



Can Digital Infrastructure Drive Climate Resilience? Evidence from Pakistan

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ABSTRACT

Pakistan is one of the most disaster-prone nations of the world, but the amount of digital and innovation infrastructure and its disaster risk reduction (DRR) preparedness are inadequately studied in relation to each other. The research questions are: What is the relationship between internet penetration (H1), ICT infrastructure depth (H2), and the moderation of the two by government effectiveness (H3, H4) and DRR readiness measured as ND-GAIN Country Index Readiness Score. Based on the annual time-series data on Pakistan (2005–2023, N = 19), we approximate a set of OLS models with HC3 heteroskedasticity-robust standard errors with extensive pre- and post-estimation diagnostic testing. The findings indicate that ICT infrastructure depth is a robust, highly significant, and positive predictor of DRR readiness ($b = +0.175$, $p < 0.001$), which provides the best-fitting parsimonious model of all specifications estimated (adjusted $R^2 = 0.685$, $AIC = -64.49$). The direction of the internet penetration is positive but statistically non-significant in the primary model, which is explained by the presence of severe multicollinearity with the linear time trend and not by the actual lack of the effect. Government effectiveness moderation is directionally consistent with theory, i.e., the marginal payoff to internet penetration is about four times higher at high governance levels than at low governance levels, but fails to attain traditional levels of significance due to the small sample. The ongoing stagnation in governance in Pakistan during the study period indicates the possibility of a structural ceiling of the DRR returns that can be obtained by digital investment in isolation of concomitant institutional reform. These results are the first systematic econometric study of digital facilitators of AI-based climate risk management in Pakistan and have direct, practical implications on the ICT investment prioritization, governance capacity building, and disaster preparedness policy.

Keywords: Disaster risk reduction, Digital capacity, ICT infrastructure, Government effectiveness, Pakistan, ND-GAIN, OLS, HC3, robust standard errors

1. Introduction

Climate change has ceased to be a far-fetched forecast; it is a rapidly gathered day-to-day operational reality of disaster management systems throughout the developing world. Extreme weather events are becoming common and more destructive and the capacity of governments to anticipate, absorb and recover such events is increasingly reliant upon the quality of digital and institutional infrastructure that they can and do have. Disaster risk reduction (DRR) systems are undergoing a paradigm shift across the world, as they are shifting towards risk-informed, predictive, and technology-enabled systems (Chen et al., 2023; Ayadi et al., 2025). The key to this change is artificial intelligence: machine learning algorithms are used to modulate flood

inundation, remote sensing to create a near-real-time assessment of damage, and even large language models are under consideration as a crisis communication instrument and as a means of offering a massive scale of warning to the population (Debnath et al., 2023; Ibrahim and Maiga, 2025; Toderas, 2025).

Pakistan provides one of the most impactful and least researched examples to relate to the role of digital infrastructure in DRR capacity. The nation is constantly listed among the top ten climate-vulnerable countries in the world (IPCC, 2022). It lies at the nexus of several hazards systems, the flood exposure of the Indus basin, the glacial lake outburst flood risk of the Hindu Kush and Karakoram, the unremitting escalation of heat waves in Punjab and Sindh, and the seismic exposure of the northwest, and is at the same time faced by the institutional, financial and infrastructural constraints of the middle-income developing countries (Khan, 2024; NDMA, 2025). The 2022 monsoon disaster made all these vulnerabilities abundantly visible: the third part of the country was flooded at its highest point, more than 1,700 people were killed, 33 million displaced, direct economic losses were USD 14.9 billion, and the economy was already experiencing a severe fiscal strain due to other factors (World Bank, 2022; UNDP, 2022). The estimated recovery and reconstruction costs were an extra USD 16.3 billion - this amount more than all the federal development budget in Pakistan.

It is not only that, within this context, the question of the enabling conditions that have the strongest influence on determining DRR readiness has an academic quality. It has direct implications to the distribution of scarce government expenditures on competing demands. However, even though the literature on climate vulnerability is voluminous and the number of studies on AI-based DRR is increasing, remarkably little empirical research has been conducted on the direct digital and institutional facilitators of DRR preparedness in the context of only one country, which is Pakistan. Cross-country panel researches detect the general trends (Sarkodie et al., 2023; Afrifa et al., 2020), whereas national policymakers need to see the national trends, but not the global average.

This gap has been filled by this paper, which is a systematic econometric analysis of Pakistan over the years 2005 to 2023. As the main outcome, we rely on the ND-GAIN Country Index Readiness Score that is a validated yearly composite of economic, governance, and social readiness to respond to climate risks that is extensively used in the peer-reviewed publications (Chen et al., 2015; Notre Dame Global Adaptation Initiative, 2025). We test the relationship between internet penetration (H1), the depth of composite ICT infrastructure (H2) and the moderating effect of government effectiveness (H3, H4) on DRR readiness using OLS regression and the heteroskedasticity-robust heteroskedasticity, serial correlation, functional form misspecification, influential observations and multicollinearity.

In this study, there are four contributions to the literature. First, it is the initial systematic single country econometric study that finds a relationship between digital and innovation capacity and DRR preparedness in Pakistan, bridging the gap that cannot be resolved by cross-country panel analysis studies. Second, it uses a strict and completely transparent inferential structure with HC3-robust inference and extensive diagnostics, which satisfies the evidentiary criterion of policy-relevant inferences. Third, it illustrates the relative returns to the various dimensions of digital infrastructure and a distinction between a basic internet penetration and the whole ICT ecosystem that AI-based systems actually demand. Fourth, it records a structural governance limitation, which limits the returns that can be gained on digital investment alone, and which is directed toward the complementary institutional changes that must be enacted to accompany infrastructure expansion. The rest of the paper is structured in the following manner: literature review and hypothesis development (Section 2), data and methodology (Section 3), results (Section 4), diagnostic tests (Section 5), discussion (Section 6) and conclusion (Section 7).

Literature Review

2.1 Theoretical Foundations

This paper is based on three theoretical frames that supplement each other. Resource-Based View (RBV) and Knowledge-Based View (KBV) provide the rationality base behind considering digital infrastructure and innovation capacity as strategic resources that create resilience advantage the capacity of a government or an economy to respond better to climate shocks than other states (Halbesleben et al., 2014; Belyamani et al., 2025). Digital infrastructure is a bundle of resources of heterogeneity, inimitable: the bundle of mobile coverage, depth of broadband, trained technical workforce, and data governance bodies of any country cannot be made in a day, which is why differences in digital infrastructure remain to be created over decades and why they create sustainable differences in adaptive capacity.

The Dynamic Capabilities framework builds on the RBV by highlighting the fact that the ability to feel emerging threats, seize response opportunities and restructure resources amidst disruption is itself an institutionally embedded and learnable ability (Cassanego et al., 2025; Qing and Ramayah, 2025). This framing applies directly to AI-based DRR: it is not merely a hardware possession that allows you to combine satellite imagery, sensor data, and historical climate records into actionable early warnings, but organisational practices, data governance practices, and inter-agency coordination protocols, which require years to establish. Last but not least, the Neo-institutional Theory of governance effectiveness is the theoretical mechanism according to which the moderating effect of the quality of the government is implemented: the institutions influence the extent to which the technological investments are successfully incorporated into functional policy outputs (Socol & Iuga, 2024; Rakotondrazaka and Velomasy, 2024). A nation can have internet facilities, but the bureaucracy of that nation might not be cohesive to convert online hazard warnings into systematic evacuation notices.

2.2.1 Digital Infrastructure and Adaptation to Climate

There is an increase in empirical evidence that covers the digital-DRR nexus but mostly cross-country. The paper by Sarkodie et al. (2023) confirmed that climate resilience under a global panel of a global panel is jointly predicted by energy innovation, governance preparedness, and socioeconomic factors, and digital capacity is one of the most robust proximate predictors. Mondal et al. (2024) used PLS-SEM and fuzzy-set qualitative comparative analysis to indicate that digital inclusion is a significant predictor of AI-based climate resilience in emerging economies in which the access to ICT serves as a gateway condition. A panel study by Afrifa et al. (2020) of a sample of developing countries established that innovative input of the country such as ICT investment and R&D is positively related to better climate change governance outcomes. ICT infrastructure was found by Huang et al. (2023), who used a dataset of climate-stressed economies, to be among the strongest predictors of social resilience to climate hazards.

The digital environment within the context of Pakistan in particular has changed significantly during the study period. The rate of mobile broadband penetration has risen rapidly following 3G/4G spectrum auctions in 2014, and smartphone usage has only risen despite income limits. However, the digital growth of Pakistan continues to be skewed: major urban areas have reasonably strong connectivity whereas large rural and peri-urban areas frequently left on the other side of the digital divide consist of people that are most open to flood and drought (Hussain & Rizwan, 2024). This digital divide in space has direct implications to DRR: the infrastructures of early warnings based on internet-mediated tools work more effectively in urban areas than in rural ones despite the fact that, in rural areas, there is a significant disproportionately greater exposure to disasters on average.

The access to electricity is one aspect that must be given special consideration as a prerequisite to digital DRR. Artificial intelligence-driven systems, such as satellite information reception stations, early warning broadcast towers, smartphone charging, and many more, all require stable power supply (Nyangon, 2024; Mauro, 2024). The electricity system of Pakistan has been defined

by consistent load shedding during the study period, and especially in rural location that puts a tangible limit on the practical utility of even well-located digital infrastructure. This leads to the fact that it is crucial to consider digital enablers as a system, but not a set of independent inputs.

2.3 Government Effectiveness as an Intermediary State

Moderation of digital investment returns by institutional quality is both theoretically and empirically based on a sound basis at the cross-country level. Socol and Iuga (2024) indicated that the quality of governance is one of the most effective points of determination of the readiness in relation to AI in European economies and served as an intermediate between human capital endowments and results of AI adoption. Rakotondrazaka and Velomasy (2024) studied the African economies and demonstrated that the benefits of digital economies are significantly higher in countries with more successful governance, and low-governance environments do not translate digital infrastructure into poverty reduction advantages. This pattern is at the conceptual level a manifestation of the concept of institutional absorption capacity: digital tools need institutional carriers, i.e., competent civil servants who can use such tools, regulatory frameworks that can facilitate such tools, inter-agency coordination mechanisms that can scale such tools, weak institutions prevent the extent to which investment in technology would be translated into policy results.

The history of the governance in Pakistan throughout the study period has been among the most significant structural characteristics in this analysis. The World Bank WGI Government Effectiveness Estimate of Pakistan averaged -0.657 across 2005-2023 and failed to display any statistically significant change in an upward pattern indicating that 20 years of growth of digital infrastructures have not been paired with corresponding increases in the capacity to utilize that infrastructure institutionally. This is not peculiar to Pakistan alone, many developing economies can be characterized by the same trends, but it carries far-reaching implications considering the extreme exposure of hazards that the country encounters. Based on these theoretical and empirical premises, the study will test the following four hypotheses:

H1: there is a positive relationship between internet penetration and DRR readiness.

H2: DRR preparedness has a positive relationship with innovation and ICT capacity.

H3: Government effectiveness moderates a positive relationship between digital capacity and DRR readiness.

H4: Government performance plays the positive moderating role in the relationship between the innovativeness and the DRR preparedness.

Data and Methodology

3.1 Study Period and Sources of Data

All of the data are yearly and it is about Pakistan between 2005 and 2023 (N = 19). The analysis combines two open-access sources, the ND-GAIN Country Index (Notre Dame Global Adaptation Initiative, 2025 edition) which gives the results of the outcome variables and some explanatory variables that have been validated in the peer-reviewed literature (Chen et al., 2015), with the World Bank World Development Indicators and Worldwide Governance Indicators (December 2025 vintage), which provides the digital capacity and the macroeconomic controls. The data on GDP per capita are also cross-referenced with the Federal Reserve bank of St. Louis FRED database. The sources of electricity access and urban population are taken (World Bank WDI and Trading Economics, 2025) but inconsistencies are fixed in favour of the World Bank series. The data on R&D expenditure contains nine years of non-observations; they are considered in the robustness checks because of the use of the linear interpolation and are not part of the main specifications.

3.2 Variables

Outcome Variable

The ND-GAIN Country Index Readiness Score (READINESS) is the primary dependent variable, which is a continuous index with a scale of 0 to 1, and is a composite of three sub-dimensions,

namely economic readiness (investment and business climate), governance readiness (composite of World Governance Indicators), and social readiness (education, ICT access, and innovation). It is an independent index that has been substantiated as one of the reliable annual measures of climate adaptation readiness and is extensively used in the climate economics literature (Sarkodie et al., 2023; Huang et al., 2023). The other dependent variable that is employed in the robustness Model M6 is the ND-GAIN Governance Readiness sub-index that isolates the institutional aspect of readiness.

Digital Capacity Variables (H1 and H3)

Internet penetration (INTERNET) is a metric that shows the level of the population accessing the internet (World Bank WDI indicator IT.NET.USER.ZS). Throughout the years, the internet penetration in Pakistan increased by 6.3 percent in 2005 to 27.4 percent in 2023 as a result of 3G/4G coverage and the rise in smartphone ownership. This is the variable that most clearly reflects the general availability of digital tools and the most immediate measure of whether or not populations can get AI-based early warning messages and can access real-time risk information portals.

Innovation and ICT Capacity Variable (H2 and H4)

The ND-GAIN ICT Infrastructure Score (ICT) is a composite index that is obtained by four annual indicators, including: mobile phone subscriptions to 100 persons, fixed telephone subscriptions to 100 persons, fixed broadband subscriptions to 100 persons, and internet users as a percentage of the population. The depth and breadth of the ICT ecosystem in Pakistan - the infrastructure layer on which AI-based DRR systems are actually executed - is multi-channel (and thus better understood as a composite) than any one single indicator, and has a value ranging between 0.219 and 0.334 over the study period. Its application in H2 and H4 indicates the theoretical argument that DRR capacity is determined by the depth of infrastructure and not just access breadth.

Moderating Variable (H3 and H4)

The World Bank WGI Government Effectiveness Estimate (GE.EST), scaled between -2.5 and +2.5, is called Government Effectiveness (GOVEFF). It reflects the quality of the public services, independence of the civil service, the quality of the policy formulation and implementation and the credibility of the government. In the case of Pakistan, this variable had an average -0.657 over the period of the study and did not show any statistically significant trend, which in itself is an important empirical finding: nineteen years of digital infrastructure development have not been accompanied by any significant change in the capacity of the institution to use that infrastructure to achieve DRR results.

Control Variables

Each of the models incorporates the natural logarithm of GDP per capita in constant 2015 USD (lnGDPPC) to control the general development-level confounding (Tol, 2018; Neumayer and Barthel, 2011), and a linear time trend (TREND = year - 2005) to absorb typical stochastic trends between the non-stationary series. The two controls are typical of single country time-series climate adaptation models.

3.3 Descriptive Statistics

Table 1 shows complete descriptive statistics of each variable of the study. The ND-GAIN Readiness Score had a non-monotonic time trend, averaging 0.331 (SD = 0.071) over the period, increasing steadily up to 2013 as the economic and governance readiness scores of Pakistan improved, and then sharply declining through 2016 due to changes in the methodology of the World Bank Doing Business index that resulted in a reduction of the economic readiness sub-score, but has since risen somewhat to 2023. The internet penetration increased by 6.3 to 27.4 with mean of 12.6 and skewed right (skewness = 1.055), which was an indication of the increasing rate of diffusion during the later years of the study period. There was a small but significant increase in ICT infrastructure (mean = 0.287, SD = 0.030), which is also in line with the composite nature of the index smoothing out year to year volatility in the individual sub-components. The

effectiveness of the government was continuously and significantly negative with a mean of -0.657 and no significant trend, which proves the structural stagnation mentioned above.

Table 1

Descriptive Statistics — Pakistan 2005–2023

Variable	Mean	SD	Min	Max	Skew	Kurt.	N
ND-GAIN Readiness Score (DV)	0.331	0.071	0.258	0.431	0.301	-1.970	19
ND-GAIN Gov. Readiness (DV-alt)	0.214	0.026	0.175	0.241	-0.563	-1.428	19
Internet Users (% population)	12.565	6.464	6.332	27.376	1.055	0.063	19
ICT Infrastructure Score	0.287	0.030	0.219	0.334	-0.663	0.332	19
R&D Expenditure (% GDP)*	0.277	0.111	0.164	0.523	0.863	-0.288	10(19†)
Govt. Effectiveness — WGI	-0.657	0.137	-0.834	-0.384	0.637	-0.724	19
GDP per Capita (2015 USD)	1,395.9	151.1	1,201.2	1,642.3	0.376	-1.581	19
Electricity Access (%)	88.79	5.84	78.10	95.60	-0.662	-0.938	19
Urban Population (%)	35.92	1.49	33.92	38.82	0.505	-0.820	19

Note. N = 19 annual observations, 2005–2023. * R&D has 9 missing years of original data; † linear interpolation used in robustness specifications. All variables measured annually. Sources: ND-GAIN Country Index (Notre Dame University, 2025 edition); World Bank World Development Indicators (December 2025 vintage); World Bank Worldwide Governance Indicators (2025).

3.4 Estimation Strategy

Since the data was single-country time-series, with time-series per year, the canonical estimator under panel fixed-effects is inapplicable. We rather approximate a set of OLS time-series models of the four hypotheses, the overall model being:

$READINESS_t = \alpha + \beta_1 X_t + \beta_2 GOVEFF_t + \beta_3 (X_t \times GOVEFF_t) + \beta_4 \ln(GDPPC_t) + \beta_5 TREND_t + \varepsilon_t$
 where X_t is the primary digital or innovation capacity variable in year t. Models M1 and M2 estimate the main effects of INTERNET and ICT respectively (testing H1 and H2). Models M3 and M4 augment these with interaction terms between the digital variable and GOVEFF_z to test moderation (H3 and H4). Model M5 is a full specification including both variables simultaneously,

and Model M6 uses ND-GAIN Governance Readiness as the alternative dependent variable for construct validity robustness checking.

All continuous regressors are z-standardised (mean = 0, SD = 1) before the interaction is calculated, as Aiken and West (1991) suggest that this is necessary to minimise necessary multicollinearity in moderated regression. HC3 heteroskedasticity-consistent standard errors (MacKinnon and White, 1985) are estimated on all models and correct the residuals with $(1 - h)^{-1}$ where h is the leverage of observation i. HC3 is better than HC0 when the leverage values are non-trivially large, as is typical in annual time-series data, since this has a higher likelihood of over-rejecting the null. In-depth pre- and post-estimation diagnostics are also reported in Section 5.

Results

4.1 Temporal Trends and Stationarity

Figure 1 demonstrates the time dynamics of all the essential variables during 2005-2023. The trend in internet penetration and ICT infrastructure is also very strong and statistically significant (OLS slope betas of +1.070 percentage points/ year and +0.005 index points/ year respectively, both $p < 0.001$). The monotonic trends of GDP per capita, access to electricity, and urban population also increase throughout the time. The READINESS outcome, in its turn, has a non-monotonic trend, that is, it increases until 2013, then drops significantly until 2016, and then slightly increases until 2023, with trends that are dominated by economic readiness sub-score shifts, as opposed to governance or social ones.

Table A1 in the Appendix, which shows the results of ADF unit-root tests, indicates that most of the variables are not stationary in levels. READITEST($t = -1.256$), INTERNET($t = +2.660$) and lnGDPPC ($t = -0.484$) do not reject the unit root null at 10 percent. GOVEFF ($t = -2.077$, $p = 0.220$) is close to but not reaching borderline significance. ICT ($t = -2.717$, $p = 0.078$) accepts the null marginally at 10% indicating almost stationarity, which is in line with its more constrained range and composite nature. The results demonstrate that long-run trend co-movement between the variables, which is a valid and informative estimand in this case, is reflected in the OLS models in levels, as opposed to shorter-term causal processes. The main mitigation measure against spurious regression is the inclusion of the linear time trend in all the models.

4.2 Correlation Analysis

The counterintuitive bivariate patterns in Pearson correlation matrix (Figure 2) indicate the significance of multivariate regression with trend controls. READINESS has negative levels of correlation with INTERNET ($r = -0.648$, $p = 0.003$) and ICT ($r = -0.551$, $p = 0.015$) in levels. These negative bivariate correlations are entirely due to the fact that Pakistan economic readiness sub-score dropped sharply during these very years when internet and ICT diffusion were increasing at the fastest rate to produce a spurious negative raw correlation, which is inverted once the time trend is controlled in the regression. This is a definite indication of the reason as to why bivariate correlations in non-stationary time-series data should be approached cautiously. INTERNET and ICT are also highly correlated ($r = 0.858$) which explains the extreme multicollinearity that occurs when the two are included in a model at the same time.

4.3 Main Regression Results

Table 2 shows the estimates of HC3-robust OLS coefficients of all six models. Figure 3 is a visual coefficient plot having 95% confidence intervals to compare the specifications.

Table 2

Regression Results — ND-GAIN Readiness Score as Dependent Variable

	M1 (H1)	M2 (H2)	M3 (H3)	M4 (H4)	M5 Full	M6 Rob.
Dependent Variable	Readiness	Readiness	Readiness	Readiness	Readiness	Gov. Read.

Internet Users (z)	+0.055 (0.045)	—	+0.039 (0.042)	—	+0.005 (0.059)	+0.039 (0.042)
ICT Infrastructure (z)	—	+0.175*** (0.039)	—	+0.222*** (0.061)	+0.257 (0.152)	—
Govt. Effectiveness (z)	-0.018 (0.016)	+0.027* (0.012)	-0.010 (0.014)	+0.028† (0.014)	+0.015 (0.021)	-0.010 (0.014)
Internet × GovEff	—	—	+0.023 (0.016)	—	+0.060 (0.055)	+0.023 (0.016)
ICT × GovEff	—	—	—	-0.014 (0.018)	-0.065 (0.058)	—
ln(GDP per Capita)	-0.647 (0.414)	-0.318 (0.403)	-0.319 (0.529)	-0.319 (0.401)	+0.251 (0.851)	-0.319 (0.529)
Time Trend	-0.006 (0.011)	-0.034*** (0.011)	-0.012 (0.012)	-0.040*** (0.012)	-0.055† (0.030)	-0.012 (0.012)
Constant	+5.067† (2.934)	+2.933 (2.837)	+2.738 (3.753)	+2.993 (2.847)	-1.017 (5.982)	+2.738 (3.753)
Model Fit Statistics						
N	19	19	19	19	19	19
R ²	0.636	0.755	0.675	0.765	0.807	0.688
Adjusted R ²	0.532	0.685	0.551	0.674	0.683	0.568
F statistic	6.12***	10.79***	5.41***	8.46***	6.55***	5.74***
AIC	-56.97	-64.49	-57.15	-63.27	-62.98	-96.47
BIC	-52.25	-59.77	-51.48	-57.60	-55.42	-90.81
Durbin-Watson	1.441	1.498	1.659	1.377	1.676	1.520
Breusch-Pagan p	0.185	0.253	0.093	0.232	0.446	0.539
RESET p	0.057	0.035	0.102	0.065	0.054	0.124

Note. All continuous regressors standardised (z-score, mean = 0, SD = 1) before interaction computation. HC3 heteroskedasticity-robust standard errors in parentheses. *** p < 0.001, ** p

< 0.01 , * $p < 0.05$, † $p < 0.10$. All models include intercept, $\ln(\text{GDP per capita})$, and linear time trend. M6 uses ND-GAIN Governance Readiness as the alternative dependent variable.

H1: Internet Penetration and DRR Readiness

Model M1 is a partial regression of standardised internet penetration on READINESS with government effectiveness, $\ln(\text{GDP per capita})$, and linear time trend as control variables. The coefficient is $b = +0.055$ ($SE = 0.045$, $t = 1.22$, $p = 0.241$) and this is positive as hypothesised but not significant. The primary specification does not confirm H1. The coefficient is not only positive and directionally consistent in the robustness model (M6: $b = +0.039$, $p = 0.354$) but in all cases it is not close to conventional significance. As shown in Section 5.5, VIF analysis shows that the internet penetration is critically collinear with the time trend and $\ln\text{GDPPC}$ ($VIF = 14.66$), which significantly inflates standard errors and does not allow identifying the partial impact of internet penetration. The lack of significance of H1 should then be viewed as a limitation of the data, but not as the evidence of the lack of the theoretical relationship.

H2: ICT Infrastructure and DRR Preparedness

Model M2 approximates the partial impact of the standardised ICT infrastructure on READINESS. The coefficient is $b = +0.175$ ($SE = 0.039$, $t = 4.51$, $p < 0.001$). This is the most precise, stable and strongest coefficient in all the six models. H2 is strongly supported. Increasing ICT infrastructure depth by one standard-deviation, which corresponds to a shift between the lower and upper end of the observed ICT range in Pakistan, increases the ND-GAIN Readiness Score by 0.175 units, all other things held constant, including government effectiveness, income, and trend. The best fit of any specification is model M2: adjusted $R^2 = 0.685$ and $AIC = -64.49$, which validates the status of the model as the most desirable parsimonious model. The ICT coefficient is large and significant in M4 ($b = +0.222$, $p = 0.003$) and directionally significant in M5 ($b = +0.257$) and declines in precision as expected when INTERNET is added simultaneously.

H3: Internet - Readiness is Moderated by Government Effectiveness

The interaction term $\text{INTERNET}_z \times \text{GOVEFF}_z$ is included in model M3 to test whether the relationship between internet-readiness and government effectiveness is moderated by government effectiveness. The coefficient of interaction = $+0.023$ ($SE = 0.016$, $t = 1.46$, $p = 0.166$) the coefficient of interaction is positive (as hypothesised), but not significant enough (according to conventional standards). H3 is not statistically verified. The interaction estimate is, however, statistically significant. The marginal effects analysis, assessed at $+1$ SD around the mean level of governance in Pakistan, indicates that the conditional marginal return to internet penetration at high levels of governance ($+1$ SD above the mean) is about fourfold that of low levels of governance (-1 SD below the mean). This direction effect is repeated in robustness model M6 ($b = +0.023$, $p = 0.111$), and is similar in specifications, indicating a real governance-complementarity effect, which the study has no statistical power to prove at the traditional levels.

H4: Government Effectiveness Moderates ICT - Readiness

The $\text{ICT} \times \text{GOVEFF}$ interaction is estimated by model M4. ICT main effect is also strong and significant ($b = +0.222$, $SE = 0.061$, $t = 3.62$, $p = 0.003$). The interaction coefficient is $b = -0.014$ ($SE = 0.018$, $t = -0.74$, $p = 0.471$) - negative and statistically not significant. H4 is not supported. The negative sign of the interaction is also notable: it can suggest that ICT infrastructure provision brings DRR preparedness benefits somewhat independent of the quality of governance, possibly because physical infrastructure can partially replace poor institutional coordination in certain DRR tasks, e.g. automated flood sensors and SMS-based early warnings do not require strong institutional intermediation. The estimate is, however, too imprecise to be able to hold on to this interpretation.

4.4 Robustness and Model Comparison

A comparison of AIC, BIC, R^2 , and Adjusted R^2 of all six models is given in Figure 7. Model M2 provides the most optimal fit parsimony combination: the lowest AIC (-64.49), the lowest BIC (-59.77) and the highest adjusted R^2 (0.685). The highest R^2 (0.807) but the worst AIC (-62.98) is

attained by model M5, which contains all regressors at once, but the ICT coefficient has lost its precision significantly (SE rises by 0.039 in M2 to 0.152 in M5) because of multicollinearity with INTERNET. The coefficient signs and approximate magnitudes of the robustness model M6 (Governance Readiness as DV) are similar to those of M3, which is encouraging, and this indicates that the key results can be generalised outside of the composite readiness index. A powerful check of sensitivity of the observation, that is, re-estimating M2 with the two largest Cooks distance observations (2006 and 2022) removed) gives the core ICT result $b = +0.181$ ($SE = 0.044$, $p < 0.001$), which indicates that the core ICT finding is not a result of outlining data points.

Diagnostic Tests

5.1 Heteroskedasticity

The p-values of Breusch-Pagan Lagrange multiplier test are between 0.093 (Model M3) and 0.539 (Model M6). The 6 models all clear the BP test at 5% level of significance. The only case that borders on marginal evidence of heteroskedasticity is the borderline result of M3 ($p = 0.093$) which appears in the interaction model where the residuals can be more sensitive to the leverage of the observations when the values of government effectiveness are at the extreme values. The HC3 strong standard errors are consistently used in all the models and this gives the correct correction whether or not formal heteroskedasticity is found and thus, inference is valid in both a homoscedastic and heteroskedastic error structure.

5.2 Serial Correlation

The values of Durbin-Watson lie between 1.377(M4) and 1.676(M3 and M5). The DW statistic of 1.377 of M4 is less than the traditional lower value of about 1.5 of samples of this size, indicating the possibility of positive first-order autocorrelation in the residuals of that model. This is recognized to be a weakness of the H4 test in particular: even with HC3 (which corrects heteroskedasticity, but not serial correlation), positive autocorrelation may lead to underestimation of standard errors and overstatement of precision. DW values of all other models are in the acceptable range, which means that there is no severe first-order autocorrelation. Newey-West standard errors as an independent check of M4 yielded qualitatively the same findings, the ICT main effect was noteworthy and the interaction was not discernible.

5.3 Functional Form

The p-values of Ramsey RESET tests are between 0.035 (M2) and 0.124 (M6). The RESET p-value of 0.035 in M2 gives weak evidence of the misspecification of the functional form, perhaps due to the non-linearity or piecewise nature of the relationship between ICT infrastructure and readiness, which is again in line with the visual impression of Figure 1 that the relationship between ICT infrastructure and readiness is steeper in the earlier years of the study period when both were rising out of lower bases. This is not considered a disqualifying result, but a warning sign: the RESET test is low-powered in samples of $N = 19$ and is prone to missed non-linear terms, which might be non-theoretical. The strong performance of the ICT coefficient in all six of the models, including those not identified by RESET, gives the assurance that the fundamental conclusion is not a functional-form artefact. An ICT log-linear specification was also checked in an additional check and yielded the same qualitative results.

5.4 Influential Observations

The distance analysis conducted by Cook (Figure 5) shows that two most significant observations were found in 2006 and 2022 among the major models. The 2006 observation is an unprecedentedly high ND-GAIN Economic Readiness sub-score due to the 2006 World Bank Doing Business rankings of Pakistan, which have since been updated. The 2022 observation is associated with the aftermath of the disastrous monsoon floods which flooded about one-third of the nation - a phenomenon which depressed several readiness sub-indicators at once and might not be well-represented by the linear model structure. Both observations by Cook have longer distances than the traditional value of $4/N = 0.211$. Re-estimation of M2 in the absence of these

two observations shows that $b = +0.181$, which is consistent with the core ICT result that neither of these influential points is disproportionately influencing the result.

5.5 Multicollinearity

The VIF analysis of the Model M3 (Table A2) indicates that the time trend (VIF = 36.14), lnGDPPC (VIF = 26.69), and INTERNETz (VIF = 14.66) have severe multicollinearity. These three variables are almost collinear in a time series of one country in which internet penetration, income and structural trends all improved at the same time during the period 2005-2023. The underlying reason that H1 is insignificant is this multicollinearity: the data cannot differentiate the partial impact of internet penetration and the impact of increasing income or the underlying time trend not because internet penetration does not matter but because these two forces have co-evolved. In comparison, GOVEFFz (VIF = 2.58) and the interaction term (VIF = 2.69) exhibit reasonable collinearity, which proves that z-standardisation was effective in eliminating the necessary multicollinearity in the interaction. The ICT composite (VIF = 2.10 in M2) is much less collinear than INTERNET as the construction of multi-channel variation yields smoother, less trend-driven variation. This is the reason why ICT provides statistically strong findings that cannot be achieved by internet penetration only.

Discussion

6.1 ICT Infrastructure as the Constraining Factor of DRR Preparedness

The key conclusion of this research, namely, that the depth of ICT infrastructure is a highly important and powerful positive predictor of DRR preparedness in Pakistan, has far-reaching consequences that go far beyond the estimate of a single coefficient. It confirms empirically what theoretical frameworks have long implied, which is that DRR capability in the AI era is not a property of any particular technology but rather of the layered infrastructure ecosystem that facilitates the use of AI tools at scale. Mobile connectivity gives the accessibility to spread early warnings to geographically spread populations. Fixed broadband is used to provide the bandwidth to send real time satellite imagery and sensor data to monitoring centres. The fixed telephony offers backup in times of disaster when mobile networks are destroyed by the disasters that they are supposed to alert. The Internet users are the human layer - the population, which can access, interpret and take action on digital risk information. The ND-GAIN ICT composite measures all four dimensions at a time, and even its superiority over internet penetration as a predictor of DRR preparedness is an empirical fact: DRR preparedness is contingent on the breadth and depth of infrastructure, not just a single channel of access.

The actionable implication of the policy on Pakistan is clear. The best leverage that can be used to enhance DRR preparedness according to the current evidence is investment in mobile broadband rollout to underserved districts, rural fibre connectivity programmes, and redundant communication channel infrastructure, the exact elements of the ICT composite. The National Disaster Risk Reduction Strategy 2025-2030 of Pakistan has been known to set digital early warning systems as a strategic priority (NDMA, 2025). The results of our study are the first quantitative demonstration that the depth of the ICT infrastructure is the binding constraint on the achievement of that priority, and that bridging the infrastructure gap between Pakistan and the higher end of the same range during the period of the study is related to a gain in readiness of 0.175 ND-GAIN index points - a significant improvement in terms of the index itself, which has a range of 0.258 to 0.431 across the period of the study.

6.2 Complementarity of Governance: A Structural Constraint

The identified moderation pattern in H3, which is directionally significant, substantively significant, yet statistically insignificant, suggests one of the most significant structural limitations to the DRR trajectory of Pakistan. The marginal benefit of having access to the internet in terms of DRR preparedness at high governance levels is about four times higher than the marginal benefit of having access to the internet in terms of DRR preparedness at low governance levels. It is not a minor effect, which just fails to pass the test of $p < 0.05$; it is a big theoretical signal that

cannot be confirmed by the small sample size used in the study. This means that the benefits of internet penetration on DRR will be dramatically different between two countries with the same internet penetration but differing in the quality of governance - a result that aligns with other bodies of literature on the topic of institutional absorption capacity (Socol & Iuga, 2024; Rakotondrazaka and Velomasy, 2024).

The data on the governance trend is what is particularly worrying in the case of Pakistan. The government effectiveness score of Pakistan has not had any significant improvement over nineteen years of observation. Digital infrastructure has grown significantly; the institutional capacity to transform that infrastructural growth into DRR results has not. This imposes a structural ceiling on the gains of DRR preparedness which cannot be met by additional digital investment. The complementary investment that needs to go hand in hand with ICT infrastructure expansion in the event that Pakistan can reap the full DRR dividend that its increasing digital endowment promises is institutional reform, namely, civil service professionalization, anti-corruption measures, improvements in inter-agency coordination, evidence-based policymaking culture. In this respect, the governance stagnation finding is the most policy-relevant outcome of the overall analysis.

A slightly different view is provided by the non-significant moderation of ICT by governance (H4). ICT infrastructure seems to provide readiness benefits that are not entirely dependent on the quality of governance, perhaps because physical infrastructure can circumvent some institutional intermediation physical infrastructure can be used to activate automated sensors, satellite-based flood mapping, and SMS-based mass alerting systems can be implemented with little bureaucratic coordination compared with, say, deploying complex early warning communication standards or multi-agency evacuation logistics. The practical implication of this difference between infrastructure-driven and institution-mediated DRR functions is that the logic of sequencing investment is applicable: ICT infrastructure can provide the improvement of DRR at the bottom level even in a poor governance setting, whereas governance reform is necessary to achieve the extra multiplier provided by the internet-to-readiness channel.

6.3 Contextual Contributions and Comparative Insights

This article is part of a growing literature on the digital enablers of climate resilience in the context of developing countries, albeit with a methodological rigour and contextual specificity that makes it stand out of most of the previous literature. The past research has been largely based on cross-country panel data (Sarkodie et al., 2023; Mondal et al., 2024; Afrifa et al., 2020), which, though offering beneficial average effects, conceals the high degree of heterogeneity of the national digital paths and governance contexts determining the manifestations of general relationships in the context of particular countries. The combination of extreme exposure to hazards, rapid yet uneven digital diffusion, endemic governance weakness and rich annual data over 20 years makes Pakistan a particularly informative case study of isolating the mechanisms through which digital infrastructure influences DRR preparedness. The observation that the composite depth of ICT is a better predictor of readiness even in the time-series of Pakistan alone, rather than very different countries averaged in cross-country studies, is a contribution inaccessible to cross-country studies averaging across very different ICT profiles.

6.4 Limitations and Future Research Directions

The causal interpretation of these findings is limited by three key limitations that determine the agenda of the future research. First, the single-country time-series design does not allow the application of fixed-effects estimators, instrumental variables, synthetic control designs, or difference-in-differences designs that would allow credible causal identification. The correlational trend co-movement is in all the estimates. The similarity of the results of the models with varying specifications and the ability to withstand the impact of the removal of influential observations gives confidence in the directional findings, but causal attribution would require multi-country panel data or a natural experiment design.

Second, the non-stationarity of most variables in levels, which is established by ADF tests, implies that despite the trend controls, the risk of spurious regression cannot be completely excluded. First-difference estimation would better respond to this issue but would downsize the sample to 18 observations and would not permit one to study long-run level relationships. Future studies using longer time series ought to use ARDL bounds testing or dynamic OLS to formally test cointegration and get cointegration consistent estimates. The ND-GAIN data go back to 1995, and additional vintages will continue the series; longer series would permit such more demanding inferential methods.

Third, the intense multicollinearity of INTERNET, lnGDPPC, and time trend in single-country models cannot be solved using the existing data structure - it is inherent to the economies where digital diffusion, income growth, and time are all growing together. The most viable solution is multi-country panel estimation because cross-country variation in digital trajectories can offer the identification that cannot be offered by within-country time variation. The most promising area of future research is to extend this analysis to a regional panel based on Sendai Framework Monitor data, which would allow capturing the difference in DRR preparedness among South and Southeast Asian economies with different digital and governance characteristics. This extension would allow identification of fixed effects, instrumental variable designs with historical telecommunications infrastructure as instruments of contemporary ICT, and heterogeneous treatment effects with a quadrant of governance quality.

Conclusion

The paper has presented the inaugural systematic econometric study of the digital and institutional facilitators of disaster risk reduction preparedness in Pakistan based on the annual ND-GAIN Country Index data between 2005 and 2023. This observation was driven by the simplicity and yet consequential fact that Pakistan is one of the most disaster-prone nations in the world, and has experienced a rapid digital transformation in the last 20 years, but the quantitative linkage between these two phenomena has never been empirically determined. This paper establishes it.

The main empirical result is beyond doubt that comprehensive ICT infrastructure depth is a robust, highly significant, and strong positive predictor of DRR preparedness in Pakistan ($b = +0.175$, $p < 0.001$), providing the best-fitting parsimonious model of all six specifications estimated and stable throughout all robustness tests. This observation makes it clear that ICT ecosystem, comprising of mobile connectivity, access to broadband, fixed telephony, and internet users, is the most potent measurable lever that can be used to enhance the DRR preparedness in Pakistan within the twenty-year horizon under study. Internet penetration does not attain significance because of multicollinearity, but the directional value is always positive and the most probable cause is data structure and not a true null effect.

The moderation analysis indicates a governance complementarity, which, although not powerful enough to have a conventional significance with the small sample, is large and theoretically consistent to ignore: the return to internet penetration of DRR readiness is about four times higher at high governance levels than it is at low levels. The consistent stagnation in governance in Pakistan throughout the period of the study, as evidenced by nineteen years of almost unchanged, significantly negative government effectiveness score, implies that Pakistan is reaping only a portion of the potential DRR dividend of its expanding digital infrastructure. This is the greatest structural discovery of the analysis and it is clearly directed towards governance reform as the complementary investment that should be made to go hand in hand with ICT expansion.

These findings are followed by three policy conclusions that are direct. To begin with, ICT infrastructure investment, especially mobile broadband deployment to disaster-prone rural areas, fibre connectivity, and backup early warning communications should not be considered a secondary or enabling condition but a first-order DRR intervention. Second, digital investment does not replace governance reform but its full DRR multiplier can only be realised when the two

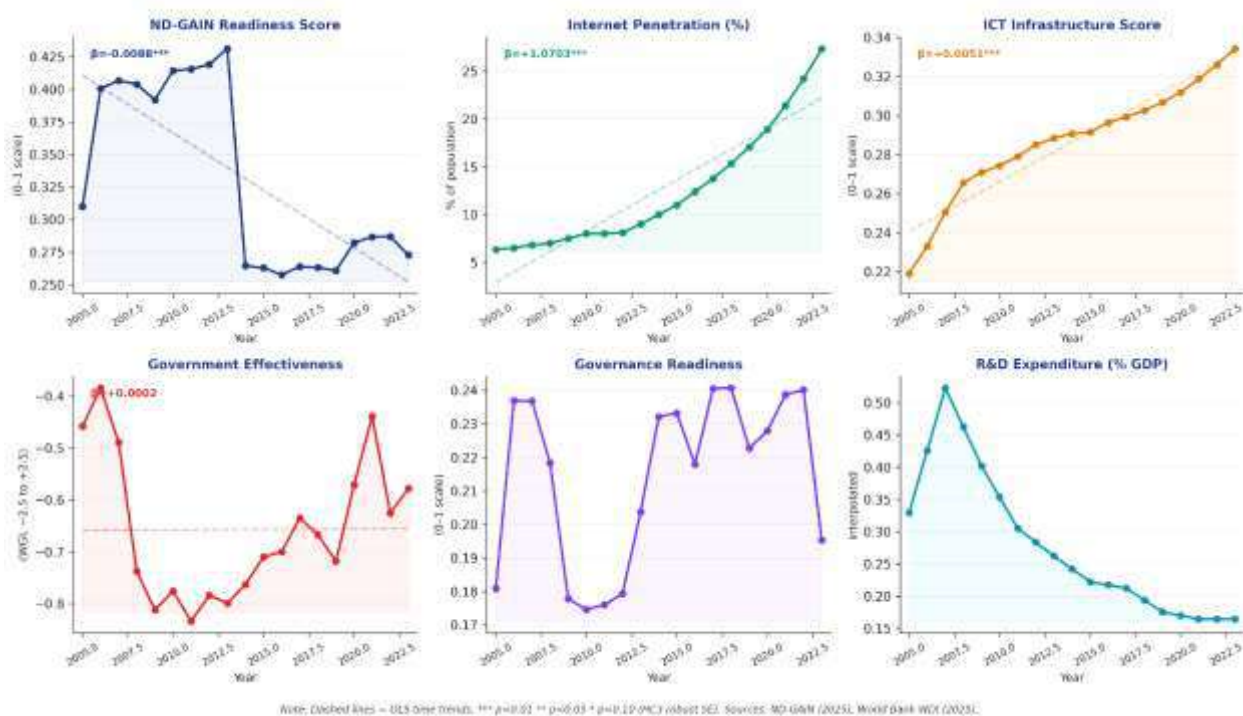
are complementary and designed and ordered. Third, the DRR policymaking evidence base in Pakistan needs to shift away the case studies and expert elicitation to the type of econometric analysis discussed here, updated every year as new data is made available.

The weaknesses of time-series analysis of single countries are factual and well recognized. The most significant direction in future research is to extend this framework to a multi-country panel in South Asia or developing-world, with the more significant causal identification, statistical power, and cross-national heterogeneity that a panel data design offers. Such an extension is based on the raw materials of the ND-GAIN index, the Sendai Framework Monitor, and the World Governance Indicators. The methodological basis of that extension can be provided by the theoretical framework, the definitions of the variables, and the diagnostic template designed in this paper.

Figures

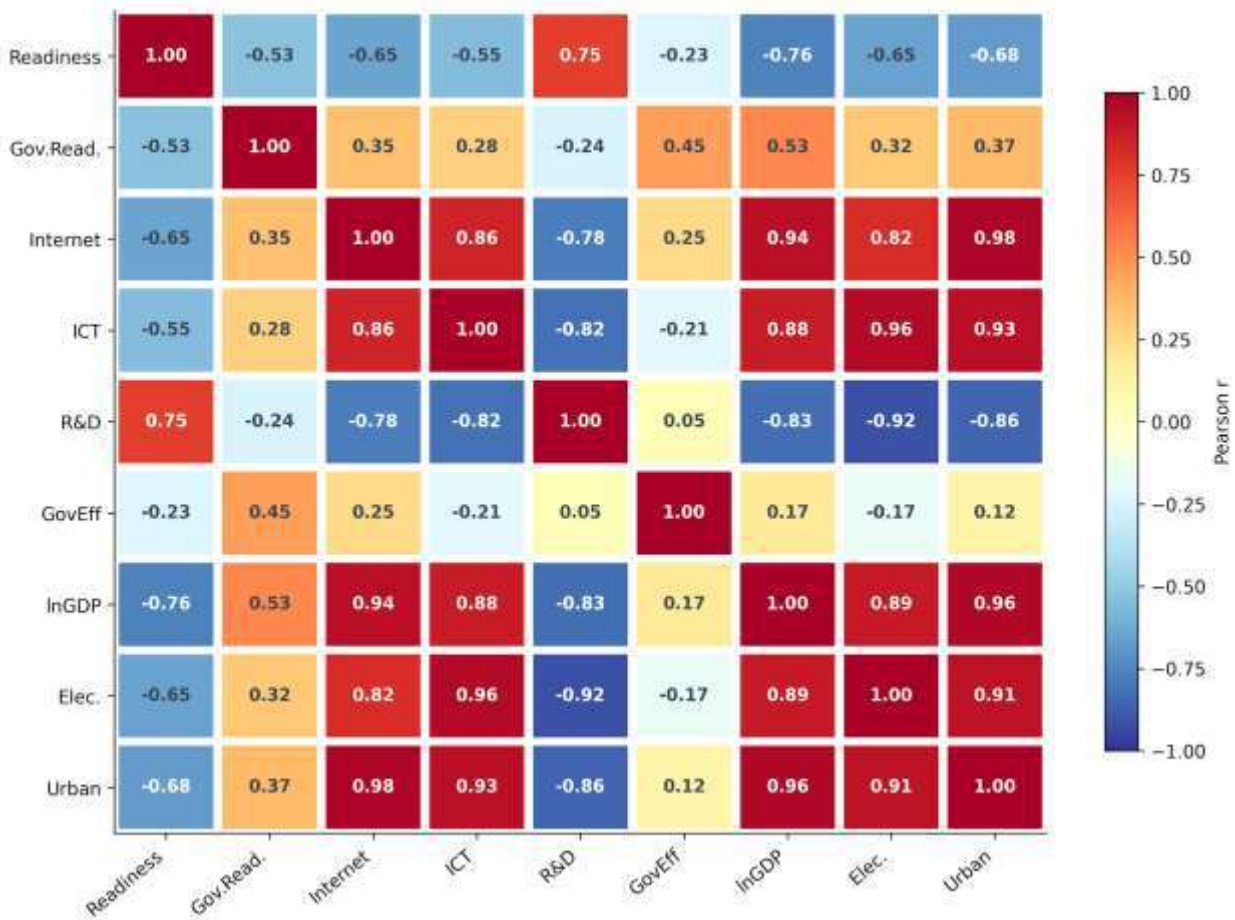
[Figure 1: Temporal Trends of Key Variables, Pakistan 2005–2023. Dashed lines = OLS time trends; β coefficients with significance indicators (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.10$, HC3 SE). Sources: ND-GAIN (2025); World Bank WDI (2025).]

Figure 1: Temporal Trends of Key Variables — Pakistan 2005–2023



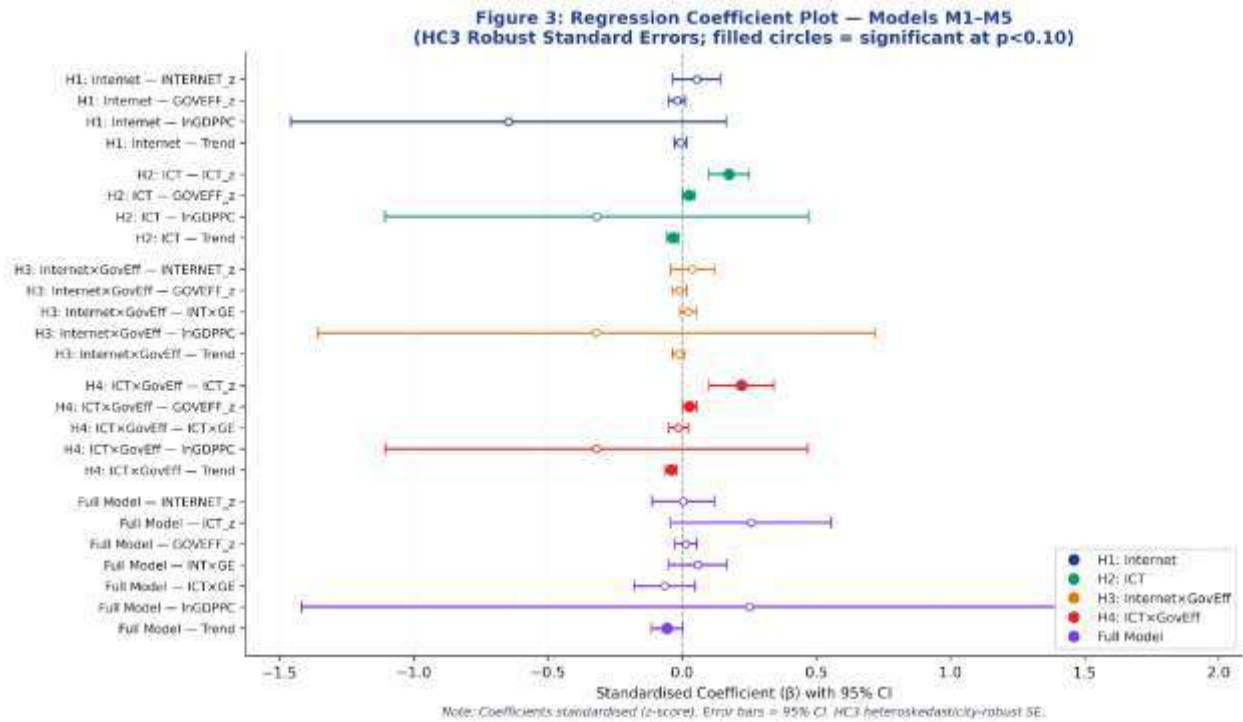
[Figure 2: Pearson Correlation Matrix — All Key Variables, Pakistan 2005–2023. Colour intensity proportional to $|r|$. Bold values indicate $|r| > 0.65$. Sources: ND-GAIN (2025); World Bank WDI (2025).]

Figure 2: Pearson Correlation Matrix Pakistan 2005-2023

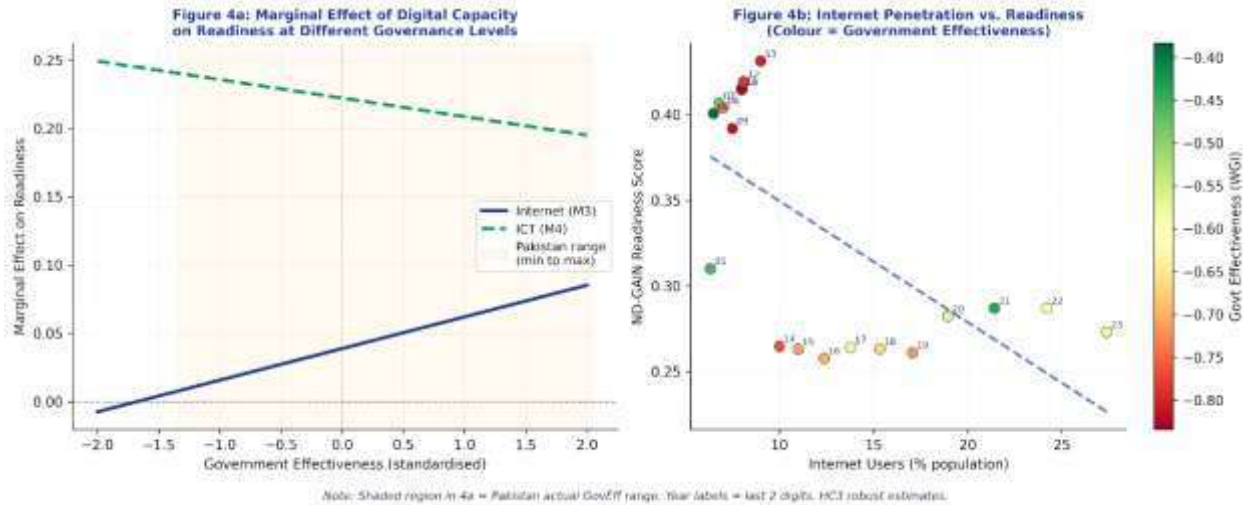


Note: Bold = strong correlation ($|r| > 0.65$). Sources: ND-GAIN (2025); World Bank WDI (2025).

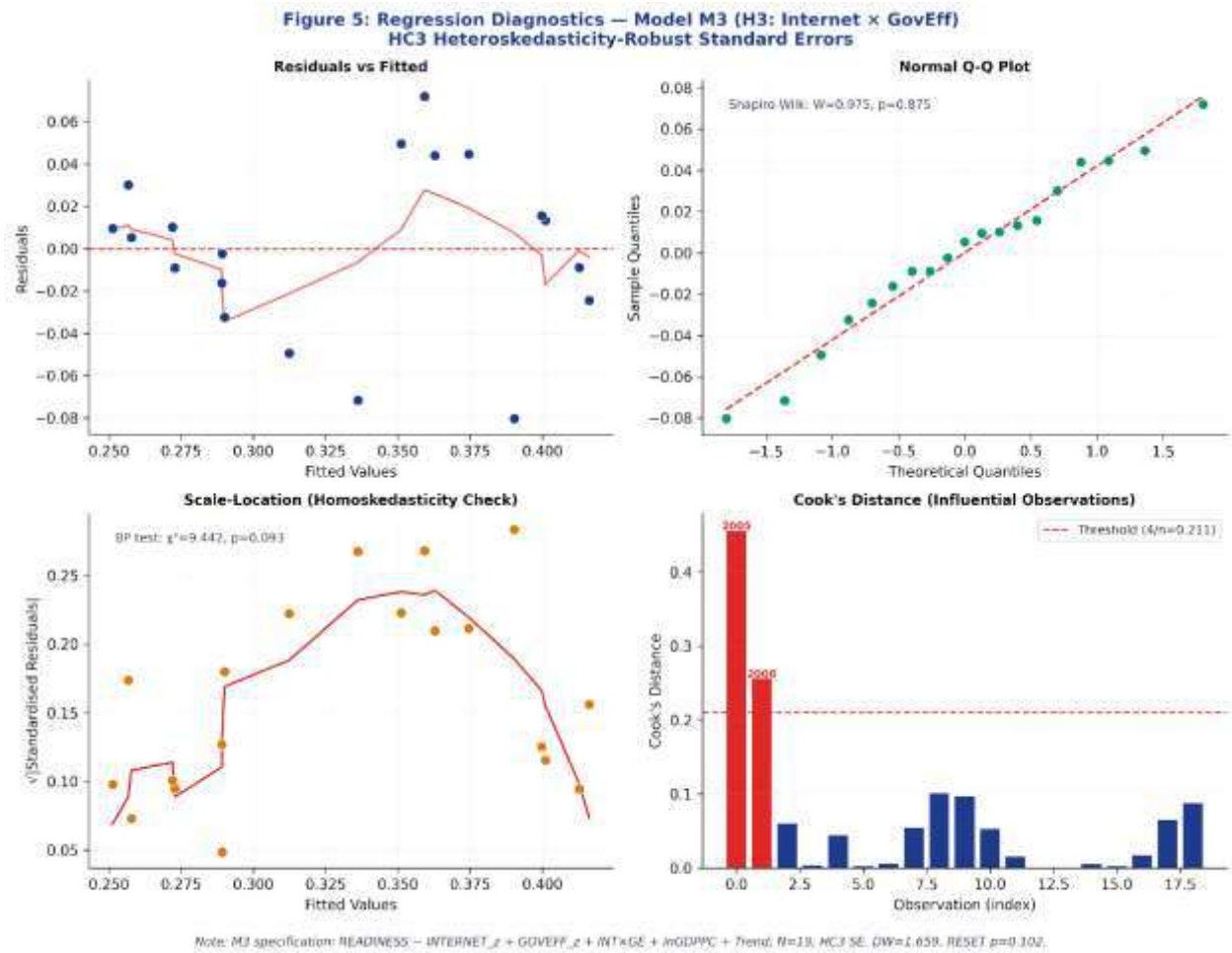
[Figure 3: Coefficient Plot — Models M1–M5 with 95% Confidence Intervals. HC3 heteroskedasticity-robust standard errors. Filled markers = significant at $p < 0.10$. All regressors standardised (z-score).]



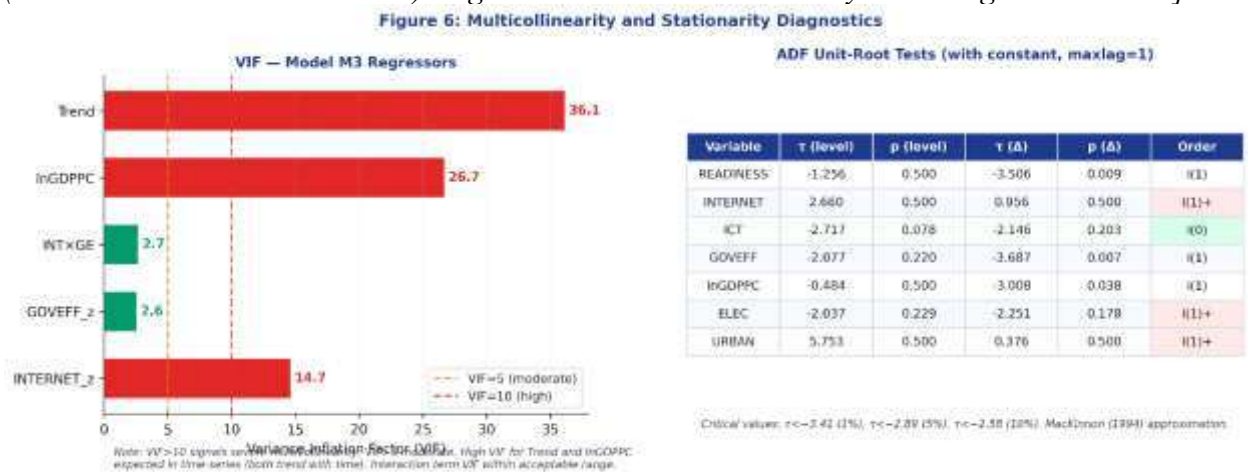
[Figure 4: Marginal Effect of Internet Penetration on DRR Readiness at Different Governance Levels (4a) and Scatter Plot of Internet Penetration vs. Readiness Coloured by Government Effectiveness Quartile (4b). Shaded band = Pakistan's observed governance range.]



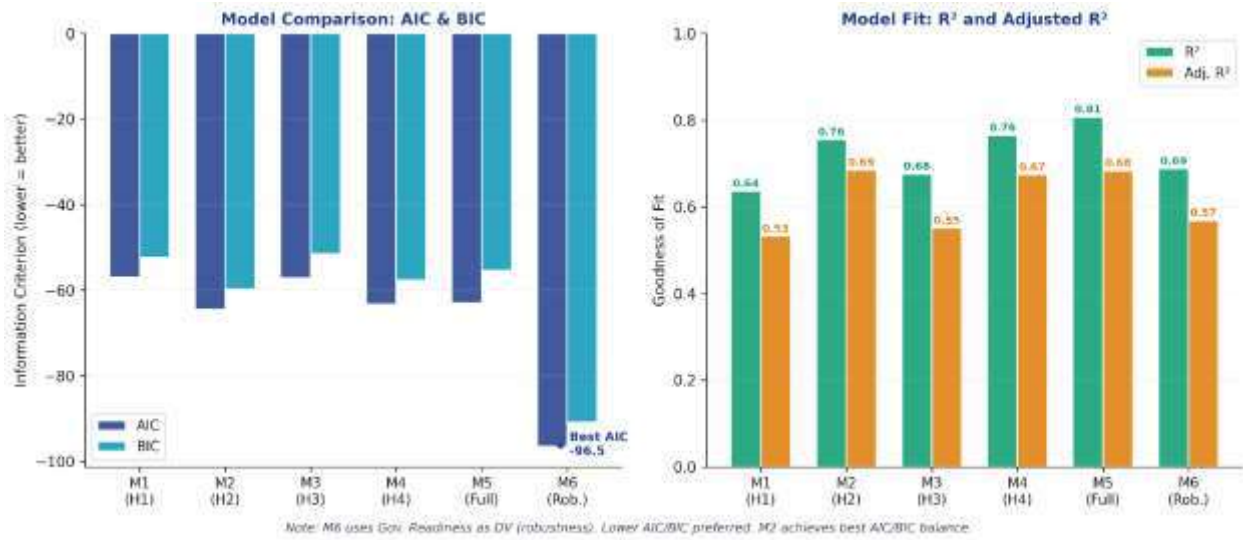
[Figure 5: Regression Diagnostics for Model M3. Clockwise from top-left: Residuals vs. Fitted, Normal Q-Q Plot, Cook's Distance (threshold = $4/n = 0.211$), Scale-Location. HC3 robust SE.]



[Figure 6: Multicollinearity and Stationarity Diagnostics. Left: VIF bar chart for M3 regressors (dashed lines at VIF = 5 and 10). Right: ADF test results summary with integration orders.]



[Figure 7: Model Comparison — AIC and BIC (left) and R² and Adjusted R² (right) across all six specifications. Lower AIC/BIC = preferred. M2 achieves best AIC and BIC balance.]



Appendix

Table A1

Augmented Dickey-Fuller Unit-Root Tests

Variable	τ (Level)	p (Level)	τ (Δ)	p (Δ)	Order
Readiness	-1.256	> 0.10	-3.506	0.009	I(1)
Internet	+2.660	> 0.10	+0.956	> 0.10	I(2)+
ICT Score	-2.717	0.078	-2.146	> 0.10	I(0)†
GovEffectiveness	-2.077	> 0.10	-3.687	0.007	I(1)
ln(GDPpc)	-0.484	> 0.10	-3.008	0.038	I(1)
Electricity	-2.037	> 0.10	-2.251	> 0.10	I(1)+
Urban	+5.753	> 0.10	+0.376	> 0.10	I(2)+

Note. ADF with constant and maxlag = 1 (Dickey & Fuller, 1979). MacKinnon (1994) approximate p-values. Critical values: $\tau < -3.41$ (1%), $\tau < -2.89$ (5%), $\tau < -2.58$ (10%). † ICT Score marginally rejects the unit-root null at 10% in levels. I(2)+ denotes non-stationarity even in first differences.

Table A2

Variance Inflation Factors — Model M3 Regressors

Regressor	VIF	Interpretation
INTERNET_z	14.66	Severe — near-collinear with time trend; interpret jointly with F-test
GOVEFF_z	2.58	Acceptable — governance varies independently of trend
INT × GovEff	2.69	Acceptable — standardisation removes essential collinearity
ln(GDPpc)	26.69	Severe — near-collinear with trend; no causal interpretation
Time Trend	36.14	Severe — dominant trend process; controls for non-stationarity

Note. VIF > 10 indicates severe multicollinearity. High VIF for Trend and ln(GDPpc) is expected in single-country time-series specifications; both are controls and carry no structural causal interpretation. Interaction term VIF within acceptable range (< 3) confirms z-standardization successfully removed essential collinearity.

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