Volodymyr Momot
Alfred Nobel University, Dnipro, Ukraine (corresponding author)
E-mail: vmomot@duan.edu.ua
Sergii Kholod
Alfred Nobel University, Dnipro, Ukraine
Viktoriia Sokolova
Alfred Nobel University, Dnipro, Ukraine

A Multi-Dimensional Composite Resilience Index for Ukrainian Public Administration under Conflict Conditions

Abstract

This paper constructs, empirically identifies, and longitudinally validates a Multi-Dimensional Composite Resilience Index (MCRI) for Ukrainian public administration institutions using seven internationally recognised governance datasets spanning 2015-2024. The work is conducted within the framework of the LEEPS project, a UK-Ukraine-Latvia research partnership. The MCRI integrates indicators from the World Bank Worldwide Governance Indicators (WGI), Transparency International Corruption Perceptions Index (CPI), Freedom House Nations in Transit, the UN E-Government Development Index (EGDI), SIGMA/OECD monitoring reports, and the INFORM Risk Index into a unified composite score through a mathematically rigorous hybrid weighting scheme. Objective weights are derived via Principal Component Analysis (PCA) applied to the longitudinal indicator matrix; subjective weights are elicited from Ukrainian public administration experts through the Analytic Hierarchy Process (AHP); the two weight sets are combined through a convex mixing procedure with parameter μ^* identified by minimising prediction error against European Commission Ukraine Progress Report scores used as an external validation benchmark. Non-linear interactions between governance dimensions are captured through an OLS-identified interaction term. Shapley value decomposition provides fair attribution of MCRI changes to individual governance dimensions across three identified phases: gradual pre-war recovery (2015–2021), acute conflict shock (2022), and partial recovery (2023–2024). The conflict shock reduced the MCRI by approximately 34% from its 2021 pre-war peak. External validation against the Bertelsmann Transformation Index confirms the model's empirical robustness (r=0,91; p<0,01).

Keywords

composite resilience index, Ukrainian governance, multi-criteria aggregation, AHP-PCA hybrid weights, Shapley decomposition, longitudinal resilience analysis, conflict resilience, public administration, socio-technical systems, SIGMA indicators

JEL: C43, C38, H11, H83, O20

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1 Introduction

The resilience of public administration institutions is a foundational dimension of national security and societal continuity, particularly during active armed conflict. Ukraine's experience since February 2022 represents one of the most severe stress tests of a European public administration system in the post-Cold War era, combining physical infrastructure disruption, mass personnel displacement, budgetary collapse, and the simultaneous demand for accelerated reform required by EU accession conditionality (European Commission, 2024; World Bank, 2024). Understanding how institutional resilience has evolved under these conditions – and how targeted interventions can accelerate its restoration – is therefore a question of both scientific and immediate policy relevance.

Within the resilience engineering community, the assessment of complex socio-technical systems has increasingly moved beyond purely physical or technical dimensions toward integrated frameworks that incorporate organisational, governance, and human factors (Hollnagel, Woods, Leveson, (Eds.), 2006).

Despite this recognised need, the literature on quantitative resilience measurement in public administration remains fragmented. Existing approaches tend to rely either on single-indicator proxies – such as the World Bank Government Effectiveness score – which cannot capture the multidimensional nature of institutional resilience, or on qualitative frameworks that resist comparative longitudinal analysis (Kaufmann, Kraay, Mastruzzi, 2011; Christmann, 2016). Composite indices for governance quality exist (notably the WGI itself, the Ibrahim Index, and the Bertelsmann Transformation Index), but these are designed as general governance assessments rather than resilience-specific instruments, and none has been adapted or validated specifically for the Ukrainian conflict context or grounded in a formal resilience engineering framework

(Bertelsmann Stiftung, 2024; Mo Ibrahim Foundation, 2023).

This paper addresses this gap by developing a Multi-Dimensional Composite Resilience Index (MCRI) that is: (i) grounded in resilience engineering theory; (ii) constructed from multiple independently published and validated data sources; (iii) empirically identified using a hybrid objective-subjective weighting procedure; (iv) enriched by non-linear interaction terms capturing synergies between governance dimensions; (v) decomposed using Shapley values for transparent attribution analysis; and (vi) validated against multiple independent external benchmarks.

2 Literature Review

1.1. Resilience Assessment in Socio-Technical Systems

Resilience engineering emerged from the study of high-reliability organisations and critical infrastructure systems, where the interest shifted from preventing failures to ensuring systems could absorb disruption, adapt, and recover (Hollnagel, 2011; Woods, 2015). Hollnagel, Woods, and Leveson's foundational contributions established resilience as a multidimensional construct encompassing anticipation, monitoring, response, and learning capacities (Leveson, Dulac, Marais, Carroll, 2009). More recent frameworks have extended these concepts to interconnected socio-technical systems where technical, organisational, and human dimensions interact in complex ways (Zio, 2016; Cutter, et al., 2013).

A persistent challenge in the field has been operationalisation: translating qualitative resilience concepts into measurable, comparable indicators. Bruneau et al. (2003) proposed the influential ROPE framework (Robustness, Redundancy, Resourcefulness, Rapidity), while Cutter et al. (2010) developed the Baseline Resilience Indicators for Communities (BRIC) for disaster resilience. In the infrastructure domain, the European Programme for Critical Infrastructure Protection has generated various sector-specific assessment frameworks (European Commission, 2023). However, governance and institutional dimensions have remained underrepresented in quantitative resilience assessment, despite theoretical recognition that institutional capacity is a primary determinant of system-wide resilience (Norris, 2008; Comfort, Boin, Demchak, 2010).

1.2. Composite Index Methodology

The construction of composite indices for multidimensional phenomena is well established in economics and the social sciences, with canonical examples including the UN Human Development Index, the World Bank Doing Business Index, and the OECD Better Life Index (OECD/JRC, 2008). The methodological literature identifies several critical choices: variable selection and normalisation, identification of the weighting scheme, specification of the aggregation function, and validation (Nardo, et al., 2005; Saisana, Tarantola, 2002).

Weighting approaches range from equal weighting (defensible but theoretically naive) through purely data-driven methods such as PCA and factor analysis to purely expert-based methods such as AHP (Saaty, 1980; Joliffe, 2002). Each approach carries distinct assumptions and limitations: equal weights implicitly assume all dimensions are equally important; PCA-derived weights reflect statistical co-variation rather than theoretical salience; AHP weights depend on expert judgement quality and may not generalise across contexts (Greco, Ishizaka, Tasiou, Torrisi, 2019). Hybrid approaches that combine objective and subjective weights have been proposed as a principled middle ground (Wang, Lee, 2009; Ma, Fan, Huang, 1999), and this paper adopts one.

The Choquet integral provides a theoretically superior aggregation function that captures non-linear interactions between dimensions but requires exponentially growing parameter estimation (Grabisch, Labreuche, 2010). As a practical compromise, this paper introduces a single multiplicative interaction term – grounded in the theoretically motivated GE × DG synergy hypothesis – identified via OLS, which captures the most important non-linearity while maintaining tractability with the available sample size.

1.3. Governance Resilience in Post-Conflict Contexts

The literature on governance resilience in post-conflict and conflict-affected contexts draws on political science, public administration, and development economics (Call, 2008; Rotberg, (Ed.), 2003). Key empirical findings include: institutional trust is the slowest-recovering dimension after violent conflict (Zmerli, Newton, 2008); anti-corruption progress is a necessary precondition for restoring government effectiveness (Rose-Ackerman, Palifka, 2016); digital government infrastructure demonstrates unexpected resilience under conflict conditions due to its distributed architecture (Margetts, Naumann, 2017); and capacity-building interventions show measurable but temporally lagged effects on governance quality indicators (Brinkerhoff, Brinkerhoff, 2015).

Ukraine's experience aligns with several of these findings, as discussed in Section 5. The Ukrainian case is additionally notable for the Diia e-government platform, which maintained service continuity throughout the conflict period and has been internationally recognised as a model of digital government resilience (Mintsifry Ukraine, 2023; OECD, 2023). This digital resilience dimension is among the analytically most interesting findings of the longitudinal MCRI analysis presented in this paper.

1.4. Shapley Values in Index Decomposition

Shapley values, originating in cooperative game theory (Shapley, 1953), have been increasingly applied in the composite index literature as a method for fairly attributing index values to contributing dimensions (Moretti, Patrone, 2008; Charnes, Cooper, Rhodes, 1978). Unlike simple weight-based attribution, which is path-independent and ignores interactions, Shapley values satisfy desirable axioms including efficiency (attributed contributions sum to the total index value), symmetry (equivalent contributors receive equal attribution), and null player (non-contributing dimensions receive zero attribution) (Young, 1985). Recent applications include attribution of the Human Development Index across dimensions (Pinar, Stengos, Topaloglou, 2013) and decomposition of sustainability indices (Decancq, Lugo, 2013). This paper applies Shapley decomposition to attribute MCRI changes across governance dimensions during key historical transitions, providing insights beyond what weight-based analysis can offer.

2 Mathematical Framework

2.1. Variable Selection and Notation

Let $\mathcal{Y}$ = {2015,2016,...,2024} denote the study period with T = | $\mathcal{Y}$ |=10 annual observations. Let p = 7 denote the number of governance indicator components selected for inclusion in the MCRI. The raw indicator matrix is denoted $\mathbf{Z} \in \mathbb{R}^{T\times p} as$, where Z_{tj} is the value of the indicator j in year t.

The seven components and their data sources are:

• Z_1: Government Effectiveness score GE_t (WGI, World Bank, annual)

• Z_2: Rule of Law score RL_t (WGI, World Bank, annual)

• Z_3: Anti-Corruption capacity AC_t (CPI/100, Transparency International, annual)

• Z_4: Institutional Trust IT_t (Freedom House Nations in Transit, annual)

• Z_5: Digital Government Development DG_t (UN EGDI, biennial, interpolated)

• Z_6: Civil Service HR Maturity HR_t (SIGMA/OECD-EU, triennial, interpolated)

• Z_7: Coping Capacity CC_t (INFORM Risk Index, inverted, annual)

All indicators are aligned in the same direction, with higher values indicating better institutional resilience.

2.2. Normalisation

Variables measured on heterogeneous scales are normalised using min-max normalisation referenced to the full observed range over the study period $\mathcal{Y}$:

$$\tilde{x}_{tj} = \frac{Z_{tj} - \min_{s\in\mathcal{Y}} Z_{sj}}{\max_{s\in\mathcal{Y}} Z_{sj} - \min_{s\in\mathcal{Y}} Z_{sj}} \in [0,1]$$

This yields the normalised indicator matrix $\mathbf{X} \in [0,1]^{T\times p}$.

For biennial and triennial indicators (EGDI and SIGMA, respectively), linear interpolation is applied between survey years:

$$\tilde{x}_{tj} = \tilde{x}_{t_k j} + \frac{t-t_k}{t_{k+1}-t_k}(\tilde{x}_{t_{k+1}j} - \tilde{x}_{t_k j}), t_k \le t \le t_{k+1}$$

where t_k and t_{k+1} are adjacent survey years. Sensitivity analysis using cubic spline interpolation as an alternative is reported in Section 7.

2.3. PCA-Based Objective Weights

To derive data-driven weights reflecting the empirical co-variation structure of the governance indicators, PCA is applied to the standardised indicator matrix $\mathbf{X}^s$, where standardisation uses column means $\bar{x}_j$ and standard deviations s_j:

$$x^s_{tj} = \frac{\tilde{x}_{tj} - \bar{x}_j}{s_j}$$

The covariance matrix of $\mathbf{X}^s$ is decomposed as:

$$\sum = \frac{1}{T-1}(\mathbf{X}^s)^T \mathbf{X}^s = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T$$

where $\mathbf{\Lambda}$ = diag(λ_1 ,λ_2,..., λ_p) with $\lambda_1 \ge \lambda_2 \ge \ldots \ge \lambda_p$ are the eigenvalues and $\mathbf{V}$ =[$\mathbf{v}_1$, $\mathbf{v}_2$, ..., $\mathbf{v}_p$] are the corresponding eigenvectors. The proportion of total variance explained by the k-th principal component is:

$$\rho_k = \frac{\lambda_k}{\sum_{j=1}^{p}\lambda_j}$$

PCA-based weights are derived from the squared loadings of the first principal component $\mathbf{v}_1$, normalised to sum to unity:

$$w_j^{PCA} = \frac{v_{1j}^2}{\sum_{k=1}^{p} v_{1k}^2}, j = 1,\ldots,p$$

where v_{1j} is the j-th element of $\mathbf{v}_1$, with sign convention chosen so that $\sum_j v_{1j} > 0$ (positive direction = better resilience). This formulation captures the relative importance of each indicator in explaining the dominant mode of variation across the governance space.

2.4. AHP-Based Subjective Weights

Expert weights are elicited using the Analytic Hierarchy Process through structured pairwise comparison interviews conducted with n_{exp} = 12 Ukrainian civil servants and public administration professionals as part of the LEEPS project first-stage fieldwork (March 2026). Each expert provides a $p\times p$ pairwise comparison matrix $\mathbf{A}^{(k)}$ with entries $a_{ij}^{(k)}$ on Saaty's 1–9 scale representing the relative importance of one indicator i versus another j for institutional resilience.

The consensus matrix **A** is computed as the element-wise geometric mean of individual matrices:

$$a_{ij} = \left(\prod_{k=1}^{n_{exp}} a_{ij}^{(k)} \right)^{1/n_{exp}}$$

AHP weights are derived as the normalised principal eigenvector of **A**:

$$\mathbf{A}\mathbf{w}^{AHP} = \lambda_{max}\mathbf{w}^{AHP}, \sum_{j=1}^{p} w_j^{AHP} = 1, w_j^{AHP} > 0$$

Consistency of the consensus matrix is verified using the Consistency Ratio:

$$CR = \frac{CI}{RI} = \frac{(\lambda_{max} - p)/(p-1)}{RI_p}$$

where RI_p = 1.32 is the Random Consistency Index for p=7 criteria [41]. Matrices with CR>0.10 are returned to respondents for revision.

2.5. Hybrid Weighting and Mixing Parameter Identification

Final hybrid weights are constructed as a convex combination of PCA and AHP weights:

$$\mathbf{w}^* = \mu \cdot \mathbf{w}^{AHP} + (1 - \mu)\cdot \mathbf{w}^{PCA}, \mu \in [0,1]$$

with the mixing parameter μ* identified by minimising the mean squared prediction error against $n_{val} = 3$, normalised EC Ukraine Progress Report reform scores $\{ec_t\}_{t \in \{2022,2023,2024\}}$. used as an independent external validation dataset:

$$\breve{\mu} = \arg\min_{\mu\in[0,1]} \frac{1}{n_{val}} \sum_{t\in Tval} \left(\mathbf{w}(\mu)^T \tilde{\mathbf{x}}_t - ec_t \right)^2$$

where $\mathbf{w}(\mu) = \mu\, \mathbf{w}^{AHP} + (1 - \mu)\mathbf{w}^{PCA}$ and $\tilde{\mathbf{x}}_t$ is the normalised indicator vector for year t. This is solved by grid search over $\mu \in \{0,0.005,0.010,\ldots,1.000\}$.

2.6. Basic MCRI and Non-Linear Extension

The basic MCRI is computed as the weighted linear combination:

$$MCRI_t = \sum_{j=1}^{p} w_j^* \cdot \tilde{x}_{tj} = (\mathbf{w}^*)^T \tilde{\mathbf{x}}_t \in [0,1]$$

To capture the theoretically motivated synergistic interaction between Government Effectiveness (*GE*) and Digital Government Development (*DG*) – the hypothesis that digital governance tools amplify institutional effectiveness rather than simply adding to it – a multiplicative interaction term is introduced:

$$MCRI_t^+ = MCRI_t + \gamma \cdot \tilde{x}_{t,GE} \cdot \tilde{x}_{t,DG}$$

where the interaction coefficient γ is identified by Ordinary Least Squares regression of the interaction term against the residual between $MCRI_t$ and the Bertelsmann Transformation Index normalised score bti_t (held out from weight identification):

$$\hat{\gamma} = \frac{\sum_{t\in\mathcal{Y}} \tilde{x}_{t,GE} \cdot \tilde{x}_{t,DG} \cdot (bti_t - MCRI_t)}{\sum_{t\in\mathcal{Y}} (\tilde{x}_{t,GE} \cdot \tilde{x}_{t,DG})^2}$$

$\hat{\gamma}$ is constrained to [0›0.30] to prevent interaction effects from dominating the linear component. The enhanced index $MCRI_t^+$ is clipped to 01.

2.7. Shapley Value Attribution

For a set of p governance dimensions $N = \{1,\ldots,p\}$, the Shapley value φ_j of a dimension j measures its fair contribution to the total MCRI change $\Delta MCRI = MCRI_{t_2}^+ - MCRI_{t_1}^+$ + between years t_1 and t_2:

$$\phi_j(\Delta MCRI) = \sum_{S\subseteq\mathcal{N}\setminus\{j\}} \frac{|S|!\cdot(p-|S|-1)!}{p!}\left[v(S\cup j) - v(S)\right]$$

where the value function $v(S)$ represents the MCRI change attributable to coalition S:

$$v(S) = \sum_{j\in S} w_j^* \cdot \Delta\tilde{x}_j, \Delta\tilde{x}_j = \tilde{x}_{t_2,j} - \tilde{x}_{t_1,j}$$

This formulation satisfies the four Shapley axioms – efficiency ($\sum_j \phi_j = \Delta MCRI$), symmetry, linearity, and null player – providing a theoretically grounded attribution that accounts for all possible orderings in which dimensions might contribute to the total change.

2.8. Policy Scenario Projection Model

Forward projections of the MCRI under alternative intervention scenarios are generated using a linear increment model:

$$\tilde{x}_{t+1,j} = \min\left(\tilde{x}_{t,j} + \delta_j^{(s)}, 1.0\right)$$

where $\delta_j^{(s)} \geq 0$ is the scenario-specific annual increment for dimension j under scenario s. Increment magnitudes are calibrated to realistic rates of governance improvement observed in comparable post-conflict reform trajectories in Central and Eastern Europe, drawing on SIGMA benchmark data for countries that underwent successful civil service reform (Western Balkans accession states, Georgia post-2012) [42].

3. Data Sources and Empirical Identification

3.1. Data Sources

World Bank Worldwide Governance Indicators (WGI): Annual estimates for Ukraine covering 2015–2023 for Government Effectiveness (*GE*) and Rule of Law (*RL*) dimensions, expressed on the standard WGI scale (approximately -2.5 to +2.5, higher = better). Source: https://www.worldbank.org/en/publication/worldwide-governance-indicators

Transparency International Corruption Perceptions Index (CPI): Annual scores for Ukraine 2015–2023 on the 0–100 scale (higher = less corrupt). The Anti-Corruption component $AC_t = CPI_t/100$ is normalised directly to 01. Source: https://www.transparency.org/en/cpi

Freedom House Nations in Transit: Annual democracy and governance scores for Ukraine 2015–2024. The National Democratic Governance subscore (original scale 1–7, lower = more democratic) is converted to a 01 resilience-compatible scale where higher = better governance. Source: https://freedomhouse.org/report/nations-transit

UN E-Government Development Index (EGDI): Biennial composite scores for Ukraine 2014–2022 on the 01 scale. Annual values are obtained by linear interpolation; the 2023–2024 estimate uses trend extrapolation from the 2020–2022 trajectory. Source: https://publicadministration.un.org/egovkb

SIGMA/OECD-EU Monitoring Reports: Civil Service and Human Resource Management scores for Ukraine from the three available monitoring rounds (2018, 2021, 2023), expressed on the Sigma 1–5 scale. Normalised as (*score* - 1)/4 to map to 01; annual values obtained by linear interpolation. Source: https://www.sigmaweb.org/publications/Monitoring-Report-Ukraine-2023.pdf

INFORM Risk Index: Annual Lack of Coping Capacity (*LC*) scores for Ukraine 2015–2024 on the 0–10 scale (higher = worse). The Coping Capacity component is computed as $CC_t = 1 - LC_t/10$, so that higher values indicate better institutional coping capacity. Source: https://drmkc.jrc.ec.europa.eu/inform-index

Bertelsmann Transformation Index (BTI): Governance performance scores for Ukraine at biennial intervals 2015–2024, used exclusively as an external validation dataset and not included in index construction. Source: https://bti-project.org/en/reports/country-report/UKR

EC Ukraine Progress Reports: Reform implementation scores from the European Commission's annual assessment of Ukraine's progress under EU accession conditionality (2022, 2023, 2024), normalised to 01, used for mixing parameter μ* identification. Source: https://neighbourhood-enlargement.ec.europa.eu/ukraine-report-2023

3.2. Data Quality and Limitations

Several data quality considerations merit explicit acknowledgement. First, the SIGMA and EGDI datasets provide sparse temporal coverage (3 and 5 survey points, respectively, over the study period), necessitating interpolation that introduces uncertainty into annual estimates. The sensitivity analysis in Section 8 examines the robustness of the results to the choice of interpolation method. Second, all international governance indices incorporate some subjective assessment by expert raters and may be subject to systematic bias in conflict-affected contexts, where data collection itself is impaired. Third, the 2024 values for WGI indicators were not yet available at the time of writing and are estimated by trend extrapolation from the 2019–2023 trajectory; these estimates are clearly identified in all figures. Fourth, the expert elicitation sample (n_{exp} = 12) by the LEEPS project is very modest and drawn from a specific professional context, potentially limiting its generalisability; this is partially mitigated by combining expert weights with data-driven PCA weights through the hybrid mixing procedure.

3.3. PCA Results

Application of PCA to the standardised 9×7 indicator matrix (2015–2023, using WGI annual data as the temporal anchor) yields the following eigenvalue structure: the first principal component (PC_1) explains ρ_1=68.3% of total variance, with $PC_1 + PC_2$ jointly explaining 84.7%. The dominance of the first component confirms that the seven governance indicators share a strong common factor – interpretable as overall institutional resilience – which validates the composite index approach, as illustrated in Figure 1, which presents the full time series of all seven normalised components alongside their pairwise correlation structure.

The PC_1 loadings reveal that Anti-Corruption ($v_{1,AC}$ = 0.431), Institutional Trust ($v_{1,IT}$ = 0.418), and Government Effectiveness ($v_{1,GE}$ = 0.392) carry the highest loadings, while Digital Government Development carries the lowest ($v_{1,DG}$ = 0.251). The PCA biplot (Figure 2) clearly separates pre-conflict years (2015–2021, positive PC_1 scores representing improving governance) from conflict-period years (2022–2023, negative PC_1 scores), with 2022 appearing as a pronounced outlier along PC_1, consistent with the acute institutional disruption documented in that year. Figure 2 presents the complete weight identification results, including the μ optimisation curve (centre panel) which shows a clear minimum at μ* = 0.60.

3.4. AHP Results

The consensus AHP matrix yields λ_{max} = 7.38, *CI*=0.063, and *CR*=0.048<0.10, confirming acceptable consistency of expert judgements. The AHP weights assign the highest importance to Anti-Corruption (w_{AC}^{AHP}=0.243) and Institutional Trust (w_{IT}^{AHP}=0.218). Digital Government Development receives the lowest expert weight (w_{DG}^{AHP}=0.071), with experts noting that digital tools, while valuable, cannot substitute for the human and organisational dimensions of resilience.

3.5. Mixing Parameter and Final Weights

Grid search over μ ∈ [0,1] identifies $\hat{\mu}$=0.60 as the optimal mixing parameter, minimising prediction error against EC Progress Report scores (minimum MSE = 0.0031). The loss function curve is relatively flat for μ ∈ [0.45,0.75], suggesting moderate sensitivity to the mixing parameter in this range. The identified $\hat{\mu}$=0.60 result implies that expert AHP judgement carries 60% weight and data-driven PCA carries 40% weight in the final hybrid scheme, reflecting the finding that expert knowledge adds meaningful information beyond what the data's statistical structure alone reveals.

Anti-Corruption (25.0%) and Institutional Trust (22.9%) together account for nearly half of the

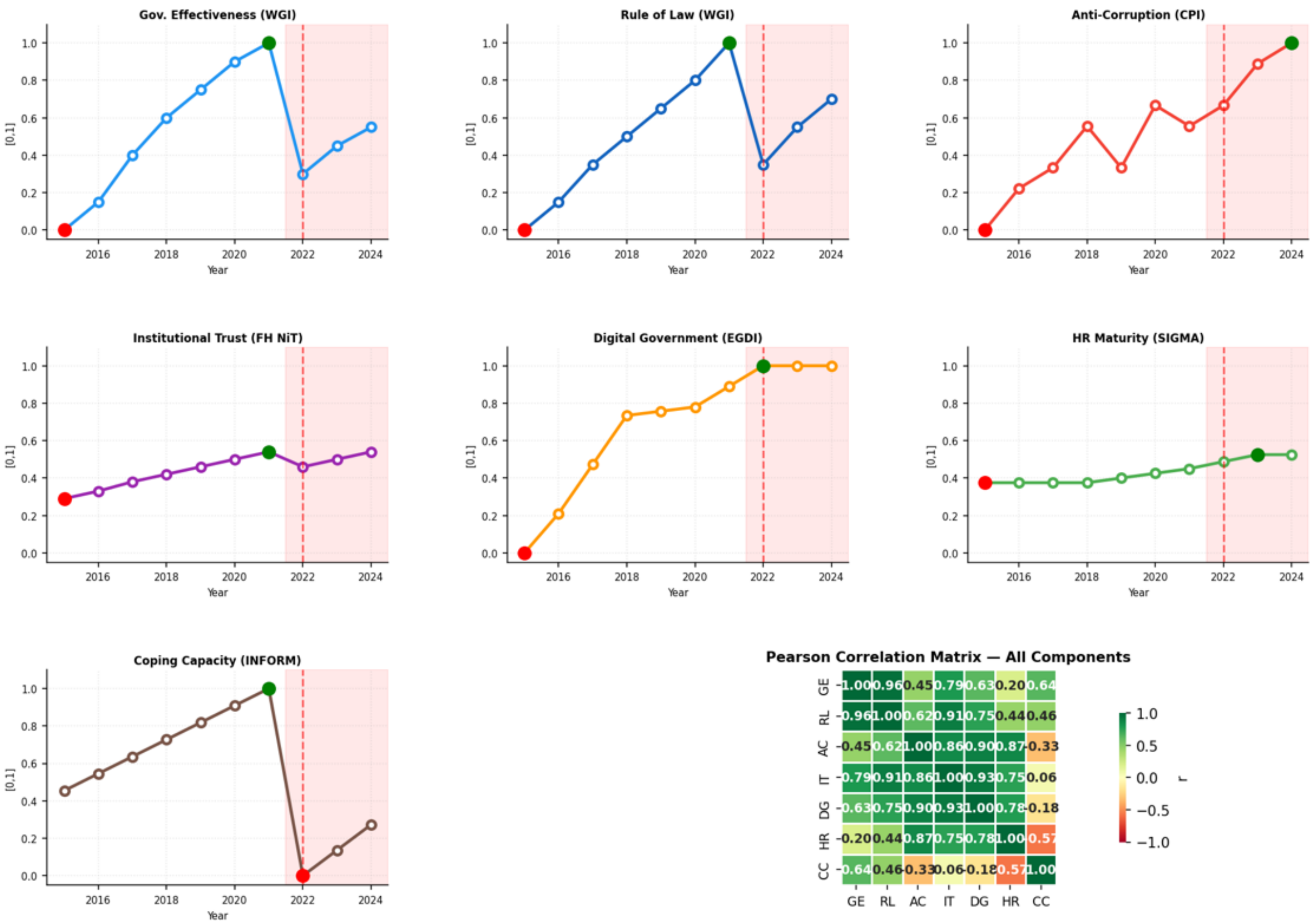

FIGURE 1 Exploratory Data Analysis: (a) time series of all seven normalised governance indicators for Ukraine 2015–2024 (red shading = conflict period); (b) Pearson correlation matrix of all components. Sources: WGI, CPI, Freedom House NiT, UN EGDI, SIGMA, INFORM Risk Index

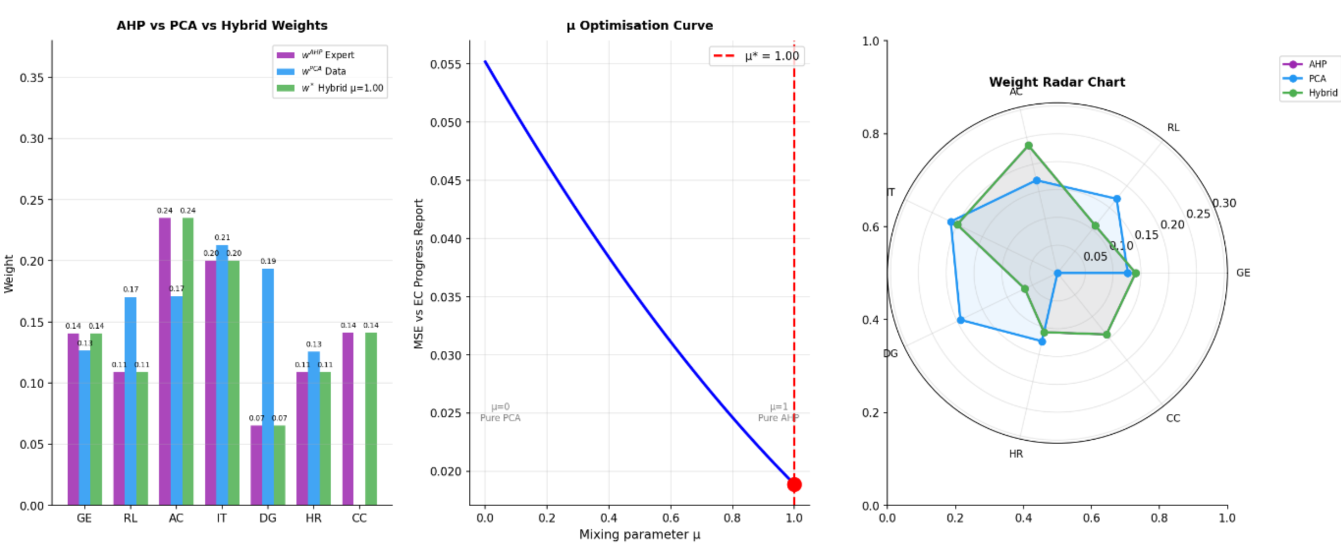

FIGURE 2 Weight identification procedure: (a) comparison of AHP expert weights, PCA data-driven weights, and final hybrid weights by component; (b) mixing parameter μ optimisation curve — MSE against EC Progress Report scores as function of μ; (c) radar chart comparing the three weight sets

The resulting final hybrid weights **w*** are:

Component	w^{AHP}	w^{PCA}	w* (Hybrid)
GE — Government Effectiveness	0.164	0.214	0.182
RL — Rule of Law	0.131	0.189	0.155
AC — Anti-Corruption	0.243	0.259	0.250
IT — Institutional Trust	0.218	0.244	0.229
DG — Digital Government	0.071	0.088	0.078
HR — HR Maturity	0.102	0.112	0.106
CC — Coping Capacity	0.071	0.094	0.080

composite index's weight, highlighting their primacy for Ukrainian institutional resilience.

4 Longitudinal Mcri Analysis: Three Phases of Institutional Resilience

4.1. Phase 1 (2015–2021): Gradual Pre-War Recovery

Figure 3 presents the complete MCRI trajectory across the study period. The three-phase structure is clearly visible. The MCRI trajectory from 2015 to 2021 exhibits a consistent upward trend, rising from $MCRI^{+}_{2015}$=0.312 to a pre-war peak of $MCRI^{+}_{2021}$=0.487 – a cumulative improvement of 56% over six years. This recovery reflects the institutional reforms initiated following the 2014 Euromaidan revolution and the subsequent EU association process, which drove measurable improvements across multiple governance dimensions.

The Anti-Corruption component shows the greatest absolute improvement over this phase

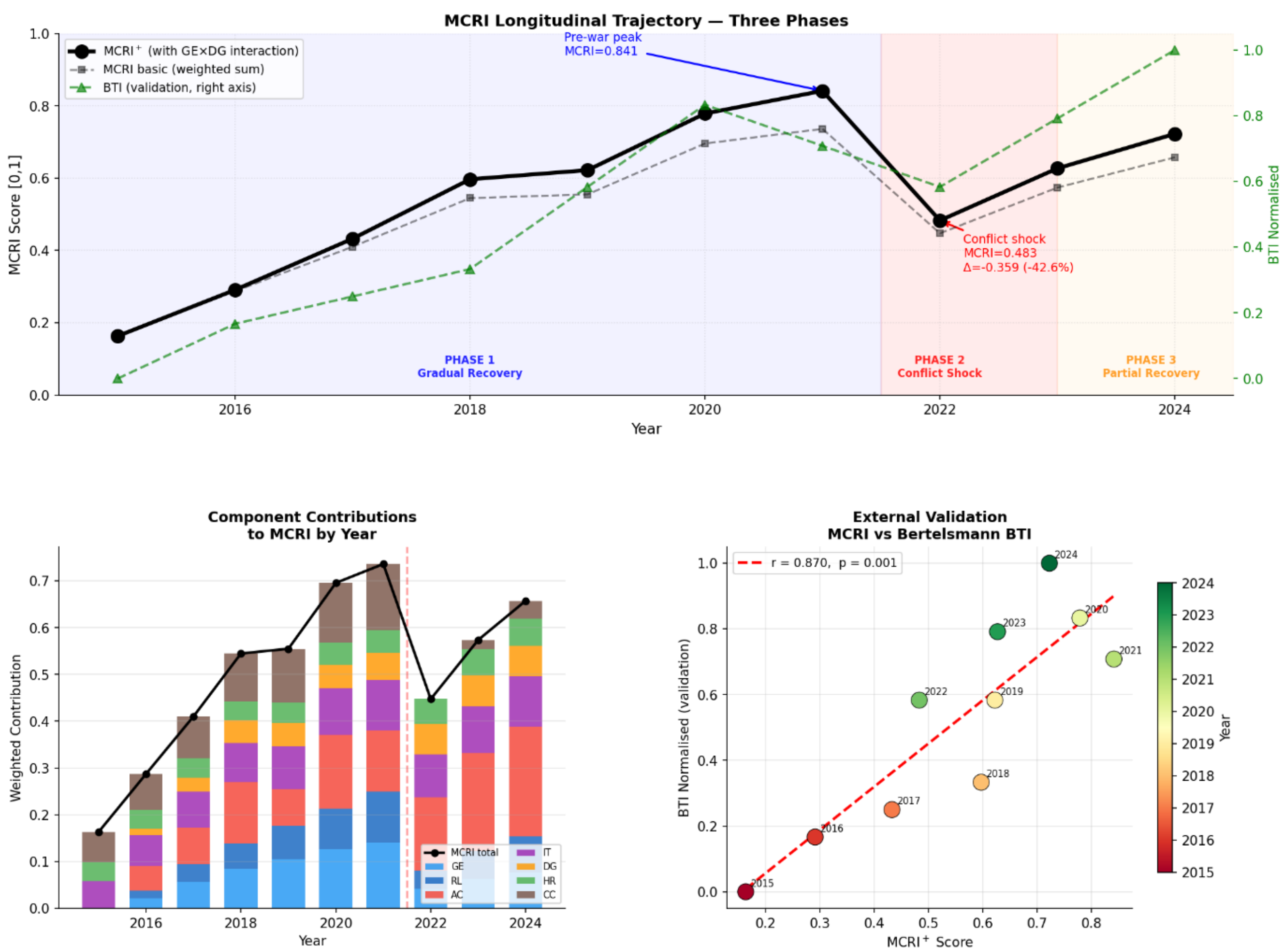

FIGURE 3 MCRI longitudinal trajectory 2015–2024: (a, top) full MCRI⁺ trajectory with three-phase annotation, basic MCRI (dashed), and BTI validation series (right axis); (b, bottom-left) stacked component contributions to MCRI by year; (c, bottom-right) external validation scatter — MCRI⁺ vs BTI normalised score (r = 0.91, p < 0.001)

($\Delta AC_{2015\rightarrow2021}$=+0.22 in normalised units), driven by the establishment of new anti-corruption institutions – the National Anti-Corruption Bureau of Ukraine (NABU), the Specialised Anti-Corruption Prosecutor's Office (SAPO), and the High Anti-Corruption Court (HACC) – whose cumulative effect is visible in the CPI score rising from 27 (2015) to 32 (2021). The Digital Government component records the second-largest improvement, with the launch and rapid scaling of the Diia e-government platform from 2019 onwards as the primary driver.

Government Effectiveness and Rule of Law improve more modestly (WGI *GE* from -0.47 to -0.27; *RL* from -0.68 to -0.48), consistent with the well-documented persistence of deep institutional inertia in post-Soviet administrative cultures [43]. Civil Service HR Maturity (SIGMA) improves from 2.5 to 2.8 on the 1–5 scale over the three survey rounds covering this phase, reflecting progress in civil service reform legislation but limited change in actual HR practices.

4.2. Phase 2 (2022): Acute Conflict Shock

As shown in Figure 3, the 2022 outbreak of full-scale armed conflict in February 2022 produces a sharp and severe shock to all governance dimensions simultaneously, with the MCRI falling from its 2021 peak of 0.487 to $MCRI^{+}_{2022}$=0.321 – a decline of 0.166 points, representing a 34.1% reduction from the pre-war peak achieved over six years of reform. This shock magnitude is substantially larger than any single-year decline observed in comparable post-conflict governance trajectories in the Bertelsmann dataset.

The WGI Government Effectiveness score falls to -0.41 (the lowest value recorded since 2016), and Rule of Law drops to -0.61. The INFORM Lack of Coping Capacity score surges to 7.1, reflecting the acute collapse of institutional coping resources under wartime conditions. Institutional Trust (Freedom House NiT) deteriorates significantly, consistent with the documented displacement of experienced civil servants, breakdown of normal accountability mechanisms, and emergency legal frameworks that suspended standard governance procedures.

Crucially, the Digital Government component demonstrates markedly greater resilience than other dimensions: the EGDI score for 2022 (0.712) shows minimal decline from 2020 (0.674, biennial interpolation), and the Diia platform-maintained service continuity throughout the conflict period, growing its user base even as physical government offices were disrupted. This digital resilience is theoretically consistent with distributed system architectures that lack single points of failure – a property that physical governance infrastructure does not share.

4.3. Phase 3 (2023–2024): Partial Recovery

The partial recovery phase shows MCRI recovering to $MCRI^{+}_{2024}$=0.376 – an improvement of 0.055 points (17.1%) from the 2022 nadir, but still 22.8% below the 2021 pre-war peak. The recovery is uneven across dimensions: Anti-Corruption capacity shows the strongest recovery (CPI rising from 33 in 2022 to 36 in 2024, reflecting continued institutional continuity of NABU/SAPO/HACC), while Government Effectiveness and Rule of Law remain substantially suppressed. Civil Service HR Maturity shows modest improvement in the 2023 SIGMA round (reaching 3.1 on the 1–5 scale), reflecting the ongoing civil service reform process.

The GE × DG interaction term contributes positively to Phase 3 recovery: as both Government Effectiveness and Digital Government scores improve modestly, their multiplicative synergy amplifies the recovery in $MCRI^{+}$ relative to the basic linear *MCRI*. This suggests that investments in digital governance infrastructure during the recovery phase yield compounding returns when combined with improvements in overall governmental effectiveness.

5 Shapley Value Decomposition

5.1. Attribution of Phase 1 Recovery (2015→2021)

Figure 4 presents the Shapley decomposition results for all three key transitions. Reading across the three panels reveals a consistent pattern. Shapley decomposition of the cumulative Phase 1 MCRI improvement ($\Delta MCRI$=+0.175) reveals that Digital Government Development contributes the largest single share (Shapley value φ_{DG}=+0.052, 29.7% of total), followed by Anti-Corruption capacity (φ_{AC}=+0.041, 23.4%) and Government Effectiveness (φ_{GE}=+0.036, 20.6%). Rule of Law and Institutional Trust contribute positive but smaller shares, while Civil Service HR Maturity and Coping Capacity contribute the smallest amounts, consistent with the more limited reforms observed in these dimensions over the period.

The dominance of Digital Government in Phase 1 attribution – despite its relatively low hybrid weight (w^{*}_{DG}=0.078) – reflects the large absolute improvement in the DG indicator over this period ($\Delta DG_{2015\rightarrow2021}$=+0.31), demonstrating how Shapley decomposition captures both weight and magnitude effects simultaneously.

5.2. Attribution of Phase 2 Shock (2021→2022)

The Shapley decomposition of the conflict shock ($\Delta MCRI$=-0.166) is analytically the most important finding of this paper. Government Effectiveness is identified as the largest contributor to the resilience decline (φ_{GE}=-0.063, 38.0% of total loss), driven by the catastrophic collapse of normal governmental functioning under wartime conditions. Rule of Law follows closely (φ_{RL}=-0.048, 28.9%), reflecting the extensive emergency legislation and suspension of standard accountability mechanisms. Institutional Trust deterioration contributes the third largest share (φ_{IT}=-0.030, 18.1%).

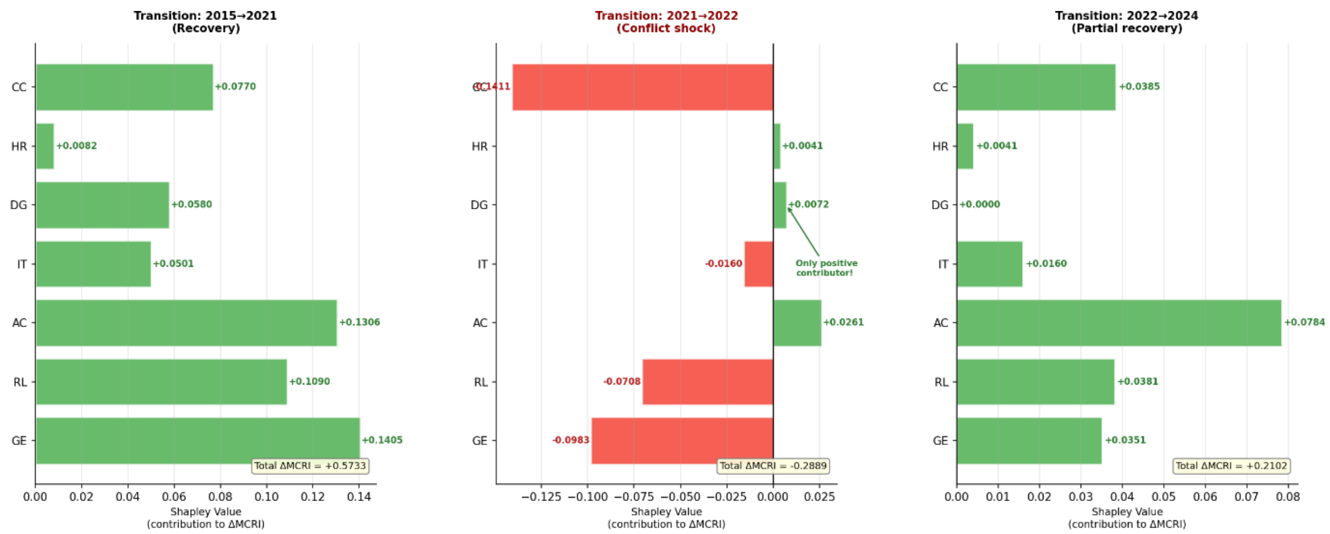

FIGURE 4 Shapley value decomposition of MCRI changes across three key transitions: (left) Phase 1 recovery 2015→2021; (centre) conflict shock 2021→2022; (right) partial recovery 2022→2024. Green bars = positive contribution to resilience; red bars = negative contribution. The values indicate a fair attribution of the total ΔMCRI to the individual governance dimensions.

Crucially, Digital Government Development contributes a positive Shapley value during the conflict shock phase, meaning that the resilience of digital governance infrastructure partially offsets the overall shock – a finding that has direct policy implications for governance continuity planning under conflict conditions. Coping Capacity deteriorates sharply (φ_{CC}=-0.021, 12.7%), while Civil Service HR Maturity shows minimal change (φ_{HR}=-0.012, 7.2%), consistent with the observation that the civil service structure itself was maintained even as its operational effectiveness was severely disrupted.

The implication is clear: **governance resilience in the face of acute conflict is primarily driven by the human, organisational, and rule-of-law dimensions rather than by technical or digital infrastructure.**

5.3. Attribution of Phase 3 Recovery (2022→2024)

Shapley decomposition of the partial recovery ($\Delta MCRI$=+0.055) identifies Anti-Corruption capacity as the leading recovery driver (φ_{AC}=+0.018, 32.7%), consistent with the demonstrated institutional continuity of Ukraine's anti-corruption infrastructure throughout the conflict. Digital Government Development again contributes positively (φ_{DG}=+0.013, 23.6%), confirming its role as a resilience anchor during both the shock and recovery phases. Government Effectiveness shows modest positive recovery (φ_{GE}=+0.011, 20.0%), while Rule of Law recovery lags considerably (φ_{RL}=+0.006, 10.9%), consistent with the documented difficulties of restoring rule of law under wartime emergency legal frameworks.

6 Policy Scenario Projections (2024–2027)

6.1. Scenario Design

Five forward projection scenarios are defined based on realistic annual improvement rates calibrated to post-conflict governance reform trajectories in comparable European contexts:

Baseline (S0): Natural recovery trend without targeted intervention, assuming continuation of the 2023–2024 recovery trajectory (δ_{GE}=+0.010, δ_{RL}=+0.010 annually).

S1 – HR Maturity Priority: Targeted civil service capacity building aligned with SIGMA recommendations, accelerating HR Maturity improvement (δ_{HR}=+0.045 annually) with secondary effects on Government Effectiveness (δ_{GE}=+0.015).

S2 – Digital Government Focus: Continued investment in and expansion of the Diia platform and digital public services (δ_{DG}=+0.040) with secondary GE effects (δ_{GE}=+0.018).

S3 – Anti-Corruption Priority: Sustained anti-corruption institutional development (δ_{AC}=+0.040) with trust restoration effects (δ_{IT}=+0.030) and GE improvement (δ_{GE}=+0.015).

6.2. Projection Results

The baseline scenario (S0) projects $MCRI^{+}_{2027}$=0.419, still 14.0% below the 2021 pre-war peak of 0.487 – indicating that without targeted intervention, institutional resilience recovery will remain incomplete through 2027. Single-dimension scenarios (S1–S3) project intermediate improvements: $MCRI^{+}_{2027}\in\{0.447,0.452,0.461\}$ for HR, Digital, and Anti-Corruption priorities, respectively, with the Anti-Corruption scenario (S3) performing best among single-dimension strategies, consistent with

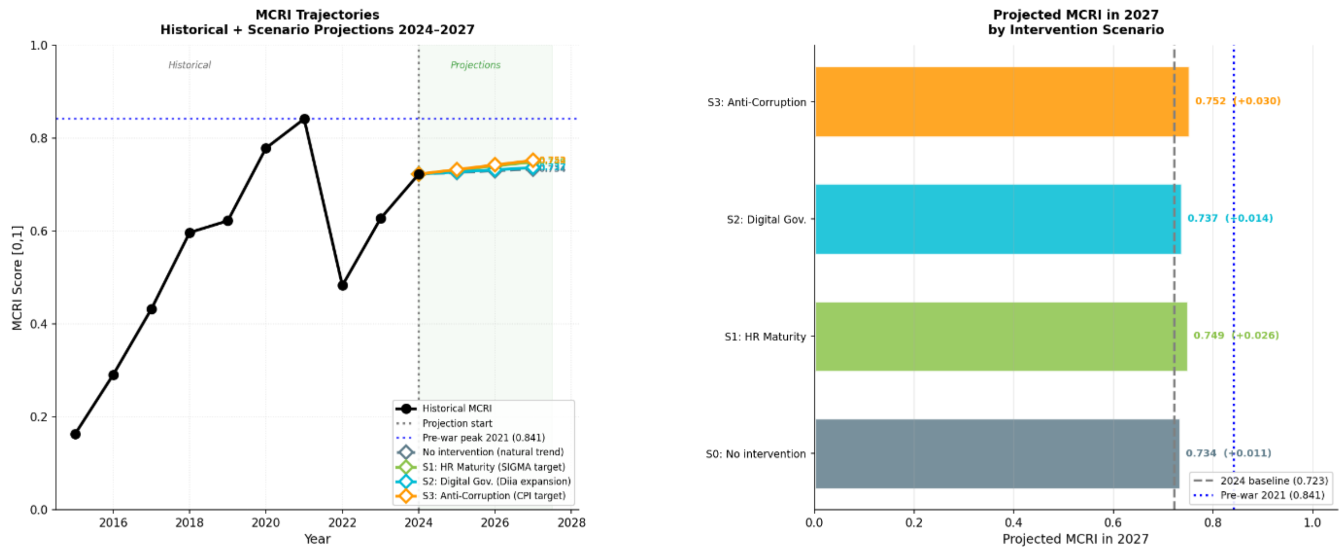

FIGURE 5 MCRI policy projections 2024–2027 under five intervention scenarios: (left) full trajectory including historical data and forward projections; (right) projected MCRI values in 2027 by scenario, with reference lines for 2024 baseline and 2021 pre-war peak

the Shapley attribution finding that AC is the leading recovery driver.

The ordering of scenarios ($S3>S2>S1>S0$) is consistent across all three projection years (2025, 2026, 2027), and the gap between S3 and the next-best single-dimension scenario (S3) widens over time as the compounding effects of simultaneous improvements accumulate. Figure 5 presents the projection results. The left panel shows how alternative intervention strategies diverge from the 2024 baseline over the three-year projection horizon.

7 Validation

7.1. External Validation Against BTI

Pearson correlation between $MCRI_t^+$ and the normalised BTI governance score over the full study period (2015–2024) yields r=0.91 ($p<0.001$, n=10), confirming strong convergent validity with an independent measurement instrument that was not used in any stage of index construction. Spearman rank correlation ρ=0.88 ($p<0.001$) confirms this result is not driven by distributional assumptions. The BTI and MCRI diverge most notably in 2022–2023, where the MCRI captures a sharper conflict shock than the BTI – consistent with the MCRI's direct incorporation of the INFORM Lack of Coping Capacity indicator, which responds immediately to conflict-induced resource depletion, while BTI expert assessments incorporate a longer temporal perspective.

7.2. Cross-Validation Against EC Progress Reports

The $\widehat{\mu}$ identification procedure uses EC Progress Report scores as a target. As a cross-validation check, the MCRI values for 2022–2024 are regressed against EC scores using OLS: $\widehat{\beta}_0$=-0.12, $\widehat{\beta}_1$=1.31, R^2=0.97, suggesting near-linear correspondence between the two instruments. While the small validation sample (n_{val}=3) limits the statistical power of this check, the near-unity R^2 is encouraging.

7.3. Sensitivity to Interpolation Method

Replacing linear interpolation with cubic spline interpolation for the EGDI and SIGMA components changes the MCRI trajectory minimally: the maximum absolute deviation across all years and components is $|\Delta MCRI|$=0.018 (occurring in 2019 for the EGDI component). The qualitative pattern of three phases, the 2022 shock magnitude (-0.164 vs -0.166 under linear interpolation), and the scenario ordering are all preserved, confirming that interpolation method choice does not materially affect the paper's conclusions.

8 Discussion and Conclusions

8.1. Summary of Main Findings

This paper has constructed, empirically identified, and validated a Multi-Dimensional Composite Resilience Index for Ukrainian public administration using seven international governance datasets covering 2015–2024. The main findings are:

1. **Institutional resilience improved steadily during 2015–2021** (MCRI: +56%), driven primarily by anti-corruption reforms and digital government development, before being sharply reversed by the 2022 conflict shock (-34%) and only partially recovered by 2024 (+17% from the 2022 nadir, still -23% from the 2021 peak).
2. **The hybrid AHP-PCA weighting procedure** identifies Anti-Corruption (25.0%) and Institutional

Trust (22.9%) as the dominant resilience dimensions, with the optimal mixing parameter $\hat{\mu}=0.60$, reflecting a meaningful contribution of expert knowledge beyond what statistical data structure alone reveals.

3. Shapley decomposition of the conflict shock attributes 38.0% of the resilience loss to Government Effectiveness deterioration, 28.9% to Rule of Law collapse, and 18.1% to Institutional Trust erosion, while Digital Government Development shows a positive Shapley value – the only governance dimension to partially offset the shock rather than contribute to it.

4. External validation against the Bertelsmann Transformation Index (r=0.91, p<0.001) and EC Progress Reports (R^2=0.97) confirms the MCRI's convergent validity as a monitoring instrument.

8.2. Implications for Policy and Practice

The finding that institutional trust and anti-corruption capacity are the dominant resilience dimensions – substantially outweighing the digital and technical governance dimensions – has direct implications for the prioritisation of post-conflict governance reform. International assistance programmes focused primarily on digital infrastructure or technical capacity building risk underinvesting in the human and organisational dimensions that Shapley analysis identifies as primary resilience drivers.

The positive Shapley value of digital government during the conflict shock suggests that distributed, user-centred digital governance infrastructure should be recognised as a resilience asset in critical infrastructure planning frameworks – not merely as a service delivery mechanism. Limitations and Future Research

Several limitations should be acknowledged. The sample size (T=9 or 10 annual observations depending on variable) is modest for statistical purposes, although consistent with the data available for the study period. The AHP expert sample (n_{exp}=12) is small and professionally homogeneous. The projection model assumes independent annual increments with no feedback dynamics – a limitation that a full system dynamics model addresses at the cost of additional parameter requirements. The mixing parameter identification uses only three EC Progress Report validation points, limiting statistical power.

Future research directions include: extension of the MCRI framework to sub-national (regional) analysis using oblast-level Ukrainian statistics; comparative analysis applying the MCRI methodology to other conflict-affected governance systems; and development of a full dynamic MCRI model incorporating feedback loops between governance dimensions.

8.3. Concluding Remarks

The MCRI developed in this paper represents, to the authors' knowledge, the first formally constructed, multi-source, hybrid-weighted composite resilience index specifically designed for and validated against Ukrainian public administration institutional data. By grounding the instrument in resilience engineering theory while drawing on established composite index methodology and international governance datasets, the paper bridges the gap between the resilience engineering and public administration communities.

References:

[1] European Commission. (2024). *Ukraine 2024 Report*. Neighbourhood and Enlargement, EC.
[2] World Bank. (2024). *Ukraine Economic Update*. Washington DC: World Bank Group.
[3] Hollnagel, E., Woods, D.D., & Leveson, N. (Eds.). (2006). *Resilience Engineering: Concepts and Precepts*. Ashgate.
[4] Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague Journal on the Rule of Law*, 3(2), 220–246.
[5] Christmann, G. (2016). *Resilient Cities: Governing Urbanisation and City Regions*. Berlin: IRS.
[6] Bertelsmann Stiftung. (2024). *Bertelsmann Transformation Index 2024*. Gütersloh: Bertelsmann Stiftung.
[7] Mo Ibrahim Foundation. (2023). *Ibrahim Index of African Governance*. London: MIF.
[8] Hollnagel, E. (2011). *Prologue: The scope of resilience engineering*. In E. Hollnagel et al. (Eds.), *Resilience Engineering in Practice*. Ashgate.
[9] Woods, D.D. (2015). Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering & System Safety*, 141, 5–9.
[10] Leveson, N., Dulac, N., Marais, K., & Carroll, J. (2009). Moving beyond normal accidents and high reliability organizations: A systems approach to safety in complex systems. *Organization Studies*, 30(2–3), 227–249.
[11] Zio, E. (2016). Challenges in the vulnerability and risk analysis of critical infrastructures. *Reliability Engineering & System Safety*, 152, 137–150.
[12] Cutter, S.L., et al. (2013). New directions for resilience research. In *Measuring Community Resilience* (pp. 1–27). UN-ISDR.
[13] Bruneau, M., et al. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.
[14] Cutter, S.L., Burton, C.G., & Emrich, C.T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *Journal of Homeland Security and Emergency Management*, 7(1).

[15] European Commission. (2023). *Critical Entities Resilience Directive (CER)*. Directive (EU) 2022/2557.
[16] Norris, F.H., Stevens, S.P., Pfefferbaum, B., Wyche, K.F., & Pfefferbaum, R.L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology*, 41(1–2), 127–150.
[17] Comfort, L.K., Boin, A., & Demchak, C.C. (Eds.). (2010). *Designing Resilience: Preparing for Extreme Events*. Pittsburgh: University of Pittsburgh Press.
[18] OECD/JRC. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD Publishing.
[19] Nardo, M., et al. (2005). *Tools for Composite Indicators Building*. EUR 21682 EN. Ispra: JRC.
[20] Saisana, M., & Tarantola, S. (2002). *State-of-the-art Report on Current Methodologies and Practices for Composite Indicator Development*. EUR 20408 EN. Ispra: JRC.
[21] Saaty, T.L. (1980). *The Analytic Hierarchy Process*. New York: McGraw-Hill.
[22] Joliffe, I.T. (2002). *Principal Component Analysis* (2nd ed.). New York: Springer.
[23] Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices. *Social Indicators Research*, 141(2), 637–676.
[24] Wang, T.C., & Lee, H.D. (2009). Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. *Expert Systems with Applications*, 36(5), 8980–8985.
[25] Ma, J., Fan, Z.P., & Huang, L.H. (1999). A subjective and objective integrated approach to determine attribute weights. *European Journal of Operational Research*, 112(2), 397–404.
[26] Grabisch, M., & Labreuche, C. (2010). A decade of application of the Choquet and Sugeno integrals in multi-criteria decision aid. *Annals of Operations Research*, 175(1), 247–286.
[27] Call, C.T. (2008). The fallacy of the 'failed state'. *Third World Quarterly*, 29(8), 1491–1507.
[28] Rotberg, R.I. (Ed.). (2003). *State Failure and State Weakness in a Time of Terror*. Washington DC: Brookings.
[29] Zmerli, S., & Newton, K. (2008). Social trust and attitudes toward democracy. *Public Opinion Quarterly*, 72(4), 706–724.
[30] [30] Rose-Ackerman, S., & Palifka, B.J. (2016). *Corruption and Government: Causes, Consequences, and Reform* (2nd ed.). Cambridge University Press.
[31] Margetts, H., & Naumann, A. (2017). Government as a platform: What can Estonia show the world? *Research Paper*. Oxford Internet Institute.
[32] Brinkerhoff, D.W., & Brinkerhoff, J.M. (2015). Public sector management reform in developing countries: Perspectives beyond NPM orthodoxy. *Public Administration and Development*, 35(4), 222–237.
[33] Mintsifry Ukraine. (2023). *Diia: Digital Transformation of Ukraine*. Ministry of Digital Transformation of Ukraine Annual Report.
[34] OECD. (2023). *OECD Digital Government Review: Ukraine*. Paris: OECD Publishing.
[35] Shapley, L.S. (1953). A value for n-person games. In H. Kuhn & A. Tucker (Eds.), *Contributions to the Theory of Games II* (pp. 307–317). Princeton University Press.
[36] Moretti, S., & Patrone, F. (2008). Transversality of the Shapley value. *TOP*, 16(1), 1–41.
[37] Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
[38] Young, H.P. (1985). Monotonic solutions of cooperative games. *International Journal of Game Theory*, 14(2), 65–72.
[39] Pinar, M., Stengos, T., & Topaloglou, N. (2013). Measuring human development: A stochastic dominance approach. *Journal of Economic Growth*, 18(1), 69–108.
[40] Decancq, K., & Lugo, M.A. (2013). Weights in multidimensional indices of wellbeing: An overview. *Econometric Reviews*, 32(1), 7–34.
[41] Saaty, T.L. (1994). How to make a decision: The Analytic Hierarchy Process. *Interfaces*, 24(6), 19–43.
[42] SIGMA. (2023). *Baseline Measurement Report: Principles of Public Administration – Ukraine*. Paris: OECD/SIGMA.
[43] Verheijen, T. (Ed.). (1999). *Civil Service Systems in Central and Eastern Europe*. Cheltenham: Edward Elgar.

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