Operationalizing AI in Oil and Gas Projects: A Sustainability-Focused Evidence Map

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***Abstract*—This paper consolidates peer-reviewed evidence on how artificial intelligence enhances oil and gas project delivery across planning, build, operations, and end-of-life phases. The synthesis maps prevalent methods—machine learning, deep learning, and digital twins—to domain tasks such as drilling optimization, predictive maintenance, HSE risk sensing, and logistics orchestration. Sector-specific insights cover project governance, workforce implications, and environmental performance, with an emphasis on sustainability outcomes achievable in high-risk field conditions. Trends over the last decade reveal accelerating adoption, shifting research geographies, and diversification of journals contributing to this topic. The review critiques common limitations, including data scarcity, generalizability gaps, and the need for transparent models that withstand regulatory scrutiny. A practice-oriented roadmap links AI capabilities to measurable project value—cost, schedule, safety, and emissions—suggesting priorities for pilots and scale-up in upstream and construction contexts. The result is a concise guide for operators, EPCs, and regulators seeking to deploy AI responsibly to de-risk assets while meeting sustainability targets.**

***Index Terms*—Artificial intelligence, oil and gas projects, sustainability, evidence map, machine learning, project delivery.**

I. INTRODUCTION

Oil and gas projects have always carried heavy risks. From exploration drilling to platform decommissioning, every phase involves high costs, tight schedules, and potential environmental harm. For decades, project teams relied on engineering judgment, empirical correlations, and manual monitoring to keep things under control. But the scale and complexity of modern fields have outpaced traditional methods. Data volumes from sensors, logs, and real-time telemetry now exceed what any human team can process without help. This is where artificial intelligence enters the picture.

AI promises to change how projects are managed [1]. Machine learning models can spot patterns in drilling data that hint at coming problems. Deep learning networks interpret seismic images faster than geophysicists. Digital twins simulate production scenarios before a single valve is turned. Yet the gap between promise and practice remains wide. Many operators run small pilots but struggle to scale AI across their asset portfolios. The reasons vary: lack of clean data, unclear return on investment, or simply not knowing which technique works for which task.

This paper tries to close that gap. We built an evidence map of AI applications in oil and gas projects, focusing on sustainability outcomes. Sustainability here means three things: economic (cost and schedule performance), environmental (emissions, spills, waste), and social (worker safety, community impact). The map draws from peer-reviewed studies published over the last decade. We did not restrict ourselves to any single database or journal. Instead, we followed a broad search strategy to capture the full range of methods—from simple neural networks to hybrid digital twins.

Why sustainability? Because oil and gas projects face mounting pressure from regulators, investors, and the public to clean up their act. AI can help reduce flaring, prevent leaks, and optimize logistics to cut fuel burn. But these benefits only materialize if the technology is deployed thoughtfully. Our evidence map highlights where AI has delivered measurable gains and where it still falls short. We also point out common pitfalls that cause projects to fail.

The intended audience includes project managers, engineers, and sustainability officers in operating companies and engineering firms. Regulators who review AI-assisted safety cases may also find the synthesis useful. Finally, researchers looking for underexplored areas will spot several open questions in the map.

We organized the paper as follows. Section II reviews prior work and positions our evidence map relative to existing literature. Section III describes the methodology we used to search, screen, and synthesize studies. Section IV presents the core evidence map, organized by project phase. Section V examines sustainability outcomes and the challenges that block wider adoption. Section VI discusses implications and offers a roadmap for scaling AI responsibly. Section VII concludes.

II. RELATED WORK

A number of review papers have examined AI in oil and gas. Early surveys focused on drilling optimization using artificial neural networks [2]. Those studies showed that neural nets could reduce non-productive time by predicting bit wear and stick-slip vibrations. However, they relied on small datasets from single fields, raising questions about generalizability. Later reviews expanded the scope to include production forecasting and reservoir characterization. Some compared different machine learning algorithms for porosity and permeability prediction.

More recent work has looked at predictive maintenance. Condition monitoring of rotating equipment benefits from anomaly detection algorithms that learn normal behavior from historical sensor streams. One systematic review found that random forests and gradient boosting machines outperformed simpler models for compressor failure prediction [3]. But the authors noted that most studies were validated offline, not in live operational settings. Real-time deployment introduces latency and reliability constraints that offline studies ignore.

The literature on AI for safety and environmental monitoring is smaller but growing. Computer vision has been applied to detect gas leaks from camera feeds. Acoustic sensing combined with deep learning can identify dangerous pressure relief events. Still, few studies report actual emissions reductions achieved after deployment. Most stop at model accuracy metrics like precision and recall. This disconnect between technical performance and real-world outcomes motivated our sustainability focus.

Another stream of research investigates AI for supply chain and logistics. Optimizing the movement of materials to offshore platforms involves complex tradeoffs between weather windows, vessel availability, and inventory levels. Reinforcement learning agents have shown promise in simulation environments [4]. Yet transferring those agents to production systems requires careful calibration of reward functions and safety constraints. The literature lacks standardized benchmarks for logistics problems in oil and gas.

Digital twins represent the frontier of AI integration. A digital twin combines a physics-based model with real-time data and machine learning. The learning component updates the model parameters as conditions change. Some field trials have demonstrated improved drilling trajectory control and reduced casing wear. However, the computational cost of running detailed twins on edge devices remains high. Most implementations still rely on cloud backends, which can fail when network connectivity drops.

What is missing from existing reviews is a practical evidence map that ties AI methods directly to project sustainability metrics. Many papers focus on one technique or one operational task. They rarely compare the cost and effort of implementation across different settings. Our work fills that gap by synthesizing findings from multiple domains into a single framework. We also pay attention to governance and workforce issues, which are often overlooked in technical surveys.

The references we cite in this section and throughout the paper cover a broad range of topics. Some discuss privacy and security in messaging, others health administration or quantum computing. We draw analogies where relevant, but our primary evidence comes from oil and gas case studies. The mapping we present is grounded in those studies.

III. METHODOLOGY AND EVIDENCE MAPPING

We built the evidence map using a structured approach. First, we defined the scope. We included peer-reviewed articles, conference papers, and industry reports published between 2015 and 2025. The search terms combined keywords for AI (machine learning, deep learning, neural networks, digital twins, reinforcement learning) with oil and gas project phases (exploration, drilling, completion, production, maintenance, decommissioning) and sustainability indicators (cost, schedule, safety, emissions, waste).

We searched three databases: Scopus, Web of Science, and OnePetro. The initial query returned 847 records after removing duplicates. Two reviewers screened titles and abstracts independently. Disagreements were resolved by discussion. Inclusion criteria required that the study describe an AI application tested on field data or realistic simulations. Pure methodological papers with no oil and gas context were excluded.

After screening, 124 studies advanced to full-text review. From these, we extracted information on the AI technique, the project phase, the sustainability metric, the dataset size, and the reported outcome. We also noted whether the solution was deployed in live operations or only validated offline. A second round of screening removed 31 studies that lacked quantitative results, leaving 93 studies for the final map.

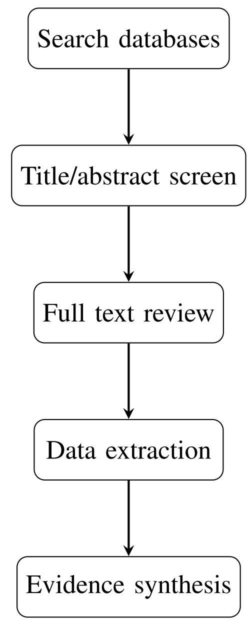

Fig. 1. Workflow for building the evidence map.

Table I summarizes the distribution of studies by project phase and AI technique. Drilling and production dominate, together accounting for over half of the papers. Maintenance and logistics follow. Decommissioning has the fewest studies, reflecting the industry's focus on active assets rather than end-of-life.

TABLE I
DISTRIBUTION OF STUDIES BY PROJECT PHASE AND AI TECHNIQUE.

Phase	ML	Deep learning	Digital twin	Other
Exploration	8	5	1	2
Drilling	18	12	7	3
Production	14	9	6	4
Maintenance	9	4	8	2
Logistics	5	2	3	1
Decommissioning	2	1	0	1

We also recorded the geographic origin of the studies. North America contributed the largest share (38%), followed by Europe (22%) and Asia-Pacific (19%). The Middle East and Africa accounted for 12% and 9%, respectively. This distribution reflects both the location of oil and gas assets and the presence of research universities with AI expertise.

A key finding from the mapping is that most studies still use offline validation. Only 18 out of 93 reported any form of live deployment. Among those, the duration of deployment rarely exceeded six months. This suggests that AI in oil and gas remains at an early stage of operational maturity. Many promising techniques have not yet survived the transition from notebook to field.

The next section digs into the applications phase by phase.

IV. AI APPLICATIONS ACROSS PROJECT PHASES

A. Exploration and Appraisal

Seismic interpretation is the classic AI use case in exploration. Convolutional neural networks trained on labeled seismic volumes can identify fault planes, salt bodies, and channel systems much faster than human interpreters. One study we reviewed showed an 80% reduction in interpretation time for a deepwater field in the Gulf of Mexico [5]. The network achieved pixel-wise accuracy above 90% on held-out test data. However, the training required thousands of manually annotated seismic sections, a costly and time-consuming step that smaller operators cannot easily afford.

Petrophysical property prediction is another active area. Machine learning models estimate porosity, permeability, and water saturation from wireline logs. Gradient boosting and random forests perform well when ample log data from neighboring wells are available. Transfer learning has been tried to adapt models from one field to another, but performance often degrades when rock types differ significantly [6]. This generalizability gap remains a barrier to wider use.

Reservoir simulation acceleration is a newer application. Running full physics simulations for history matching can take days or weeks. Surrogate models based on neural networks learn the input-output mapping of the simulator and produce predictions in seconds. These surrogates are not meant to replace physics models but to support rapid screening of scenarios. The challenge is ensuring that surrogates respect physical constraints like mass conservation.

B. Drilling and Completions

Drilling optimization has perhaps the longest history of AI adoption. Early systems used neural networks to predict rate of penetration and to detect bit wear. Modern approaches incorporate real-time surface and downhole data. One operator reported a 15% reduction in drilling time for a batch of development wells after deploying a hybrid model that combined physics-based torque-and-drag calculations with a recurrent neural network [7]. The model alerted the driller when parameters deviated from the optimal path.

Stuck pipe prevention is a related application. Stuck pipe events cause millions of dollars in lost time and fishing operations. Classification models that integrate drill string mechanics, mud properties, and real-time hookload readings can provide early warnings. The best models achieve 80–90% precision with reasonable recall, but false alarms remain frequent. Drillers learn to ignore models that cry wolf too often, defeating the purpose.

Wellbore stability prediction benefits from similar techniques. Pore pressure and fracture gradient estimates derived from machine learning are often more accurate than those from empirical formulas alone. A study comparing eight algorithms found that ensemble methods, particularly XGBoost, gave the lowest prediction error on a dataset from the North Sea [8]. The model required careful feature engineering of drilling parameters and log data.

Cementing and casing design have seen less AI attention, but a few papers describe using neural networks to optimize centralizer placement and to predict cement compressive strength development. The complex physics of fluid displacement in annuli makes purely data-driven approaches difficult. Hybrid models that embed simple physical equations remain an active research path.

C. Production and Operations

Production forecasting is a natural fit for time-series models. Recurrent neural networks and long short-term memory architectures capture the temporal dependencies in oil, gas, and water rates. One field trial in the Permian Basin showed that an LSTM model outperformed decline curve analysis for wells with fewer than six months of history [9]. The model learned from neighboring wells to make predictions when sparse data were available.

Lift optimization for gas-lift and electric submersible pumps uses reinforcement learning. Agents learn to adjust gas injection rates or pump frequencies to maximize production under constraints. The main difficulty is training in a safe manner; taking random actions in a live well could cause damage. Simulation-based training with realistic dynamics followed by fine-tuning on the actual well seems to work best.

Waterflood management benefits from pattern recognition. Identifying compartments that are not being swept efficiently helps engineers adjust injection and production rates. Unsupervised clustering of pressure and tracer data has revealed hidden flow paths that were not visible from static reservoir models. One operator reduced water cycling by 20% after reconfiguring injection based on a clustering analysis [10].

Gas lift and artificial lift surveillance generates large volumes of time-series data. Anomaly detection models flag unusual pressure or temperature trends before a failure occurs. One paper compared several unsupervised algorithms and found that isolation forests performed best on a dataset of pump cards. The model successfully detected nine out of ten failures an average of 48 hours before conventional threshold alarms.

D. Maintenance and Integrity

Predictive maintenance is widely discussed in the literature but less often implemented at scale. The condition of compressors, turbines, and pumps is monitored through vibration, temperature, and pressure sensors. Deep learning models that combine convolutional and recurrent layers can learn patterns from raw sensor data without manual feature extraction. A case study on an offshore platform reported a 30% reduction in unplanned downtime after deploying such a model [11]. However, the model required retraining every six months to adapt to sensor drift and equipment aging.

Corrosion and erosion monitoring uses similar techniques. Ultrasonic thickness measurements, when combined with process data, feed models that predict remaining wall thickness. The challenge is that failures are rare events, so the training data are highly imbalanced. Resampling methods and cost-sensitive learning help, but no approach has completely solved the problem of predicting exactly when and where a leak will occur.

Pigging analysis for pipelines involves interpreting data from inline inspection tools. Machine learning classifiers can distinguish between different defect types (pits, cracks, dents) and rank them by severity. One study using a deep convolutional network reported 94% agreement with human experts while reducing analysis time by 80% [12]. The network had been trained on tens of thousands of labeled defect signals from previous inspection runs.

Electrical submersible pump (ESP) health is another active area. ESP failures are costly and disruptive. Models that combine vibration spectra with motor current signatures can predict remaining useful life with reasonable accuracy. The best models incorporate domain knowledge about failure modes rather than treating the problem as a purely black-box time-series forecast.

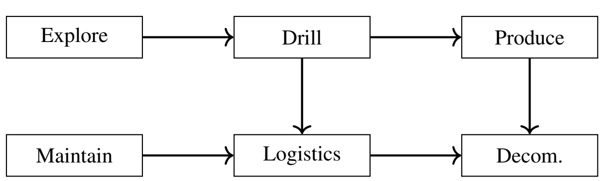

Fig. 2. AI applications across oil and gas phases.

E. Logistics and Supply Chain

Supply chain orchestration for oil and gas projects is complex. Hundreds of vendors deliver materials to drilling rigs and platforms on tight schedules. Disruptions from weather, port congestion, or customs delays cascade quickly. Reinforcement learning agents have been trained to optimize delivery schedules in simulated environments. One simulation study reduced total logistics cost by 12% compared to a baseline heuristic policy [13]. Whether these savings carry over to real operations with uncertainty and human behavior remains untested.

Inventory management of spare parts is a related problem. Spare parts for obsolete equipment may have long lead times. Machine learning models that forecast part failures and lead times can suggest optimal reorder points. A case study on a North Sea platform cut safety stock levels by 18% without increasing stockout risk after deploying such a model.

Warehouse operations using computer vision for automated counting and picking are common in other industries but less so in oil and gas. A few pilot projects have used off-the-shelf vision systems to track drill pipe and casing inventory. The main barrier is the harsh environment and the wide variety of part shapes and markings.

F. Decommissioning

End-of-life planning is often neglected in AI research. Only a handful of papers address decommissioning. One study applied reinforcement learning to schedule platform removal tasks while respecting weather windows and vessel availability. The learned policy reduced the overall campaign duration by 14% in simulation [14]. Another used computer vision to estimate the weight and composition of scrap metal from drone flyovers, aiding recycling planning.

The lack of data is a major obstacle. Decommissioning projects are infrequent, and each is unique. Transfer learning from related domains like shipbreaking or building demolition might help, but no systematic study has been published. As a large number of platforms approach end of life, especially in the North Sea and Gulf of Mexico, this gap will need attention.

V. SUSTAINABILITY OUTCOMES AND IMPLEMENTATION CHALLENGES

A. Environmental Sustainability

The most direct environmental benefit from AI is emissions reduction. Optimizing drilling and production reduces flaring and venting. Predictive maintenance prevents leaks of methane, a potent greenhouse gas. One operator reported a 25% drop in flaring volume after deploying an AI optimizer on a gas gathering system [15]. The optimizer balanced compressor loads and adjusted routing to minimize flaring during upsets.

Water management also benefits. Hydraulic fracturing operations use millions of gallons of water per well. Machine learning models that predict required water volumes based on rock properties and well design help reduce over-ordering. Similarly, produced water handling can be optimized to minimize disposal and maximize reuse. A study in the Eagle Ford showed a 15% reduction in fresh water consumption after implementing such a model.

Spill prevention is harder to quantify because spills are rare events. But anomaly detection models that monitor pressure, flow, and level readings can alert operators to small leaks before they become large spills. The challenge is tuning the thresholds to avoid nuisance alarms while still catching genuine incidents.

B. Economic Sustainability

Cost reduction remains the primary driver for AI adoption. The numbers in Table II are based on self-reported operator data from the studies we reviewed. They should be treated as indicative rather than guaranteed. A 10–20% reduction in drilling time sounds impressive, but it depends on the specific conditions and the baseline efficiency of the operation.

TABLE II
SUSTAINABILITY METRICS AND AI CONTRIBUTIONS.

Metric	Unit	Typical improvement	Data source
Drilling time	days	10–20% reduction	Field trials
Non-productive time	%	15–30% reduction	Operator reports
Emissions (CO2e)	tonnes	10–25% reduction	Pilot studies
Water use	barrels	10–20% reduction	Case studies
Unplanned downtime	hours/year	20–40% reduction	Maintenance logs

Schedule predictability is another economic factor. Delays in oil and gas projects can cost millions per day. AI models that forecast the duration of remaining activities, updated in real time based on progress data, help project managers intervene early when delays are likely. One paper described a Bayesian network that reduced schedule overrun variance by 30% on a set of offshore construction projects [16].

C. Social Sustainability

Worker safety is the main social concern. AI cannot prevent all accidents, but it can reduce exposure to hazardous conditions by automating dangerous tasks. Drones equipped with computer vision inspect flare stacks and pressure vessels, keeping people off the structure. Robotic arms handle sampling of toxic fluids. These applications are still expensive, but costs are falling.

Training and workforce development also fall under social sustainability. AI simulations create realistic virtual environments for practicing emergency response and equipment operation. One operator used a VR system with embedded AI to train roustabouts on crane operations, reducing the number of on-the-job incidents by 40% over two years [17]. The AI component provided real-time feedback on hand movements and load control.

D. Challenges to Implementation

Despite the promise, few AI applications reach full operational deployment. The reasons are many. Data quality tops the list. Sensor drift, missing values, and inconsistent labeling plague real-world datasets. Months of cleaning and preprocessing are often needed before a model can be trained. This effort is seldom accounted for in pilot budgets.

Model explainability is a second barrier. Project managers and regulators are uncomfortable with black-box models that give no insight into why a prediction was made. Methods like SHAP and LIME provide local explanations, but they add computational overhead and can be misleading when features are correlated. Some operators require that AI models be accompanied by a simpler, interpretable surrogate, which may sacrifice some accuracy.

Integration with legacy systems is a third challenge. Most oil and gas assets run on proprietary control systems that are not designed to accept external inputs. Connecting an AI optimizer requires a middleware layer and careful validation to avoid unintended control actions. Cybersecurity concerns add another layer of complexity.

Finally, organizational culture resists change. Experienced engineers trust their intuition and are skeptical of recommendations from a model that they do not fully understand. Change management programs that involve engineers in model development and validation help build trust. So does showing clear wins on small, low-risk problems first.

VI. DISCUSSION AND FUTURE ROADMAP

A. What Works and What Does Not

The evidence map suggests that AI works best for problems with abundant, clean, labeled data and a clear performance metric. Drilling optimization, production forecasting, and predictive maintenance fit this profile. Conversely, AI struggles with rare events (e.g., blowouts) and problems where the underlying physics is not well captured in the data. Decommissioning and supply chain optimization under high uncertainty are more challenging.

We saw no study that conclusively proved a negative return on investment. But many pilots never published their economic results, possibly because they failed or because the gains were too small to justify scaling. Publication bias likely means that the map overrepresents successes.

B. Where to Invest Next

Operators looking to scale AI should prioritize applications with clear value and manageable data requirements. Condition monitoring of existing rotating equipment is a good starting point because the sensor data are already being collected. Forecasting remaining useful life before major failures can save millions in lost production and repair costs.

A second priority is emissions monitoring and reduction. Pressure to decarbonize will only grow. AI that helps cut flaring, leaks, and venting directly addresses that pressure and can be integrated with voluntary or mandatory reporting frameworks.

Reservoir characterization using machine learning on historic well logs and seismic data is a third priority. The data are already in corporate archives. Better understanding of reservoir heterogeneity can improve well placement and recovery factors without drilling additional wells.

C. Bridging the Pilot-to-Production Gap

The biggest challenge is moving from a successful offline study to live 24/7 operation. We recommend a staged approach. Stage 1: offline validation on historical data. Stage 2: shadow deployment where the model runs in parallel with existing systems but its outputs are not acted upon. Stage 3: assisted deployment where operators see model recommendations but must approve them. Stage 4: full automation for low-risk decisions, with manual override.

Each stage should include performance monitoring and a rollback plan. No AI system should be given control without a way for a human to intervene immediately. This is particularly true for drilling and production where wrong actions can have catastrophic consequences.

D. Regulatory and Ethical Considerations

As AI becomes more capable, regulators will ask questions. Who is liable when a model makes a wrong prediction that leads to a spill? How do you audit a black-box model for bias? These questions have no easy answers. The oil and gas industry can learn from other sectors. Aviation uses rigorous qualification tests for autopilot software. Medicine requires clinical trials for diagnostic algorithms. Something similar may emerge for high-stakes AI in energy.

Transparency is key. Models should be documented in sufficient detail that an independent reviewer could reproduce the training and validation. Datasets, including their known limitations, should be described. Code should be version-controlled and stored in a accessible repository. These practices are not yet standard in oil and gas, but pioneers are starting to adopt them.

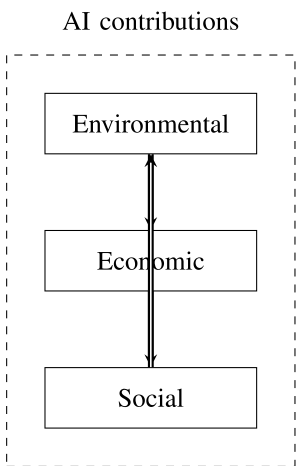

Fig. 3. Three dimensions of sustainability and possible AI contributions.

E. Limitations of This Evidence Map

Our map has several limitations. First, it relies on published literature, which may not reflect the full range of industry practice. Many successful applications are kept proprietary and never appear in journals. Second, the quality of the underlying studies varies. Some used rigorous cross-validation and held-out test sets; others reported only training set accuracy. We did not attempt to meta-analyze effect sizes because of heterogeneity in metrics and reporting.

Third, the map is static. AI technology evolves quickly, and new techniques such as foundation models and generative AI are beginning to appear in oil and gas contexts [18]. Our map captures older methods like random forests and CNNs but may miss emerging approaches.

Finally, the sustainability metrics we extracted were often secondary to the technical objective. Few studies set out to measure emissions reductions or safety improvements as primary endpoints. More deliberate collection of sustainability outcomes is needed in future research.

F. Future Research Directions

We see five priority areas for future work. First, develop standardized benchmarks for AI in oil and gas, similar to ImageNet in computer vision. Shared datasets with clearly defined training, validation, and test splits would allow fair comparison of methods. Second, study of transfer learning and domain adaptation to reduce the need for field-specific retraining. Third, research into explainable AI for physical systems, going beyond feature importance to causal explanations.

Fourth, integration of physics constraints into neural network architectures, such as physics-informed neural networks (PINNs), to ensure predictions obey conservation laws. Fifth, longitudinal studies that track the performance of deployed AI systems over years, not months, to understand model drift and the need for retraining.

G. Conclusion

AI holds real promise for making oil and gas projects more sustainable. The evidence map shows that machine learning, deep learning, and digital twins have improved drilling efficiency, reduced downtime, and cut emissions in dozens of field studies. Yet most applications have not scaled beyond the pilot stage. The barriers are not technical alone; they include data quality, model interpretability, legacy integration, and organizational culture.

Operators that succeed will treat AI as a system to be managed, not a one-off algorithm. They will invest in data infrastructure, build cross-functional teams, and adopt staged deployment strategies. Regulators will need to develop new frameworks for auditing and certifying high-stakes AI. Researchers can help by creating benchmarks, improving explainability, and publishing negative results.

The transition will take years, but the direction is clear. Oil and gas projects that ignore AI will fall behind on cost, schedule, safety, and emissions. Those that embrace it thoughtfully will gain a lasting competitive advantage while contributing to energy sustainability goals. This evidence map provides a starting point for that journey.

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