Review Article

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Beyond Oil Rents: Artificial Intelligence, Governance and Renewable Energy Transitions in the Gulf

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Abstract

Artificial intelligence (AI) is increasingly used to support renewable-energy transitions through forecasting, optimisation, resource assessment, and decision support. However, the extent to which these technical capabilities address the economic and institutional conditions governing renewable-energy deployment remains unclear, particularly in hydrocarbon-dependent economies. This study systematically reviews AI applications in renewable-energy transitions across Saudi Arabia and the Gulf Cooperation Council (GCC), with particular attention to energy economics and governance. Following PRISMA 2020, Scopus and Web of Science searches identified 33 eligible studies published between 2021 and 2026, comprising 27 GCC studies and six comparators. Descriptive bibliometric analysis, deductive coding across technical, economic, and governance layers, and covariate topic modelling with latent Dirichlet allocation robustness testing were applied. The findings show that AI research is dominated by forecasting and optimisation of individual renewable-energy systems, while economic evaluation remains concentrated on project-level costs under largely fixed price assumptions. Only six studies extend to governance-related questions, indicating limited integration of procurement, pricing, subsidy reform, sustainable finance, and institutional conditions. Three themes emerge: energy-transition economics, hydrogen-system optimisation, and solar–wind design and forecasting. Drawing on rentier-state theory, the study shows that GCC-focused research has yet to fully incorporate the region's distinctive political economy. A research agenda is proposed to connect AI-enabled technical innovation with pricing, investment, procurement, sustainable finance, and governance for more effective renewable-energy transitions.

Keywords: artificial intelligence; renewable energy transition; energy economics; energy governance; gulf cooperation council; rentier-state theory

1. INTRODUCTION

Few economies have staked as much on a simultaneous energy and digital transition as Saudi Arabia. Vision 2030 commits the Kingdom to diversify away from hydrocarbon rents [1]. The 2023 revision of its renewables programme raised the target to 130 GW of renewable capacity by 2030 (GlobalData [2]). In parallel, the government has made artificial intelligence (AI) a national priority. The Saudi Data and Artificial Intelligence Authority (SDAIA) anchors a national data and AI strategy, and the Cabinet designated 2026 the Year of Artificial Intelligence [3]. Similar ambitions, at different scales, run through the other Gulf Cooperation Council (GCC) states. The implicit premise of these programmes is that the two transitions reinforce each other: that AI can make renewable energy cheaper to design, easier to integrate and more attractive to finance.

The evidence on delivery tempers that premise. Installed renewable capacity in Saudi Arabia reached roughly 13 GW by 2025, and industry analysts now project between 74 GW and 82 GW by 2030, well short of the stated 130 GW ambition (GlobalData [2]; [4]). Achieving the stated target would require an exceptionally rapid annual expansion in installed capacity, alongside coordinated investment and grid integration. Implementation shortfalls cannot be understood in technological terms alone. They arise in the economic and institutional channels through which projects are procured, priced, financed and governed: auction design, tariff setting, subsidy reform, investor confidence and disclosure [5, 6].

In the Gulf, these channels are shaped by the political economy of the rentier state. The state captures external hydrocarbon rents and redistributes them, in part through administered energy prices [7, 8]. This weakens price signals for efficiency and for low-carbon investment [9, 10]. It also means that the main economic value of domestic renewables lies in the oil and gas they free up for export, a value that end-user tariffs do not reveal [11].

Whether AI helps to close this delivery gap is therefore an economic and governance question as much as a technical one. A large literature now documents what AI can do for climate and energy systems, from forecasting and dispatch to materials discovery and market design [12, 13]. Econometric evidence from the GCC suggests that AI and digitalisation are positively associated with the energy transition, while high oil prices slow it [14]. Parallel literature maps the use of AI in green and sustainable finance. That literature is growing rapidly but is dominated by Chinese research and has little to say about Gulf renewables [15].

At the same time, Gulf capital markets are building a disclosure infrastructure on which ESG-oriented finance depends. The Saudi Exchange issued voluntary ESG disclosure guidelines in 2021, and the Capital Market Authority made disclosure binding for issuers of green, social and sustainability-linked debt in 2025 [16].

The literature would benefit from a systematic account of how research on AI in Gulf renewables connects its technical outputs to these economic and governance outcomes. Existing reviews treat the technical, financial and regional strands separately. Single-country empirical studies, however rigorous, cannot show which AI applications act through which economic or ESG channels. Nor can they show whether research set in the GCC engages the region's distinctive rentier conditions or simply uses the Gulf primarily as a setting with favourable solar resources. Accordingly, the review combines descriptive bibliometric analysis, deductive coding against a three-layer framework (technical, economic and governance/ESG), and covariate topic modelling. It addresses four research questions:

RQ1. How has research on AI in economics and ESG governance of renewable energy in the GCC developed, in terms of timing, setting, outlets and impact?

RQ2. How is AI used, in which renewable domains, and towards which economic or ESG outcomes?

RQ3. How far does literature connect the technical, economic and governance/ESG layers of the transition, and does this differ between GCC and comparator studies?

RQ4. What latent themes structure the literature, and are they shaped by GCC context, layer scope or recency?

The study makes three contributions. Empirically, it provides a systematic map of AI research on Gulf renewable transitions across the technical, economic and ESG layers. It shows that the link between engineering analysis and project-level economic appraisal is comparatively well developed, but the governance and ESG layer is comparatively underrepresented. Theoretically, it brings rentier-state theory into the study of AI-enabled energy transitions. The finding that GCC research is thematically indistinguishable from comparator studies is read as evidence that the literature has not yet engaged in the region's institutional economics. Methodologically, it pairs deductive coding with a covariate topic model and an LDA robustness check. This allows the study to test whether the literature is organised by geography, by the economic scope of the questions it asks, or by time.

2. THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

Rentier-state theory explains how states that derive a large share of revenue from external resource rents differ from states financed by domestic taxation [7, 8]. Because the state's income comes from abroad, its main economic function is allocation rather than production. Citizens receive a share of the rent through public employment, transfers and low administered prices for fuel, electricity and water [10, 17].

In the Gulf, energy subsidies have long been one of the most visible channels of this distribution, and reforming them is politically sensitive [9]. Low domestic prices raise consumption and lock in oil- and gas-fired generation. They also mean that the national value of renewable electricity is hidden from the tariff. The real gain is the hydrocarbons that renewables free up for export, together with the fiscal relief from lower subsidy costs [11].

The theory has three implications for how AI might support Gulf renewable transitions. First, the economics of a renewable project measured at administered prices understates its national value. An analysis that optimises a plant's levelised cost against a subsidised tariff therefore answers a narrower question than the one policymakers face. Second, the state, through ministries, utilities and sovereign investment vehicles, is the dominant buyer, investor and risk-bearer. Decision support aimed at private developers alone misses the principal decision-maker. Third, governance instruments are central to how the transition is financed and legitimised: procurement rules, tariff reform, disclosure regimes and sustainable-debt markets. Research that reaches these instruments engages the region's institutional economics. Research confined to plant design addresses a different, more limited set of questions.

Transition studies conceptualise energy transitions as co-evolving changes in technologies, markets, user practices, regulation and finance, not as the substitution of one technology for another [5,18]. From this perspective, the contribution of AI depends on the level at which it intervenes. At the technical level, machine learning improves resource forecasting, system design, dispatch and maintenance [12]. At the economic level, it can sharpen cost estimation, price forecasting and investment appraisal. At the governance level, it can inform planning, policy evaluation and the analysis of disclosure and financial risk [13].

Gains at one level do not translate automatically into gains at the next. Research on human–AI decision-making shows that algorithmic outputs shape organisational decisions only when they are embedded in the judgement, incentives and accountability structures of decision-makers [19].

Drawing these strands together, this review organises the literature through a three-layer framework (Figure 1). AI methods can act on a technical layer (forecasting, design, dispatch, siting and maintenance), an economic layer (project costs, prices, markets, investment, subsidies and tariffs) and a governance/ESG layer (policy and planning, ESG disclosure, green finance and sukuk, and regulation).

The framework's central proposition is that AI's contribution to transition outcomes depends on the links between layers. Technical outputs become cost and price signals, and economic signals become capital, policy and disclosure decisions. In a rentier context, the second link is decisive, because that is where administered prices and state investment shape whether projects proceed. The framework is used deductively to code each included study by the layers it addresses and the cross-layer links it demonstrates (RQ3). The topic model provides an independent, data-driven test of whether the literature is organised along these lines (RQ4).

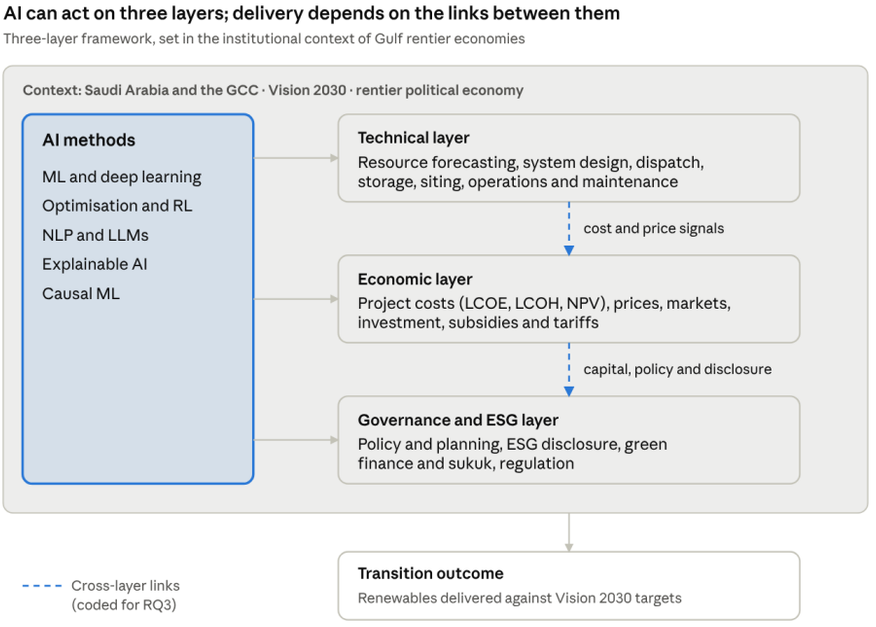


Figure 1. *Conceptual Framework (Author's Construction)*

3. METHODOLOGY

The study is a systematic literature review, designed and reported in line with PRISMA 2020 [20]. Search reporting follows PRISMA-S [21]. Following the evidence-informed tradition of systematic review in management and the social sciences [22], the review combines three analytical strands applied to a single screened corpus:

- descriptive bibliometric analysis, to profile the timing, setting, outlets and impact of the research (RQ1);
- deductive content coding against the three-layer framework, to characterise how AI is used and how far studies connect the layers (RQ2 and RQ3);
- covariate topic modelling, to identify the latent themes of the literature and test what shapes them (RQ4).

The search targeted Saudi Arabia, the wider GCC and comparable oil-exporting contexts. Studies that met every eligibility criterion but were set outside the GCC were retained as comparators and flagged in the coding. This flag allows the GCC literature to be read against a reference group within the same corpus.

Scopus and the Web of Science Core Collection were searched. Both databases are multidisciplinary, index the energy, engineering, economics and management journals relevant to the review, and export full bibliographic records. The search string combined four concept blocks with the Boolean operator AND (Table 1). Terms within each block were joined with OR, and truncation captured spelling and morphological variants. In Scopus the string was applied to titles, abstracts and keywords; in Web of Science, to the Topic field. The documented Scopus string is reproduced in Appendix A. The exact Web of Science string was not supplied and is identified there as requiring verification against the original search record.

Table 1. *Concept Blocks of the Search String*

Block	Concept	Representative terms
A	Artificial intelligence	"artificial intelligence", "machine learning", "deep learning", "reinforcement learning", "large language model*", "explainable AI", "digital twin*"
B	Renewable energy	"renewable energ*", solar, photovoltaic*, "wind energ*", "green hydrogen", "energy transition", "energy storage"
C	Energy economics and ESG	LCOE, "electricity pric*", "electricity market*", "project financ*", subsid*, tariff*, "carbon pric*", ESG, "green financ*", "green bond*", sukuk, "sustainability disclosure*"
D	Geographic and economic context	Saudi, GCC, "United Arab Emirates", Qatar, Oman, Kuwait, Bahrain, MENA, "Middle East", "oil-exporting", rentier, hydrocarbon*

The manuscript's search log reports 92 Scopus records. Four database filters reduced these to 55: publication years 2010–2026, five subject areas (Energy, Engineering, Environmental Science, Mathematics and Computer Science), articles and reviews, and English-language final-stage publications. The manuscript reports 45 Web of Science records (filter details require confirmation from the original search export). The reported 100 exported records were merged and deduplicated on exact normalised DOI, with exact normalised title matching used only where a DOI was missing. This removed 33 cross-database duplicates and left 67 unique records: 33 indexed in both databases, 22 in Scopus only and 12 in Web of Science only.

A study was included only if it met four substantive criteria simultaneously (Table 2). The eligibility window, 2016–2026, begins with the launch of Vision 2030; the broader 2010 database limit was used to identify any precursor work. Geographic setting was not an exclusion criterion.

The 67 records were screened on title, abstract, keywords and bibliographic metadata, and each decision was logged with its exclusion code and a justification. Screening excluded 34 records. As reported in the screening log, twenty records failed the AI criterion (E1), six the renewable-energy criterion (E2), two the economic/ESG criterion (E3), three were reviews or bibliometric studies (E4), and three predated the eligibility window or were proceedings volumes (E5). These counts require confirmation against the original screening spreadsheet. The full texts of the remaining 33 articles were retrieved and assessed. The reported final corpus comprises 33 journal articles published between 2021 and 2026, 27 set in a GCC context and six non-GCC comparators (Figure 2).

For each study, bibliographic data were exported from both databases, and six groups of analytical variables were coded from the full text:

- study context (country or region of the data or case) and a binary GCC flag;
- the framework layers addressed and their combination;
- the AI method family and the role AI plays in the analysis;

- the renewable domain;
- the economic or ESG outcome analysed;
- publication year.

The role of AI was classified into six categories that emerged inductively during coding: surrogate-based system design optimisation, forecasting for economic appraisal, ML-augmented econometric or causal analysis, metaheuristic or reinforcement-learning sizing, spatial siting and suitability, planning and policy decision support.

Table 2. *Eligibility Criteria and Exclusion Codes*

Code	Criterion	Include if	Exclude if
E1	AI/ML	AI/ML is central to the analysis, model, optimisation, forecasting or decision support, or AI is analysed as a driver of the transition	AI/ML is absent, incidental or not substantively central
E2	Renewable energy	Renewable generation, storage, green hydrogen/ammonia or the renewable transition is explicit	No substantive renewable focus
E3	Economic or ESG dimension	Cost, LCOE/LCOH, price, market, investment, finance, revenue, NPV/payback, ESG, governance or policy outcome is substantive	Technical performance only
E4	Study design	Primary empirical, modelling, case or conceptual research	Review or bibliometric study
E5	Time and type	Journal article published 2016–2026	Published before 2016, or a proceedings volume

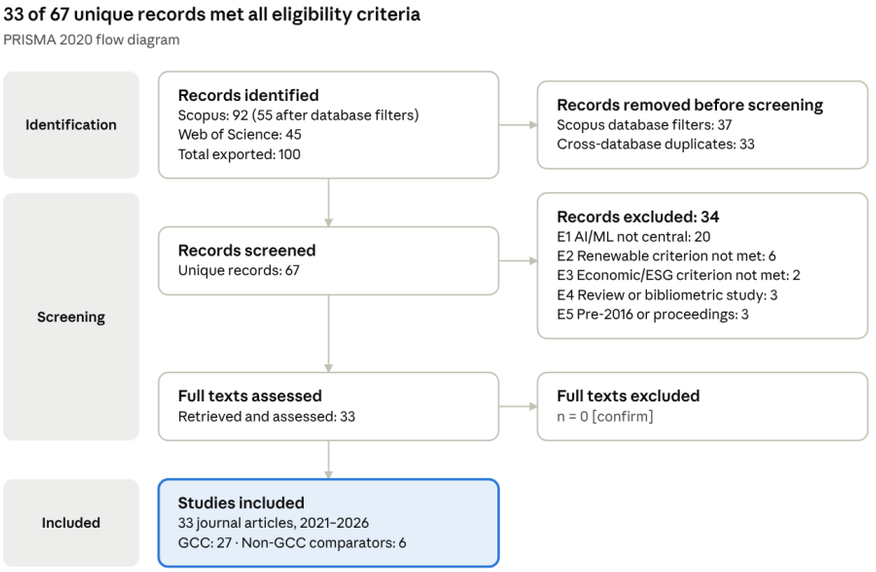


Figure 2. *PRISMA 2020 Flow Diagram*

Annual output, study settings, source journals, citation counts, and author affiliations were tabulated. Interpretation of annual counts takes account of the incomplete 2026 calendar year. Citation counts were taken as the higher of the Scopus and Web of Science counts at the date of export. Given the size and recency of the corpus, network-based science mapping was not used to infer research clusters; that task was assigned to the topic model.

Topic models infer latent themes from the co-occurrence of words across documents. They are increasingly used in the social sciences to analyse large bodies of text without imposing a prior coding scheme [23, 24]. The structural topic model (STM) extends conventional topic models by allowing document-level covariates to shape topic prevalence [25].

The original analysis used a Dirichlet-multinomial regression implementation because the R stm package was reportedly unavailable in that environment. A Dirichlet-multinomial regression (DMR) model [26] was therefore estimated with the tomotopy library (version 0.14). DMR shares STM's core feature, a prevalence model in which each document's prior topic distribution depends on its covariates, but it does not model covariate effects on topical content.

Each study's title, abstract and keywords were combined into one text. Texts were lower-cased, with hyphenated compounds kept as single terms. Numbers, punctuation, standard English stop words and generic academic terms were

removed, and plural forms were normalised. Terms appearing in fewer than two documents or in more than 80% of them were dropped, as were country and place names, so that geography entered the model only through the GCC covariate. The resulting vocabulary comprised 604 terms and 3,454 tokens.

Three binary covariates entered the prevalence model: GCC context (27 vs 6 studies), layer scope (technical–economic only, 22, vs beyond, 11) and period (2025–2026, 22, vs 2021–2024, 11). The number of topics was selected by fitting K = 2–6 and comparing semantic coherence [27], exclusivity and held-out log-likelihood estimated by five-fold document completion. The final model was the best of 20 random seeds by log-likelihood per token. Topic stability was assessed as the mean cosine similarity between its topics and the matched topics of the remaining runs.

Covariate effects were estimated by regressing document–topic proportions on the three covariates jointly and bootstrapping the 33 studies (5,000 resamples; 95% percentile intervals), a resampling analogue of STM's method-of-composition approach. Given the corpus size, these effects are interpreted as descriptive tendencies rather than confirmatory tests.

Robustness was assessed in two ways. First, a latent Dirichlet allocation (LDA) model [28] was estimated at the same K, and its topics were matched to the DMR topics with the Hungarian algorithm on cosine similarity. Second, each study's dominant topic was cross-tabulated against its deductive codes.

4. RESULTS

The evidence base is strikingly recent. Although the eligibility window opened with Vision 2030 in 2016, no eligible study appeared before 2021 (Figure 3). The earliest included study, Boretti [29], examined the AI-enabled integration of solar, wind and storage for NEOM. Output then rose from three studies in 2023 to seven in 2024 and eleven in each of 2025 and 2026, so that two-thirds of the corpus (22 of 33) was published in the last two years. The 2026 count reflects a partial publication year and should not be compared directly with complete calendar years. Coverage across databases was complementary: 19 studies were indexed in both, 10 only in Scopus and 4 only in Web of Science.

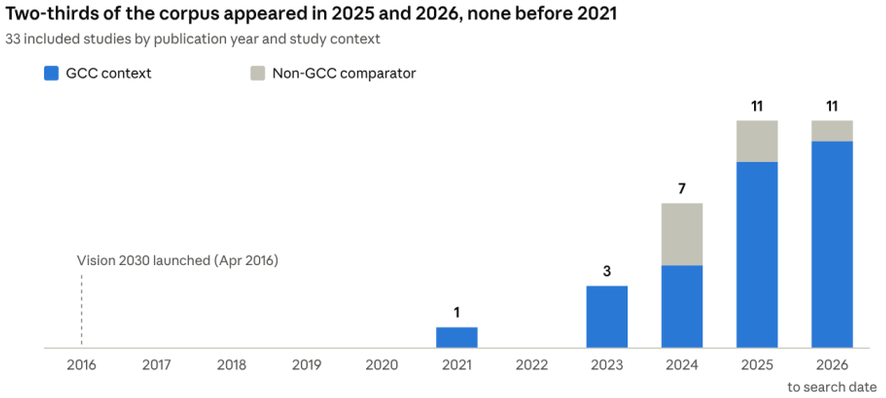


Figure 3. *Included Studies by Year and Context (n = 33)*

The literature is geographically concentrated (Table 3). Saudi Arabia is the setting for 16 studies (48%) and Oman for five. Two studies analyse the six GCC states as a panel [14, 30], and Qatar, Kuwait, Bahrain and the UAE contribute one study each. The six comparators comprise two Iranian studies, one Italian, one regional Middle Eastern, one global and one without a specific national setting.

Table 3. *Studies by Context of Data or Case*

Context	Studies	Share
Saudi Arabia	16	48%
Oman	5	15%
GCC (six-state panel)	2	6%
Qatar, Kuwait, Bahrain, UAE (one each)	4	12%
GCC subtotal	27	82%
Iran	2	6%
Italy; Middle East (regional); global; not country-specific (one each)	4	12%
Non-GCC subtotal	6	18%

Authorship is more international than the settings. Counting the studies with at least one author affiliated in a given

country, Saudi Arabia leads (17 studies), followed by Oman and Iraq (6 each), India and Uzbekistan (5 each) and the UAE (4). Ten of the 16 Saudi-context studies include at least one co-author affiliated outside the GCC.

The 33 studies appeared in 25 journals, so no single outlet accounts for a majority of articles. Energy published four, and Energy Strategy Reviews, Scientific Reports, Process Safety and Environmental Protection, International Journal of Hydrogen Energy and Mathematics published two each. The outlets are overwhelmingly engineering and energy-technology journals. Only Energy Strategy Reviews, Energy, Ecology and Environment and Sustainability lean towards policy or economics, and none is a finance, management or area-studies journal.

The recorded citation counts total 494, with a median of eight per study, and nine studies are not yet cited. Impact is highly concentrated: the three most-cited studies account for 52% of all citations (Table 4).

Table 4. *Most-Cited Studies*

Study	Setting	Focus	Citations
Imam et al. [31]	Saudi Arabia	SVM resource forecasting, GIS siting and techno-socio-economic feasibility of solar PV and wind	99
Boretti [29]	Saudi Arabia (NEOM)	AI-enabled integration of solar PV, CSP, wind and battery storage	97
Tahir et al. [32]	UAE (Masdar)	BiLSTM PV forecasting linked to project NPV and IRR	63
Ismail et al. [33]	Saudi Arabia	ANN–GA optimisation of a CSP-driven power and hydrogen system	28
Kaabinejadian et al. [34]	Iran	ANN-based techno-economic-environmental optimisation of solar-boosted hydrogen and methanol	22

AI functions predominantly as an engineering instrument (Table 5). In ten studies, a neural network or machine-learning surrogate emulates a thermodynamic or physical model, which a genetic or similar algorithm then optimises (e.g., [33, 35]). In another ten, deep-learning or ML models forecast solar irradiance, wind speed or plant output, and the forecasts feed an economic appraisal (e.g., [32, 36]). Together these two roles account for 61% of the corpus.

Fewer studies apply AI to economic or policy questions. Four use machine learning alongside econometric or causal analysis [30,37,38]. Al-Maadid et al. [14] belong to this group but treat AI as an explanatory variable rather than a method. Three studies provide planning or policy decision support (e.g., [39, 40]).

Table 5. *Roles of AI in the Included Studies*

Role of AI	Studies	GCC / non-GCC	Typical methods
Surrogate-based system design optimisation	10	9 / 1	ANN–genetic algorithm; random-forest and other ML surrogates
Forecasting for economic appraisal	10	9 / 1	LSTM, BiLSTM, GRU, CNN-LSTM, SVM, XGBoost, physics-informed neural networks
ML-augmented econometric or causal analysis	4	3 / 1	Causal forests; ML with panel econometrics; ML regression with wavelets
Metaheuristic or reinforcement-learning sizing	3	3 / 0	Grey wolf, particle swarm, evolutionary and RL neural-network algorithms
Spatial siting and suitability	3	1 / 2	Gaussian process regression; TabNet with explainable AI; geospatial multicriteria analysis
Planning and policy decision support	3	2 / 1	AHP with ANN; neural-network strategic planning; AI-integrated system design

Green hydrogen and ammonia systems form the largest renewable domain (8 studies, 7 of them in the GCC), followed by solar PV (7), sector-level or macro transition studies (6) and hybrid solar–wind–storage systems (5). Wind (3), solar-powered water production (2), concentrated solar power with thermal storage (1) and wave energy (1) complete the corpus.

The economic content of the literature is overwhelmingly project-level. In 23 studies, the economic outcome is a plant metric levelised cost of electricity, hydrogen or ammonia; net present value; payback period; cost rate; or annualised system cost calculated under fixed price and tariff assumptions. Four studies analyse markets or prices: profit in a deregulated electricity market [36], long-run wind competitiveness [41], electricity-price uncertainty in desalination planning [42] and oil-price dynamics [38]. Six address macro, policy or finance questions.

The ESG layer is nearly empty. Within the reported screened corpus, no study was coded as analysing ESG disclosure, green bonds, or sukuk; this observation is limited by the database and subject-area restrictions described in the methodology. Only one examines green finance, estimating its causal effects across eight Saudi cities with causal forests [37]. Vision 2030 is named in only two of the 27 GCC studies.

The framework coding confirms this imbalance (Table 6). The technical layer appears in 29 studies (88%), and in 22 of them the analysis stops at a project-level economic metric. Only six studies reach the governance/ESG layer, and

only three connect all three layers: Alabbasi et al. [39] in Bahrain, Imam et al. [31] in Saudi Arabia and Sadeghi et al. [40] in Iran. GCC studies are also narrower than the comparators. Seven of the 27 GCC studies (26%) go beyond the technical–economic pairing, compared with four of the six comparators (67%).

Table 6. *Framework Layers Addressed by Context*

Layer combination	GCC	Non-GCC	Total
Technical–economic only	20	2	22
Technical–economic + governance	2	1	3
Technical–economic + market	1	1	2
Technical–economic + environmental	1	1	2
Economic–governance (no technical layer)	2	0	2
Economic–ESG/governance	1	0	1
Economic–market	0	1	1
Total	27	6	33

Models with two to six topics were compared on semantic coherence, exclusivity and held-out likelihood (Figure 4). The three-topic solution was selected. It has the highest exclusivity (0.950), and its coherence (−34.7) is close to that of the four-topic solution (−34.1). Held-out likelihood varies by less than 0.03 nats per token across all solutions, within seed-to-seed variation, and so does not discriminate between them.

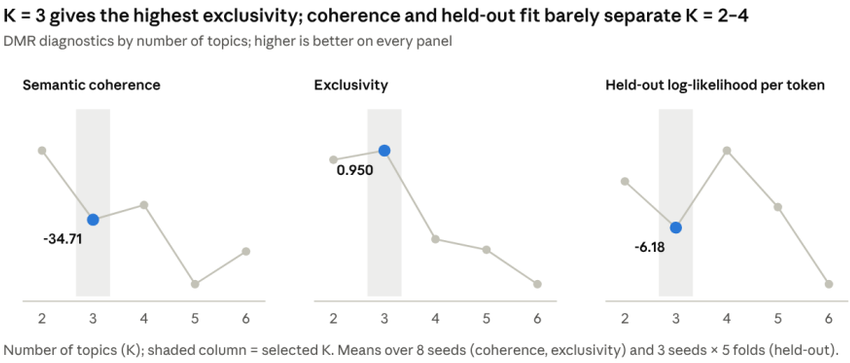


Figure 4. *DMR Model Diagnostics (K = 2–6)*

The two-topic solution is more coherent but merges the hydrogen-system engineering studies with the macro-economic transition studies, which the deductive coding treats as distinct. The four-topic solution adds a sub-theme on machine-learning forecasting and siting under climate variability. That sub-theme is the least stable across seeds (mean matched cosine 0.55) and is therefore not treated as a separate topic. As is common with small corpora, the diagnostics identify K only weakly, and the final choice rests on exclusivity, stability and interpretability together.

The corpus divides into three topics of similar size (Table 7). One is an economics topic, in which AI meets the transition at the level of sectors and economies. The other two are engineering topics, in which AI optimises or forecasts specific renewable systems.

Table 7. *Topics Identified by the DMR Model (K = 3)*

Topic	Prevalence	Dominant in	Highest-probability terms	Most representative studies (θ)
T1 AI and the economics of the energy transition	34.9%	11	renewable, learning, machine, economic, transition, source, artificial, price, technology, resource	Al-Maadid et al. [14], 0.97; Omer et al. [30], 0.92; Magazzino et al. [38], 0.79
T2 Surrogate-optimised hydrogen and multigeneration systems	28.8%	8	power, optimization, hydrogen, generation, neural, cycle, sustainable, production, hybrid, efficiency	Marouani et al. [35], 0.68; Kaabinejadian et al. [34], 0.67; Ismail et al. [33], 0.66
T3 Cost-optimal solar–wind design and forecasting	36.3%	14	solar, wind, cost, network, water, algorithm, electricity, optimal, photovoltaic, deep	Sanan et al. [43], 0.80; Boretti [29], 0.77; Almazam et al. [44], 0.73

Topic 1 gathers the econometric, causal and policy-oriented studies. These treat AI as a driver of the GCC transition, relate renewable uptake to macroeconomic conditions, trace links between oil prices and renewable production, and esti-

mate the effects of green finance. It is the only topic whose leading vocabulary includes economic, price and transition, and it dominates seven of the eleven studies that go beyond the technical–economic pairing.

Topic 2 is a tightly bounded engineering literature. Integrated concentrated-solar, geothermal–solar or wind–solar plants co-produce hydrogen, power and fresh water; a neural network or machine-learning surrogate emulates the plant; and an optimisation algorithm minimises cost rate or levelised cost of hydrogen, or maximises net present value.

Topic 3 covers the cost-optimal sizing, siting and forecasting of solar PV, wind, hybrid storage and solar-powered water systems, in which deep-learning and metaheuristic algorithms minimise the cost of energy or water.

Layer scope is the only covariate that clearly shifts topic prevalence (Figure 5). Studies that go beyond the technical–economic pairing devote, on average, 26 percentage points more of their text to Topic 1 (95% CI: 4 to 48) and 29 points less to Topic 3 (95% CI: -45 to -11). GCC context has no detectable effect on any topic: every interval spans zero, and the point estimates lie within ± 8 points. Recency shows a weak tendency away from Topic 3 (-12 points; 95% CI: -27 to 2) and towards Topic 2, consistent with the growth of hydrogen-system studies in 2025–2026, but the interval includes zero.

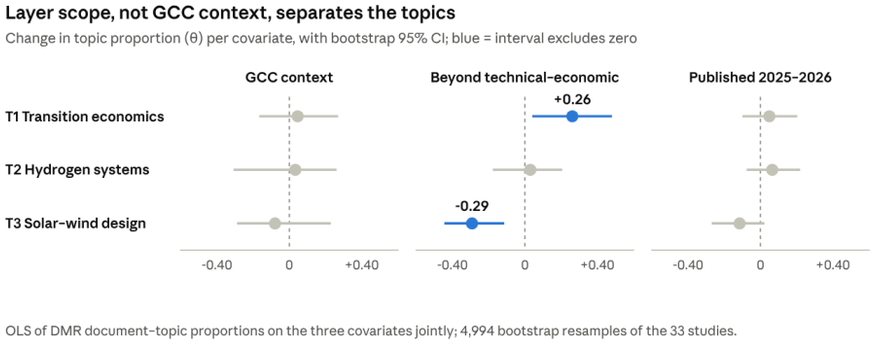


Figure 5. *Covariate Effects on Topic Prevalence*

The three-topic structure showed substantial agreement between the two models used in the reported robustness check. An LDA model at K = 3 recovers the same topics: matched topic–word distributions have cosine similarities of 0.94, 0.96 and 0.96; document–topic proportions correlate at r = 0.97–0.98; and 32 of the 33 studies (97%) have the same dominant topic under both models. Across 20 random seeds, topics matched to the best-fitting run have a mean cosine similarity of 0.72 for DMR and 0.74 for LDA.

The topics also align with the independent deductive codes (Table 8). All eight hydrogen studies were assigned to Topic 2, all six sector-level transition studies to Topic 1, and all five hybrid solar–wind–storage studies to Topic 3. Treating Topic 1 as the economic–governance end of the framework and Topics 2 and 3 as the technical–economic pairing, the dominant topic agrees with the layer coding for 25 of the 33 studies (76%). Of the eight disagreements, four technical–economic studies are drawn into Topic 1 by their machine-learning, climate-risk and financial vocabulary, and four broader studies are placed in Topics 2 and 3 by their engineering vocabulary.

Table 8. *Dominant Topic Against the Deductive Codes*

Dominant topic	Studies	Beyond technical–economic	Main AI roles	Main renewable domains
T1 Transition economics	11	7	Econometric/causal (4), forecasting (3), planning support (2)	Sector/macro transition (6), solar PV (3)
T2 Hydrogen systems	8	2	Surrogate optimisation (7), metaheuristic sizing (1)	Green hydrogen/ammonia (8)
T3 Solar–wind design	14	2	Forecasting (7), siting (2), metaheuristic sizing (2), surrogate optimisation (2)	Hybrid solar–wind–storage (5), solar PV (4), wind (2), solar for water (2)

5. DISCUSSION

This review examined the extent to which research on AI in Gulf renewable-energy transitions connects technical outputs to the economic and governance conditions required for implementation. The included studies provide comparatively strong evidence of technical and project-economic integration but much less attention to procurement, financing arrangements, and policy institutions.

The field is young and fast-growing (RQ1). It uses AI mainly to optimise and forecast individual renewable systems, and it evaluates them through project-level metrics (RQ2). The link from the technical to the economic layer is well established, but the governance and ESG layer is reached by only a handful of studies, and GCC research is narrower

in scope than comparable work elsewhere (RQ3). The topic model reaches the same conclusion from the data side: the literature is organised by engineering domain and economic scope, not by geography (RQ4). This section interprets these findings, considers their implications for theory and policy, sets out a research agenda and acknowledges the study's limitations.

The dominant pattern in the corpus is that economics is an output of engineering design rather than an object of analysis. In a typical study, a neural-network or machine-learning surrogate is trained on a thermodynamic model, the plant configuration is optimised, and the result is expressed as a levelised cost, net present value or payback period. The prices, tariffs and discount rates behind these metrics are fixed assumptions. AI thus sharpens an engineering estimate while leaving untouched the economic variables that are most uncertain in practice.

This is a reasonable division of labour for engineering research. It is, however, a poor fit with the problem Gulf policymakers face. The shortfall between Saudi Arabia's renewables targets and installed capacity (GlobalData [2]; [4]) arises in procurement, pricing, financing and governance. These are the channels that transition scholarship identifies as decisive for the pace of energy transitions [5, 6], and the corpus models them in very few cases.

The exceptions are instructive. Imam et al. [31] connect machine-learning resource forecasts to tariff and power-purchase-agreement thresholds for Saudi solar and wind. Tahir et al. [32] link deep-learning forecasts to the net present value and internal rate of return of the 10 MW Masdar project. Alabbasi et al. [39] embed an artificial neural network in a decision-support system for national generation-expansion planning in Bahrain. Two of these three are among the three most-cited studies in the corpus. This suggests that work connecting AI to real investment or policy decisions attracts disproportionate scholarly attention, even if it remains rare.

The pattern echoes research on human–AI decision-making, which finds that algorithmic outputs change organisational outcomes only when they are embedded in the judgement and accountability structures of decision-makers [19]. The literature reviewed here produces optimised designs and cost estimates, but rarely traces how these reach the procurement agencies, utilities, investors and regulators who decide whether projects are built. The authorship profile is consistent with this reading. The outlets are almost entirely energy-technology journals, and ten of the sixteen Saudi-context studies involve co-authors from outside the GCC. Much of the literature thus appears to use the Gulf as a resource-rich case setting rather than to start from the region's policy problems.

The near-absence of governance and ESG research is the review's most consequential finding. Within the screened and coded studies, none was classified as analysing ESG performance or disclosure, green bonds, or sukuk, and one study was classified as estimating the effects of green finance [37]. This absence is out of step with institutional change in the region. Gulf capital markets have moved from voluntary ESG guidance towards binding disclosure for sustainable-debt issuers [16]. These are precisely the instruments through which renewable investment is increasingly financed and legitimised, and they generate the text and transaction data that machine-learning and natural-language-processing methods handle well.

The gap is regional rather than methodological. A bibliometric analysis of AI in green finance identified 268 Web of Science documents and a rapidly growing literature, led by Chinese research [15]. The methods exist; they have not been applied to Gulf renewable finance.

Two explanations are plausible, and neither can be tested with the present corpus. Disclosure regimes in the region are recent and still largely voluntary, so the data that such studies require are only now accumulating. Alternatively, Gulf ESG research may exist in finance and accounting journals without an energy or AI component, and so fall outside this review's search. The second possibility is considered further in Section 5.7.

The topic model found no thematic difference between GCC and comparator studies. Read through rentier-state theory, this absence is itself a substantive finding. If research were shaped by the political economy of the Gulf, GCC studies would place more weight on the economics of the transition: administered prices, subsidy reform, the export value of displaced hydrocarbons and the role of the state as investor [7, 9, 11]. They do not. In most studies, the Gulf supplies irradiance and wind data rather than a distinct economic problem.

A project levelised cost calculated at subsidised fuel and electricity prices captures none of the features that distinguish a rentier economy. Only three GCC studies engage them directly:

- Al-Maadid et al. [14] show that high oil prices slow the GCC transition;
- Omer et al. [30] relate renewable uptake to hydrocarbon dependence;
- Abidi et al. [37] frame green finance in the context of oil-dependent cities.

It is telling that one of the comparator studies, an Iranian planning model, is more explicitly framed around heavily subsidised fossil fuels than almost any GCC study [40].

The geographic distribution adds a further caution. Saudi Arabia and Oman account for 21 of the 27 GCC studies, while the UAE contributes only one despite its prominent utility-scale solar programme. This may reflect where AI-and-

economics work on the region is published, or how it is worded, rather than where activity is concentrated. The evidence base should not therefore be read as representative of the GCC as a whole.

6. IMPLICATIONS AND AGENDA

The findings carry two implications for theory.

First, for the study of AI in energy transitions, they show the value of distinguishing the layer at which AI intervenes. Aggregate claims that AI "supports" the transition (e.g., [13, 14]) conceal a strong asymmetry. The technical–economic link is well researched, while the economic–governance link, which multi-level transition theory treats as decisive [18], is barely studied. The three-layer framework offers a simple way to make this asymmetry visible and to locate future contributions.

Second, for rentier-state theory, the findings point to a missing mechanism. The theory explains why administered prices weaken the private economics of low-carbon investment [9, 10]. It has not yet been extended to the question of how new analytical technologies are deployed within rentier institutions. The absence of a GCC effect in the topic model suggests that, so far, much AI research appears to follow a broadly applicable engineering agenda rather than adapted to the allocative logic of the rentier state.

For research funders and agencies such as SDAIA, the review suggests a reorientation from optimising plants to supporting delivery. Priorities would include AI applications that model procurement and auction outcomes, value displaced domestic hydrocarbon consumption, simulate tariff and subsidy reform, and analyse disclosure and credit risk in renewable project finance.

For capital-market regulators, the growing body of ESG and sustainable-debt disclosures is an under-used analytical resource that AI methods could help to verify and compare.

For researchers in the region, the most cited work in the corpus shows that studies linking AI to real financial and policy decisions are both feasible and valued.

Table 9 translates the findings into six research directions, each linked to the evidence that motivates it and to a Vision 2030 instrument or target.

Table 9. *Research Agenda*

Gap	Evidence	Research direction	Policy link
Design–delivery gap	23 of 33 studies stop at project metrics computed at fixed prices	AI models linking optimised designs to procurement, auction bids and PPA pricing; forecasting delivery against targets	Renewables capacity targets
ESG and disclosure	No study on ESG, disclosure, green bonds or sukuk	NLP of sustainability reports and sustainable-debt disclosures; greenwashing detection; ESG and credit-risk scoring for renewable project finance	Saudi Exchange ESG guidance; CMA sustainable-debt disclosure rules
Rentier economics	No GCC effect in the topic model; three GCC studies engage oil dependence	AI-supported valuation of displaced domestic oil and gas; simulation of tariff and subsidy reform	Fiscal diversification; energy-price reform
Hydrogen economics	All eight hydrogen studies optimise a single plant	AI for export pricing, offtake risk and certification costs of green hydrogen and ammonia	Hydrogen export ambitions
Decision use and explainability	One study uses explainable AI; three provide decision support	Explainable, human-in-the-loop AI for regulators, utilities and investors	National data and AI strategy
Geographic and causal breadth	Saudi Arabia and Oman hold 21 of 27 GCC studies; four use ML for causal or econometric analysis	Comparative cross-GCC panels; causal machine learning to evaluate auctions, green finance and price reform	GCC-wide transition; evidence-based policy evaluation

The source-level audit also identified internal reporting inconsistencies that cannot be resolved through language editing alone. In particular, the original Methodology reports 33 records indexed in both databases, whereas the Results reports 19 such studies; the original Web of Science search string and filtering history were not provided. These discrepancies do not alter the descriptive values reproduced here, but they limit independent assessment of the search, deduplication, and study-classification process. The underlying bibliographic exports, screening spreadsheet, and model outputs should be reconciled before the analysis is submitted for publication.

7. LIMITATIONS

The study has four main limitations.

First, the corpus is small and recent: 33 studies, 22 of them from 2025–2026. The topic model identifies the number of topics only weakly, and its covariate effects should be read as descriptive tendencies.

Second, the Scopus search was restricted to five subject areas that exclude economics, business, the social sciences and decision sciences. These are the categories in which AI-and-ESG or AI-and-finance studies are most likely to appear, so the filter may understate the very layer the review finds missing. The concern is reduced, though not removed, by two

observations. The Web of Science search (the application of a category filter to the original search requires confirmation) returned only two business and economics records, neither with an AI component. And the global literature on AI in green finance is dominated by non-GCC studies [15]. A re-run without the subject restriction would provide a useful robustness check.

Third, the search was limited to two databases, English-language journal articles and title, abstract and keyword fields, and no citation snowballing was undertaken.

Fourth, a DMR model was used in place of STM because the stm package could not be installed. DMR models covariate effects on topic prevalence but not on content, and publication year entered as a binary variable. The close agreement with LDA suggests the topic structure is robust; a replication script for stm is available from the authors.

8. CONCLUSION

Saudi Arabia and its Gulf neighbours have tied their economic futures to two transitions at once, one towards renewable energy and one towards artificial intelligence. This review asked whether the research linking the two addresses the conditions on which the first transition will succeed or fail. Drawing on 33 peer-reviewed studies, it finds a young and rapidly expanding literature that is technically sophisticated but economically and institutionally narrow.

AI is used predominantly to optimise and forecast individual renewable systems, from hydrogen-producing solar plants to hybrid microgrids. Its economic contribution is measured mainly through project-level costs computed at fixed prices. The governance and ESG layer of the transition is almost entirely absent: there is no research on disclosure, sustainable debt or ESG performance, and little on the policy and pricing instruments through which Gulf renewables are procured. Topic modelling shows that what distinguishes studies is how far up this chain of economic and governance questions they reach, not whether they are set in the Gulf. GCC research has yet to engage the region's rentier political economy in any distinctive way.

The main message for scholars is that the next contribution of AI to Gulf energy transitions is more likely to come from economics and governance than from further engineering optimisation. The main message for policymakers is that national AI and renewable strategies would benefit from directing analytical capacity towards the delivery gap—procurement, pricing, finance, and disclosure rather than towards ever more refined designs for individual plants. As Gulf disclosure regimes mature and the evidence base grows, a re-examination of these questions with broader search coverage and a larger corpus will show whether the field moves beyond oil rents in its analysis as well as in its ambitions.

Conflicts of Interest

The author declares no competing interests.

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Data Availability

Data sharing is not applicable.

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APPENDIX A: SEARCH STRINGS

Scopus (title, abstract and keywords; limits as reported in Section 3.2):

TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "reinforcement learning" OR "large language model*" OR "generative AI" OR "natural language processing" OR "explainable AI" OR "digital twin*") AND TITLE-ABS-KEY ("renewable energ*" OR "clean energ*" OR solar OR photovoltaic* OR "wind power" OR "wind energ*" OR "green hydrogen" OR "energy transition" OR "energy storage") AND TITLE-ABS-KEY ("energy economic*" OR "levelized cost" OR "levelised cost" OR lcoe OR "electricity pric*" OR "energy pric*" OR "electricity market*" OR "project financ*" OR "renewable investment*" OR "energy investment*" OR subsid* OR tariff* OR "techno-economic" OR "economic feasibility" OR "carbon pric*" OR esg OR "environmental, social and governance" OR "sustainable financ*" OR "green financ*" OR "climate financ*" OR "green bond*" OR sukuk OR "sustainability report*" OR "sustainability disclosure*") AND TITLE-ABS-KEY (saudi OR "Kingdom of Saudi Arabia" OR ksa OR gcc OR "Gulf Cooperation Council" OR "Gulf countries" OR "Gulf states" OR "Arabian Gulf" OR "United Arab Emirates" OR uae OR qatar OR oman OR kuwait OR bahrain OR neom OR mena OR "Middle East" OR "oil-exporting" OR "oil exporting" OR "resource-rich" OR rentier OR hydrocarbon*)

Web of Science Core Collection (Topic field): The exact executed search string was not included in the supplied manuscript and must be inserted from the original search history before submission.