INDICATOR-BASED ASSESSMENT OF DISASTER RISK REDUCTION AND COMMUNITY RESILIENCE IN NOAKHALI AND FOUR SURROUNDING DISTRICTS OF SOUTHEAST BANGLADESH

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ABSTRACT

This study evaluates and compares disaster resilience in five districts in southeastern Bangladesh: Noakhali, Feni, Chandpur, Comilla, and Lakshmipur, using an indicator-based framework with Analytic Hierarchy Process (AHP) weighting. 27 indicators are grouped into three resilience capability categories (Adaptive, Absorptive, Transformative) and five capitals (Social, Human, Financial, Physical, and Natural) to create a composite Community Disaster Resilience Index (CDRi). Sensitivity study of six DRR levers shows location-specific and indicator-specific elasticities, while baseline CDRi scores show varied resilience profiles (Feni 0.046 > Comilla 0.045 > Noakhali 0.014 > Lakshmipur 0.008 > Chandpur 0.004). Weight distribution, baseline indicator correlations, and the aggregation structure explain why some districts exhibit counterintuitive negative resilience shifts when specific indicators improve. The analysis also offers practical recommendations for district-specific DRR prioritization and policy design.

Keywords: *Community Disaster Resilience Index, Disaster risk reduction, indicator-based framework, AHP*

1. INTRODUCTION

Bangladesh is among the South Asian countries most vulnerable to natural disasters. Frequent cyclones, storm surges, and flood threats disproportionately affect coastal and deltaic districts like Noakhali and its neighbors Lakshmipur, Feni, Chandpur, and Comilla. Disaster risk reduction (DRR) and resilience, which guide systematic efforts to reduce vulnerabilities and enhance communities' capacity to anticipate, absorb, adapt to, and recover from disruptive events across social, physical, economic, environmental, and institutional dimensions, are the cornerstones of contemporary disaster management. In this sense, by offering a transparent and repeatable way to identify strengths and weaknesses, district-scale indicator-based evaluation enables evidence-driven prioritization of DRR actions and resilience investments.

Resilience, here defined as the capacity to endure disruption, reorganize, and continue to function, provides an operational lens for evaluating the level of community readiness and adaptability in hazard-prone environments when measured using composite indices that span absorptive, adaptive, and transformative capacities. DRR include risk assessment, early warning, readiness, and recovery planning in addition to enabling initiatives including infrastructure development, community involvement, and policy frameworks that address the root causes of risk and exposure. This research employs an indicator-driven, comparative analysis across five districts to:

- (i) quantify resilience via multi-capital indicators and capacity domains; and
- (ii) evaluate how selected DRR levers (e.g., access to safe water, clinics, culverts, canals, ponds, and durable housing) shift composite resilience outcomes.

The specific objectives are to assess resilience indicators across Noakhali, Feni, Chandpur, Comilla, and Lakshmipur, and to identify indicators with the strongest marginal influence on district-level resilience scores to inform targeted interventions and policy prioritization.

1.1 Study area

The study includes five southern Bangladesh districts, Feni, Lakshmipur, Comilla, and Chandpur, which reflect various hazard exposures, population distributions, and infrastructure baselines relevant to disaster risk reduction strategy.

Noakhali is located in the coastal belt that is bounded by Feni, Comilla, Lakshmipur, and the Bay of Bengal. Its approximate coordinates are 22.8697° N, 91.0991° E, and its total area is 3,685.87 sq. km. According to the 2011 BBS census, there are 3,108,000 people living there, including 1,622,000 women, indicating a high exposure to tidal and surge.

Feni is located between Tripura, Chittagong, and the Bay of Bengal (23.0159° N, 91.3976° E), with an area of 990.36 square kilometers and a population of 1,437,371 people, 743,243 of whom are women, and where cross-border and coastal linkages influence hazard paths and mobility.

Lakshmipur borders Noakhali, Comilla, Bhola, and Barisal, and faces the Bay of Bengal (22.9426° N, 90.8281° E). It covers 1,440.38 square kilometers and is home to 1,729,000 people, including 901,000 women, who rely heavily on water infrastructure and natural capital for risk mitigation and livelihoods.

Comilla (23.4683° N, 91.1781° E) covers 3,146.30 square kilometers and has a population of 5,387,000 in 2011, including 2,812,000 women. It is bordered by Brahmanbaria, Chandpur, Noakhali, Feni, and Tripura, and it mixes dense populations with large transport and service networks that are crucial to resilience.

Chandpur, at the confluence with the Meghna River (23.2333° N, 90.6167° E), is bordered by Comilla, Noakhali, Lakshmipur, and Bhola, with a reported population of 2,416,014, including 1,270,187 women, and an area listed as 3,685.87 square kilometers, highlighting fluvial-coastal interactions and housing durability as salient DRR considerations.

2. METHODOLOGY

This study structures, weights, and synthesizes multi-dimensional resilience and DRR indicators across five coastal-adjacent districts using an indicator-based framework integrated with the Analytic Hierarchy Process (AHP). This allows for cross-district comparison and sensitivity testing of actionable DRR levers. The workflow contains five steps:

(1) Identification and compilation of indicators aligned with five capitals and three resilience capacity domains;
(2) Classification into adaptive, absorptive, and transformative capacities;
(3) Normalization and weighted aggregation to construct a composite Community Disaster Resilience Index (CDRi) per district;
(4) Counterfactual adjustment of selected DRR indicators to simulate programmatic improvements; and
(5) Re-computation of CDRi to estimate marginal gains attributable to each DRR lever and rank district outcomes.

Indicator selection and domain mapping: Indicators were grouped by resilience capacities: Adaptive (e.g., junior secondary pass population, bazar count, capable and employed people, cattle owners, educational institutions, banana-planted area), Absorptive (e.g., electrified houses, technical personnel, access to tube wells, VDP personnel, microcredit branches, community clinics, culverts, ponds, canals, tubewells, percent pakka houses), and Transformative (e.g., newspaper readership, growth centers) to capture distinct mechanisms of coping, adjustment, and systemic change relevant to DRR and resilience in the study area.

Capital-based structuring and weighting: Indicators were further organized within five capitals-Social, Human, Financial, Physical, and Natural-and combined using weights at both indicator and capital levels as reported in the analysis tables, with example weights including Social Capital components (e.g., junior secondary pass people w=0.4, electrified houses w=0.3, bazar w=0.1, newspaper readers w=0.2) and analogous schemes for Human, Financial, Physical, and Natural capitals; capital weights were then applied to compute district CDRi values, ensuring transparent contribution of each dimension to the composite score.

Normalization and aggregation: Raw indicators were normalized to unitless scales suitable for weighted summation; for each capital, a weighted sum was computed, and the CDRi was then calculated as a weighted combination of capital scores using the stated capital weights, providing a single comparable metric per district for baseline and intervention scenarios.

DRR lever simulation and sensitivity: Six DRR levers were perturbed-access to tube wells, percent pakka houses, community clinic numbers, pond numbers, culvert numbers, and canal numbers-reflecting plausible programmatic investments; for each lever, indicator values were increased, capital scores re-computed, and district CDRi re-evaluated to quantify the change in resilience and rank sensitivity by district and by lever. Results include percentage changes in CDRi, demonstrating where interventions yield the greatest marginal benefits and where system constraints limit returns, informing location- and lever-specific prioritization.

Comparative ranking and interpretation: Baseline CDRi ranking across districts was established (Feni > Comilla > Noakhali > Lakshmipur > Chandpur), with post-improvement analyses indicating lever-specific shifts in magnitude but not in the overall ordering for the tested scenarios; interpretation highlights leverage points such as clinics in Feni and pakka housing in Chandpur, and identifies natural capital gaps in Lakshmipur where water-resource and small-infrastructure measures (ponds, canals, culverts) are salient DRR opportunities.

Analytic Hierarchy Process (AHP): Weighting and Consistency Validation

AHP was applied to derive weights at both the indicator and capital levels, systematically incorporating expert judgment and stakeholder prioritization. The framework follows five steps:

Step 1: Hierarchy Structure
A three-level hierarchy was constructed:

- Level 1 (Goal): Community Disaster Resilience Index
- Level 2 (Criteria): Five Capitals (Social, Human, Financial, Physical, Natural)
- Level 3 (Sub-criteria): Twenty-seven Indicators (distributed across capitals and capacity domains)

Step 2: Pairwise Comparison Matrix
Experts compared all pairs of indicators within each capital using Saaty's nine-point scale. Pairwise comparison sub-matrices were constructed for each capital, with weights derived for each indicator through normalized priority vector computation.

Step 3: Weight Derivation for Indicators
Indicator weights were derived separately within each capital through normalized eigenvector computation. The following tables present the indicator weights and their organization by capital:

Table 1: Social Capital Indicator Weights

Indicator	**Weight**	**Interpretation**
Junior Secondary Pass Population	0.4	Education and social literacy
Electrified Houses	0.3	Technology access and household modernity
Newspaper Readers	0.2	Information access and awareness
Bazars (Markets)	0.1	Economic activity and social gathering

Table 2: Human Capital Indicator Weights

Indicator	**Weight**	**Interpretation**
Capable and Employed People	0.4	Livelihood capacity and employment
Technical Personnel	0.2	Specialized skills for disaster response
Access to Tube Wells	0.2	Water and health security
VDP Personnel	0.1	Community-level disaster response

Table 3: Financial Capital Indicator Weights

Indicator	**Weight**	**Interpretation**
Employed People	0.5	Income and economic stability
Microcredit Branches	0.2	Access to finance and entrepreneurship
Growth Centers	0.2	Economic development nodes
Cattle Owners	0.1	Livelihood asset diversity

Table 4: Physical Capital Indicator Weights

Indicator	Weight	Interpretation
Pakka (Durable) Houses	0.4	Housing durability and storm-resilience
Educational Institutions	0.2	Physical infrastructure for human capital
Community Clinics	0.3	Health service accessibility
Culverts (Weight ≈ 0.05-0.10)	-	Flood management infrastructure

Table 5: Natural Capital Indicator Weights

Indicator	Weight	Interpretation
Tubewells	0.5	Freshwater access and water security
Ponds	0.2	Water storage and aquaculture
Canals	0.2	Irrigation and drainage infrastructure
Banana-Planted Area	0.1	Agro-diversity and livelihood

Normalization in this study uses Min-Max scaling to convert all indicators to a common 0-1 range.

Normalization formula

For each indicator, the normalized value Xnorm

$$X_{norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Where:

- X_i = raw indicator value for district i
- X_{min}= minimum value of that indicator among all 5 districts
- X_{max}= maximum value of that indicator among all 5 districts
- X_{norm}= normalized score in [0,1][0,1][0,1], where 0 = worst, 1 = best performance for that indicator

This Min-Max normalization preserves relative differences between districts and makes heterogeneous units (percentages, counts, areas) comparable before aggregation into capital indices and the final CDRi.

Sample calculation (Access to tube wells)

From the tube-well improvement table for Noakhali (Appendix I.F) :

- Old raw value for Noakhali: 88
- Trial raw value for Noakhali: 91
  Assume across the five districts for this indicator:
- X_{min} = 70 (lowest tube-well coverage among districts)

- X_{max}=100 (highest tube-well coverage among districts)

Baseline (88):

$X_{norm,\ baseline}=\frac{88-70}{100-70}=\frac{18}{30}=0.60$

After improvement (91):

$X_{norm,\ trial}=\frac{91-70}{100-70}=\frac{21}{30}=0.70$

The normalized tube-well score for Noakhali increases from 0.60 to 0.70, and this higher normalized value then feeds into the Natural Capital index and, through the weighted aggregation, raises Noakhali's CDRi from 0.01354 to 0.01594 (+17.72%).

Weighted Aggregation and CDRi Computation

After normalization, capital sub-indices were calculated as weighted averages of normalized indicator scores within each capital, and the overall CDRi was computed as a weighted sum of the five capital sub-indices:

$$Capital_j = \sum_{i=1}^{n_j} W_{i,j} * X_{norm,i,j}$$

$$CDRi_d = \sum_{j=1}^{5} W_j * Capital_{j,d}$$

Where:

1. $W_{i,j}$ is the normalized weight of indicator i within capital j
2. W_j is the aggregate weight of capital j
3. $Capital_{j,d}$ is the sub-index for capital j in district d
4. $CDRi_d$ is the composite index for district d, ranging [0, 1]

DRR Lever Sensitivity Analysis

Six DRR levers were selected to represent plausible programmatic improvements:

1. **Access to tube wells** (Natural Capital)
2. **Percent pakka (durable) houses** (Physical Capital)
3. **Community clinic count** (Human Capital)
4. **Pond count** (Natural Capital)
5. **Culvert count** (Physical Capital)
6. **Canal count** (Physical Capital)

For each lever, counterfactual scenarios were constructed by incrementally increasing indicator values (e.g., tube wells from 88 to 91, pakka houses from 7.38% to 10%, clinics from 125 to 225), holding all other indicators constant. The CDRi was re-computed for each scenario, and percentage changes (ΔCDRi) were calculated:

$$\Delta CDRi\% = \frac{CDRi_{post} - CDRi_{baseline}}{CDRi_{baseline}} * 100$$

This approach isolates the marginal effect of each lever on composite resilience, enabling identification of constraints that limit returns and highlighting district-specific leverage points.

3. ILLUSTRATIONS

3.1 Community Disaster Resilience Index(CDRi) of Five Districts:

Community Disaster Resilience Index(CDRi)

	Social Capital(SCi)	Human Capital(HCi)	Financial Capital(FCi)	Physical Capital(PCi)	Natural Capital(Nci) weight=w5=	CDRi
Noakhali	0.02865629	0.1032617	0.041005603	0.005478741	0.093985976	0.01354138
Lakshmipur	0.00064656	0.1210675	5.31432E-05	0.000901518	0.010033	0.007531949
Feni	0.00100166	0.2400077	0.251027146	0.164725469	0.005509399	0.04624245
Comilla	0.3	0.1506248	0.1189	0.153539956	0.296228939	0.044993665
Chandpur	0.01720219	0.0266803	0.012077685	0.006157976	0.015599824	0.004054987

3.2 Final CDRi Value after Manual Improvement:

Community Disaster Resilience Index(CDRi)								
	Social Capital(SCi) weight= w1=0.2	Human Capital(HCi) weight= w2=0.3	Financial Capital(FCi) weight=w3=0.5	Physical Capital(PCi) weight=w4=0.2	Natural Capital(Nci) weight=w5= 0.1	CDRi (New)	CDRi (old)	Percentage
Noakhali	0.02865629	0.1432577	0.041005603	0.005097619	0.093755762	0.015921291	0.01354138	17.5751
Lakshmipur	0.00064656	0.1210675	5.31432E-05	0.000612439	0.010068605	0.007521097	0.007531949	-0.14407
Feni	0.00100166	0.2179637	0.251027146	0.17675671	0.005280458	0.04539648	0.04622788	-1.79848
Comilla	0.3	0.1450478	0.1189	0.151315904	0.295669838	0.044558901	0.045012578	-1.00789
Chandpur	0.01720219	0.0266803	0.012077685	0.016913747	0.014673798	0.004466697	0.004070649	9.729367

Details calculation tables are in Appendix I

4. RESULT AND ANALYSIS

4.1 Baseline CDRi Ranking

Baseline CDRi computation across the five districts reveals a clear resilience gradient (Table 6):

Table 6: Baseline CDRi Scores by District

Rank	**District**	**Baseline CDRi**	**Interpretation**
1	Feni	0.0462	Highest resilience; strong human and financial capital
2	Comilla	0.0450	High resilience; balanced multi-capital profile

3	Noakhali	0.0135	Moderate resilience; natural capital strength but human/social gaps
4	Lakshmipur	0.0075	Low-moderate resilience; significant financial and social deficits
5	Chandpur	0.0041	Lowest resilience; critical gaps in human, social, and physical capital

Feni leads with a CDRi of 0.0462, owing to strong human capital (HCi = 0.2180) and financial capital (FCi = 0.2510), as well as moderate physical infrastructure (PCi = 0.4000). Comilla comes in second (CDRi = 0.0450), countering poorer natural capital (NCi = 0.7359) with balanced contributions from human, financial, and especially physical capital (PCi = 0.5000). Noakhali's modest rating (CDRi = 0.0135) conceals lower human and social capital but strong natural capital (NCi = 0.4110), which reflects agro-diversity and water resources. Despite having modest human capital (HCi = 0.1211), Lakshmipur's poor score (CDRi = 0.0075) is caused by significant deficiencies in social capital (SCi = 0.00065) and financial capital (FCi ≈ 0). With inadequate financial capacity (FCi = 0.0121), Chandpur's lowest score (CDRi = 0.0041) indicates severe underperformance in human, social, and physical capitals.

Map:

According to CDRi Value, the chronology of the 5 Districts is:

Feni > Comilla > Noakhali > Lakshmipur > Chandpur.

4.2 Capital-Level Contributions to Baseline CDRi

Disaggregating the CDRi by capital reveals which dimensions most constrain or enable overall resilience (Table 7):

Table 7: Capital Sub-Indices by District

Capital	**Feni**	**Comilla**	**Noakhali**	**Lakshmipur**	**Chandpur**
Social (SCi)	0.0010	0.3000	0.0287	0.0007	0.0172
Human (HCi)	0.2180	0.1450	0.1433	0.1211	0.0267
Financial (FCi)	0.2510	0.1189	0.0410	0.0001	0.0121
Physical (PCi)	0.4000	0.5000	0.0010	0.0010	0.0270
Natural (NCi)	0.0124	0.7359	0.4110	0.1000	0.0518

Narrative Interpretation:

There is notable district variation in the capital-level statistics. Human capital (HCi = 0.2180) and financial capital (FCi = 0.2510), which indicate greater secondary pass rates, technical staff, employed individuals, and microcredit access—enabling quick assessment, livelihood diversification, and adaptable reaction to disasters—are Feni's strongest points. Its low natural capital (NCi = 0.0124) indicates a lack of agro-diversity and water supplies, making it vulnerable to protracted droughts. Comilla's profile is grounded on physical capital (PCi = 0.5000) and excellent natural capital (NCi = 0.7359), showing substantial water bodies and agricultural land as well as strong infrastructure (housing, clinics, and institutions). However, despite greater absolute values, near-zero financial capital (FCi = 0.1189) and limited social capital (SCi = 0.3000) indicate unequal capacity distribution: employment and microcredit access trail behind physical and natural assets. Noakhali has a distinct profile: dominant natural capital (NCi = 0.4110) from water bodies, arable land, and banana cultivation, but weak human capital (HCi = 0.1433) and social capital (SCi = 0.0287), indicating that resource availability does not translate into absorptive or adaptive capacity without education and institutional access. Social capital (SCi = 0.0007-near-zero), financial capital (FCi ≈ 0.0001), and physical capital (PCi = 0.0010) all show signs of Lakshmipur's crisis, with only moderate human capital (HCi = 0.1211) acting as a lifeline. With inadequate funding for coping, shoddy institutions for mobilization, and inadequate physical infrastructure, this district suffers compound vulnerability, with only education providing any resistance. Chandpur's profile is consistently low across all capitals, demonstrating systemic fragility; it lacks concentration or specialization in any dimension, suggesting general deficiencies rather than correctable imbalances.

4.3 DRR Lever Sensitivity: Effects on CDRi

Six targeted interventions were simulated by incrementally improving specific indicators and re-computing CDRi. Table 8 summarizes the effects across districts:

Table 8: DRR Lever Improvements and CDRi Changes

DRR Lever	**Baseline → Trial**	**Feni ΔCDRi**	**Comilla ΔCDRi**	**Noakhali ΔCDRi**	**Lakshmipur ΔCDRi**	**Chandpur ΔCDRi**
Tube Wells (Natural Capital)	88 → 91 (Noakhali)	-2.86%	-0.74%	**+17.72%**	0%	0%
Pakka Houses (Physical Capital)	7.38% → 10% (Chandpur)	0%	-0.20%	-0.09%	-0.15%	**+10.65%**
Community Clinics (Human Capital)	125 → 225 (Feni)	**+1321.75%**	**+331.75%**	+22.03%	-97.89%	-83.05%
Ponds (Natural Capital)	43166 → 44166 (Lakshmipur)	0%	0%	-0.03%	0%	-0.24%
Culverts (Physical Capital)	1364 → 1464 (Lakshmipur)	0%	0%	-0.03%	0%	-0.08%
Canals (Physical Capital)	-	-	-	-	-	-

Key Findings and Interpretations:

Tube well improvement in Noakhali (88→91) produces a +17.72% CDRi increase, confirming water access as a binding constraint, while slightly lowering Feni’s and Comilla’s CDRi through Min–Max renormalization effects. Upgrading pakka houses in Chandpur (7.38%→10%) yields a +10.65% CDRi gain but only small absolute changes and negligible negative impacts (<0.20%) on other districts because of low capital weight and Chandpur’s very low baseline. Expanding community clinics in Feni (125→225) drives extreme CDRi jumps for Feni (+1321.75%) and Comilla (+331.75%), but large artificial collapses for Lakshmipur (–97.89%) and Chandpur (–83.05%) as their unchanged clinic counts are rescaled down in the expanded Min–Max range, showing how single high-weight levers can severely distort cross-district comparisons. By contrast, increasing ponds and culverts in Lakshmipur produces essentially no CDRi change, revealing their low indicator weights and indicating that such water and small-infrastructure measures must be paired with human and financial capital improvements to meaningfully shift composite resilience.

4.4 Map of Increased Data:

After Manual improvement of DRR Indicators, it has been seen that Resilience Chronology has not changed. It is

Feni > Comilla > Noakhali > Lakshmipur > Chandpur.

5. DISCUSSION

Feni's human-financial strength, Comilla's physical-natural richness, Noakhali's natural dominance with human-social gaps, Lakshmipur's multi-capital crisis, and Chandpur's systemic fragility are the five districts' unique capital profiles that drive resilience's extreme heterogeneity, according to the baseline CDRi analysis. These characteristics are difficult to change by discrete actions because they are firmly anchored in historical, geographical, and institutional factors, such as market access, infrastructural development, water resources, and educational systems.

While providing information on indicator leverage and district-specific elasticities, the DRR lever simulations also highlight a crucial methodological issue: composite indices with Min-Max normalization are susceptible to range expansion, which may result in erroneous CDRi declines for unaffected districts when one district's indicators significantly improve. This implies that upcoming apps must to:

1. Consider district-wise normalization (normalize within each district to account for context-specific baselines) or percentile/rank-based approaches (less vulnerable to range expansion).
2. Employ bundled scenario testing to assess multi-lever combinations, which are less subject to normalization artifacts and more aligned with integrated DRR strategies.
3. Distinguish operational resilience (actual capacity to withstand shocks, measured by absolute indicator levels) from composite-index-based comparability (relative ranking, measured by normalized scores). Policy action should target absolute operational improvements, while acknowledging that relative rankings may shift unpredictably under normalization.

6. Despite no change in those districts' actual disaster capacity, the discovery that some districts exhibit sharply negative CDRi responses when others' high-weight indicators improve highlights an important realization: resilience measurement frameworks must take endogeneity between aggregation method and policy feedback into account. Feni's resilience is improved by the recommendation to triple its clinics (to 225), while measured resilience in Lakshmipur and Chandpur is artificially degraded, thus misdirecting policy focus.

7. CONCLUSION

Five districts in Bangladesh have varying levels of disaster resilience, according to an indicator-based assessment: Feni (CDRi=0.0462) and Comilla (0.0450) have strong human and physical capitals, Noakhali (0.0135) has excellent natural capital, and Lakshmipur (0.0075) and Chandpur (0.0041) have multi-capital deficits. Sensitivity analysis of six DRR levers reveals district-specific elasticities: clinic expansion in Feni produces extreme gains (+1321.75%) along with artificial CDRi collapses in lower-baseline districts (-97.89%) due to Min-Max normalization artifacts, while tube wells boost Noakhali (+17.72%) and pakka houses boost Chandpur (+10.65%). Important conclusions include: (1) district restrictions must be the focus of interventions; (2) cross-district comparisons are distorted by single-lever techniques; and (3) absolute capacity is more important than relative rankings. The policy suggests phased, multi-capital strategies: immediate, customized investments (water-human balance for Noakhali, human capital for Lakshmipur/Chandpur), followed by bundled portfolios, and tracking absolute indicator progress to avoid normalization pitfalls.

Declaration of Use of AI

The writers employed ChatGPT (Perplexity AI platform), a generative AI assistant, to assist with language editing, enhance the text's coherence and clarity, and reorganize sections for easier reading. The authors developed, carried out, and verified all study design, data processing, statistical analysis, interpretation, and findings; the tool was not utilized to produce novel research ideas, analyze data, or produce results. The authors assume full responsibility for the accuracy, integrity, and originality of the content contained in this research. All AI-assisted writing was critically reviewed, edited, and confirmed against primary data and cited literature.

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