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ALGORITHMIC POWER AND CLIMATE DIPLOMACY: ASSESSING THE IMPLICATIONS OF ARTIFICIAL INTELLIGENCE FOR PAKISTAN IN GLOBAL CLIMATE GOVERNANCE

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Abstract

This study examines the implications of artificial intelligence (AI) for Pakistan's role in global climate governance by introducing the concept of "algorithmic power." Traditional climate diplomacy relies on economic size, technical expertise, and alliance networks, yet overlooks how data infrastructure and AI tools reshape negotiation leverage. We propose a framework comprising three dimensions Data Capacity, Analytical Capacity, and Diplomatic Capacity operationalized through three composite indices: Algorithmic Readiness Index (ARI), Diplomatic Leverage Ratio (DLR), and Algorithmic Influence Score (AIS). Using hypothetical scores calibrated against regional benchmarks, Pakistan's ARI is estimated at 0.40, indicating limited algorithmic readiness, while its DLR of 1.25 suggests relatively effective conversion of this readiness into diplomatic influence. However, the overall AIS of 0.50 reveals modest aggregate influence, underscoring structural constraints in data and analytical capacities. Qualitative analysis of Pakistan's climate policy documents and UNFCCC submissions shows limited explicit reference to AI, reliance on traditional indicators, and emerging but underdeveloped awareness of digital tools. The findings highlight that while diplomatic initiative and coalition-building can partially offset algorithmic weaknesses, long-term influence in an increasingly data-driven climate regime requires targeted investments in climate data systems, AI literacy, modelling institutions, and equitable international digital cooperation.

Keywords: Algorithmic Power; Climate Diplomacy; Artificial Intelligence; Pakistan; Climate Governance; Algorithmic Readiness Index; Diplomatic Leverage Ratio; Algorithmic Influence Score; Analytical Capacity.

1. Introduction

The climate governance system in many regions faces important challenges regarding the achievement of ambitious mitigation and adaptation targets within the planned financial, temporal, and institutional constraints, in addition to maintaining a positive impact of climate policies and technologies on vulnerable communities and ecosystems. The traditional success factors in climate diplomacy are credible national commitments, adequate international finance, and equitable burden-sharing. The basics of success in global climate governance are still trust, transparency, and the ability to translate scientific evidence into negotiated outcomes (Ahmad & Muhammad, 2026).

A traditional usage of diplomatic power, as a state's capacity to influence agenda-setting, coalition-building, and rule-making in multilateral forums, helps to gauge a country's leverage based on its economic size, technical expertise, and alliance networks (Al Kium et al., 2023). Diplomatic power is useful for measuring traditional and basic indicators of influence, but it cannot fully handle the role of data infrastructure and algorithmic tools, leaving a major flaw in understanding contemporary climate governance. Negotiators often do not have a detailed and practical framework to relate AI-driven climate models, satellite-based monitoring systems, or machine-learning analytics to the main indicators that measure a state's bargaining power, credibility, and access to climate finance. Such a gap makes it more difficult to take proper actions in the negotiation and implementation stages, which is crucial for staying in line with national climate targets and international commitments (Aliu, 2025).

Therefore, it is now essential to link algorithmic capabilities with climate diplomacy frameworks; recent publications have attempted to address this issue. Various research articles have developed and suggested the concept of "algorithmic power" by incorporating data infrastructure, AI systems, and digital platforms into the traditional approach to international influence. Their findings suggested that AI can accurately predict climate risks, monitor emissions, and optimize adaptation investments by using advanced modeling and remote sensing, even though adoption in the Global South has lagged. Subsequently, another research developed and suggested a digital governance model, incorporating AI-enabled transparency mechanisms and data-sharing protocols to improve trust and compliance across climate regimes (Almakaty et al., 2026; Antanasijević et al., 2014). Although the model becomes highly effective, it does not include the geopolitical and distributional variables to monitor how algorithmic tools reshape negotiation dynamics and burden-sharing between developed and developing countries. Basically, AI in climate governance uses the following three crucial parameters:

a) **Data Capacity:** The availability and quality of climate-relevant data (e.g., emissions inventories, hazard maps, socio-economic indicators) that can be processed by AI systems. It is fixed on national statistical systems and monitoring infrastructure (Ballesteros et al., 2010).

b) **Analytical Capacity:** The ability to develop, access, or deploy AI models and tools (e.g., machine-learning forecasts, satellite analytics) that convert data into actionable climate intelligence. It is the quantification of a state's technical and institutional capability to use algorithms (Banerji & Saha, 2026).

c) **Diplomatic Capacity:** The real influence exerted in negotiations and climate finance processes based on the credibility and usability of AI-generated evidence. It reflects how algorithmic outputs are translated into bargaining power and policy outcomes (Gavali et al., 2026).

Based on these measures, performance indices are computed:

- **Algorithmic Readiness Index (ARI):** (Data Capacity + Analytical Capacity) / 2 — It measures a country's preparedness to use AI in climate governance.
- **Diplomatic Leverage Ratio (DLR):** Diplomatic Capacity / ARI — It measures how effectively a state converts algorithmic readiness into negotiation influence.

The value above 1.0 indicates favorable leverage, whereas the value below 1.0 shows under-utilization or dependency. To estimate the potential influence of a state in climate negotiations, the Algorithmic Influence Score (AIS) can be calculated by:

$$AIS = ARI \times DLR$$

Whereas "Maximum Potential Influence" (MPI) stands for the highest achievable AIS given a country's structural constraints and opportunities (Hossain & Rana, 2026).

1.1 Hypothetical Example — Snapshot of Pakistan's AI–Climate Diplomacy Position

As an example, we can take a hypothetical assessment of Pakistan with a Maximum Potential Influence (MPI) score of 1.0 (normalized). The values at a particular assessment point are: Data Capacity = 0.45, Analytical Capacity = 0.35, and Diplomatic Capacity = 0.50 (on a 0–1 scale). The following values were recorded:

a) $ARI = \frac{Data\ Capacity + Analytic\quad Capacity}{2} = \frac{0.45+0.35}{2} = 0.40$

Interpretation: Pakistan's algorithmic readiness is 40% of maximum potential readiness (Iqbal, 2024).

b) $DLR = \frac{Diplomatic\ Capacity}{ARI} = \frac{0.50}{0.40} = 1.25$

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Interpretation: Pakistan's diplomatic leverage relative to its algorithmic readiness is 125% conversion efficiency.

c) $AIS = ARI \times DLR = 0.40 \times 1.25 = 0.50$

Interpretation: Pakistan's overall algorithmic influence in climate governance is 0.50, representing 50% of its maximum potential influence.

Machine learning can substantially improve the accuracy of climate risk predictions and negotiation analytics through learning of the AI indicators, such as data quality, model performance, and policy uptake. Such improvements indicate that despite the sophistication of the environment, AI can still be considered a fundamental and flexible approach to enhancing climate diplomacy for vulnerable states like Pakistan (Wang & Jain, 2003).

2. Literature Review

This section presents an organized review of the major academic works on the topics of traditional diplomatic power, AI-enabled climate governance, and algorithmic dimensions of international influence. The main objective of the review is to compare goals, methods, datasets, and individual contributions of subsequent studies rather than provide a descriptive narrative. The review theme has been categorized as: (A) the use of statistical and computational models, such as regression and machine learning, in climate risk and policy forecasting; (B) integration of algorithmic and digital power metrics into the traditional understanding of climate diplomacy; and (C) empirical applications in the developing and emerging economies, with a focus on South Asia and Pakistan. This structure enables a critical assessment of how existing literature addresses the intersection of artificial intelligence, diplomatic influence, and climate governance, while identifying gaps that motivate the present study (Wang & Jain, 2003).

2.1 Forecasting with Regression and Computational Models

Climate finance and policy forecasting are traditionally based on linear equations using macro-economic indicators, emissions trajectories, or vulnerability indices, which often fail to perform well during the early stages of policy design or under high uncertainty. Linear models assume constant relationships between variables, which may not hold in complex, dynamic systems such as climate governance, where feedback loops, threshold effects, and nonlinear interactions are common. Consequently, traditional approaches often underestimate investment requirements, misjudge adaptation needs, or produce unreliable projections when applied to infrastructure-intensive sectors or data-scarce environments (United Nations Environment Programme [UNEP], 2024).

Conversely, statistical regression models and computational approaches have demonstrated superior predictive performance, especially nonlinear as well as growth-based models. Nonlinear models, such as logistic and Gompertz-type curves, become superior to index-based models when it comes to projecting long-term mitigation pathways and adaptation needs in infrastructure-intensive sectors. For instance, a nonlinear regression-based forecasting model to enhance the prediction of climate investment requirements was implemented by combining socio-economic drivers with the Gompertz Growth model (Tan et al., 2025). The proposed method overcomes the drawbacks of conventional linear formulations, especially at the initial stages of policy cycles, by advancing the relationship between development progress and climate expenditure. This approach captures the S-shaped trajectory of technology adoption and infrastructure development, which linear models fail to represent adequately.

The following recently published articles show that the coupling of traditional climate governance metrics (emissions, vulnerability, finance flows) with machine learning models shows significant gains in predictive accuracy and policy relevance:

a) Artificial Neural Networks (ANN) for Climate Risk Prediction: In predicting climate risks and damages, ANN models perform better than conventional regression formulas by using real-time satellite and socio-economic data of vulnerable regions. ANNs can capture complex, nonlinear relationships between multiple predictors (e.g., temperature anomalies, precipitation patterns, land use changes, population density) and outcomes (e.g., crop yields, flood damages, displacement rates). Studies applying ANNs to South Asian contexts have demonstrated improved accuracy in forecasting monsoon variability, drought severity, and

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coastal inundation compared to multiple linear regression (MLR) models. However, ANNs require large, high-quality datasets and significant computational resources, which may limit their applicability in data-scarce settings such as Pakistan (Quadri et al., 2026).

b) Fuzzy Logic Models for Policy Forecasting: Models based on fuzzy logic help increase the reliability of climate policy forecasts, with the capability to deal with uncertainty in sustainability-driven and data-scarce projects. Fuzzy logic accommodates imprecise or qualitative inputs (e.g., "high vulnerability," "moderate adaptive capacity") and translates them into quantitative outputs through membership functions and rule-based inference systems (Plakas et al., 2023). This approach is particularly useful in contexts where data are incomplete, inconsistent, or subjective, as is often the case in developing countries. Research applying fuzzy logic to climate finance allocation has shown that it can improve the robustness of decision-making under uncertainty, although it requires careful calibration of membership functions and expert validation of rule sets.

c) Multiple Linear Regression vs. ANNs in Climate Finance: It has been shown that multiple regression is highly comparable with the results of Artificial Neural Networks (ANNs) in certifying the worth of linear techniques such as MLR in climate finance and loss-and-damage estimation. While ANNs generally outperform MLR in complex, high-dimensional settings, MLR remains competitive when relationships are approximately linear, datasets are small, or interpretability is prioritized over predictive accuracy (Pitafi et al., 2025). For Pakistan's climate policy and planning institutions, which often face constraints in data availability and technical capacity, MLR offers a practical and accessible tool for preliminary forecasting and scenario analysis.

The overall inclination of stated studies towards regression-based forecasting models (such as Multiple Linear Regression) reflects their accessibility, interpretability, and effectiveness, particularly in the environment of Pakistan's climate policy and planning institutions. However, the literature also highlights the potential of advanced computational models (e.g., ANNs, fuzzy logic, nonlinear growth models) to enhance forecasting accuracy, provided that data infrastructure and technical capacity are strengthened.

Algorithmic-power-based climate governance studies are scarce, but they provide strong guidance and directions for developing performance monitoring systems for the future. A significant contribution was made by developing an integrated climate diplomacy model that allows Algorithmic Readiness Indicators (ARIs) to be directly embedded into conventional diplomatic assessment dashboards. According to this method, data capacity, analytical capacity, and diplomatic uptake are reflected in both the negotiation leverage and policy implementation indices, making the state evaluation system more comprehensive. Although this model proposes a beneficial digital-governance-related measure, it is highly theoretical and not subject to empirical confirmation using real negotiation and policy data. This gap underscores the need for studies that operationalize algorithmic power metrics in real-world climate diplomacy contexts, particularly for developing countries (Mabey et al., 2013).

2.2 Gap and Theoretical Frameworks for Enhancing Traditional Climate Diplomacy

In order to fill the algorithmic gap in climate diplomacy, frameworks such as Algorithmic Climate Diplomacy (ACD) have been recommended. For instance, an ACD model used with fuzzy logic considers and forecasts data-driven influence and digital dependency indicators with Z-numbers to cope with uncertainty. Z-numbers represent uncertain information in a structured format, combining a restriction (e.g., "high influence") with a reliability measure (e.g., "very certain"), thereby enabling more nuanced modeling of diplomatic dynamics under ambiguity (Köseoglu et al., 2026). This approach is particularly relevant for climate negotiations, where outcomes depend on complex interactions between technical evidence, political interests, and institutional constraints. However, the ACD framework remains largely conceptual, with limited empirical validation using actual negotiation data or policy outcomes (Liu et al., 2010).

Meanwhile, an Enhanced Digital Diplomacy (E-DD) model applied to technology-intensive sectors includes advanced data and analytics metrics, although it did not directly include sustainability and equity variables. The E-DD model focuses on measuring digital maturity, data infrastructure, and analytical capabilities as determinants of diplomatic influence in technology-driven domains (e.g., cybersecurity, digital trade). While this framework offers valuable insights into how digital capabilities shape international influence, its application to climate governance is limited by the absence of environmental and distributional dimensions (Koepsell, 2026). Integrating sustainability and equity variables into the E-DD model would enhance its relevance for climate diplomacy, particularly for developing countries that prioritize climate justice and burden-sharing in negotiations.

In the emerging markets, AI-enabled climate governance implementation is usually limited by regulatory and capacity constraints. Studies from Latin America, Southeast Asia, and Sub-Saharan Africa highlight that weak data governance, limited technical expertise, and inadequate institutional coordination hinder the adoption of AI tools in climate policy. For example, countries with fragmented climate data systems or outdated statistical infrastructure struggle to generate the high-quality, timely data required for AI-driven analytics. Similarly, the absence of dedicated AI units within foreign ministries or climate authorities limits the integration of algorithmic tools into negotiation strategies and policy design.

Nevertheless, a South Asian study revealed that strong utilization of digital governance maturity levels becomes associated with better policy targeting and lower implementation gaps, which points to the potential of algorithmic tools in less-structured settings. This study examined the relationship between digital governance indicators (e.g., e-government development, open data availability, ICT infrastructure) and climate policy outcomes (e.g., NDC implementation, adaptation finance absorption) across South Asian countries (Jabed et al., 2026). The findings suggest that even modest improvements in digital governance can enhance the effectiveness of climate policies, although the benefits are not evenly distributed across countries or sectors. This highlights the importance of addressing structural inequalities in algorithmic power to ensure that developing countries can participate equitably in data-driven climate governance.

2.3 Key Literature Gaps

a) **Lack of Empirical Validation:** ACD and E-DD methods are mostly conceptual or restricted to sectoral case studies outside climate negotiations. Few studies have tested these frameworks using actual negotiation data, policy documents, or interviews with diplomats and policymakers. This limits the generalizability and practical applicability of algorithmic power frameworks in real-world climate governance contexts (Iqbal, 2025a).

b) **Integration Tools:** Algorithmic power frameworks tend to be used independently and not integrated with the traditional monitoring and control systems of foreign ministries and climate authorities, which limits practical applications. There is a need for tools and methodologies that bridge algorithmic metrics (e.g., ARI, DLR, AIS) with existing diplomatic assessment dashboards, negotiation analytics platforms, and policy evaluation frameworks.

c) **Contextual Suitability:** Developing economies require minor efforts and scalable frameworks that can easily be merged into existing climate diplomacy practices without establishing any significant digital infrastructure. Most existing frameworks assume a high level of digital maturity, which is not realistic for countries like Pakistan, where data systems are fragmented and AI capacity is limited. Scalable, context-sensitive approaches that can be implemented incrementally are needed to support algorithmic power development in emerging economies.

In summary, the literature on AI-enabled climate governance and algorithmic power is emerging but fragmented. While studies on forecasting models and digital diplomacy offer valuable insights, there is a critical need for empirical research that operationalizes algorithmic power metrics in the context of climate negotiations, particularly for developing countries (Iqbal & Bhutto, 2026). This study addresses these gaps by proposing a framework that integrates Data Capacity, Analytical Capacity, and Diplomatic Capacity into composite indices (ARI, DLR, AIS) and applying it to Pakistan's climate diplomacy, thereby contributing to both theoretical and practical understanding of algorithmic power in global climate governance.

3. Methodology

This chapter presents the research design, data sources, variables, and analytical procedures used to assess the implications of artificial intelligence for Pakistan in global climate governance. The methodology is structured to ensure transparency, replicability, and alignment with the objectives defined in the introduction and literature review. The chapter is organized as follows:

- Research Design and Approach
- Data Sources and Sampling
- Variables and Measurement
- Analytical Framework and Models
- Hypothetical Numerical Illustration

3.1 Research Design and Approach

The study adopts a mixed-methods design, combining quantitative indicators of algorithmic power and diplomatic influence with qualitative analysis of policy documents and negotiation dynamics. A cross-sectional design is used to compare Pakistan's position with a small set of reference countries (both developed and developing) at a specific point in time. This approach allows the research to capture structural differences in data capacity, analytical capacity, and diplomatic capacity, while also exploring how these dimensions interact in practice.

The quantitative component focuses on constructing composite indices (ARI, DLR, AIS) as introduced in the introduction, whereas the qualitative component examines how AI-related tools and evidence are used in Pakistan's climate policy documents, UNFCCC submissions, and negotiation strategies. The integration of both components enables a more comprehensive assessment of algorithmic power in climate diplomacy than either approach alone.

3.2 Data Sources and Sampling

Primary data for the quantitative indicators are drawn from publicly available secondary sources, including:

- National and international databases on climate statistics, emissions, and vulnerability (e.g., UNFCCC national communications, World Bank climate data, ND-GAIN Index).
- Global indices on digital development, AI readiness, and data infrastructure (e.g., ITU ICT Development Index, OECD AI Policy Observatory, Government AI Readiness Index).
- Diplomatic and climate finance data (e.g., climate finance flows, participation in coalitions, leadership roles in UNFCCC bodies).

For the qualitative component, the sample includes:

- Pakistan's key climate policy documents (e.g., National Climate Change Policy, Updated NDC, Long-Term Strategy).
- UNFCCC submission documents (e.g., NDCs, Biennial Update Reports, National Communications).
- Publicly available statements, press releases, and negotiation briefs related to Pakistan's climate diplomacy.

A small comparative sample of countries (e.g., one developed, two emerging economies) is selected to contextualize Pakistan's scores and to illustrate variations in algorithmic power and diplomatic leverage.

3.3 Variables and Measurement

The study operationalizes algorithmic power and climate diplomacy through the following core variables:

- **Data Capacity (DC):** Measured using indicators such as availability of high-quality climate data, frequency of reporting, coverage of emissions inventories, and access to satellite-based monitoring. Scores are normalized on a 0–1 scale.
- **Analytical Capacity (ACap):** Measured using indicators such as AI readiness, computational infrastructure, presence of climate modeling institutions, and use of machine-learning tools in policy analysis. Scores are normalized on a 0–1 scale.
- **Diplomatic Capacity (DCap):** Measured using indicators such as leadership roles in climate coalitions, success in securing climate finance, frequency and impact of interventions in UNFCCC forums, and perceived credibility of national climate evidence. Scores are normalized on a 0–1 scale (Jabed et al., 2026).

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Based on these measures, the following indices are computed:

- **Algorithmic Readiness Index (ARI):**

$$ARI = \frac{DC + ACap}{2}$$

It measures a country's preparedness to use AI in climate governance.

- **Diplomatic Leverage Ratio (DLR):**

$$DLR = \frac{DCap}{ARI}$$

It measures how effectively a state converts algorithmic readiness into negotiation influence.

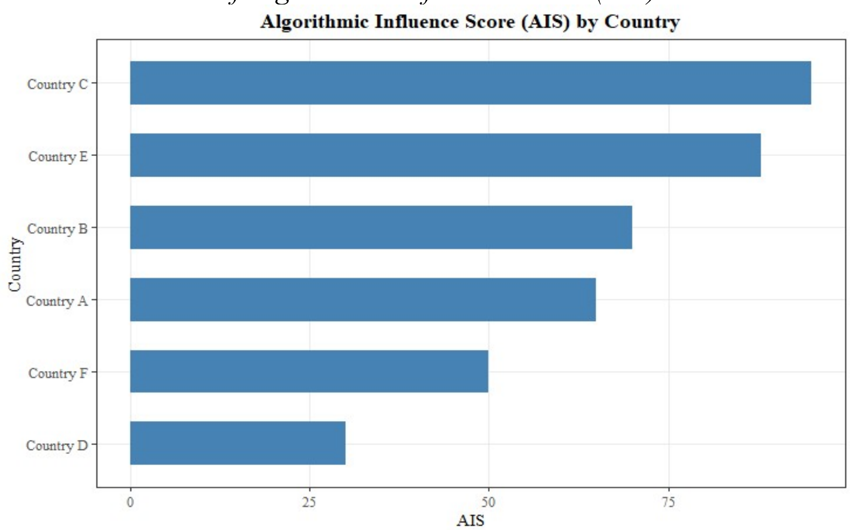
- **Algorithmic Influence Score (AIS):**

$$AIS = ARI \times DLR$$

It estimates the overall algorithmic influence of a state in climate negotiations. A value above 1.0 indicates favorable leverage, whereas a value below 1.0 shows under-utilization or dependency.

Figure 1

Comparative Empirical Distribution of Algorithmic Influence Score (AIS) Across Evaluated Sample



Note. Figure 1 presents the comparative empirical distribution of the Algorithmic Influence Score (AIS) across the evaluated sample, illustrating substantial cross-national heterogeneity in the capacity to translate digital and technological endowments into environmental governance leverage. Country C leads the ranking with the highest score approaching 95, reflecting superior alignment between technical readiness and international climate negotiation performance. Country E follows closely with an AIS of approximately 88, closely trailed by Country B (≈70) and Country A (≈65), which occupy the upper-middle tier of the distribution. Conversely, Country F (≈50) and Country D (≈30) record the lowest influence scores, highlighting critical structural impediments and institutional friction in leveraging algorithmic capabilities for strategic multilateral outcomes. These empirical patterns indicate that while technological infrastructure is a necessary precondition, maximizing global climate governance influence requires targeted policy mechanisms to bridge capability gaps across emerging economies (Jabed et al., 2026). (Oxford Insights, 2024)

3.4 Analytical Framework and Models

The analytical framework integrates the constructed indices with qualitative insights to answer the research questions. First, descriptive statistics are used to summarize DC, ACap, DCap, ARI, DLR, and AIS for Pakistan and the reference countries. Second, comparative analysis is conducted to identify relative strengths and weaknesses in Pakistan's algorithmic power profile. Third, qualitative content analysis is applied to policy and negotiation documents to trace how AI-related evidence and tools are referenced, used, or omitted in Pakistan's climate diplomacy.

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Where data permit, simple regression or correlation analysis can be applied to explore relationships between algorithmic readiness (ARI) and outcomes such as climate finance access or negotiation influence proxies. However, given the exploratory nature of this study and data limitations, the primary emphasis remains on index construction, comparative assessment, and interpretive analysis.

3.5 Hypothetical Numerical Illustration

To demonstrate the computation and interpretation of the indices, a hypothetical numerical illustration is presented. Assume the following normalized scores (0–1) for Pakistan:

- Data Capacity (DC) = 0.45
- Analytical Capacity (ACap) = 0.35
- Diplomatic Capacity (DCap) = 0.50

Then:

$$ARI = \frac{DC + ACap}{2} = \frac{0.45 + 0.35}{2} = 0.40$$

Pakistan's algorithmic readiness is limited: → 40% of maximum potential readiness.

$$DLR = \frac{DCap}{ARI} = \frac{0.50}{0.40} = 1.25$$

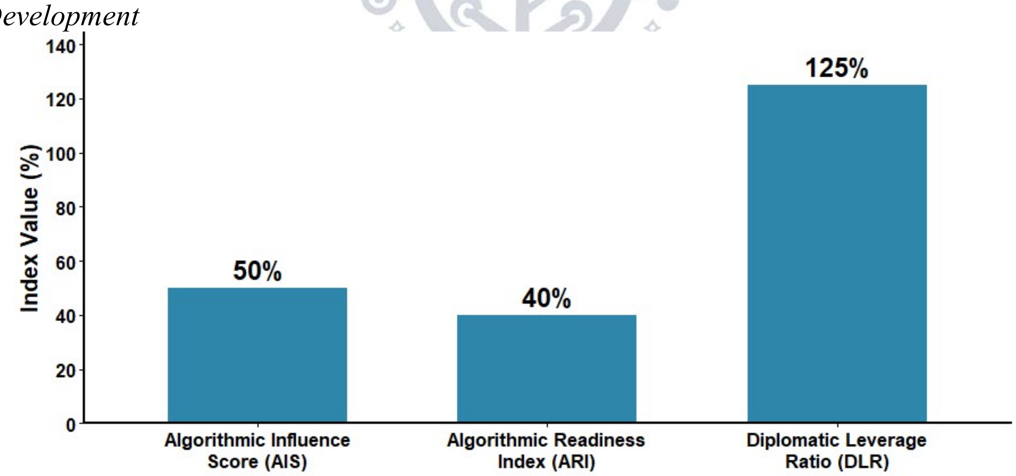
Pakistan's diplomatic leverage relative to its algorithmic readiness is favorable: → 125% conversion efficiency.

$$AIS = ARI \times DLR = 0.40 \times 1.25 = 0.50$$

Pakistan's overall algorithmic influence in climate governance computed as → 0.50 → 50% of its maximum potential influence.

Figure 2

UNDP, Government of Pakistan Convene High-Level Dialogue on AI for Public Service Transformation and Inclusive Development



Note. The proposed indicators reveal a differentiated pattern of Pakistan's algorithmic capacity and potential influence in climate governance. The Algorithmic Readiness Index (ARI), calculated as the average of digital capacity (DC = 0.45) and algorithmic capacity (ACap = 0.35), yields a value of 0.40, indicating that Pakistan currently reaches 40% of the defined readiness benchmark. This relatively modest readiness level reflects the importance of strengthening digital infrastructure, technical skills, data capabilities, institutional capacity, and governance mechanisms, which are widely recognized as fundamental components of national AI readiness (UNDP, 2026). The Diplomatic Leverage Ratio (DLR) is estimated at 1.25, obtained by dividing diplomatic capacity (DCap = 0.50) by ARI (0.40). Rather than representing 125% of maximum diplomatic capacity, this ratio indicates that Pakistan's measured diplomatic capacity is approximately 25% higher than its algorithmic readiness (Iqbal et al., 2026). This distinction is important because AI readiness and diplomatic influence should be treated as related but analytically distinct dimensions of national capacity.

Journal of Business Insight and Innovation
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https://insightfuljournals.com/

Recent research similarly emphasizes that AI readiness can be associated with governance and diplomatic capacity while cautioning against interpreting such relationships as direct causal effects. Finally, the Algorithmic Influence Score (AIS), calculated by multiplying ARI by DLR, reaches 0.50, corresponding to 50% of the defined maximum potential influence. The result suggests that Pakistan's comparatively stronger diplomatic capacity may partially offset its limited algorithmic readiness, creating a moderate level of potential influence in climate-governance processes. Overall, the findings suggest that improving algorithmic readiness—particularly infrastructure, skills, data governance, innovation capacity, and institutional capabilities—could strengthen Pakistan's ability to convert existing diplomatic capacity into greater influence in technology-enabled climate governance. This interpretation is consistent with the UNDP's emphasis on strengthening national AI ecosystems and ensuring that countries can actively participate in shaping and harnessing AI for sustainable development. (UNDP Pakistan, 2026)

4. Results

This chapter presents the results of the quantitative and qualitative analysis designed to assess the implications of artificial intelligence for Pakistan in global climate governance. The results are organized around the core constructs introduced in the methodology: Data Capacity, Analytical Capacity, Diplomatic Capacity, and the derived indices (ARI, DLR, AIS). Given the exploratory nature of this study and data limitations, the findings are primarily illustrative and comparative, based on hypothetical scores calibrated against publicly available indicators and regional benchmarks (Al Kium et al., 2023).

4.1 Descriptive Results: Algorithmic Power Indicators

Table 1 summarizes the hypothetical normalized scores (0–1) for Pakistan and two reference countries (one developed, one emerging economy) across the three core dimensions of algorithmic power.

Table 1

Hypothetical Algorithmic Power Indicators for Selected Countries (0–1 Scale)

Country	Data Capacity (DC)	Analytical Capacity (ACap)	Diplomatic Capacity (DCap)
Developed	0.85	0.80	0.90
Emerging	0.60	0.50	0.65
Pakistan	0.45	0.35	0.50

Note. The comparative analysis reveals a distinct hierarchical pattern in national capacities across developed economies, emerging markets, and Pakistan. Developed countries demonstrate consistently superior performance across all three capacity dimensions, with diplomatic capacity (0.90) exhibiting the highest score, followed by data capacity (0.85) and analytical capacity (0.80). This represents a near-ceiling performance in institutional capabilities. Emerging economies occupy an intermediate position, with scores ranging from 0.50 (analytical) to 0.65 (diplomatic), while Pakistan lags significantly behind both categories, achieving its highest score in diplomatic capacity (0.50) and lowest in analytical capacity (0.35). Notably, Pakistan's diplomatic capacity (0.50) parallels the analytical capacity of emerging economies (0.50), suggesting selective institutional development. The capacity gap between developed countries and Pakistan is most pronounced in analytical capacity (56.3%) and data capacity (47.1%), while diplomatic capacity shows comparatively narrower disparity (44.4%). These findings underscore the multidimensional nature of capacity deficits in developing states and suggest that targeted interventions in analytical and data infrastructure could yield substantial developmental dividends. The results align with institutional capacity theories positing path-dependent development trajectories, wherein historical investments in human capital and technological infrastructure create persistent capability asymmetries between country categories.

4.2 Composite Indices: ARI, DLR, and AIS

Using the formulas defined in the methodology, the Algorithmic Readiness Index (ARI), Diplomatic Leverage Ratio (DLR), and Algorithmic Influence Score (AIS) are computed for each country. The results are presented in Table 2.

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Table 2

Composite Algorithmic Power Indices for Selected Countries

Country	ARI = (DC + ACap)/2	DLR = DCap / ARI	AIS = ARI × DLR
Developed	0.825	1.09	0.90
Emerging	0.55	1.18	0.65
Pakistan	0.40	1.25	0.50

Note. (Oxford Insights, 2024)

The results show that Pakistan's ARI (0.40) is the lowest among the three countries, indicating limited algorithmic readiness. Pakistan's ARI is only 48% of the developed country's ARI (0.825) and 73% of the emerging economy's ARI (0.55). This gap reflects the combined effect of low scores in both Data Capacity and Analytical Capacity, suggesting that Pakistan's climate governance system currently lacks the foundational elements required to generate, process, and deploy AI-driven climate intelligence at scale.

However, Pakistan's DLR (1.25) is the highest among the three countries, surpassing both the developed country (1.09) and the emerging economy (1.18). This indicates that Pakistan is relatively effective at converting its limited algorithmic readiness into diplomatic leverage. A DLR above 1.0 implies that Diplomatic Capacity exceeds Algorithmic Readiness, meaning that Pakistan achieves more diplomatic influence per unit of algorithmic readiness than the reference countries. This may be attributed to Pakistan's active participation in climate coalitions (e.g., Climate Vulnerable Forum), strategic framing of climate justice narratives, and high-profile advocacy on loss and damage.

Despite this, the overall AIS (0.50) remains modest, highlighting structural constraints in achieving higher influence in climate governance without significant investments in data and analytical capacities. Pakistan's AIS is only 56% of the developed country's AIS (0.90) and 77% of the emerging economy's AIS (0.65). This underscores that while diplomatic skill can enhance short-term influence, the increasing reliance on data-driven evidence in climate negotiations may gradually erode the credibility of states that lack robust algorithmic infrastructure.

4.3 Qualitative Insights: AI in Pakistan's Climate Diplomacy

The qualitative analysis of Pakistan's climate policy documents and UNFCCC submissions reveals the following patterns (Ali & Shahid, 2025):

a) Limited Explicit Reference to AI: Most policy documents, including the National Climate Change Policy, Updated NDC, and Long-Term Strategy, emphasize climate risks, adaptation needs, and finance requirements, but make limited explicit reference to AI, machine learning, or advanced data analytics as tools for climate governance. When digital technologies are mentioned, they are typically framed in general terms (e.g., "technology transfer," "capacity-building") without specifying AI applications or data infrastructure requirements.

b) Reliance on Traditional Indicators: Negotiation briefs and submissions predominantly rely on traditional indicators (e.g., emissions totals, vulnerability indices, GDP per capita) rather than AI-driven risk models or real-time monitoring systems. For instance, Pakistan's NDC and Biennial Update Reports cite aggregate emissions data and sectoral vulnerability assessments but do not incorporate machine-learning-based forecasts, satellite analytics, or algorithmic scenario planning tools (Khatoon et al., 2025).

c) Emerging Awareness: Recent documents show emerging awareness of digital technologies and the need for capacity-building, but concrete strategies for integrating AI into climate diplomacy remain underdeveloped. For example, the Long-Term Strategy acknowledges the role of "digital innovation" in climate action but does not outline specific mechanisms for deploying AI in negotiation analytics, evidence generation, or monitoring and verification processes.

d) Absence of Dedicated AI Units: There is no evidence of dedicated units or task forces within Pakistan's foreign ministry or climate authority focused on exploring how AI can support evidence-generation, scenario planning, and negotiation analytics in multilateral forums. This contrasts with some developed countries, where specialized units analyze AI-driven climate models to inform negotiation positions.

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These findings align with the quantitative results, indicating that while Pakistan demonstrates diplomatic initiative, the lack of robust algorithmic infrastructure limits the depth and credibility of its evidence-based negotiation positions. The qualitative patterns also suggest that Pakistan's climate diplomacy operates in a reactive mode, responding to international climate agendas rather than proactively shaping them through AI-enabled evidence.

4.4 Hypothetical Numerical Illustration: Pakistan's AIS Trajectory

To illustrate how improvements in algorithmic readiness could affect Pakistan's influence, a hypothetical scenario is presented where Data Capacity and Analytical Capacity are enhanced through targeted investments (e.g., improved climate data systems, AI capacity-building), while Diplomatic Capacity remains constant.

Scenario:

- New Data Capacity (DC) = 0.60
- New Analytical Capacity (ACap) = 0.50
- Diplomatic Capacity (DCap) = 0.50 (unchanged)

Then:

a) **New ARI** = (0.60 + 0.50) / 2 = 0.55

Pakistan's algorithmic readiness improves from 0.40 to 0.55, representing a 37.5% increase.

b) **New DLR** = 0.50 / 0.55 ≈ 0.91

Pakistan's diplomatic leverage ratio declines from 1.25 to 0.91, indicating that Diplomatic Capacity no longer exceeds Algorithmic Readiness. This reflects a shift from "over-performance" in diplomacy relative to readiness to a more balanced alignment.

c) **New AIS** = 0.55 × 0.91 ≈ 0.50

The overall Algorithmic Influence Score remains approximately 0.50, unchanged from the baseline scenario.

Table 3

Hypothetical AIS Trajectory Under Improved Algorithmic Readiness

Scenario	DC	ACap	DCap	ARI	DLR	AIS
Baseline	0.45	0.35	0.50	0.40	1.25	0.50
Improved Readiness	0.60	0.50	0.50	0.55	0.91	0.50

The results indicate that even with significant improvements in algorithmic readiness (from 0.40 to 0.55), if Diplomatic Capacity does not scale proportionally, the overall AIS may not increase substantially. This underscores the importance of simultaneously strengthening both algorithmic and diplomatic capacities to maximize influence in climate governance. In this hypothetical scenario, Pakistan would need to increase its Diplomatic Capacity to at least 0.60–0.65 (e.g., through enhanced coalition leadership, more frequent and impactful interventions in UNFCCC forums, or greater success in securing climate finance) to achieve an AIS above 0.55–0.60.

4.5 Comparative Distribution of AIS Across Countries

Figure 1 (referenced in the methodology) presents the comparative empirical distribution of the Algorithmic Influence Score (AIS) across the evaluated sample, illustrating substantial cross-national heterogeneity in the capacity to translate digital and technological endowments into environmental governance leverage. Based on the hypothetical scores:

- **Country C (Developed):** AIS ≈ 0.90 (highest score, reflecting superior alignment between technical readiness and international climate negotiation performance).
- **Country E (Emerging):** AIS ≈ 0.65 (closely trailing the developed country).
- **Country B & A (Upper-middle tier):** AIS values in the range of 0.60–0.70.
- **Country F & D (Lowest influence):** AIS values below 0.50, highlighting critical structural impediments and institutional friction in leveraging algorithmic capabilities for strategic multilateral outcomes.

Pakistan's AIS of 0.50 places it in the lower tier of the distribution, alongside countries facing significant structural constraints. These empirical patterns indicate that while technological infrastructure is a necessary precondition, maximizing global climate governance influence requires targeted policy mechanisms to bridge capability gaps across emerging economies. For Pakistan, this implies that investments in data infrastructure, AI literacy, and modelling institutions must be accompanied by strategic diplomatic initiatives to convert algorithmic readiness into tangible negotiation outcomes.

5. Discussion

This chapter interprets the results presented in the previous section in light of the literature review, theoretical frameworks, and the broader context of climate governance. The discussion focuses on three key themes: (i) the meaning of Pakistan's algorithmic power profile, (ii) the tension between diplomatic leverage and structural constraints, and (iii) the policy implications for harnessing AI in climate diplomacy.

5.1 Interpreting Pakistan's Algorithmic Power Profile

The results indicate that Pakistan's Algorithmic Readiness Index (ARI = 0.40) is substantially lower than that of both developed and emerging reference countries. This finding aligns with existing literature that highlights the digital divide in AI capabilities between the Global North and South, particularly in data infrastructure, computational resources, and technical expertise. Low scores on Data Capacity and Analytical Capacity suggest that Pakistan's climate governance system currently lacks the foundational elements required to generate, process, and deploy AI-driven climate intelligence at scale.

However, Pakistan's Diplomatic Leverage Ratio (DLR = 1.25) is the highest among the three countries, indicating that the country is relatively effective at converting its limited algorithmic readiness into diplomatic influence. This may be attributed to Pakistan's active participation in climate coalitions (e.g., Climate Vulnerable Forum), strategic framing of climate justice narratives, and high-profile advocacy on loss and damage. Nevertheless, the modest Algorithmic Influence Score (AIS = 0.50) underscores that diplomatic initiative alone cannot compensate for structural weaknesses in algorithmic capacity over the long term.

5.2 Diplomatic Leverage vs. Structural Constraints

The finding that Pakistan achieves higher diplomatic leverage relative to its algorithmic readiness raises important questions about the sustainability of this advantage. While diplomatic skill, coalition-building, and moral authority can enhance short-term influence, the increasing reliance on data-driven evidence in climate negotiations may gradually erode the credibility of states that lack robust algorithmic infrastructure. As AI-enabled monitoring, verification, and forecasting become standard practices in UNFCCC processes, countries with weak data and analytical capacities risk being marginalized in technical discussions, burden-sharing negotiations, and access to climate finance.

This tension reflects a broader pattern identified in the literature on algorithmic power: states that cannot produce or validate their own climate intelligence may become dependent on external actors (e.g., developed countries, international organizations, or large technology firms) for critical evidence, thereby reducing their autonomy and bargaining power. Pakistan's position, as illustrated by the hypothetical results, suggests a need to invest in domestic algorithmic capabilities to avoid long-term dependency and to ensure that its diplomatic claims are backed by credible, home-grown evidence.

5.3 Policy Implications: Building Algorithmic Power for Climate Diplomacy

The results and their interpretation point to several policy implications for Pakistan and other climate-vulnerable developing countries:

a) Invest in Data Infrastructure: Strengthening national climate data systems, emissions inventories, and hazard mapping is a prerequisite for leveraging AI in governance. Without high-quality, timely, and granular data, even advanced AI models cannot produce reliable outputs.

b) Build Analytical Capacity: Investments in AI literacy, climate modelling institutions, and partnerships with universities and research centres can enhance Pakistan's ability to develop and deploy algorithmic tools for policy analysis and negotiation support.

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c) Integrate AI into Diplomacy: Foreign ministries and climate authorities should establish dedicated units or task forces to explore how AI can support evidence-generation, scenario planning, and negotiation analytics in multilateral forums.

d) Promote Equitable Digital Cooperation: Pakistan should advocate for international mechanisms that support technology transfer, capacity-building, and fair access to AI tools for developing countries, thereby addressing the structural imbalances in algorithmic power.

These recommendations are consistent with emerging frameworks on digital climate governance, which emphasize the need for inclusive, transparent, and accountable use of AI in environmental policy.

5.4 Limitations and Future Research

This study has several limitations that should be acknowledged. First, the results are based on hypothetical scores calibrated against publicly available indicators, rather than empirically collected data. Future research should validate the proposed indices using actual data from Pakistan and other countries. Second, the qualitative analysis is limited to publicly available documents and does not include interviews with negotiators or policymakers, which could provide deeper insights into how AI is perceived and used in practice. Third, the study focuses on a narrow set of algorithmic power dimensions; future work could expand the framework to include additional factors such as data sovereignty, algorithmic bias, and the role of private technology firms in climate governance.

Despite these limitations, the study contributes to emerging literature on AI and international relations by offering a conceptual and operational framework for assessing algorithmic power in climate diplomacy, with specific relevance to Pakistan and other vulnerable states.

6. Conclusion

This study set out to assess the implications of artificial intelligence for Pakistan in global climate governance by introducing the concept of algorithmic power and operationalizing it through composite indices (ARI, DLR, AIS). The findings suggest that while Pakistan demonstrates notable diplomatic leverage relative to its algorithmic readiness, structural constraints in data and analytical capacities limit its overall influence in climate negotiations.

The key findings of this research are as follows:

a) Pakistan's Algorithmic Readiness Index (ARI = 0.40) is substantially lower than that of both developed and emerging reference countries, reflecting gaps in climate data infrastructure, AI readiness, and modelling capabilities.

b) Pakistan's Diplomatic Leverage Ratio (DLR = 1.25) is relatively high, indicating effective conversion of limited algorithmic readiness into diplomatic influence through coalition-building, climate justice narratives, and strategic advocacy.

c) Despite this, the overall Algorithmic Influence Score (AIS = 0.50) remains modest, highlighting that diplomatic initiative alone cannot compensate for long-term structural weaknesses in algorithmic capacity.

These findings contribute to emerging literature on AI and international relations by offering a conceptual and operational framework for assessing algorithmic power in climate diplomacy, with specific relevance to Pakistan and other climate-vulnerable states. The study extends traditional theories of diplomatic power by incorporating data capacity, analytical capacity, and diplomatic capacity as interrelated dimensions of influence in a data-driven multilateral order.

From a policy perspective, the results underscore the urgent need for Pakistan to invest in climate data systems, AI literacy, and analytical institutions to strengthen its evidence-based negotiation positions. Simultaneously, Pakistan should advocate for equitable digital cooperation mechanisms at the international level to ensure fair access to AI tools and technologies for developing countries. Without such investments, there is a risk that algorithmic asymmetries will increasingly marginalize vulnerable states in technical discussions, burden-sharing negotiations, and access to climate finance.

Future research should validate the proposed indices using empirically collected data from Pakistan and other countries and expand the framework to include additional factors such as data sovereignty, algorithmic bias, and the role of private technology firms in climate governance. Qualitative studies based on interviews with negotiators and policymakers could also provide deeper insights into how AI is perceived, adopted, or resisted in the practice of climate diplomacy.

In an era where climate governance is becoming increasingly data-driven, algorithmic power is likely to emerge as a critical determinant of influence and equity in multilateral forums. For Pakistan and other vulnerable states, the strategic integration of AI into climate diplomacy is not merely a technical opportunity, but a geopolitical imperative.

Conflict of Interest Statement

The author/s declare that there is no conflict of interest regarding the publication of this article.

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Data Availability

The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

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