate appropriate information sharing among supply chain participants.

Fourth, policymakers should encourage collaboration across the hydrogen ecosystem. Government-supported innovation platforms, research consortia, pilot projects, and industry-academia partnerships can facilitate knowledge transfer and accelerate the development of AI capabilities. Such initiatives are particularly important because the causal structure of AI adoption extends beyond individual organizations and involves interactions among technology providers, hydrogen producers, renewable energy companies, logistics providers, regulators, research institutions, and end users.

Overall, the DEMATEL findings suggest that AI adoption in GHSCs should be approached as a system-level transformation rather than as an isolated technology investment. Managers should first strengthen the major causal drivers, Top Management Support, Technological Capability, and Digital Infrastructure Readiness, and then use these foundations to improve the remaining adoption conditions. Policymakers, in parallel, can accelerate this process by providing appropriate digital infrastructure, investment mechanisms, regulatory clarity, and collaborative ecosystems. This coordinated approach can increase the likelihood that AI adoption generates sustained improvements in the efficiency, resilience, competitiveness, and sustainability of GHSCs.

Future research directions

Although this study provides a causal framework for understanding AI adoption enablers in GHSCs, several directions warrant further investigation. First, future studies could validate the causal relationships identified through DEMATEL using complementary methods, such as ISM, MICMAC, SEM, or hybrid MCDM approaches. Such methodological triangulation would help examine whether the driving and dependent positions of the identified enablers remain stable under alternative analytical approaches. Second, future research could investigate whether the importance and causal structure of AI adoption enablers differ across individual stages of the GHSC, including hydrogen production, compression and storage, transportation, distribution, and end-use applications. This would provide a more granular understanding of whether, for example, Digital Infrastructure Readiness or Technological Capability is more influential at particular stages of the supply chain.

Third, cross-country and cross-institutional comparative studies are recommended to examine how differences in regulatory frameworks, public funding mechanisms, energy policies, and digital infrastructure affect the causal structure of AI adoption. Such research could determine whether the findings of this study are context-specific or transferable to different national and institutional environments. Fourth, future studies could employ larger and more diverse stakeholder samples, incorporating hydrogen producers, technology providers, logistics operators, policymakers, investors, and AI specialists. Comparing the judgments of different stakeholder groups could reveal important differences in how technological, organizational, financial, and institutional enablers are perceived. Fifth, because AI adoption and GHSC development are dynamic processes, longitudinal research could examine how the causal position of the identified enablers changes over time. For instance, an enabler that functions as a major driver during the early stages of AI adoption may become a dependent factor as technological and organizational maturity increases. Finally, future research should move beyond expert-based causal assessment toward empirical validation using real-world organizational and supply-chain data. Quantitative studies could examine the relationship between the identified enablers and measurable outcomes such as AI adoption intensity, operational efficiency, supply-chain resilience, cost reduction, emissions performance, and overall sustainability. This would provide stronger empirical evidence regarding whether strengthening the causal enablers identified in this study actually translates into improved AI-enabled GHSC performance.

Conclusion

This study aimed to identify and analyze the key enablers influencing Artificial Intelligence adoption in the GHSCs using the DEMATEL methodology. A comprehensive framework consisting of thirteen enablers was developed through an extensive literature review and expert evaluation. The DEMATEL approach enabled the examination of both direct and indirect relationships among the enablers and provided insights into their causal structure. The findings revealed that Top Management Support, Technological Capability, Digital Infrastructure Readiness, Regulatory and Policy Support, and Stakeholder Collaboration constitute the primary driving factors that influence the successful adoption of AI technologies. In contrast, Investment and Financial Support, Expected Operational Benefits, and Sustainability and Environmental Commitment were identified as dependent factors that are largely shaped by improvements in the causal enablers. The study contributes to the literature by extending current knowledge on AI adoption and digital transformation within emerging hydrogen energy systems. Unlike previous studies that primarily focused on identifying adoption factors, this research uncovers the causal relationships among the enablers and provides a structured understanding of their interactions. From a practical perspective, the findings offer valuable guidance for managers and policymakers seeking to accelerate AI implementation within GHSCs. By prioritizing the most influential drivers, organizations can improve digital readiness, strengthen operational efficiency, enhance sustainability performance, and support the transition toward a resilient and low-carbon hydrogen economy.

Data Availability Statement

Data available on request from the authors.

Ethical considerations

The authors avoided data fabrication, falsification, plagiarism, and any form of misconduct.

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Conflict of interest

The authors declare no conflict of interest.

Declaration of Generative AI

During the preparation of this work the author(s) used CHATGPT in order to checking grammar and drawing the figures. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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