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Presenting a Sustainable Supply Chain Model Based on Blockchain Technology in Iran's Oil and Gas Industry (Case Study: Fajr Jam Refinery)

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A B S T R A C T

Considering the increasing complexity of supply chains in the oil and gas industry and the growing pressures arising from sustainability, transparency, and accountability requirements, the application of emerging technologies—particularly blockchain—has attracted attention as an innovative solution. However, the absence of indigenous, comprehensive, and empirically grounded models for implementing blockchain-based sustainable supply chains in Iran's oil and gas industry constitutes a fundamental challenge. The objective of the present study is to design and explain an integrated model for a blockchain-based sustainable supply chain with a focus on Fajr Jam Refinery. This research is applied–developmental in purpose and employs a mixed-methods (qualitative–quantitative) approach. In the qualitative phase, the principal dimensions and components of a blockchain-based sustainable supply chain were identified through a meta-synthesis method and a systematic review of the literature. To evaluate the quality of the studies, the CASP methodological criteria were applied, resulting in the selection of 30 high-quality scientific articles as the analytical foundation. Subsequently, in order to validate and refine the indicators, a Hesitant Fuzzy Delphi technique was employed with the participation of experts from the oil and gas industry and the supply chain field. Thereafter, to analyze the causal relationships among the indicators and to determine their degrees of influence and dependence, the Hesitant Fuzzy DEMATEL technique was utilized. The findings led to the identification of five main dimensions—economic, environmental, social, technological, and governance—which were organized into 26 final sub-criteria. The results of the analysis indicate that the technological and governance dimensions play a causal and driving role in the establishment of a blockchain-based sustainable supply chain, whereas the social and environmental dimensions exhibit the highest levels of susceptibility to influence from other components.

Keywords: *Sustainable supply chain, blockchain technology, Iran's oil and gas industry, meta-synthesis, Hesitant Fuzzy Delphi, Hesitant Fuzzy DEMATEL*

1. Introduction

Oil and gas supply chains are among the most complex industrial systems due to multi-tier sourcing, hazardous-material logistics, stringent safety requirements, capital-intensive assets, and high exposure to geopolitical and market volatility. In such environments, performance is no longer evaluated only through cost, time, and quality, but increasingly through sustainability criteria that integrate economic resilience, environmental stewardship, and social legitimacy across the full value chain. The growing managerial emphasis on sustainable supply chain management reflects both regulatory pressure and stakeholder expectations for traceability, responsible operations, and credible reporting in sectors with material environmental footprints. In parallel, the operational risk profile of oil and gas supply chains has intensified, prompting firms to seek governance and technology-enabled mechanisms to anticipate disruptions, assure compliance, and strengthen coordination across organizational boundaries (Chowdhury et al., 2022; Kumar & Barua, 2022).

Digital transformation has been widely positioned as a strategic response to these pressures, particularly through Industry 4.0 technologies that enable real-time visibility, advanced analytics, and process automation. Among these technologies, blockchain has attracted substantial attention because it promises tamper-resistant records, distributed verification, and programmable transactions that can reduce information asymmetry and improve trust in multi-actor networks. The concept of a blockchain-enabled sustainable supply chain aligns with the managerial logic that sustainability performance is fundamentally information dependent: firms cannot manage what they cannot measure, and they cannot credibly report what they cannot verify across tiers. Consequently, blockchain is increasingly discussed as an infrastructure for provenance tracking, auditability, and cross-firm accountability, particularly in high-risk supply chains characterized by multiple intermediaries and fragmented data ownership (Esmaeilian et al., 2020; Wamba & Queiroz, 2020).

The sustainable supply chain literature has proposed multiple pathways through which blockchain can create value, including improving traceability of products and materials, enabling real-time or near-real-time disclosure of critical operational metrics, supporting compliance monitoring, and strengthening governance through transparent records of transactions and responsibilities. Empirical and conceptual studies in operations and supply chain management have emphasized that these capabilities may be especially relevant when sustainability outcomes depend on the coordination of many stakeholders and when opportunistic behavior, fraud, or data manipulation undermine trust. As a result, researchers have increasingly shifted from general claims of technological benefits toward more explicit identification of critical success factors, adoption barriers, and implementation contingencies that shape whether blockchain deployments can actually deliver sustainability improvements (Kouhizadeh et al., 2020; Yadav & Singh, 2020).

Systematic reviews have further consolidated the field by mapping dominant themes, methodological patterns, and future research directions in blockchain for sustainable supply chains. These syntheses underscore that blockchain research is moving from conceptual enthusiasm toward more structured frameworks addressing governance design, organizational readiness, standards, interoperability, and the socio-technical nature of adoption. Notably, state-of-the-art reviews emphasize that sustainability outcomes are not automatic consequences of blockchain implementation; rather, they depend on complementary organizational capabilities, institutional alignment, and credible integration with existing enterprise systems and operational processes. This orientation frames blockchain not as a standalone solution but as a component within a broader configuration of managerial practices and digital infrastructures (Paliwal et al., 2020; Sahoo et al., 2024).

Despite this momentum, adoption remains uneven, and the oil and gas context introduces distinctive constraints. Petroleum supply chains often operate under stringent security requirements, legacy information systems, and inter-firm contracting structures that are difficult to standardize. Modeling work on petroleum supply chains highlights challenges such as multi-echelon planning complexity, coordination frictions, and structural barriers that can constrain digital innovations even when strategic interest exists (Kumar & Barua, 2022). Sector-specific studies of blockchain adoption in oil-related settings show that adoption decisions are shaped by factors such as perceived strategic value, compatibility with existing processes, data governance concerns, and partner readiness, indicating that managerial and institutional drivers can be as decisive as technical feasibility (Aslam et al., 2021; Munim et al., 2022).

At the same time, evidence from other industries suggests that blockchain's contribution to sustainability performance may be contingent on the stage of green supply chain management development and the specific environmental performance mechanisms in place. This implies that managers should avoid generic implementation templates and instead align blockchain deployment with the maturity of sustainability practices, measurement systems, and supplier development programs. A stage-wise perspective further suggests that early benefits may concentrate on visibility and compliance, while more advanced benefits may arise through process redesign, circular economy integration, and policy-enabled collaboration across networks (Jasrotia et al., 2024; Tathavadekar, 2025).

A recurring theme in the literature is that blockchain adoption is best understood through integrated frameworks that capture institutional, market, and technical dimensions simultaneously. In this view, adoption is not merely a technology selection problem but a governance transformation that touches regulatory compliance, inter-organizational trust, standards, and data-sharing arrangements. Adoption frameworks emphasize that institutional pressures, competitive dynamics, and technical constraints interact to shape readiness and outcomes, making context-specific modeling essential for high-stakes industries where compliance and accountability are critical. Such integrative framing is particularly relevant for developing-country settings, where infrastructure gaps, regulatory variability, and capability constraints may reshape adoption trajectories and risk profiles (Janssen et al., 2020; Kshetri, 2021).

In emerging and developing contexts, blockchain is frequently discussed as a mechanism to improve transparency and reduce opportunism, but the literature also stresses constraints such as limited digital infrastructure, skills shortages, and weak inter-organizational coordination. These constraints can be amplified in oil and gas networks that involve contractors, logistics providers, and public stakeholders, where governance and legitimacy considerations are central. Therefore, localized models that incorporate regulatory realities, governance structures, and sector-specific sustainability priorities are necessary to translate general blockchain capabilities into operationally feasible and policy-relevant solutions (Didehgah Seyed Amir & Sohrabi, 2023; Kshetri, 2021).

From a managerial perspective, barriers and challenges represent a major research stream because they inform implementation sequencing, capability investments, and risk mitigation. Studies examining blockchain adoption barriers have identified issues such as scalability constraints, integration complexity, lack of standards, uncertain legal frameworks, and data privacy concerns. Decision-aid and multi-criteria approaches have been proposed to evaluate these challenges systematically, enabling managers to prioritize interventions and allocate resources to the most binding constraints. Such approaches are useful for oil and gas organizations because blockchain initiatives often span multiple functions—procurement, logistics, HSE, compliance, and finance—and require consistent evaluation across competing priorities (Karuppiah et al., 2021; Vafadarnikjoo et al., 2021).

The governance and compliance environment is also critical. Blockchain implementations can generate new types of accountability, but they also raise questions about data ownership, legal admissibility of records, jurisdictional rules, and the governance of permissioned networks. Research on expected value and challenges emphasizes that organizations must articulate the value logic—cost reduction, risk reduction, transparency, stakeholder trust—while also addressing governance design and partner alignment as prerequisites for adoption. In high-regulation sectors, blockchain can be strategically appealing for auditability and reporting, yet the same contexts heighten sensitivity to regulatory interpretation and institutional acceptance of digital records (Chowdhury et al., 2022; Toufaily et al., 2021).

Another important managerial dimension is organizational readiness. Readiness frameworks propose that successful implementation requires capabilities in IT governance, process management, data quality, cybersecurity, and human capital, alongside leadership commitment and cross-functional coordination. In practice, readiness gaps can cause blockchain projects to underperform even when the technology is technically sound, because blockchain depends on reliable data inputs and consistent operational discipline across participants. This is especially salient for sustainable supply chain applications where performance indicators are multi-dimensional and must be collected consistently across sites and partners. Consequently, readiness assessment and capability building should precede or accompany implementation roadmaps (Hosseinpouli Mamaghani et al., 2022; Khan et al., 2021).

Beyond operational and compliance functions, sustainability finance is increasingly part of supply chain governance, as firms face expectations to connect sustainability performance with financing conditions, supplier incentives, and reporting credibility. The emerging literature on sustainable supply chain finance highlights how sustainability metrics, verification mechanisms, and governance structures can influence financing arrangements and stakeholder confidence. Blockchain can potentially support this domain by improving data integrity and traceability of sustainability claims, but finance-related outcomes require careful alignment with reporting standards, assurance practices, and contractual mechanisms. Case-based insights suggest that finance-related sustainability initiatives depend on multi-actor collaboration and credible data infrastructures, reinforcing the value of blockchain only when governance and measurement architectures are well designed (Slavinskaitė et al., 2025; Zhou & Masi, 2025).

The sustainability implications of automation and digitalization also extend to workforce outcomes, which are particularly important in heavy industries. While automation can improve efficiency and reduce environmental impacts, it can also create concerns about worker welfare, job redesign, and occupational health. Systematic evidence on automation's implications for worker welfare suggests that sustainability must be interpreted as a balanced construct, where social dimensions—fair work, safety, skills development—are not secondary to environmental or economic objectives. In oil and gas settings, where safety is mission-critical and labor arrangements can be complex, this reinforces the need for models that explicitly integrate social criteria alongside technological and governance drivers (Park & Li, 2021; Putra & Baharum, 2025).

Research examining sustainability performance outcomes of blockchain likewise shows that effects may vary by dimension and depend on managerial choices. Evidence on sustainability performance suggests that blockchain may strengthen sustainability primarily when integrated with broader sustainability practices, stakeholder collaboration mechanisms, and measurement systems rather than being pursued as a purely technological upgrade. This perspective is particularly relevant to oil and gas networks where environmental monitoring, emissions reporting, and asset life-cycle management require rigorous data pipelines and multi-party verification. Thus, a comprehensive model should account for technological foundations (e.g., security, interoperability), governance capacity (e.g., compliance, auditing), and sustainability outcomes (economic, environmental, social) as interacting elements (Esmaeilian et al., 2020; Park & Li, 2021).

A further stream of research emphasizes risk management and resilience. Supply chains face disruptions from operational accidents, cyber threats, policy changes, and market shocks, and blockchain is increasingly framed as a technology that can support risk visibility, data integrity, and coordinated response. Evidence from operational and supply chain risk contexts indicates that blockchain adoption decisions are often shaped by perceived risk mitigation benefits and the organization's ability to mobilize inter-organizational collaboration. For oil and gas, where the cost of disruptions can be exceptionally high, resilience-oriented digital transformation may be a strategic imperative that intersects directly with sustainability and governance goals (Chowdhury et al., 2022; Krimi et al., 2025).

However, the literature also shows that implementation is constrained by sector-specific challenges, including energy intensity, regulatory obligations, and infrastructure requirements. Studies in adjacent domains, such as renewable energy supply chains, illustrate that blockchain adoption faces barriers related to technical integration, stakeholder coordination, and policy uncertainty, which can mirror issues in conventional energy sectors. These findings reinforce that successful blockchain adoption requires aligning technology decisions with regulatory structures and partner ecosystems, rather than focusing solely on internal system deployment (Almutairi et al., 2023; Janssen et al., 2020).

In the Iranian context, research has begun to examine blockchain-based approaches for sustainable supply chains through cognitive mapping and interpretive modeling, emphasizing that sustainability challenges and governance structures require localized conceptualization. Such evidence suggests that indigenous modeling can capture context-specific drivers such as regulatory compliance structures, institutional arrangements, and the practical realities of technology diffusion in local industries. At the same time, international studies demonstrate the value of multi-criteria decision models—fuzzy AHP, fuzzy DEMATEL, Bayesian approaches—to prioritize sustainability factors and reveal causal relationships, supporting the methodological logic of integrating qualitative synthesis with quantitative causal-weighting techniques in complex supply chain settings (Hosseini Seyed et al., 2022; Munim et al., 2022; Paul & Mahapatra, 2025).

Methodologically, there is increasing recognition that sustainable supply chain problems are multi-dimensional and interdependent, making purely linear modeling inadequate. Integrated fuzzy approaches have been used to evaluate adoption challenges and causal structures under uncertainty, particularly when expert judgments are required and data are incomplete or ambiguous. Studies combining fuzzy DEMATEL with other modeling approaches show that identifying cause–effect structures can clarify which dimensions function as drivers (e.g., governance, technological infrastructure) and which respond more strongly as outcomes (e.g., environmental and social performance), thereby informing managerial sequencing and policy design (Karuppiah et al., 2021; Piliwari Selmasi et al., 2021).

At the same time, the broader blockchain and operations literature emphasizes that the field still requires more evidence-based, sector-specific, and implementation-oriented models that translate theoretical potential into practical pathways. Researchers call for designs that incorporate adoption barriers, readiness, governance, and performance outcomes in a coherent structure, enabling decision-makers to prioritize investments and design interventions that are feasible and measurable. This need is particularly salient for oil and gas organizations and policymakers seeking to strengthen transparency, accountability, and sustainability performance under complex institutional constraints and high stakeholder scrutiny (Kouhizadeh et al., 2020; Sahoo et al., 2024; Wamba & Queiroz, 2020).

Accordingly, this study aims to design and validate an integrated, evidence-based model for a blockchain-enabled sustainable supply chain in Iran's oil and gas industry (case: Fajr Jam Refinery) by identifying its key dimensions and sub-criteria and prioritizing them through a mixed-method approach combining meta-synthesis, hesitant fuzzy Delphi, and hesitant fuzzy DANP.

2. Methods and Materials

The present study is applied–developmental in terms of purpose and employs a mixed-methods (qualitative–quantitative) design. Using a systematic and multi-stage approach, it seeks to develop and propose a blockchain-based sustainable supply chain model for Iran's oil and gas industry, with a specific focus on Fajr Jam Refinery. The selection of a mixed-methods approach was necessitated by the complex, multidimensional, and interdisciplinary nature of sustainable supply chains and the need to integrate theoretical knowledge with expert judgment.

In the first stage, the qualitative component of the study was conducted using the meta-synthesis method. Meta-synthesis, as a systematic approach for aggregating, interpreting, and reconstructing knowledge derived from previous qualitative studies, enabled the comprehensive identification of the dimensions and components of a blockchain-based sustainable supply chain. At this stage, a systematic literature review of authoritative national and international scientific articles related to sustainable supply chains, blockchain technology, and the oil and gas industry was performed. The source screening process was conducted in multiple stages using the CASP methodological criteria to ensure the credibility, validity, and relevance of the selected studies. Ultimately, 30 eligible articles were selected as the basis for qualitative data extraction and analysis. The analysis led to the identification of the principal dimensions and related sub-criteria, forming the preliminary conceptual framework of the research.

In the second stage, to validate and refine the extracted indicators, the Hesitant Fuzzy Delphi method was employed. At this stage, the identified indicators were compiled into a structured questionnaire and distributed among 10 experts in the fields of supply chain management, the oil and gas industry, and emerging technologies. The experts evaluated the importance of each indicator using a Likert scale. The application of hesitant fuzzy logic made it possible to capture uncertainty and variations in expert opinions. The results of this phase led to the elimination of low-importance indicators and the final confirmation of 26 sub-criteria across five main dimensions: governance, technological, social, environmental, and economic.

In the third stage, the Hesitant Fuzzy DEMATEL technique was applied to analyze causal relationships and determine the internal structure of the model. This method enabled the identification of the strength and direction of mutual influences among the sub-criteria and classified them into cause and effect groups. The experts' pairwise judgments regarding the degree of influence among the criteria formed the basis of the relational network analysis, and causal maps for each dimension were constructed.

In the final stage, to calculate relative weights and determine the final prioritization of the indicators, the results of DEMATEL were integrated into a supermatrix framework, and the final weights of each sub-criterion were extracted. This process enabled precise ranking of the factors influencing the blockchain-based sustainable supply chain. Overall, the integration of qualitative and quantitative methods in this research enhanced the robustness of the findings and resulted in the development of a comprehensive, localized, and reliable model for Iran's oil and gas industry.

The DANP technique, as a contemporary approach combining DEMATEL and ANP, was also applied in this study. Using the total influence matrix derived from DEMATEL, ANP supermatrices were constructed to compute the final weights of the research indicators. The procedural steps of this method are presented below.

Step 1: Construction of the Direct Relation Matrix (D)

At this stage, experts determined the degree of influence among the criteria using the linguistic scale presented in Table 1.

Table 1

Linguistic Scale and Corresponding Fuzzy Numbers

Code	Linguistic Term	Fuzzy Number
N	No influence	(0, 0, 0.25)
VL	Very low influence	(0, 0.25, 0.5)
L	Low influence	(0.25, 0.5, 0.75)
H	High influence	(0.5, 0.75, 1)
VH	Very high influence	(0.75, 1, 1)

At this stage, the hesitant fuzzy matrix is constructed through the following three steps.

Stage 1. Determination of indices *i* and *j* of hesitant fuzzy numbers, indicating the range of hesitation among linguistic comparison levels and whether $i + j$ is even or odd.

i represents the index of the lower bound of the linguistic variable; for example, “relatively low importance” corresponds to index 2.

j represents the index of the upper bound of the linguistic variable; for example, “relatively high importance” corresponds to index 8.

Stage 2. Determination of α_1 and α_2 for constructing the first and second type weighting vectors, which are complementary.

Note: α_1 and α_2 are complementary and calculated as:

$\alpha_2 = ((j - i) - 1) / (g - 1)$

$\alpha_1 = 1 - \alpha_2$

Stage 3. Determination of the lower, middle, and upper values of trapezoidal fuzzy numbers as follows.

Element *a* is the minimum lower bound of triangular fuzzy numbers.

Element *d* is the maximum upper bound of triangular fuzzy numbers.

Element *b* is obtained from the second type weighting vector, denoted by w^2, as:

$b = OWA_{w^2}$ {

if $i + j$ is even $\rightarrow \alpha_2 \times a_i + \alpha_1 \times a_{(i+j)/2}$

if $i + j$ is odd $\rightarrow \alpha_2 \times a_i + \alpha_1 \times a_{(i+j-1)/2}$

}

Practical note: The first critical step is ranking linguistic variables according to the linguistic scale table.

Element *c* is derived from the first type weighting vector, denoted by w^1, as:

$c = 2a_{(i+j)/2} - b$

In this step, the hesitant fuzzy matrix is defuzzified using the following formula, assuming a hesitant fuzzy number A = (a, b, c, d):

$(a + b + c + d) / 4$

Step 2: Normalization of the Direct Relation Matrix

According to the following equation, the average matrix from Step 1 is normalized and denoted as matrix H. For normalization, the formulas for *r* and $\hat{H}_{ij}$ are applied:

$\hat{H}_{ij} = \tilde{z}_{ij} / r = (l'_{ij}/r,\ m'_{ij}/r,\ m''_{ij}/r,\ u'_{ij}/r) = (l''_{ij}, m'_{ij}, m''_{ij}, u''_{ij})$

where

$r = \max \{ \max_{1\le i\le n} (\sum_{j=1}^{n} u'_{ij}),\ \max_{1\le j\le n} (\sum_{i=1}^{n} u'_{ij}) \}$

Step 3: Calculation of the Total Relation Matrix (TC)

After computing the above matrices, the total hesitant fuzzy relation matrix is obtained using:

$T = \lim_{k\to\infty} (\hat{H}^1 \oplus \hat{H}^2 \oplus \dots \oplus \hat{H}^k)$

Each element of T is a hesitant fuzzy number:

$\tilde{t}_{ij} = (l_{ij}{}^t, m'_{ij}{}^t, m''_{ij}{}^t, u_{ij}{}^t)$

and is calculated as:

$[l_{ij}{}^t] = H_l \times (I - H_l)^{-1}$

$[m'_{ij}{}^t] = H_m \times (I - H_m)^{-1}$

$[m''_{ij}{}^t] = H_m \times (I - H_m)^{-1}$

$[u_{ij}{}^t] = H_u \times (I - H_u)^{-1}$

In these formulas, *I* is the identity matrix, and H_l, H_m, and H_u are $n \times n$ matrices whose elements correspond to the lower, middle, and upper values of the trapezoidal hesitant fuzzy numbers in matrix H, respectively.

Step 4 – Calculation of the Intensity and Direction of Influence

According to the following two equations, the indices r_i and c_j are calculated. The index r_i represents the sum of the *i*-th row and the index c_j represents the sum of the *j*-th column of matrix $\mathbf{T^c}$ with respect to the corresponding dimension. In the same manner, the indices $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{R}}$ are calculated. The index R_i denotes the sum of the i-th row and the index C_j denotes the sum of the j-th column of matrix $\mathbf{T^D}$. For plotting and analyzing the causal diagram, two measures are required: (1) the intensity of influence and influencedness, and (2) the direction of influence, which are derived from r_i and c_j. For each $i = j$, the following applies:

$$\tilde{D} = (\tilde{D}_i)_{n\times 1} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{n\times 1}$$

$$\tilde{R} = (\tilde{R}_i)_{1\times n} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{1\times n}$$

where $\tilde{\mathbf{D}}$ and $\tilde{\mathbf{R}}$ are respectively an $n \times 1$ and a $1 \times n$ matrix.

In the next step, the importance of criteria $(\tilde{D}_i + \tilde{R}_i)$ and the relationships among criteria $(\tilde{D}_i - \tilde{R}_i)$ are determined. If $(\tilde{D}_i - \tilde{R}_i) > 0$, the corresponding criterion is a causal factor; if $(\tilde{D}_i - \tilde{R}_i) < 0$, the corresponding criterion is an effect factor.

- $r_i + d_j$ = intensity of influence and influencedness (i.e., the larger the value of $r_i + d_j$, the more interaction the factor has with other system factors).
- $r_i - d_j$ = direction of influence or influencedness (if $r_i - d_j > 0$, the criterion is a cause; if $r_i - d_j < 0$, the criterion is an effect).

Based on the above computations, the values of $r_i + d_j$ and $r_i - d_j$ for criteria and the values of $(\tilde{D}_i + \tilde{R}_i)$ and $(\tilde{D}_i - \tilde{R}_i)$ for dimensions are obtained and subsequently defuzzified using the hesitant fuzzy defuzzification procedure.

Step 5 – Normalization of the Total Relation Matrix and Formation of the Unweighted Supermatrix

The matrix $\mathbf{T^c}$ is normalized using the relations T_C^{α} to $T_C^{(\alpha 11)}$. In this step, the sum of each row of T_C^{ij} is calculated for the corresponding dimension, and each element T_C^{ij} is divided by the sum of its respective row. For example, if T_C^{α} consists of a set of $T_C^{(\alpha ij)}$, then $T_C^{(\alpha 11)}$ is obtained by normalizing T_C^{11}. By transposing T_C^{α}, the **unweighted supermatrix** is obtained.

$$d_{ci}^{11} = \sum_{j=1}^{m_1} t_{cij}^{11}, i = 1,2,\dots,m_1$$

$$T_C^{(\alpha 11)} = \begin{bmatrix} \frac{t_{c11}^{11}}{d_{c1}^{11}} & \cdots & \frac{t_{c1j}^{11}}{d_{c1}^{11}} & \cdots & \frac{t_{c1m_1}^{11}}{d_{c1}^{11}} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{ci1}^{11}}{d_{ci}^{11}} & \cdots & \frac{t_{cij}^{11}}{d_{ci}^{11}} & \cdots & \frac{t_{cim_1}^{11}}{d_{ci}^{11}} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{cm_1 1}^{11}}{d_{cm_1}^{11}} & \cdots & \frac{t_{cm_1 j}^{11}}{d_{cm_1}^{11}} & \cdots & \frac{t_{cm_1 m_1}^{11}}{d_{cm_1}^{11}} \end{bmatrix}$$

Step 6 – Construction of the Weighted Supermatrix

In this stage, matrix T_D^{α} is multiplied by the unweighted supermatrix. The matrix T_D^{α} is calculated as follows:

$$d_i = \sum_{j=1}^{m} t_{ij}^{(D_{ij})}, i = 1,2,\dots,m$$

$$T_D^{\alpha} = \begin{bmatrix} \frac{t_{11}^{(D_{11})}}{d_1} & \cdots & \frac{t_{1j}^{(D_{1j})}}{d_1} & \cdots & \frac{t_{1m}^{(D_{1m})}}{d_1} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{i1}^{(D_{i1})}}{d_i} & \cdots & \frac{t_{ij}^{(D_{ij})}}{d_i} & \cdots & \frac{t_{im}^{(D_{im})}}{d_i} \\ \vdots & & \vdots & & \vdots \\ \frac{t_{m1}^{(D_{m1})}}{d_m} & \cdots & \frac{t_{mj}^{(D_{mj})}}{d_m} & \cdots & \frac{t_{mm}^{(D_{mm})}}{d_m} \end{bmatrix}$$

The resulting matrix is the weighted supermatrix.

Step 7 – Construction of the Limit Supermatrix

According to the following relation, the weighted supermatrix is raised to successive powers (odd integers) until the values in each row converge:

$$\lim_{Z\to\infty}(W^{(\alpha l)})^Z, \lim_{Z\to\infty}(W'^m)^Z, \lim_{Z\to\infty}(W''^m)^Z, \lim_{Z\to\infty}(W^{(\alpha u)})^Z$$

This process yields the limit supermatrix, from which the final priority weights of the criteria are extracted.

3. Findings and Results

Meta-synthesis is a qualitative method used to generate knowledge and interpret results from prior studies. This approach is systematic and combines the findings and results of multiple qualitative studies to discover new sub-themes and main themes, thereby advancing knowledge and providing a more comprehensive understanding of the domain under investigation. In meta-synthesis, researchers are required to conduct a careful and in-depth examination of previous qualitative studies in order to offer a more comprehensive representation of the phenomenon under study.

Accordingly, in the present dissertation, to identify the dimensions and components of a blockchain-based sustainable supply chain in Iran's oil and gas industry, the meta-synthesis approach proposed by Barroso and Sandelowski was adopted.

Figure 1

Stages of the Meta-synthesis Method

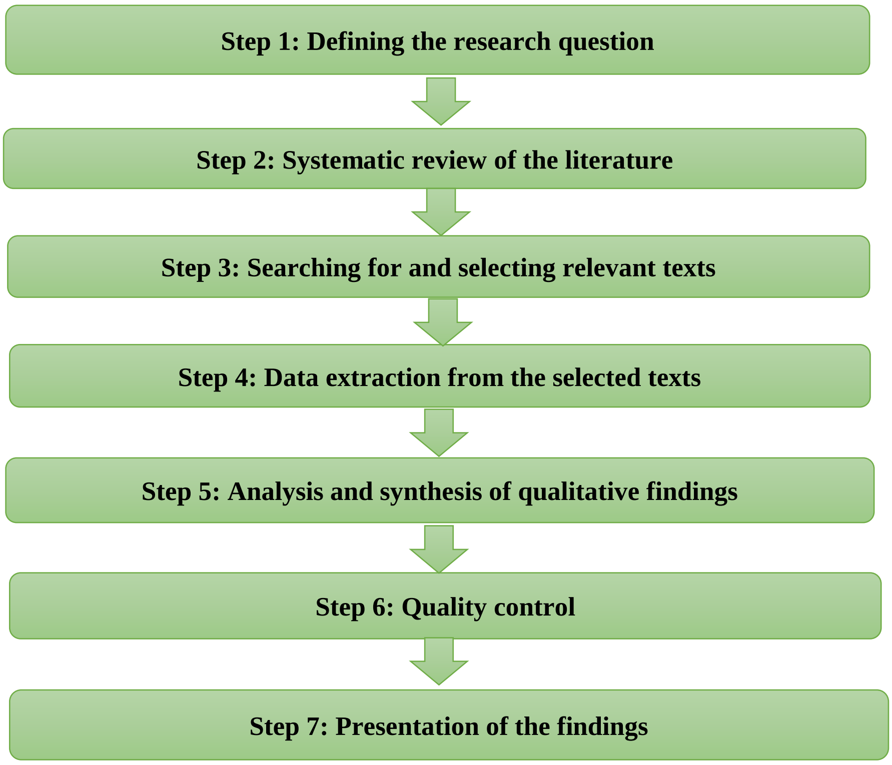
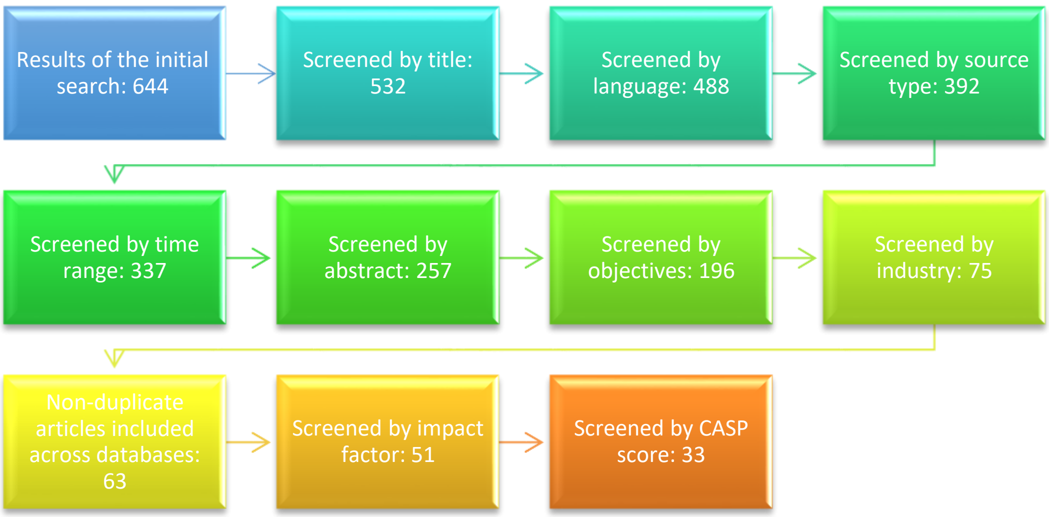


Figure 2

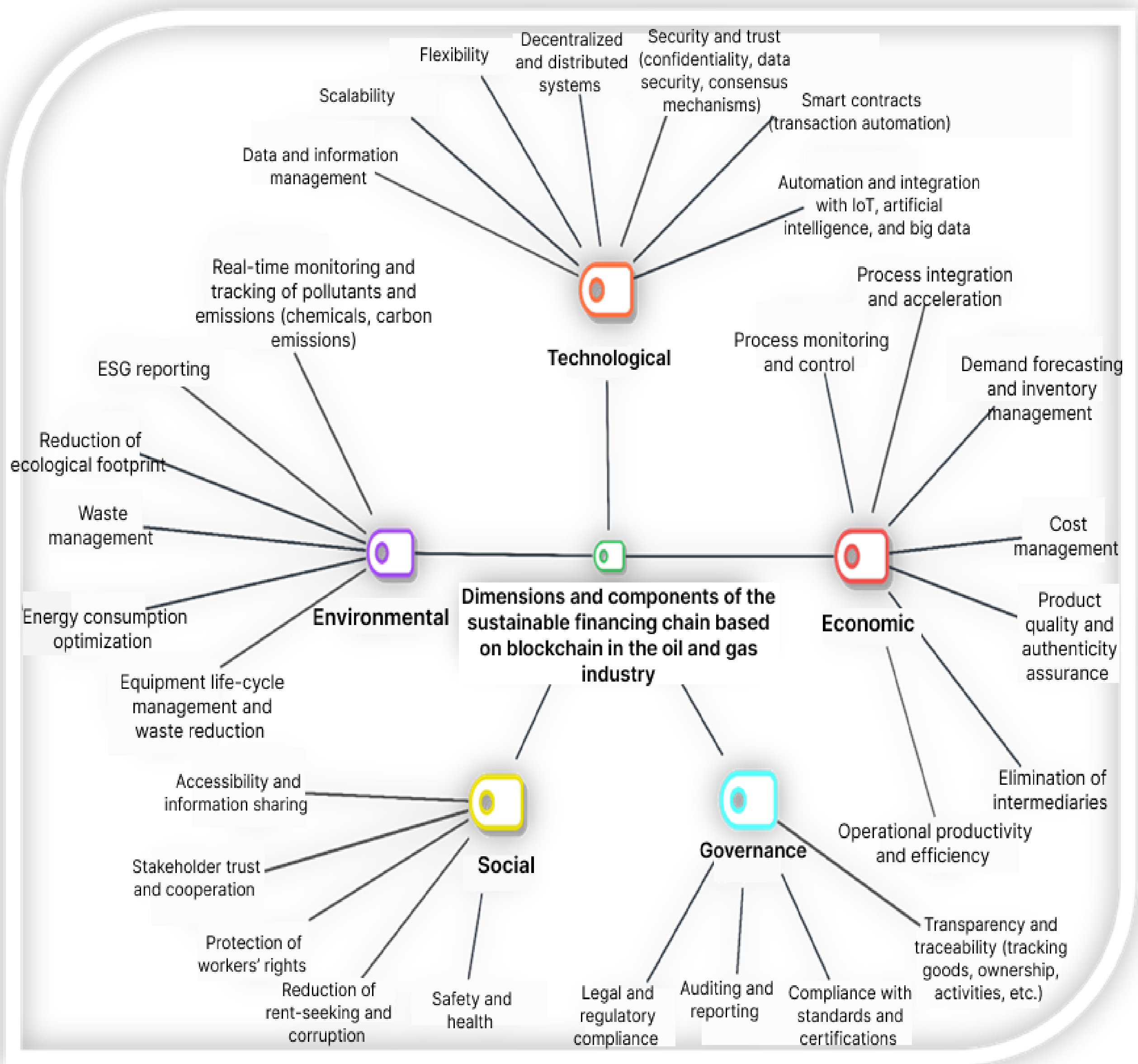
Source Screening Stages



The screening process and CASP appraisal were conducted for the articles. In the third screening stage, the CASP method was applied. Based on the results obtained from text selection and the appraisal of article credibility, 30 articles were selected as the final studies for information extraction. Based on the qualitative data analysis and the research findings—as described and interpreted—the dimensions and components of the blockchain-based sustainable supply chain in Iran's oil and gas industry are presented in the model below.

Figure 3

Blockchain-Based Sustainable Supply Chain in Iran's Oil and Gas Industry



In this section, the indicators extracted from the qualitative phase of the research were provided to 10 subject-matter experts via a questionnaire so that they could assign a score to each indicator based on a 1–5 Likert scale (1 = very low importance, 2 = low importance, 3 = moderate importance, 4 = high importance, 5 = very high importance). This stage was conducted for the final confirmation of the criteria.

Table 2

Results of Expert Opinions

Dimension	Sub-criterion	Very low	Low	Moderate	High	Very high
Governance	Legal and regulatory compliance	0	0	0	6	4
Governance	Auditing and reporting	0	0	0	1	9
Governance	Compliance with standards and certifications	0	0	1	1	8
Governance	Transparency and traceability (tracking goods, ownership, activities, etc.)	0	1	1	3	5
Technological	Data and information management	0	0	3	3	4
Technological	Automation and integration with IoT and AI, big data	0	0	0	5	5
Technological	Flexibility	1	1	5	3	0
Technological	Scalability	0	0	3	0	7
Technological	Security and trust (confidentiality, data security, consensus mechanism)	0	1	1	0	8
Technological	Decentralized and distributed systems	0	1	2	1	6
Technological	Smart contracts (transaction automation)	0	1	0	3	6
Social	Protection of workers’ rights	0	0	1	5	4
Social	Accessibility and information sharing	0	0	1	4	5
Social	Stakeholder trust and collaboration	0	0	1	2	7
Social	Reduction of rent-seeking/corruption	0	0	1	3	6
Social	Safety and health	0	1	1	1	7
Environmental	Traceability/real-time monitoring of pollutants and emissions (chemicals, carbon emissions)	0	0	3	1	6
Environmental	Waste management	0	0	2	2	6
Environmental	ESG reporting	0	1	2	3	4
Environmental	Energy consumption optimization	0	1	1	3	5
Environmental	Reduction of ecological footprint	2	1	4	3	0
Environmental	Equipment life-cycle management and waste reduction	0	0	2	3	5
Economic	Assurance of product quality and authenticity	0	6	4	0	0
Economic	Process monitoring and control	0	0	0	4	6
Economic	Cost management	0	2	4	2	2
Economic	Operational productivity and efficiency	0	0	1	2	7
Economic	Demand forecasting and inventory management	0	0	0	5	5
Economic	Elimination of intermediaries	0	1	1	1	7
Economic	Process integration and acceleration	0	0	0	3	7

Prior to this, a hesitant fuzzy number is represented in trapezoidal form with components $A = (a, b, c, d)$. To compute these components, the following procedure is applied. For the first criterion, based on expert judgments, the scores fall between “high” and “very high,” meaning:

$C_{(\text{first criterion})} = H_{\text{high}}$ between $VH_{\text{very high}}$.

Therefore:

$i = 4, j = 5 \;\Rightarrow\; i + j = 9$(odd).

$$\alpha_2 = \frac{(j-i)-1}{g-1} = \frac{(5-4-1)}{5-1} = 0$$

$$\alpha_1 = 1 - \alpha_2 = 1 - 0 = 1$$

Now, to obtain element b of the trapezoidal fuzzy number:

Since $i + j$ is odd:

$$b = \alpha_2 \times a^{i}_{(\text{middle})} + \alpha_1 \times a^{\frac{i+j-1}{2}}_{(\text{middle})} = 0 \times 0.75 + 1 \times 0.75 = 0.75$$

Similarly, to obtain element c:

$$c = 2 \times a^{\frac{i+j-1}{2}}_{(\text{middle})} - b = 2 \times 0.75 - 0.75 = 0.75$$

Elements a and d of the hesitant fuzzy number are, respectively, the minimum lower bound and the maximum upper bound of the values; thus:

$a = 0.5,\ d = 1.$

Accordingly, the hesitant fuzzy number for the first criterion (legal and regulatory compliance) is $(0.5، 0.75، 0.75، 1)$. Then, based on Equation (3–4), the hesitant fuzzy number is defuzzified as follows:

$$\text{defuzzy}_{(\text{first criterion})} = \frac{0.5 + 0.75 + 0.75 + 1}{4} = 0.75$$

The calculations were also performed for the remaining criteria, and the results are reported in Table 3. Based on expert opinions, criteria that achieve at least 50% of the total importance are confirmed; therefore, the threshold value is set at 0.5. The results indicate the removal of 3 criteria and the confirmation of 26 criteria.

Table 3

Results of the Hesitant Fuzzy Delphi Method

Dimension	Sub-criterion	Hesitant Fuzzy Score	Defuzzified Score	Status
Governance	Legal and regulatory compliance	(0.5, 0.75, 0.75, 1)	0.75	Approved
Governance	Auditing and reporting	(0.5, 0.75, 0.75, 1)	0.75	Approved
Governance	Compliance with standards and certifications	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Governance	Transparency and traceability (tracking goods, ownership, activities, etc.)	(0, 0.375, 0.625, 1)	0.50	Approved
Technological	Data and information management	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Technological	Automation and integration with IoT and AI, big data	(0.5, 0.75, 0.75, 1)	0.75	Approved
Technological	Flexibility	(0, 0.125, 0.375, 1)	0.375	Rejected
Technological	Scalability	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Technological	Security and trust (confidentiality, data security, consensus mechanism)	(0, 0.375, 0.625, 1)	0.50	Approved
Technological	Decentralized and distributed systems	(0, 0.375, 0.625, 1)	0.50	Approved
Technological	Smart contracts (transaction automation)	(0, 0.375, 0.625, 1)	0.50	Approved
Social	Protection of workers' rights	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Social	Accessibility and information sharing	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Social	Stakeholder trust and collaboration	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Social	Reduction of rent-seeking and corruption	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Social	Safety and health	(0, 0.375, 0.625, 1)	0.50	Approved
Environmental	Traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions)	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Environmental	Waste management	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Environmental	ESG reporting	(0, 0.375, 0.625, 1)	0.50	Approved
Environmental	Energy consumption optimization	(0, 0.375, 0.625, 1)	0.50	Approved
Environmental	Reduction of ecological footprint	(0, 0.125, 0.375, 1)	0.375	Rejected
Environmental	Equipment life-cycle management and waste reduction	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Economic	Assurance of product quality and authenticity	(0, 0.25, 0.25, 0.75)	0.3125	Rejected
Economic	Process monitoring and control	(0.5, 0.75, 0.75, 1)	0.75	Approved
Economic	Cost management	(0, 0.375, 0.625, 1)	0.50	Approved
Economic	Operational productivity and efficiency	(0.25, 0.688, 0.813, 1)	0.6875	Approved
Economic	Demand forecasting and inventory management	(0.5, 0.75, 0.75, 1)	0.75	Approved
Economic	Elimination of intermediaries	(0, 0.375, 0.625, 1)	0.50	Approved
Economic	Process integration and acceleration	(0.5, 0.75, 0.75, 1)	0.75	Approved

Table 4

Final Approved Factors

Dimension	Sub-criterion	Symbol
Governance	Legal and regulatory compliance	A1
Governance	Auditing and reporting	A2
Governance	Compliance with standards and certifications	A3
Governance	Transparency and traceability (tracking goods, ownership, activities, etc.)	A4
Technological	Data and information management	B1
Technological	Automation and integration with IoT and AI, big data	B2
Technological	Scalability	B3
Technological	Security and trust (confidentiality, data security, consensus mechanism)	B4
Technological	Decentralized and distributed systems	B5

Technological	Smart contracts (transaction automation)	B6
Social	Protection of workers' rights	C1
Social	Accessibility and information sharing	C2
Social	Stakeholder trust and collaboration	C3
Social	Reduction of rent-seeking and corruption	C4
Social	Safety and health	C5
Environmental	Traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions)	D1
Environmental	Waste management	D2
Environmental	ESG reporting	D3
Environmental	Energy consumption optimization	D4
Environmental	Equipment life-cycle management and waste reduction	D5
Economic	Process monitoring and control	E1
Economic	Cost management	E2
Economic	Operational productivity and efficiency	E3
Economic	Demand forecasting and inventory management	E4
Economic	Elimination of intermediaries	E5
Economic	Process integration and acceleration	E6

Application of the Hesitant Fuzzy DANP Technique

Step 1: Calculation of the Direct Relation Matrix (D)

In this stage, using a 0–4 scale, the opinions of 10 experts were collected regarding the pairwise influence comparisons among the 26 research sub-criteria. Subsequently, the final aggregated expert judgments were obtained. The table indicates the range of linguistic terms used by the experts for evaluating the influence of each pair of criteria. Then, to construct the hesitant direct relation matrix, computations were performed based on Equations (1)–(3).

For example, for the element CA1–E5 (the influence of criterion A1 on criterion E5), the calculations are as follows. A hesitant fuzzy number is represented in trapezoidal form as $A = (a, b, c, d)$. To compute these components:

$$C_{15} = L_{\text{low}} \text{ between } H_{\text{high}}$$

Therefore:

$$i = 2, j = 3 \Rightarrow i + j = 5 \text{ (even)}$$

$$\alpha_2 = \frac{(j - i) - 1}{g - 1} = \frac{(3-2-1)}{5 - 1} = 0$$

$$\alpha_1 = 1 - \alpha_2 = 1$$

To obtain element b:

$$b = \alpha_2 \times a^{i}_{(\text{middle})} + \alpha_1 \times a^{\frac{i+j-1}{2}}_{(\text{middle})} = 0 \times 0.5 + 1 \times 0.5 = 0.5$$

To obtain element c:

$$c = 2 \times a^{\frac{i+j-1}{2}}_{(\text{middle})} - b = 2 \times 0.5 - 0.5 = 0.5$$

Elements $a$and $d$are respectively the minimum lower bound and maximum upper bound of the values; thus:

$$a = 0.25, d = 1$$

Therefore, the hesitant fuzzy number for the element CA1–E5 (the influence of criterion A1 on criterion E5) is $(0.25, 0.5, 0.5, 1)$.

The values of $D$and $R$are computed for each criterion, where $D_i$represents the sum of the i-th row and $R_j$represents the sum of the j-th column of matrix $T_c$with respect to the corresponding dimension.

Table 5

Causal Relationship Pattern of Criteria

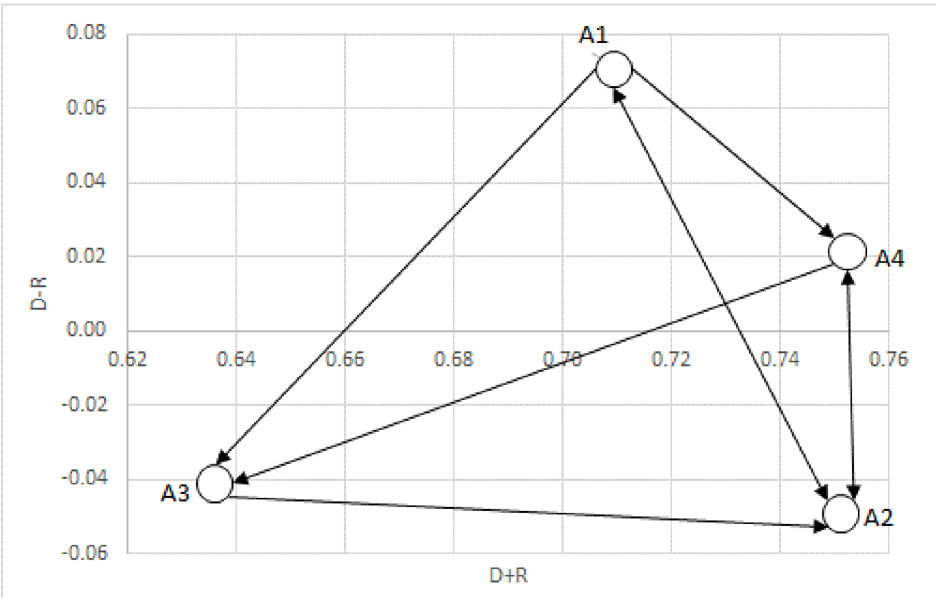
Dimension	Sub-criterion	Symbol	(D_i) defuzzy	(R_i) defuzzy	$D_i + R_i$	$D_i - R_i$	Criterion type
Governance	Legal and regulatory compliance	A1	0.391	0.320	0.710	0.071	Cause
Governance	Auditing and reporting	A2	0.351	0.401	0.751	−0.050	Effect
Governance	Compliance with standards and certifications	A3	0.298	0.339	0.637	−0.041	Effect
Governance	Transparency and traceability (tracking goods, ownership, activities, etc.)	A4	0.387	0.367	0.754	0.020	Cause
Technological	Data and information management	B1	0.555	0.618	1.172	−0.063	Effect
Technological	Automation and integration with IoT and AI, big data	B2	0.585	0.563	1.149	0.022	Cause
Technological	Scalability	B3	0.473	0.524	0.997	−0.051	Effect

Technological	Security and trust (confidentiality, data security, consensus mechanisms)	B4	0.594	0.495	1.088	0.099	Cause
Technological	Decentralized and distributed systems	B5	0.559	0.602	1.161	−0.043	Effect
Technological	Smart contracts and transaction automation	B6	0.611	0.574	1.186	0.037	Cause
Social	Protection of workers' rights	C1	0.400	0.374	0.774	0.026	Cause
Social	Accessibility and information sharing	C2	0.511	0.440	0.951	0.071	Cause
Social	Stakeholder trust and collaboration	C3	0.368	0.414	0.782	−0.046	Effect
Social	Reduction of rent-seeking and corruption	C4	0.398	0.433	0.830	−0.035	Effect
Social	Safety and health	C5	0.387	0.403	0.790	−0.016	Effect
Environmental	Traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions)	D1	0.528	0.484	1.012	0.045	Cause
Environmental	Waste management	D2	0.466	0.513	0.979	−0.047	Effect
Environmental	ESG reporting	D3	0.489	0.445	0.935	0.044	Cause
Environmental	Energy consumption optimization	D4	0.449	0.483	0.932	−0.034	Effect
Environmental	Equipment life-cycle management and waste reduction	D5	0.514	0.522	1.036	−0.009	Effect
Economic	Process monitoring and control	E1	0.503	0.444	0.946	0.059	Cause
Economic	Cost management	E2	0.467	0.559	1.026	−0.092	Effect
Economic	Operational productivity and efficiency	E3	0.413	0.570	0.983	−0.157	Effect
Economic	Demand forecasting and inventory management	E4	0.614	0.519	1.133	0.095	Cause
Economic	Elimination of intermediaries	E5	0.595	0.589	1.184	0.006	Cause
Economic	Process integration and acceleration	E6	0.652	0.563	1.215	0.088	Cause

Based on the values of $D + R$ and $D - R$, the cause–effect diagram of the criteria is plotted. Among the governance sub-criteria, legal and regulatory compliance (A1) influences the other three sub-criteria—auditing and reporting (A2), compliance with standards and certifications (A3), and transparency and traceability (tracking goods, ownership, activities, etc.) (A4). The auditing and reporting criterion (A2) is influenced by the other three sub-criteria.

Figure 4

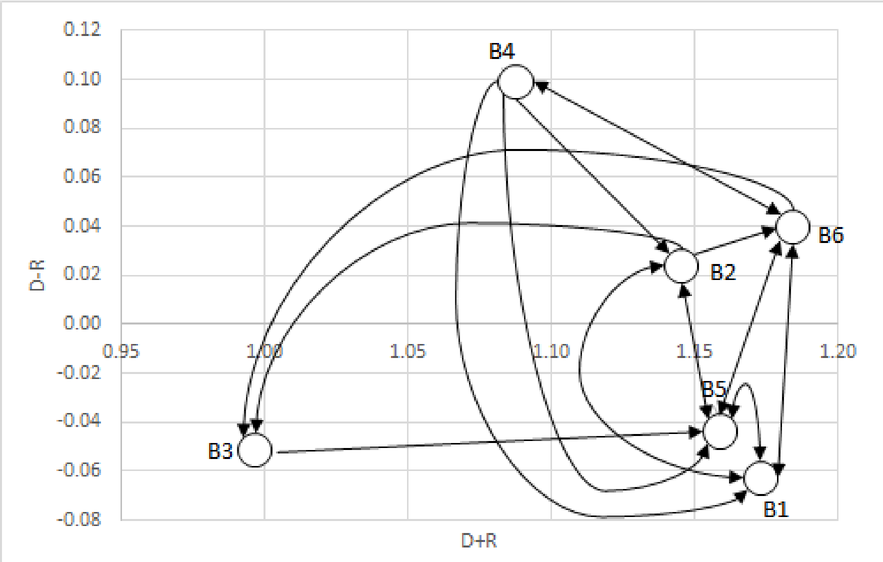
Causal Diagram of Governance Sub-criteria



Among the technological sub-criteria, smart contracts and transaction automation (B6) has the strongest linkage with the other sub-criteria, meaning that it exhibits both high influencing power and high influencedness. The scalability criterion (B3) influences only the decentralized and distributed systems criterion (B5), and is influenced by both automation and integration with IoT and AI, big data (B2) and smart contracts and transaction automation (B6).

Figure 5

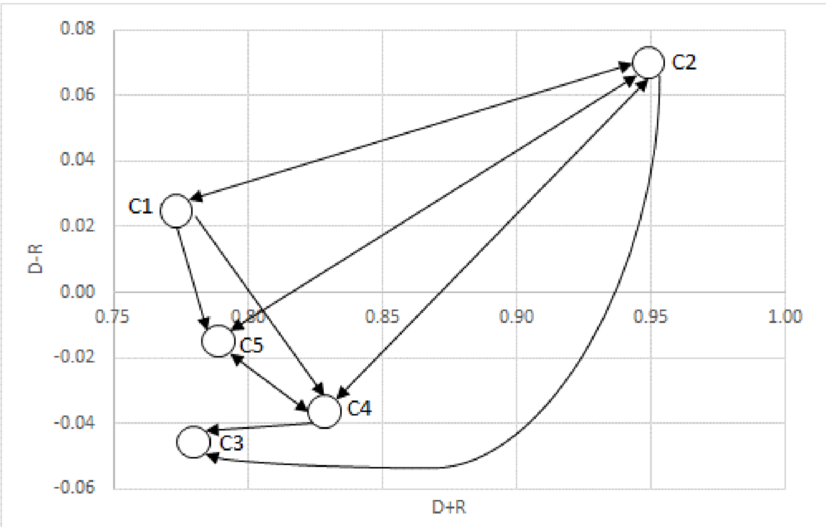
Causal Diagram of Technological Sub-criteria



Among the social sub-criteria, the two sub-criteria protection of workers’ rights (C1) and accessibility and information sharing (C2) are the most influential criteria. Criterion C2 also has the greatest influence and the strongest linkage with the other criteria. The stakeholder trust and collaboration criterion (C3) does not exert a meaningful influence on any criterion; however, it is influenced by three criteria: accessibility and information sharing (C2), reduction of rent-seeking and corruption (C4), and safety and health (C5).

Figure 6

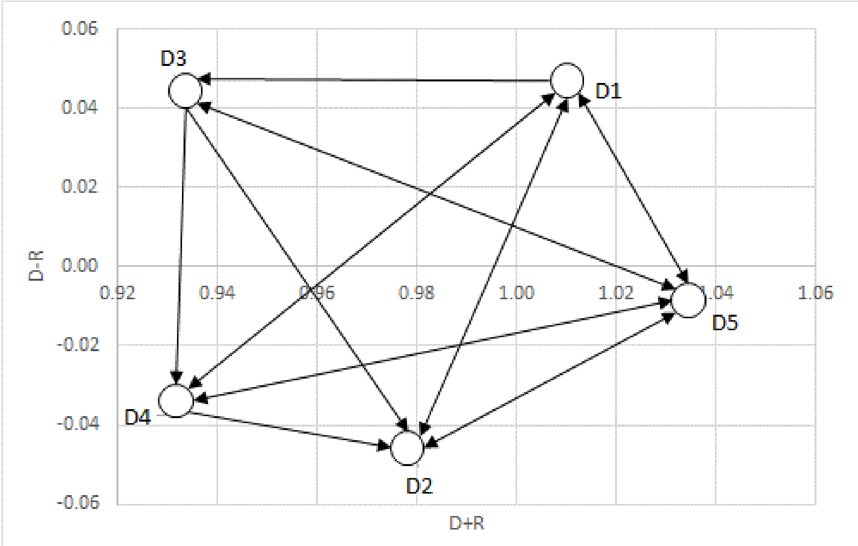
Causal Diagram of Social Sub-criteria



Among the environmental sub-criteria, equipment life-cycle management and waste reduction (D5) both influences and is influenced by all four other sub-criteria; therefore, it has the strongest linkage. Traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions) (D1) has the greatest influencing power and affects all four other criteria. Waste management (D2) influences only two sub-criteria: traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions) (D1) and equipment life-cycle management and waste reduction (D5).

Figure 7

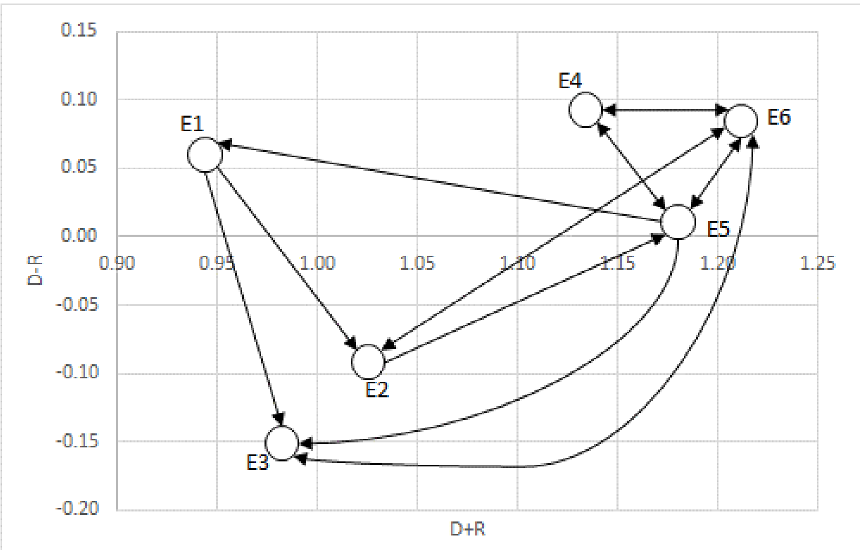
Causal Diagram of Environmental Sub-criteria



Among the economic sub-criteria, process integration and acceleration (E6) influences all criteria except process monitoring and control (E1), and is influenced by all criteria except E1. Therefore, E6 has the strongest linkage with the other criteria. Criterion E1 has the weakest linkage with other criteria because it influences only two criteria—cost management (E2) and operational productivity and efficiency (E3)—and is influenced by the elimination of intermediaries criterion (E5).

Figure 8

Causal Diagram of Economic Sub-criteria



The weights extracted from the limit supermatrix are converted into crisp values. For example, the fuzzy weight of criterion A1 based on the limit supermatrix is (0.036, 0.041, 0.043, 0.045), which is defuzzified as follows:

$$W_{A1} = \frac{0.036 + 0.041 + 0.043 + 0.045}{4} = 0.04128$$

Accordingly, auditing and reporting, with a weight of 0.05527, ranks first; transparency and traceability, with a weight of 0.05276, ranks second; and ESG reporting, with a weight of 0.04850, ranks third.

Table 6

Relative and Final Weights of Factors

Dimension	Sub-criterion	Criterion code	Weight	Rank
Governance	Legal and regulatory compliance	A1	0.04128	11
Governance	Auditing and reporting	A2	0.05527	1
Governance	Compliance with standards and certifications	A3	0.04521	6
Governance	Transparency and traceability (tracking goods, ownership, activities, etc.)	A4	0.05276	2
Technological	Data and information management	B1	0.03642	15
Technological	Automation and integration with IoT and AI, big data	B2	0.02584	25
Technological	Scalability	B3	0.03364	18
Technological	Security and trust (confidentiality, data security, consensus mechanism)	B4	0.02370	26
Technological	Decentralized and distributed systems	B5	0.03011	22
Technological	Smart contracts and transaction automation	B6	0.03129	21
Social	Protection of workers' rights	C1	0.02871	23
Social	Accessibility and information sharing	C2	0.04365	9
Social	Stakeholder trust and collaboration	C3	0.03623	16
Social	Reduction of rent-seeking and corruption	C4	0.04172	10
Social	Safety and health	C5	0.04086	12
Environmental	Traceability and real-time monitoring of pollutants and emissions (chemicals, carbon emissions)	D1	0.04543	5
Environmental	Waste management	D2	0.04396	8
Environmental	ESG reporting	D3	0.04850	3
Environmental	Energy consumption optimization	D4	0.04443	7
Environmental	Equipment life-cycle management and waste reduction	D5	0.04554	4
Economic	Process monitoring and control	E1	0.02771	24
Economic	Cost management	E2	0.03849	13
Economic	Operational productivity and efficiency	E3	0.03228	20
Economic	Demand forecasting and inventory management	E4	0.03611	17
Economic	Elimination of intermediaries	E5	0.03834	14
Economic	Process integration and acceleration	E6	0.03251	19

4. Discussion and Conclusion

The findings of this study provide strong empirical support for the central proposition that blockchain-enabled sustainability in the oil and gas supply chain is fundamentally driven by governance and technological capabilities, while environmental and social outcomes function primarily as dependent results of these upstream drivers. The causal analysis demonstrated that auditing and reporting (A2), transparency and traceability (A4), and ESG reporting (D3) achieved the highest global priorities, with auditing and reporting ranked first overall. This result reinforces the argument that sustainability in complex, high-risk supply chains is anchored not merely in operational efficiencies but in institutional trust, compliance infrastructures, and credible accountability mechanisms (Janssen et al., 2020; Sahoo et al., 2024). Blockchain's most immediate strategic contribution therefore lies in strengthening information integrity and regulatory compliance rather than in isolated technological optimization.

The dominance of auditing and reporting (A2) as the highest-ranked factor is theoretically consistent with the governance-centered view of blockchain adoption. Blockchain's immutable ledger architecture directly enhances auditability, reduces information asymmetry, and increases the credibility of disclosures across multi-tier supply networks (Toufaily et al., 2021; Wamba & Queiroz, 2020). Prior studies emphasize that in heavily regulated industries such as oil and gas, decision-makers prioritize governance mechanisms that mitigate compliance risk and reputational exposure over purely technical performance improvements (Aslam et al., 2021; Munim et al., 2022). The present results empirically validate this proposition by demonstrating that governance sub-criteria collectively exert significant causal influence on the broader sustainability structure of the supply chain.

Transparency and traceability (A4), which ranked second, further reinforce this interpretation. Blockchain's capacity to provide tamper-resistant provenance records directly addresses the chronic trust deficits and coordination failures that characterize petroleum supply chains. Previous research identifies traceability as a foundational enabler of sustainability because environmental monitoring, emissions control, and ethical sourcing all depend on reliable upstream data (Esmaeilian et al., 2020; Yadav & Singh, 2020). The high ranking of A4 indicates that managers perceive blockchain primarily as an information governance tool—one that stabilizes decision-making and enhances accountability before delivering downstream performance gains. This aligns with the findings of (Park & Li, 2021), who demonstrated that blockchain's sustainability impact is mediated by transparency and stakeholder collaboration rather than by automation alone.

The third-ranked factor, ESG reporting (D3), bridges governance and environmental domains. Its high priority reflects the increasing integration of sustainability performance with regulatory oversight, financial risk assessment, and stakeholder legitimacy. Contemporary research on sustainable supply chain finance highlights the strategic importance of verifiable ESG data for attracting capital, maintaining investor confidence, and strengthening long-term resilience (Slavinskaitė et al., 2025; Zhou & Masi, 2025). Blockchain's ability to secure ESG data streams, prevent manipulation, and support real-time disclosure explains the prominence of D3 in the final prioritization. The result confirms the argument that sustainability finance mechanisms are becoming core governance structures rather than peripheral reporting tools (Krimi et al., 2025).

Technological drivers also played a significant causal role, with smart contracts and transaction automation (B6) and security and trust mechanisms (B4) emerging as key technological enablers. Smart contracts operationalize governance rules by embedding compliance and verification logic directly into transactional processes, thereby reducing enforcement costs and coordination delays (Kouhizadeh et al., 2020; Kshetri, 2021). Their strong causal influence confirms that blockchain's strategic value arises when governance rules and technological infrastructure are tightly coupled. Likewise, security and trust mechanisms (B4) ranked as a major driver, consistent with studies identifying data integrity, confidentiality, and consensus mechanisms as prerequisites for blockchain adoption in supply chains (Karuppiah et al., 2021; Vafadarnikjoo et al., 2021).

In contrast, environmental and social factors were largely classified as effect criteria rather than causal drivers. For example, equipment life-cycle management and waste reduction (D5), waste management (D2), and energy optimization (D4) exhibited high connectivity but lower causal power. This pattern supports the structural logic that environmental outcomes are emergent properties of governance quality and technological infrastructure rather than independent levers of change (Paliwal et al., 2020; Park & Li, 2021). Similarly, social criteria such as stakeholder trust (C3) and safety and health (C5) were predominantly influenced by upstream governance and technological mechanisms. This is consistent with (Putra & Baharum, 2025), who emphasized that worker welfare and social sustainability depend strongly on how digital systems are governed and integrated into organizational routines.

The causal diagrams further reveal important structural insights. In governance, legal and regulatory compliance (A1) functioned as a primary cause influencing other governance mechanisms, which corroborates the institutional adoption framework proposed by (Janssen et al., 2020). In technology, smart contracts (B6) demonstrated the highest connectivity, reflecting their integrative role in linking data management, security, automation, and distributed architectures. This mirrors empirical findings from oil and gas adoption studies showing that smart contract deployment is central to unlocking blockchain's operational value (Aslam et al., 2021; Munim et al., 2022). In environmental dimensions, real-time monitoring of emissions and pollutants (D1) emerged as the dominant causal driver, confirming the importance of data visibility in achieving environmental performance targets (Jasrotia et al., 2024; Tathavadekar, 2025). Economically, process integration and acceleration (E6) exhibited the highest connectivity, underscoring that blockchain's economic impact is realized primarily through coordination efficiencies and transaction cost reduction rather than isolated cost management (Chowdhury et al., 2022; Kumar & Barua, 2022).

Collectively, these findings support an integrated sustainability architecture in which governance and technology form the structural backbone of sustainable supply chain transformation, while economic, environmental, and social performance emerge as system-level outcomes. This configuration is consistent with the systems perspective advocated by (Sahoo et al., 2024) and (Wamba & Queiroz, 2020), who argue that sustainable supply chains should be conceptualized as socio-technical systems rather than collections of independent practices. The present study extends this literature by providing a context-specific, empirically grounded model for Iran's oil and gas industry, thereby addressing calls for localized and implementation-oriented research (Didehgah Seyed Amir & Sohrabi, 2023; Hosseini Seyed et al., 2022).

This study relied heavily on expert judgment, which, although systematically structured through hesitant fuzzy methods, may reflect subjective perceptions shaped by individual experience and organizational context. The empirical scope was limited to a single refinery, which may restrict the generalizability of the results across different segments of the oil and gas value chain. Additionally, the cross-sectional design prevents observation of dynamic changes in adoption patterns and sustainability outcomes over time.

Future studies should validate the proposed model across multiple oil and gas organizations and in different national contexts to strengthen external validity. Longitudinal research designs could explore how blockchain-enabled sustainability capabilities evolve over time. Further research may also integrate quantitative performance metrics to empirically test the causal pathways identified in this study.

Managers should prioritize governance reform and technological infrastructure development as the foundational stages of blockchain-enabled sustainability transformation. Regulatory agencies should align compliance frameworks with digital reporting capabilities to leverage blockchain's audit and transparency potential. Organizations are advised to invest in cross-functional readiness, cybersecurity capacity, and stakeholder collaboration before large-scale blockchain deployment.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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