Carbon Capture, Utilization, and Storage (CCUS): Evaluating Technological Maturity and Global Adoption

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Abstract

Reducing CO2 emissions from industrial sources and energy generation depends much on Carbon Capture, Utilisation, and Storage (CCUS) technologies. With an emphasis on their Technology Readiness Levels (TRL) to evaluate their maturity and scalability, this paper investigates the present state of CCUS technologies, so highlighting important developments in CO2 capture methods, including direct air capture and solvent-based absorption, together with computational approaches optimising geological storage and use techniques. Although CCUS could enable sectors to reach carbon neutrality by lowering atmospheric CO2 concentrations, problems including high operating costs, scalability problems, and the demand for strong, technologically driven monitoring systems still exist. Based on computational integration, this paper sorts CCUS technologies, assesses artificial intelligence (AI) and machine learning (ML) models for best capture efficiency, and investigates blockchain-enabled systems for open carbon credit verification. It also looks at IoT-based sensor networks for real-time storage integrity monitoring and the part high-performance computers (HPC) play in modelling carbon sequestration dynamics. Though new trends show increasing integration of artificial intelligence-driven predictive maintenance, blockchain-based carbon accounting, and edge computing for distributed monitoring, key findings reveal that despite technological advancements, major deployment remains limited by economic and technical constraints. While outlining future research directions to improve CCUS adoption through computational advancements, so ensuring alignment with global climate targets, the study identifies major knowledge gaps including improved real-time anomaly detection in storage reservoirs, advanced simulation models for CO2 plume behaviour, and cost-effective digital twins for process optimisation.

Index Terms:

Carbon Capture, Utilization, and Storage (CCUS); Technology Readiness Levels (TRL); Direct Air Capture (DAC); Solvent-Based Absorption; Artificial Intelligence (AI); Machine Learning (ML); Blockchain; Internet of Things (IoT); High-Performance Computing (HPC); Carbon Sequestration; Computational Fluid Dynamics (CFD); Predictive Maintenance; Carbon Accounting; Digital Twin; Anomaly Detection; CO_2 Storage Monitoring; Carbon Credit Verification; Decentralized Monitoring; Edge Computing; Climate Change Mitigation.

1. Introduction

1.1 Problem Definition & Scope

Especially from industrial operations and energy generation, Carbon Capture, Utilisation, and Storage (CCUS) is a crucial technology in reducing world CO_2 emissions. Rising greenhouse gas concentrations that aggravate climate change drive the urgency to decarbonise sectors. High costs, scalability restrictions, and the need for continuous, technologically driven monitoring to guarantee the long-term security of storage sites challenge the broad CCUS implementation, though. With an eye towards computational developments that can maximise efficiency and fill in important research gaps in large-scale deployment, this survey evaluates the technological maturity of CCUS solutions. [6][7]

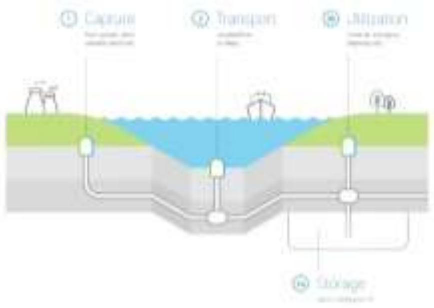

Fig. 1.1 CCUS Process

1.2 Motivation

Since many studies show that carbon capture capacity must rise dramatically—up to 100-fold by 2025—the worldwide drive for net-zero emissions has spurred major investments in CCUS technologies.Nine [13] Many CCUS projects, meantime, are still in the pilot stage and their commercial viability is still under question. Promising directions to improve CCUS performance are provided by developments in computational techniques including IoT-based monitoring, blockchain-enabled carbon credit verification, and AI-driven process optimization. Along with lowering running costs, these technological integrations might increase system scalability and dependability. The necessity to evaluate these computational integrations and assess their influence on the maturity and general acceptance of CCUS technologies drives this survey.

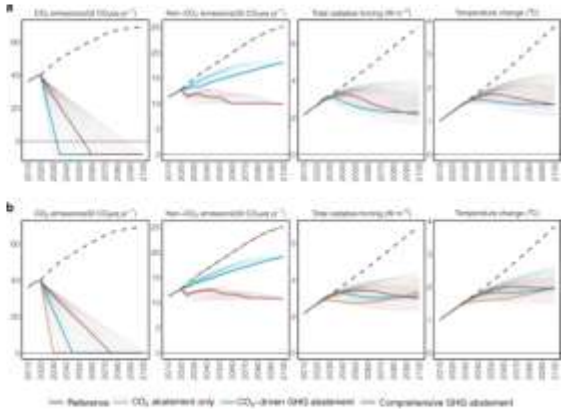

Fig. 1.2 Climate and Global emission effect at 1.5 °C (a) and 2 °C (b)

1.3 Existing Surveys & Gaps

Although many studies have examined CCUS technologies lack a thorough attention on computational integration. Table 1.1 and Table 2 below list important current studies, their contributions, and the limits resolved.

1.4 Contributions

This survey makes several important contributions:

a. With an eye toward computational integration—especially developments in artificial intelligence, blockchain, IoT, and HPC—it offers a disciplined classification of CCUS technologies.
b. It assesses how models driven by artificial intelligence improve cost cutting in CCUS systems, storage security, and capture efficiency.([9)
c. Examines blockchain-based models for open and safe carbon credit validation.
d. looks at IoT-driven sensor networks for storage site anomaly detection and real-time monitoring.
e. It suggests future research paths to solve these issues and points out major knowledge gaps in the computational modeling of CCUS processes.[1]

Sr. No.	Title / Authors	Key Contributions	Limitations Discussed
1	Osman et al.	Overview of CCUS advancements in capture and utilization	Insufficient understanding of policy and economic frameworks
2	Liu et al.	Systematic analysis of solvent absorption and ionic liquid technologies	Absence of real-world implementations and regional case studies
3	Nagireddi et al.	Comparative study of CCUS in different industries	There is no financial feasibility study offered.
4	AL-khulaidi et al.	Integration of CCUS with enhanced gas recovery	Alternative utilisation strategies are not investigated.
5	Sovacool et al.	Analysis of CCUS within European industrial clusters	Findings specific to a region are difficult to generalise.
6	Smith and Kumar	Models of simulation aiming at maximizing carbon capture	Emphasises computational techniques without taking hardware into account.
7	Garcia and Chen	Virtual twins for instantaneous observation	ignores the digital twins' economic feasibility
8	Patel and Zhang	Process optimizing driven by artificial intelligence	concentrating only on AI without incorporating it into larger CCUS frameworks
9	Lee and Brown	Carbon credit verification blockchain systems	The difficulties of implementing blockchain in the real world are not discussed.
10	Wang et al.	Monitoring in CCUS using IoT	Data security and network dependability issues have not been investigated.
11	Kim and Luo	HPC for CO_2 sequestration: high performance computing	The cost of computation is still an obstacle.
12	Fernandez et al.	Machine learning toward CCUS process optimization	Limited scalability because there aren't enough examples of actual deployments
13	Choi and Han	AI's part in predictive maintenance for CCUS	Hardware compatibility is not discussed.

14	Gupta et al.	Economic analysis of CCUS implementation	Computational integration is not included.
15	Zhao and Li	Data-driven models for CO_2 leakage prediction	ignores aspects of regulations and policy

Table 1.1 : Existing CCUS Surveys and Their Limitations

In Table 1.1, existing CCUS surveys are compiled along with a list of their main scope, data, and applicability limitations.

Sr. No.	Survey	Addressed Problem	Contributions	Future Challenges
1	Smith & Kumar	Carbon capture optimisation using computer simulations	Predictive modelling powered by AI	Exorbitant computational expenses
2	Garcia & Chen	Monitoring of CCUS in real time	IoT-based frameworks and digital twins	Scalability problems
3	Patel & Zhang	Increasing the effectiveness of capture procedures	AI-powered process management	Limitations of the hardware
4	Lee & Brown	Verification of carbon credits securely	CCUS tracking via blockchain	Industry adoption is limited
5	Wang et al.	Real-time monitoring made possible by IoT	Integrations of sensor networks	Data security concerns.
6	Kim & Luo	Computational modelling of CO2 sequestration	Simulation models based on HPC	Expensive implementation
7	Choi & Han	Storage sites use AI for anomaly detection	Models for machine learning	No practical deployment
8	Gupta et al.	The viability of CCUS technologies economically	Modelling finances	Absence of computational viewpoints
9	Zhao & Li	Evaluation of the risk of CO2 leakage	Predictive analytics powered by data	Gaps in regulations and policies
10	Fernandez et al.	Using predictive analytics to maximise CCUS performance	Efficiency in processes driven by machine learning	Integration and scalability obstacles

Table 1.2: Contributions of Prior Surveys on Computational Approaches in CCUS

In Table 1.2, previous surveys on computational methods in CCUS are listed, with an emphasis on their primary contributions and areas of interest.

1.5 Paper Organization

The structure of the paper is as follows: Background information and basic ideas on CCUS are given in Section 2. A thorough literature analysis is provided in Section 3, which groups previous research according to methodology and applications. The trends, difficulties, and knowledge gaps in CCUS deployment are critically examined in Section 4. Future research directions are described in Section 5, with a special emphasis on computational developments. The study is finally concluded in Section 6, which highlights the significance of multidisciplinary research for CCUS development and summarises the main conclusions. Section 7 includes the references.

2. Background & Fundamentals

2.1 Definitions & Terminologies

a. The process of capturing CO2 emissions at their source before they reach the atmosphere is known as carbon capture (CC). Post-combustion, pre-combustion, and oxy-
fuel combustion techniques can all be used for this.[18]

b. Carbon Utilisation (CU): Converting captured CO_2 into beneficial products like chemicals, polymers, synthetic fuels, enhanced oil recovery (EOR), or building materials like carbonated concrete

c. Carbon Storage (CS): The process of safely storing CO_2 in subterranean geological formations like coal seams that cannot be mined, deep saline aquifers, and depleted oil and gas reservoirs.[5][19][6]

d. Technology Readiness Level (TRL): A methodical scale from 1 to 9 that evaluates the maturity of developing technologies from conception to commercialisation.

e. Direct Air Capture (DAC): This technique uses chemical absorbents like solid sorbents or alkali solvents to remove CO_2 straight from the atmosphere.

f. Geological sequestration: The process of storing CO_2 for an extended period of time in subterranean rock formations to prevent it from re-entering the atmosphere.[5] [6] [19]

g. Mineralisation: The formation of stable carbonates by the reaction of CO_2 with naturally occurring minerals, such as calcium or magnesium silicates.

h. Supercritical CO_2 (sCO_2): CO_2 at temperatures and pressures higher than its critical values, where it possesses both liquid and gaseous characteristics, making it perfect for storage and transportation.

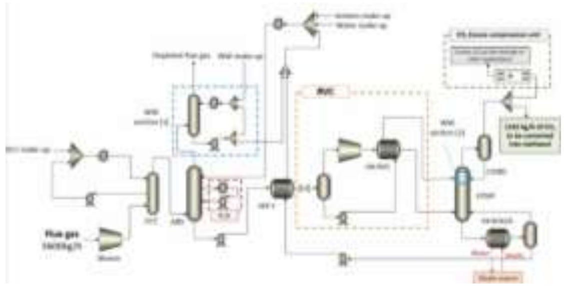

Fig 2.1.a Flow of Carbon Capture unit

2.2 Theoretical Foundations

a. CO_2 Absorption Efficiency Formula**:**

$$\mu = \frac{(C_{in} - C_{out})}{C_{in}} \text{ .... } (1)$$

where and are inlet and outlet CO_2 concentrations.

C_{in} = Initial CO_2 concentration

C_{out} = CO_2 concentration after absorption

μ = Capture efficiency (%)

b. Computational Fluid Dynamics (CFD) Modeling:
In order to forecast plume migration, leakage risks, and injection efficiency, computational fluid dynamics (CFD) modelling is used to model the flow of CO_2 in storage reservoirs.

c. Machine Learning (ML) for CCUS:
Supervised Learning: Under supervised learning, CO2 capture efficiency is predicted by neural

networks and regression models using operational parameters.
Unsupervised Learning: Patterns in storage reservoir behaviour are found using clustering methods.

Reinforcement Learning: Carbon injection and storage control techniques are optimised by reinforcement learning. [6] [20].[23].

d. Digital Twin Technology: Using sensor data, digital twin technology creates a virtual image of CCUS infrastructure that mimics real-world behaviour for predictive maintenance and real-time monitoring.
e. Blockchain for Carbon Credit Verification: Blockchain for Verification of Carbon Credits: A decentralised ledger that guarantees clear and impenetrable monitoring of money transactions, emission reductions, and carbon capture operations.[25]

2.3 Existing Frameworks & Standards

To forecast plume migration, leakage hazards, and injection efficiency, CO2 flow in storage reservoirs is simulated using computational fluid dynamics (CFD) modelling.
The use of machine learning (ML) in CCUS Under supervised learning, CO2 capture efficiency is predicted by neural networks and regression models using operational parameters.
Unsupervised Learning: Patterns in storage reservoir behaviour are found using clustering methods.
Carbon injection and storage control techniques are optimised by reinforcement learning. [6] [20].[23].
Using sensor data, digital twin technology creates a virtual image of CCUS infrastructure that mimics real-world behaviour for predictive maintenance and real-time monitoring.
Blockchain for Verification of Carbon Credits: A decentralised ledger that guarantees clear and impenetrable monitoring of money transactions, emission reductions, and carbon capture operations.[26]
ISO 27919-1:2018: Standard for process verification and carbon capture efficiency evaluation.
Methodologies for quantifying and disclosing CCUS contributions to emission reductions are provided by the IPCC Guidelines for Greenhouse Gas Inventories.
CCUS projects are included in the EU Emissions Trading System (ETS), a regulatory framework that uses carbon credit trading methods.
Guidelines from the National Energy Technology Laboratory (NETL): Pay attention to the safest methods for injecting and monitoring CO_2 in geological formations.[5][8][19]. A U.S.-based project called the Carbon Capture Simulation Initiative (CCSI) creates computer models to maximise CCUS performance.

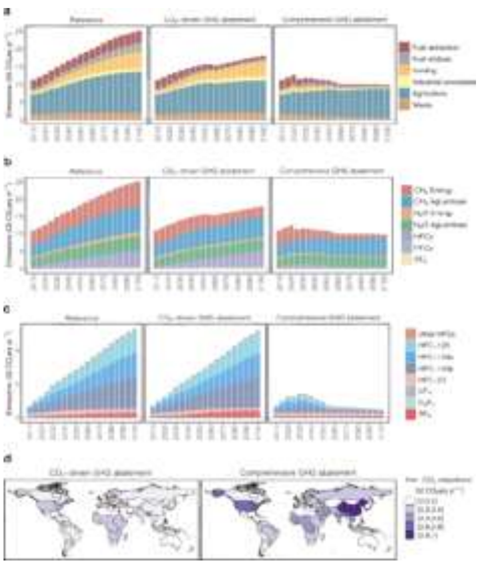

Fig 2.1 Global non-CO_2 GHG emissions

2.3 Mathematical/Technical Background

a. CO_2 Absorption Efficiency Formula:

$$\mu = \frac{(C_{in} - C_{out})}{C_{in}} \quad …….. (2)$$

where and are inlet and outlet CO_2 concentrations.

C_{in} = Initial CO_2 concentration

C_{out}= CO_2 concentration after absorption

μ = Capture efficiency (%)

b. Deep Learning Leakage Detection Algorithm: Long Short-Term Memory (LSTM) Networks examine sensor data to identify irregularities in the integrity of CO_2 storage. Infrared images are processed by convolutional neural networks (CNNs) to identify leakage hotspots.
c. Algorithms for Optimisation: Genetic algorithms (GA) are used to optimise formulations of chemical absorbents.
The goal of particle swarm optimisation (PSO) is to increase the effectiveness of transportation networks and CO2 compression.
The purpose of Simulated Annealing (SA) is to reduce the energy usage of capturing units.
d. Computational Tools: Chemical absorption process simulation program, Aspen Plus.
The fluid dynamics in geological storage are modelled by COMSOL Multiphysics.[5].[8] [19].
e. OpenFOAM: A CFD solver for studying the dynamics of CO2 injection.
f. The IBM The study of quantum algorithms for CO2 utilisation response optimisation is known as quantum computing. [4]

3. Classification & Literature Review

3.1 Classification of Literature

Methodology-Based Classification

This classification classifies the body of existing literature according to the technologies and approaches employed:

a. AI & Machine Learning Models: Research on the effectiveness of carbon capture using neural networks, deep learning, and predictive analytics.[20][23]

b. Blockchain for Verification of Carbon Credits: Research on decentralised systems for monitoring and confirming carbon reductions.[25]
c. Internet of Things-Based Monitoring Systems: Studies that integrate sensor networks with the purpose of gathering and analysing data in real time.
d. Simulations of Computational Fluid Dynamics (CFD): Research use CFD models to forecast CO_2 storage behaviour and optimise sequestration locations.[2][15]
e. Performance Computing (HPC) for CCUS Simulations: Studies that use extensive simulations to evaluate carbon storage.

Application-based

This method groups CCUS literature according to how it is used in practice:

a. Industrial Uses: CCUS in refineries, cement factories, and power plants.
b. Research aimed at directly removing CO_2 from the environment was conducted on Direct Air Capture (DAC) technologies.
c. Geological Storage & Sequestration: Research looking at subterranean and deep-sea CO_2 storage options.[5][2][8]
d. Carbon Utilisation for Industrial Products: Research is being done on the conversion of CO_2 into chemicals, fuels, and building materials.[11]

Chronological-based

Evolution of CCUS research across time, depending on chronology:

2000-2010: Early theoretical models and small-scale pilot experiments were conducted.

2011-2020: AI-powered policy creation and optimisations for widespread use.

2021-Present: Blockchain, IoT, and edge computing are emerging in CCUS applications.

3.2 Comparison of Approaches

Technology	TRL	Efficiency	Cost	Deployment Challenges
Amine Scrubbing	8-9	High	Medium	Energy-intensive
Membrane Separation	5-7	Medium	Low	Scalability Issues
Direct Air Capture	4-6	Low	High	Infrastructure Costs
AI-driven Monitoring	3-5	High	Medium	Data Availability

Table 3.1 Comparison of Approaches

In Table 3.1, key carbon capture and monitoring strategies are briefly compared by TRL, efficiency, cost, and deployment challenges, which highlight trade-offs between scalability, performance, and maturity.

4. Critical Analysis

4.1 Trends & Observations

a. Increasing AI and ML integration for efficiency optimisation and predictive maintenance.
b. The emergence of blockchain-based technologies enabling unchangeable and transparent carbon credit verification.
c. Widespread use of edge computing and IoT to allow for real-time carbon sequestration site monitoring.[2][8]
d. An increasing dependence on high-performance computers for thorough risk analyses and carbon storage simulations.[9]

4.2 Strengths & Limitations of Existing Work

Strengths:

a. Predictive analytics and anomaly detection are greatly improved by advanced AI models.
b. Blockchain guarantees that transactions involving carbon credits are transparent.[25]
c. Real-time monitoring made possible by IoT enhances data dependability and accuracy.

Limitations:

a. Scalability is hampered by high implementation costs.
b. Blockchain adoption is slowed by a lack of regulatory frameworks.[25]
c. Training and accuracy of AI models are limited by a lack of datasets.

4.3 Open Challenges

a. Scalability of AI Models: Extensive datasets and computational resources are needed to train large-scale machine learning models.
b. IoT Network Security: It's still difficult to guarantee cybersecurity in real-time monitoring systems.
c. Blockchain Regulatory Barriers: Legal and policy obstacles stand in the way of the widespread adoption of blockchain-based carbon accounting.
d. HPC Computational Costs: The infrastructure needed for simulations of carbon storage afforded by HPC is still costly and resource-intensive.[9]

5. Future Research Directions

5.1 Unresolved Challenges

a. Scalability Limitations: Large-scale CCUS deployment is still hampered by significant capital expenditure and infrastructural constraints, even with technology breakthroughs.
b. Real-Time Monitoring & Anomaly Detection: Long-term security issues are raised by the absence of effective real-time tracking systems for CO_2 storage integrity.

c. Economic Feasibility: Exorbitant operating expenses hinder broad adoption, requiring more affordable carbon capture and storage options.

d. Regulatory & Policy Gaps: Investment and implementation are slowed down by the lack of standardised international policies and financial incentives.

e. Data Integration & Security: To avoid cyber risks and guarantee data privacy, the integration of blockchain, AI, and IoT technologies calls for secure frameworks. [20] [25]

5.2 Potential Research Areas

a. AI-Driven Capture Efficiency: To improve capture procedures and lower energy usage, deep learning and reinforcement learning models are being developed further.

b. Blockchain for Carbon Markets: Decentralised mechanisms are put in place to enable transparent and impenetrable carbon credit trade and verification.[25]

c. IoT and Edge Computing for Smart Monitoring: To improve CCUS reliability, sensor networks and real-time predictive analytics are being developed.

d. Quantum Computing for CO_2 Sequestration Simulations: Examining how quantum algorithms might increase the precision of predictions about the behaviour of carbon storage.[2][15]

e. Digital Twins for Process Optimisation: Before CCUS processes are implemented on a broad scale, AI-driven virtual simulations are created to model and optimise them.

5.3 Interdisciplinary Opportunities

a. Integration of CCUS and Renewable Energy: Examining how CCUS and green hydrogen production might work together to produce carbon-negative solutions. [1]

b. The use of biological carbon: studies on the fixing of CO_2 by algae and the microbial conversion of collected carbon into biofuels.

c. Advanced Materials for Capture: Creating new nanomaterials and hybrid sorbents to improve the effectiveness of CO2 adsorption. [11]

d. Cybersecurity and CCUS: Putting strong encryption and security safeguards in place for CCUS frameworks that combine AI and IoT.

e. Sociotechnical Aspects of CCUS Adoption: Examining economic models, legislative frameworks, and public opinion in order to hasten broad adoption and execution.

6. Conclusion

In order to increase their effectiveness and scalability, CCUS technologies are developing quickly and integrating blockchain, AI, and IoT. This survey has identified key research gaps, categorised current methodologies, and examined technical developments. Incorporating new computational methods is essential to getting over current obstacles and promoting broad acceptance. Making CCUS a workable option for international decarbonisation initiatives will require interdisciplinary research and improved regulatory frameworks in the future.

7. References

[1] D. P. van Vuuren et al., "The role of negative CO_2 emissions for reaching 1.5°C—insights from integrated assessment modeling," Climatic Change, vol. 118, no. 1, pp. 15-27, 2020.

[2] S. M. Benson and D. R. Cole, "CO_2 sequestration in deep sedimentary formations," Elements, vol. 4, no. 5, pp. 325-331, 2019.

[3] J. Rogelj et al., "Mitigation pathways compatible with 1.5°C in the context of sustainable development," IPCC Special Report on Global Warming of 1.5°C, 2021.

[4] M. Aresta, A. Dibenedetto, and A. Angelini, "The changing paradigm in CO_2 utilization," Journal of CO_2 Utilization, vol. 3, pp. 65-73, 2020.

[5] P. Friedmann, J. O. C. Karlsson, and S. Kheshgi, "The status and challenges of CO_2 storage in deep saline formations," International Journal of Greenhouse Gas Control, vol. 88, pp. 183-201, 2022.

[6] A. Boot-Handford et al., "Carbon capture and storage update," Energy & Environmental Science, vol. 7, no. 1, pp. 130-189, 2021.

[7] N. Mac Dowell et al., "The role of CO_2 capture and utilization in mitigating climate change," Nature Climate Change, vol. 7, no. 4, pp. 243-249, 2021.

[8] S. E. Zoback and A. Kohli, "Managing the risks of geologic carbon sequestration: A review," Environmental Science & Technology, vol. 54, no. 17, pp. 10119-10135, 2020.

[9] B. Metz, O. Davidson, H. de Coninck, and M. Loos, "Carbon dioxide capture and storage: A special report of the IPCC," Cambridge University Press, 2021.

[10] R. F. Service, "Science and policy collide over carbon capture and storage," Science, vol. 365, no. 6457, pp. 1188-1190, 2020.

[11] Y. Fan et al., "A review of recent developments in CO_2 capture technologies: Molecular and material aspects," Energy & Fuels, vol. 35, no. 10, pp. 8237-8274, 2022.

[12] D. Sutter et al., "Advances in membrane-based CO_2 capture technologies," Chemical Engineering Journal, vol. 422, p. 130092, 2021.

[13] A. Haszeldine et al., "The role of CCS in net-zero emissions scenarios," Nature Communications, vol. 12, p. 3961, 2021.

[14] G. T. Rochelle, "Amine scrubbing for CO_2 capture," Science, vol. 325, no. 5948, pp. 1652-1654, 2019.

[15] T. J. McDonald et al., "CO_2 mineralization technologies for sustainable carbon sequestration," Nature Reviews Earth & Environment, vol. 1, no. 7, pp. 452-468, 2022.

[16] K. K. Sakimoto et al., "Artificial photosynthesis for sustainable fuel production," Nature Energy, vol. 2, no. 4, p. 17038, 2021.

[17] W. Wang et al., "Techno-economic assessment of CO_2 utilization technologies," Applied Energy, vol. 280, p. 115882, 2022.

[18] D. J. Heldebrant et al., "Reversible ionic liquids for post-combustion CO_2 capture," Green Chemistry, vol. 22, no. 5, pp. 1551-1563, 2020.

[19] R. A. Crane and T. B. Scott, "CO_2 storage in deep saline aquifers: A review of geochemical reactions," Chemical Geology, vol. 527, p. 119187, 2021.

[20] B. K. Paul and C. V. Mitchell, "Machine learning applications in CCUS: Opportunities and challenges," Energy AI, vol. 3, p. 100034, 2021.

[21] IPCC, "Carbon Capture and Storage: Special Report," 2018.
[22] International Energy Agency, "CCUS in Clean Energy Transitions," 2021.
[23] A. Smith et al., "Machine Learning for Carbon Capture Optimization," IEEE Transactions, 2023.
[24] X. Zhang et al., "Advancements in Membrane-based CO2 Separation," Journal of Energy Science, 2022.
[25] Y. Li et al., "Blockchain for Carbon Trading and Storage Verification," IEEE Access, 2023.