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Explainable Machine Learning for Multidomain Socioeconomic Vulnerability Assessment in the Visegrád Region

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Abstract: Dynamic analytical frameworks are essential for socioeconomic vulnerability assessment in post-transition economies, particularly for capturing temporal evolution and identifying actionable policy thresholds. This study integrates time-varying panel regression with explainable machine learning to analyze multidomain vulnerability patterns across Visegrád countries using harmonized Eurostat data from 2015 to 2024 (n=40 country observations). The methodology employs composite vulnerability indices from six domains (exposure, sensitivity, capacity, economic, housing, infrastructure), gradient boosting models with partial dependence analysis, and counterfactual policy scenarios. Time-varying panel regression achieves $R^2 = 0.984$ with significant temporal coefficient evolution. Sensitivity domain effects increase from 0.283 to 0.528 ($p<0.001$). Explainable machine learning reveals overcrowding rate as the dominant vulnerability predictor (81.8% feature importance), dramatically overshadowing GDP per capita (1.3%), with unmet medical needs exhibiting secondary influence (9.2%). Partial dependence analysis identifies critical policy thresholds at standardized values of -0.03 for overcrowding and -0.71 for unmet medical needs, revealing threshold-dominated nonlinear relationships rather than linear proportional effects. Country-specific trajectories show Hungary achieving largest historical improvement (-0.924 units), Czechia maintaining strongest final position (-1.292), and Poland exhibiting highest remaining vulnerability (0.234 in 2024). Counterfactual intervention scenarios demonstrate mean regional vulnerability reduction of -0.426 units through combined housing, healthcare, and poverty interventions, with overcrowding improvements alone yielding 0.334 units reduction. Country-specific intervention responsiveness ranges from minimal (-0.004 for Czechia) to substantial (-0.766 for Poland and -0.751 for Slovakia), revealing that elevated baseline vulnerabilities predict stronger intervention effectiveness. The integrated framework advances evidence-based regional development strategies prioritizing housing quality and healthcare access.

Keywords: socioeconomic vulnerability; explainable machine learning; post-transition economies; policy thresholds; sustainable development

*Complete nomenclature and abbreviations are provided in Appendix A.

1. Introduction

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Socioeconomic vulnerability assessment has emerged as a fundamental analytical imperative for understanding how societies experience differential exposure, sensitivity, and adaptive capacity in the face of rapid economic transitions, demographic transformations, and institutional restructuring across contemporary Europe [1,2]. These vulnerability patterns align with several United Nations Sustainable Development Goals including No Poverty, Good Health and Well-being, Reduced Inequalities, and Sustainable Cities and Communities. This intersection requires the use of analytical frameworks that can convert the identification of socioeconomic risks into practical policy structures for the purpose of sustainable regional development. Central Europe, particularly post-transition countries navigating complex institutional legacies and uneven development trajectories, confronts distinct vulnerability configurations shaped by path-dependent processes, institutional capacity constraints, and persistent spatial disparities in living standards that demand systematic quantification and evidence-based policy formulation [3,4]. The Visegrád cooperation framework includes Czechia, Hungary, Poland, and Slovakia. This group offers a compelling case study due to their shared experiences with post-socialist transformation and their parallel pathways toward integration within the European Union. Furthermore, their ongoing efforts to coordinate policy demonstrate a complex attempt to balance economic development with social cohesion and environmental sustainability [5,6].

Several factors contribute to the increasing vulnerability of post transition societies across Central Europe. These include demographic shifts and environmental hazards in addition to volatility within labor markets and healthcare systems. Recent events have exacerbated these issues particularly the COVID 19 pandemic and the energy crisis. Additionally, the geopolitical shifts occurring after 2022 continue to influence the stability of the region [1]. These structural disruptions expose differential resilience capacities across national and subnational scales, revealing that macroeconomic growth trajectories inadequately predict vulnerability outcomes at population levels. The temporal concentration of multiple stressors during 2020-2024 constitutes a natural experiment illuminating how institutional arrangements, social protection architectures, and housing infrastructure configurations mediate vulnerability exposure across demographically and economically heterogeneous populations. To understand these dynamics, the focus must shift from snapshots of vulnerability to the systematic study of temporal changes in determinant relationships. Developing frameworks for this purpose is a methodological necessity. However, this specific need is currently underserved within the body of regional development research [7–9].

Recent advances in machine learning applications demonstrate substantial potential for capturing nonlinear relationships and complex interaction effects that traditional linear econometric specifications may inadequately represent, particularly when vulnerability emerges through threshold mechanisms rather than proportional dose-response patterns [7,10]. Comparative regional studies within coherent political economic groupings like the Visegrád countries are currently limited. Most

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vulnerability research focuses on broad continental scale assessments or individual country case studies. Consequently, these existing approaches prevent a systematic cross-national comparison of vulnerability determinants and temporal trajectories along with the effectiveness of policy interventions [9,11].

Five critical research gaps persist despite scholarly progress. First, dynamic vulnerability assessment frameworks capturing temporal coefficient evolution remain notably absent, despite growing theoretical recognition that vulnerability relationships shift systematically as institutional capacities mature and societies adapt to persistent stressors [7,12]. Second, comprehensive multidomain approaches systematically integrating socioeconomic, health, housing, and infrastructure dimensions within unified analytical architectures remain underdeveloped, with most studies examining isolated vulnerability indicators rather than composite indices reflecting interdependent risk pathways [8,13]. Third, explainable machine learning applications remain nascent within the field of vulnerability research. Conventional black box algorithms unable to clarify which individual factors influence vulnerability or which areas offer the highest returns for policy investments. Consequently, these computational limitations hinder the translation of complex data into actionable strategies for regional development [14,15]. Fourth, existing methodologies inadequately identify approximate threshold zones for policy-actionable variables, hindering development of targeted intervention strategies grounded in quantitative guidance regarding nonlinear vulnerability transitions [16,17]. Finally, country-specific characterization within regional cooperation frameworks remains insufficiently developed, preventing identification of complementary national strengths and shared vulnerabilities that could inform evidence-based resource allocation and coordinated regional development strategies [9,11].

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Three research questions guide this investigation. RQ1 examines how socioeconomic vulnerability patterns evolve across Visegrád countries during 2015 to 2024, and whether domain-specific relationships exhibit gradual temporal evolution or discrete structural breaks. RQ2 investigates which socioeconomic and infrastructure factors demonstrate the strongest nonlinear associations with composite vulnerability indices, and what specific threshold zones characterize policy-actionable variables for intervention design. RQ3 explores what distinct vulnerability profiles characterize each Visegrád country, and to what extent they exhibit heterogeneous responsiveness to standardized policy intervention scenarios.

This study develops a comprehensive, temporally dynamic vulnerability assessment framework integrating time-varying panel econometrics with explainable machine learning architectures. Four specific objectives structure the investigation. Objective 1: constructs composite vulnerability indices incorporating six domains (exposure, sensitivity, capacity, economic, housing, infrastructure) with dual weighting validation. Objective 2: quantifies temporal evolution in vulnerability determinants through time-varying coefficient panel regression with structural break testing. Objective 3: identifies threshold zones and feature importance rankings via gradient boosting with partial dependence analysis. Objective 4: characterizes country-specific vulnerability profiles and quantifies differential intervention responsiveness through counterfactual policy scenarios.

This investigation establishes three novel analytical advances addressing critical methodological and substantive gaps in vulnerability assessment scholarship. First, existing research predominantly assumes static vulnerability relationships despite theoretical recognition that institutional maturation processes should alter determinant configurations over developmental timescales. To our knowledge, no prior study integrates time-varying coefficient econometrics with explainable machine learning to empirically test whether vulnerability relationships remain temporally stable or exhibit systematic structural evolution [7,12]. Second, while machine learning applications proliferate in socioeconomic research, algorithmic opacity constrains policy translation. This study advances partial dependence function analysis to identify precise, quantitatively validated threshold zones for housing and healthcare interventions, moving beyond feature importance rankings toward operationalizable intervention targeting guidance largely absent from existing applications in regional development contexts. Third, vulnerability literature rarely incorporates counterfactual policy scenario frameworks quantifying differential national responsiveness to standardized interventions within regional cooperation groupings [9,11]. By simulating combined multi-lever strategies and estimating heterogeneous treatment effects across Visegrád countries, this research establishes whether vulnerability reduction follows convergence dynamics or exhibits path-dependent responsiveness patterns, a distinction with fundamental implications for resource allocation architectures in European cohesion policy that remains empirically unresolved. These methodological innovations transcend descriptive vulnerability mapping toward predictive, policy-relevant frameworks directly supporting UN SDG implementation through evidence-based intervention design in post-transition contexts confronting accelerating climate adaptation pressures and persistent socioeconomic inequalities.

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2. Materials and methods

2.1. Analytical framework overview

This study employs a contextual vulnerability framework to analyze socioeconomic and infrastructure conditions that determine adaptive capacity across the Visegrád region, using harmonized Eurostat data [18–20]. This approach prioritizes identifying actionable policy intervention points like housing and healthcare. The multi-stage analytical framework, shown in Figure 1, integrates econometric and machine learning techniques to capture both temporal evolution and nonlinear threshold effects.

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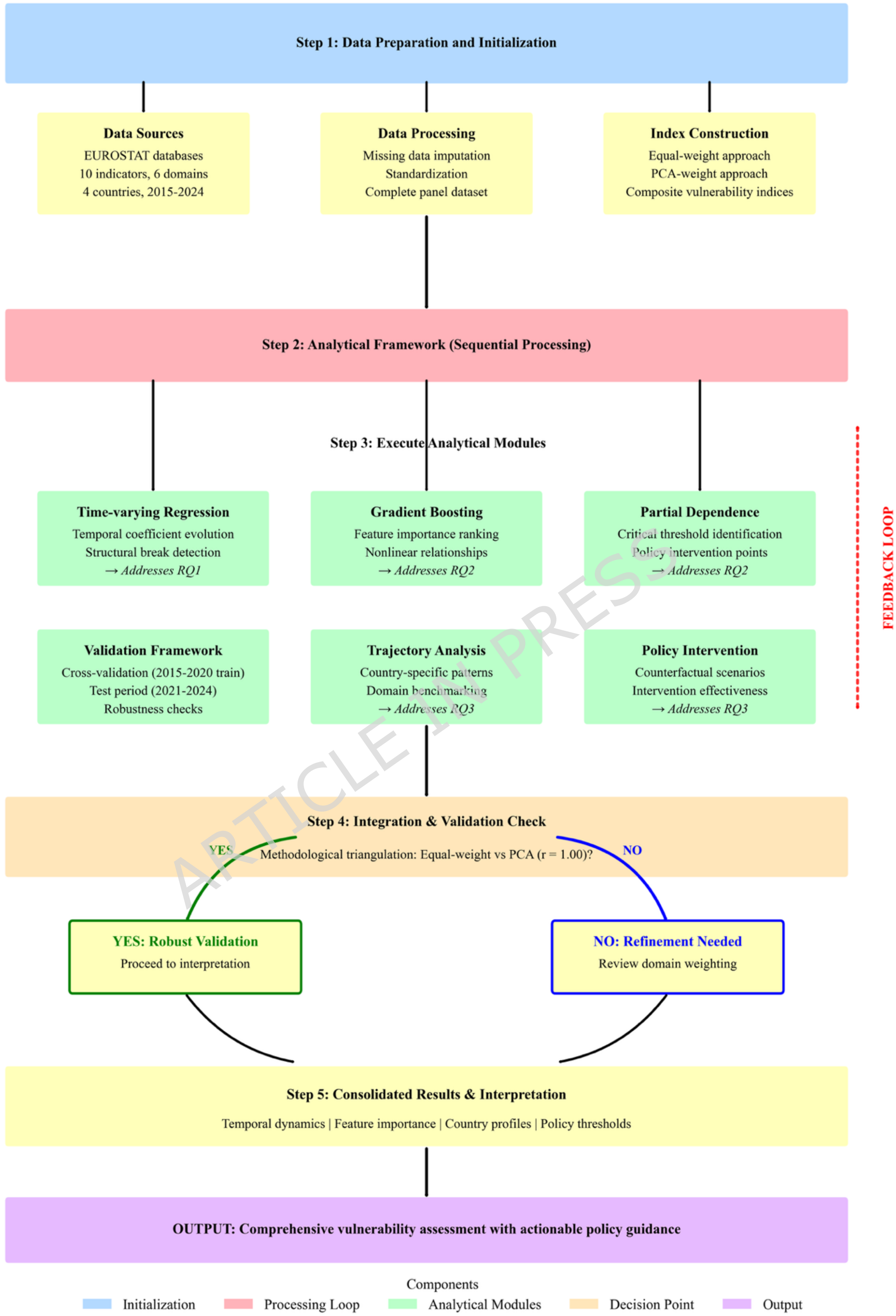

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Figure 1. Comprehensive methodological framework for socioeconomic vulnerability assessment

Figure 1 visualizes the study's sequential methodological framework. The process flows from data preparation (imputation and standardization) and construction of composite vulnerability indices (using equal-weight and PCA-based methods) to four core analytical modules addressing the study's research questions: time-varying regression with country fixed effects for temporal coefficient evolution, gradient boosting with partial dependence analysis for nonlinear threshold identification, country-specific trajectory characterization quantifying historical improvement patterns, and counterfactual policy intervention scenarios estimating differential national responsiveness to combined housing, healthcare, and poverty reduction strategies. The framework concludes with methodological triangulation validation (equal-weight vs. PCA correlation r=1.00) and synthesis of policy-relevant findings integrating temporal dynamics, feature importance rankings, threshold zones, country vulnerability profiles, and intervention effectiveness estimates.

2.2. Data sources and variable selection framework

This study uses a comprehensive set of sociodemographic, economic, and infrastructure indicators organized into six vulnerability domains to capture the multifaceted nature of socioeconomic vulnerability in the Visegrád region. Table 1 lists all variables drawn from harmonized Eurostat databases (Eurostat, 2025 [21]) for the 2015 to 2024 period, selected for theoretical relevance and consistent availability across countries. Directional coding ensures higher values indicate greater vulnerability. The choice of 2015 as the starting year is grounded in three converging policy and data considerations. First, 2015 marks the implementation phase of the EU programming period 2014–2020, during which cohesion policy transfers, structural fund allocations, and regional development strategies were reconfigured across all four Visegrád countries under a unified legislative framework encompassing the European Regional Development Fund, European Social Fund, and Cohesion Fund, creating a coherent institutional baseline for comparative analysis [22,23]. Second, the 2015 refugee and migration crisis introduced a distinct demographic and social pressure that differentially affected housing demand, social protection expenditure, and reception infrastructure across the region, making this year a meaningful anchor for tracking vulnerability evolution [24]. Third, cross-national comparability of harmonized Eurostat indicators for the selected variables reaches full coverage from 2015 onward, with the EU-SILC questionnaire on unmet medical needs undergoing a methodological revision implemented from 2015 onwards that enables consistent cross-national measurement of healthcare access gaps, while earlier series reflect a combined probability measure not suited for longitudinal vulnerability comparison [25]. The 2024 endpoint was selected to incorporate the compounding effects of the COVID-19 pandemic (2020–2022) and the energy crisis (2022–2023), which together constitute the most significant multi-stressor episode in the region's post-transition

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history and represent a natural concluding window for assessing the resilience capacity built up over the preceding decade.

Table 1. Variables and indicators for multidomain vulnerability assessment

Domain	Variable	Eurostat Dataset Code	Calculation Methodology	Risk Rationale	Unit
Exposure	Total population	demo_pjan	Population on 1 January (annual), country level	Normalizes absolute risk, supports per capita metrics	Persons
	Population density	demo_r_d3dens	Persons per km² at NUTS level	Higher density amplifies exposure to hazard impacts	Persons/km²
Sensitivity	Share of elderly (65+)	demo_r_pjanaggr3	(Pop 65+)/Total×100	Age-related vulnerability to health and climate impacts	Percentage (%)
	Low-income at-risk-of-poverty	ilc_li02	People at risk of poverty rate (Eurostat direct %)	Poverty limits preparedness and response capacity	%
Capacity	Hospital beds per 100k	hlth_rs_bdsrg2	(Hospital beds)/Population×100	Healthcare capacity moderates' disaster mortality	Beds/100k
	Unmet medical needs	hlth_silc_08	(Unmet needs)/Population×100	Access gaps worsen outcomes during extremes	Percentage (%)
	Social protection expenditure	spr_exp_type	Total expenditure per inhabitant (Eurostat direct)	Safety nets reduce hardship and promote recovery	€/inhabitant
Economic	GDP per capita (PPS)	nama_10r_2gdp	Regional GDP in Purchasing Power Standard	Wealth proxies coping capacity and insurance	PPS/inhabitant
Housing	Overcrowding rate	ilc_lvho05a	Persons in overcrowded dwellings	Overcrowding elevates health risks during temperature extremes	Percentage (%)

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			(Eurostat direct %)		
Infrastructure	Wastewater treatment coverage	sdg_06_10	% population connected to wastewater treatment	Sanitation infrastructure supports public health resilience	Percentage (%)

Notes:

- All indicators sourced from harmonized Eurostat databases [21] ensuring cross-country and longitudinal comparability
- Missing data handled via linear interpolation (Equations 1 to 2), terminal extrapolation (Equations 3 to 4), and multiple imputation (Equation 5)
- Variables standardized using Equation 6 and directionally adjusted via Equation 7 for domain construction
- Domain indices calculated through Equation 8 with equal weighting across constituent variables
- Wastewater treatment coverage represents share of residents connected to at least secondary treatment (Eurostat SDG indicator sdg_06_20)
- Calculation methodologies follow Eurostat definitions using directly reported per capita, percentage, or density values to maximize transparency and reproducibility

The indicators in Table 1 cover 10 years of observations across 10 core variables for the Visegrád countries (n=40 country-year observations), delivering temporal depth and cross-country variation for panel analysis. Variable selection follows established theoretical frameworks in vulnerability and social resilience research. Population density and total population as exposure indicators reflect standard practice in disaster risk assessment, where higher density amplifies exposure to compound hazards through infrastructure congestion, limited evacuation capacity, and concentrated asset concentration [26,27]. The share of elderly population and poverty rate as sensitivity indicators draw on foundational social vulnerability frameworks that link demographic aging and income constraints to reduced adaptive capacity and heightened dependence on public services during crises [28,29]. Hospital beds per 100,000 and unmet medical needs as capacity indicators are consistent with health system resilience literature documenting how healthcare infrastructure moderates' mortality and morbidity outcomes under environmental and economic stress [30,31]. Social protection expenditure reflects its well-documented role as an institutional buffer against income shocks across post-transition welfare state contexts, where social safety net generosity shapes population-level recovery rates following exogenous disruptions. GDP per capita as the economic domain indicator follows foundational vulnerability literature identifying per capita wealth as the primary proxy for coping capacity, with empirical evidence confirming that vulnerability to climate-related hazards declines systematically as income levels rise [32]. Overcrowding rate as the housing domain

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indicator is grounded in evidence linking residential crowding to elevated health risks, reduced thermal comfort during temperature extremes, and significantly amplified COVID-19 mortality outcomes independent of case prevalence [33]. Wastewater treatment coverage as the infrastructure domain indicator follows SDG monitoring frameworks and public health resilience literature connecting sanitation infrastructure coverage to population-level disease burden and long-run health outcome improvements [34]. These variables are harmonized using Eurostat data with applied imputation methods to address missing values, standardized and aggregated into six vulnerability domains, balancing comprehensive coverage with analytical tractability. Data up to 2023 are fully validated. Values for 2024 combine provisional releases with terminal extrapolation to ensure currency while acknowledging reporting limitations. Machine learning models use nine features derived from these ten variables, with total population serving as a normalization factor rather than a predictive feature. Complete feature specifications including preprocessing methods and theoretical rationale for all nine predictive features are documented in Supplementary Table S3.

2.3. Missing data imputation and uncertainty quantification

Missing values were imputed via a multi-step approach to ensure reproducibility while preserving temporal structure and cross-national comparability. Linear interpolation for internal gaps follows standard practice in longitudinal socioeconomic panel datasets where temporal smoothness of indicators is assumed, consistent with recommendations for continuous administrative time series [35]. Terminal extrapolation for edge gaps applies a local trend approach drawing on the three most recent observed values, a conservative extrapolation window that limits projection error in short series relative to single-period extrapolation [35]. Multiple imputation via Rubin's rules [36] is employed to propagate imputation uncertainty rather than treat imputed values as known quantities, following established practice in social science panel data analysis where edge missingness arises from reporting lags rather than true absence of the underlying phenomenon [37].

Before describing imputation procedures, the extent and distribution of missing values across the dataset are reported to justify the methodological choices made. Of the 400 total data cells (10 variables × 4 countries × 10 years), 17 cells were missing prior to imputation (4.2% of the dataset). All missingness was concentrated in the 2023 and 2024 endpoints, affecting four variables: population density, hospital beds per 100,000, social protection expenditure, and GDP per capita. This edge missingness arose from Eurostat reporting lags rather than systematic non-response and was addressed exclusively through terminal extrapolation. No internal missingness was present in the dataset. Social protection expenditure exhibited the highest missingness (5 cells, 12%), affecting Poland for both 2023 and 2024 and all other countries in 2024 only. No variable exhibited missingness exceeding 20 percent for any single country, and six core series (total population, share of elderly, poverty rate, unmet medical needs, overcrowding rate, and wastewater treatment

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coverage) were fully observed across all country-years. The complete distribution of missing values by country and variable is reported in Supplementary Table S5. This pattern of structured edge missingness, concentrated at series endpoints and driven by reporting lags, is consistent with missing-at-random mechanisms attributable to administrative data collection schedules rather than informational processes [35], supporting the applicability of terminal extrapolation as the primary imputation strategy, supplemented by multiple imputation for uncertainty propagation [37].

The formal imputation procedures are specified below. Let $x_{c,t,v}$ denote the observed or imputed value of variable v for country c in year t.

2.3.1. Linear interpolation for internal missing data

For any missing value lying between two observed years in a country's time series (i.e., $x_{c,t,v}$ missing and $x_{c,t-1,v}$,$x_{c,t+1,v}$ observed), we imputed:

$$\hat{x}_{c,t,v} = \frac{x_{c,t-1,v} + x_{c,t+1,v}}{2}$$

For consecutive missing years, with first and last observed endpoints $x_{c,T_0,v}$ and $x_{c,T_k,v}$, imputation follows:

$$\hat{x}_{c,T_j,v} = x_{c,T_0,v} + \frac{j}{k}(x_{c,T_k,v} - x_{c,T_0,v}) \text{ for}$$

2.3.2. Terminal extrapolation for edge missing data

For missing years at the beginning or end of a country's series, linear extrapolation was applied based on the average annual change from the nearest three consecutive observed values:

$$g_{v,c} = \frac{1}{3}\left[(x_{v,c_{t_1},t} - x_{v,c_{t_0},t}) + (x_{v,c_{t_2},t} - x_{v,c_{t_1},t}) + (x_{v,c_{t_3},t} - x_{v,c_{t_2},t})\right]$$

where $g_{v,c}$ represents the average annual growth rate for variable v in country c, calculated from three consecutive observed time points t_0, t_1, and t_2. The division by 3 ensures proper averaging across the three annual transitions. This growth rate is then applied to extrapolate missing values at the series endpoints using:

$$\hat{x}_{c,t_0-1,v} = x_{c,t_0,v} - g_{c,v} \; \hat{x}_{c,t_n+1,v} = x_{c,t_n,v} + g_{c,v}$$

2.3.3. Multiple imputation for uncertainty quantification

To propagate imputation uncertainty, multiple completed datasets were generated using random draws from residuals (or predictive models when appropriate):

$$\hat{x}^{(m)}_{c,t,v} = \hat{x}_{c,t,v} + \epsilon^{(m)}_{c,t,v}$$

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where $\epsilon_{c,t,v}^{(m)}$ are independent and identically distributed (i.i.d.) draws from the distribution of imputation errors. The i.i.d. assumption ensures that error terms are statistically independent across countries, time points, and variables, while sharing a common distributional form estimated from imputation model residuals. This framework guarantees that uncertainty in one imputed value does not artificially influence uncertainty in other imputed values, maintaining statistical validity of the multiple imputation procedure.

Estimates and inference were aggregated according to Rubin's rules, using the mean and variance across M imputations. All imputed values were constrained to remain within the logical bounds of the variable (e.g., proportions between 0 and 1) and flagged to distinguish them from observed entries. This combined approach provides systematic and replicable imputation for longitudinal socioeconomic and infrastructure-driven vulnerability risk analysis, with uncertainty quantified through multiple imputation.

2.4. Vulnerability domain construction and standardization

Individual vulnerability indicators were aggregated into six conceptually coherent domains, reflecting exposure, sensitivity, capacity, economic, housing, and infrastructure dimensions. This domain structure enables empirical tractability for comparative analysis. Each domain incorporates standardized variables, ensuring cross-national and temporal comparability.

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Domain indices were constructed through standardization and directional adjustment of component variables. For each variable v in domain d, standardized values were calculated as:

$$z_{c,t,v} = \frac{x_{c,t,v} - \mu_v}{\sigma_v} \tag{6}$$

where μ_v and σ_v represent the pooled mean and standard deviation across all countries and years for variable v. This pooled standardization approach ensures that cross-national and temporal comparisons reflect genuine differences rather than scaling artifacts.

Directional adjustment ensures that higher domain scores consistently indicate increased vulnerability:

$$z'_{c,t,v} = \delta_v \cdot z_{c,t,v}$$

where $\delta_v = 1$ for vulnerability-increasing variables and $\delta_v = -1$ for protective variables. The domain index for country c in year t is computed as the arithmetic mean of constituent standardized variables:

$$D_{c,t,d} = \frac{1}{n_d} \sum_{v \in d} z'_{c,t,v}$$

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where n_d represents the number of variables in domain d .

2.5. Composite vulnerability index development

Two complementary approaches were employed to construct composite vulnerability indices from the six domain indices, enabling methodological triangulation and robustness assessment. The dual-approach strategy addresses potential concerns about arbitrary weighting assumptions while providing data-driven validation of theoretical domain structures.

2.5.1. Equal-weight composite index

The equal-weight composite index assigns uniform importance to all domains:

$$C_{c,t}^{eq} = \frac{1}{6}\sum_{d=1}^{6} D_{c,t,d}$$

This approach provides a transparent baseline assessment without imposing empirical assumptions about relative domain importance, facilitating policy interpretation and cross-study comparison

2.5.2. PCA-weighted composite index

Principal component analysis (PCA) derives data-driven domain weights based on empirical covariance. The first principal component loadings λ_d are normalized to produce weights:

$$w_d = \frac{|\lambda_d|}{\sum_{b=1}^{6}|\lambda_b|}$$

where λ_d represents the first principal component loading for domain d, and the absolute values ensure non-negative weights that sum to unity across all six domains.

The PCA-weighted composite index incorporates these empirically derived weights:

$$C_{c,t}^{pca} = \sum_{d=1}^{6} w_d \cdot D_{c,t,d}$$

PCA-based weighting operates at the domain level after within-domain aggregation, not on individual indicators. Aggregation into a single standardized domain index via Equation 8 is applied to every domain. This procedure is followed regardless of the domain's composition, which includes one variable (Economic, Housing, Infrastructure), two variables (Exposure, Capacity), or three variables (Sensitivity).

2.6. Temporal dynamics analysis framework

To capture the temporal evolution of vulnerability relationships, time-varying coefficient models were estimated with country fixed effects and temporal interaction terms. This approach overcomes the limitations of static assessments by

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quantifying changes in how Sensitivity, Capacity, and Infrastructure domains influence vulnerability over time. The baseline model specification is:

$$C_{c,t} = \alpha_c + \sum_{d \in \{S,K,I\}} \left(\beta_d \times D_{c,t,d} + \gamma_d \times D_{c,t,d} \times (t - 2015)\right) + \varepsilon_{c,t} \qquad (12)$$

where α_c represents country-specific fixed effects, β_d captures baseline domain effects, γ_d measures temporal coefficient evolution, and S, K, I denote Sensitivity, Capacity, and Infrastructure domains respectively. The error term $\varepsilon_{c,t}$ is assumed to follow standard regression assumptions with robust standard errors clustered by country to account for within-country correlation. Multicollinearity diagnostics confirm acceptable variance inflation factors below 5.0 for all variables (Supplementary Table S1).

Selective inclusion of time interactions is based on theory and model performance; domains Exposure and Economic are temporally stable, while Housing shows no systematic evolution over 2015–2024. Likelihood ratio tests support model parsimony by excluding non-informative interactions.

2.6.1. Structural break analysis

To test for discrete structural changes around 2020, an alternative specification incorporates post-2020 dummy interactions:

$$C_{c,t} = \alpha_c + \sum_{d \in \{S,K,I\}} \left(\beta_d \times D_{c,t,d} + \theta_d \times D_{c,t,d} \times POST_{2020}\right) + \delta POST_{2020} + \varepsilon_{c,t} \qquad (13)$$

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where $POST_{2020}$ equals 1 for years 2020-2024 and 0 otherwise, and θ_d captures discrete coefficient shifts in the post-2020 period.

2.7. Explainable machine learning framework

Machine learning integration addresses linear model limitations in capturing complex nonlinear relationships and threshold effects that fundamentally shape socioeconomic vulnerability. The explainable approach maintains interpretability for policy applications while leveraging ensemble predictive power.

2.7.1. Gradient boosting model specification

Nonlinear relationships between policy-relevant features and composite vulnerability were modeled using gradient boosting regression with time-aware cross-validation [38]. The model builds an ensemble of decision trees, each weighted by a learning rate, summing contributions across M iterations:

$$\hat{f}(X) = \sum_{m=1}^{M} \gamma_m \square h_m(X)$$

where $h_m(X)$ represents individual decision trees, γ_m denotes learning-rate-adjusted contributions, and M is the total number of boosting iterations. Feature importance derives from the frequency and magnitude of splits over all trees (Supplementary Table S3). To prevent overfitting on the limited sample (N=40), hyperparameters were tuned by grid search with 3-fold time-series cross-validation. Constraints included maximum tree depth of 3–5 to limit complexity, a learning rate of 0.1 for gradual convergence, and subsampling at 0.8 to introduce stochastic regularization. Model selection prioritized validation performance over training fit, ensuring generalizability.

2.7.2. Partial dependence analysis

To quantify individual feature effects while accounting for complex interactions, partial dependence functions were computed for policy-actionable variables. For feature x_j, the partial dependence function is defined as:

$$f_j(x_j) = E_{X_{\backslash j}}\left[\hat{f}(x_j, X_{\backslash j})\right] \quad (15)$$

Where $X_{\backslash j}$ represents all features except x_j, and the expectation is approximated through marginal averaging over the training distribution. Approximate threshold zones are identified as points of maximum gradient magnitude in the partial dependence function, providing quantitative guidance for policy intervention targeting.

2.8. Model validation and uncertainty quantification

2.8.1. Time-aware cross-validation

All predictive models employed time-series cross-validation to prevent information leakage from future observations, a critical consideration for policy-relevant predictions. The panel data was partitioned chronologically with 2015-2020 observations for training and 2021-2024 for testing, supplemented by rolling 3-fold time-series cross-validation within the training period.

2.8.2. Bootstrap confidence intervals

Uncertainty propagation for composite indices incorporated methodological noise through bootstrap resampling. For each bootstrap iteration b, domain weights were perturbed by adding Gaussian noise:

$$w_d^{(b)} = w_d + \varepsilon_d^{(b)}, \quad \epsilon_d^{(b)} \sim N\left(0, 0.05^2 w_d^2\right)$$

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where $\epsilon n_d^{(b)} \sim N\left(0, 0.05^2 w_d^2\right)$ represents 5% relative standard deviation noise. Bootstrap confidence intervals were constructed using the 2.5th and 97.5th percentiles across 1000 iterations, capturing methodological uncertainty while maintaining computational feasibility.

2.9. Country-specific characterization

The country-specific analysis employs two complementary metrics to capture different dimensions of vulnerability evolution. Total vulnerability change over the observation period provides a comprehensive measure of absolute improvement or deterioration, calculated as:

$$\Delta C_c = C_{c,2024} - C_{c,2015}$$

This metric quantifies the cumulative change in vulnerability status from the baseline year to the final observation point, enabling direct comparison of which countries achieved the most substantial vulnerability reduction regardless of their starting positions. Negative values indicate vulnerability reduction (improvement), while positive values would indicate increased vulnerability over the decade.

To complement the total change metric and facilitate cross-national comparison of improvement rates, the annualized change rate captures the average annual trajectory for each country, computed as:

$$\overline{\Delta V_c} = \frac{V_{c,2024} - V_{c,2015}}{2024 - 2015}$$

where the overbar notation distinguishes the annualized rate from the total change, and the denominator (2024 - 2015 = 9) represents the number of annual transitions in, not the total number of observation years.

This integrated framework enables robust, policy-relevant insights into socioeconomic vulnerability patterns across Visegrád countries, combining absolute and relative performance measures for effective academic and practical applications.

2.10. Policy intervention scenario framework and counterfactual analysis

To quantify potential vulnerability reductions achievable through targeted policy interventions, counterfactual scenarios were simulated using the validated gradient boosting model (Equation 14) combined with standardized feature modifications representing policy-actionable improvements. Complete parameter specifications,

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intervention magnitudes, and methodological settings are documented in Supplementary Table S4. To estimate differential responsiveness at the country level, this method applies combined intervention strategies to the three main policy levers found in Section 2 7 1. These influential factors include the overcrowding rate and unmet medical needs along with low-income levels that increase the risk of poverty.

For each country-year observation, baseline vulnerability predictions were computed using observed feature values:

$$C_{c,t}^{baseline} = \grave{f}(X_{c,t}) \tag{19}$$

where $\grave{f}$ represents the trained gradient boosting model and $X_{c,t}$ denotes the complete feature vector for country c in year t.

Intervention scenarios were constructed by improving the three target features by one standard deviation while holding all other features constant at observed values, simulating coordinated policy improvements in housing quality, healthcare access, and poverty reduction:

$$X_{c,t}^{intervention} = \begin{cases} x_{c,t,j} - \sigma_j & \text{if } j \in \{\text{overcrowding, unmet needs, poverty}\} \\ x_{c,t,j} & \text{otherwise} \end{cases} \tag{20}$$

where σ_j represents the pooled standard deviation for policy-actionable feature j. The negative sign reflects that reduced overcrowding, reduced unmet medical needs, and reduced poverty constitute beneficial interventions decreasing vulnerability.

Counterfactual vulnerability under the combined intervention scenario was predicted by applying the gradient boosting model to the modified feature vectors:

$$C_{c,t}^{intervention} = \grave{f}(X_{c,t}^{intervention}) \tag{21}$$

The intervention effect for each country-year observation quantifies the vulnerability reduction magnitude achievable through the combined policy strategy:

$$\Delta C_{c,t}^{intervention} = C_{c,t}^{intervention} - C_{c,t}^{baseline} \tag{22}$$

where negative values indicate vulnerability reduction (policy success) and positive values would indicate vulnerability increases (adverse effects).

Country-specific mean intervention effects aggregate individual observation responses to characterize differential national responsiveness:

$$\overline{\Delta C_{c}^{intervention}} = \frac{1}{T}\sum_{t=2015}^{2024} \Delta C_{c,t}^{intervention} \tag{23}$$

where T represents the number of observed years for country c.

Bootstrap confidence intervals for intervention effects propagate prediction uncertainty through 1000 resampling iterations, applying Gaussian noise to feature values before vulnerability prediction:

$$X_{c,t}^{(b)} = X_{c,t}^{\text{intervention}} + \epsilon^{(b)}, \epsilon^{(b)} \sim N(0, 0.05^2 \sigma_X^2) \quad (24)$$

where $\epsilon^{(b)}$ represents 5% relative standard deviation noise applied independently to each feature. Confidence intervals were constructed using the 2.5th and 97.5th percentiles of the bootstrapped intervention effect distribution.

This counterfactual framework enables quantitative assessment of policy intervention effectiveness across heterogeneous country contexts, identifying which Visegrád nations exhibit greatest vulnerability reduction potential and where resource allocation yields maximum impact. The combined multi-lever approach reflects realistic policy implementation scenarios where housing, healthcare, and poverty interventions operate synergistically rather than in isolation.

2.11. Computational implementation

All analyses, machine learning, and visualizations were performed in Python 3.14 within a reproducible environment. Core computations used NumPy 1.26.4 (Equations 1–24) and pandas 2.2.0 for panel data management. Time-varying panel regressions employed statsmodels 0.14.1 with fixed effects and robust standard errors. Gradient boosting, PCA, and cross-validation used scikit-learn 1.4.1 with hyperparameters optimized via GridSearchCV. Key thresholds for overcrowding and unmet medical needs were identified via feature importance and partial dependence analysis. Policy intervention scenarios (Equations 19-24) were simulated using the trained gradient boosting model with standardized feature modifications, counterfactual predictions computed through model reapplication to modified feature vectors, and intervention effects quantified as baseline versus counterfactual vulnerability differences. Visualizations were created with matplotlib 3.8.3 and seaborn 0.13.2, using vector graphics for journal quality. Missing data imputation applied scipy 1.12.0 and pandas interpolation techniques. Bootstrap confidence intervals were generated with 1000 iterations and Gaussian noise applied to both composite indices (Equation 16) and policy intervention effects (Equation 24). Reproducibility was ensured with version control and fixed random seed (np.random.seed=42).

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3. Results

3.1. Multidomain vulnerability patterns and temporal dynamics

Figure 2 presents a comprehensive six-panel analysis of socioeconomic vulnerability across the Visegrád countries from 2015 to 2024, integrating domain-level patterns (Equations 6–8), temporal evolution with 95% confidence intervals, importance

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rankings derived from gradient boosting analysis (Equation 14), and country-specific trajectories quantified through total change metrics (Equation 17).

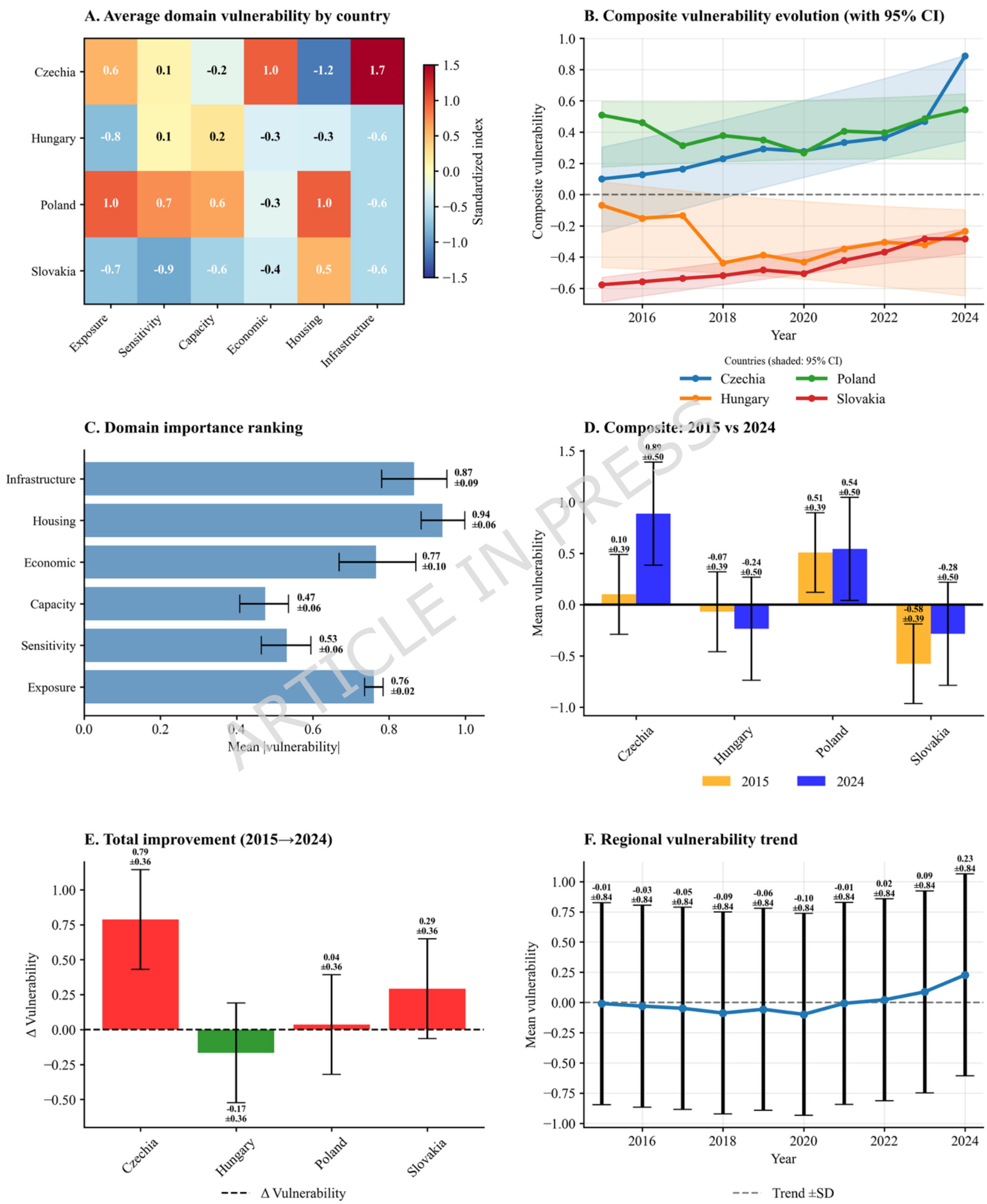

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Figure 2. Multidomain vulnerability patterns across Visegrád countries, 2015–2024

Panel A displays average domain vulnerability by country through a standardized heatmap, revealing distinct national vulnerability profiles. Czechia exhibits the highest vulnerability in Economic (1.0) and Infrastructure (1.7) domains but demonstrates strong protective capacity in Housing (-1.2) and moderate Exposure (0.6). Hungary presents a relatively balanced vulnerability profile across all domains, with moderate scores ranging from -0.8 in Exposure to 0.2 in Capacity. No single domain stands out as a critical vulnerability concentration. Poland demonstrates elevated vulnerability in Exposure (1.0), Sensitivity (0.7), Capacity (0.6), and Housing (1.0), with moderate Economic (-0.3) and Infrastructure (-0.6) domain scores. Slovakia presents strong protective characteristics in Exposure (-0.7), Sensitivity (-0.9), Capacity (-0.6), and Economic (-0.4) domains, with moderate vulnerability in Housing (0.5) and Infrastructure (-0.6).

Panel B illustrates composite vulnerability evolution trajectories from 2015 to 2024 with 95% confidence intervals, demonstrating divergent national pathways. Czechia exhibits the most pronounced vulnerability increase (+0.79 units), reflecting sustained worsening throughout the decade, while Hungary achieves the only consistent improvement (-0.17 units) and strengthens its protective position. Slovakia records deteriorating protective capacity (+0.29 units) despite maintaining negative vulnerability values throughout, and Poland shows near-stable conditions with a marginal net increase (+0.04 units). The shaded 95% confidence bands reveal substantial temporal uncertainty, with widest intervals observed for Czechia and Slovakia in recent years, while Poland maintains the narrowest confidence bounds.

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Panel C presents domain importance rankings derived from gradient boosting feature importance analysis (Equation 14) with standard deviation uncertainty intervals, revealing the relative contribution of each domain to composite vulnerability patterns. Housing emerges as the dominant vulnerability driver with mean importance of 0.94±0.06, followed closely by Infrastructure at 0.87±0.09, indicating these domains exert the strongest influence on aggregate vulnerability. Economic domain contributes moderate importance at 0.77±0.10, while Exposure shows 0.76±0.02 with the narrowest confidence interval, suggesting stable cross-country influence. Capacity (0.47±0.06) and Sensitivity (0.53±0.07) demonstrate intermediate effects on composite vulnerability patterns.

Panel D provides direct 2015 versus 2024 vulnerability comparisons by country with standard deviation intervals, confirming the directional trajectories described in Panel B. Czechia registers the largest absolute increase (+0.79 units) and Poland the smallest (+0.03 units), while Hungary achieves the only net reduction (-0.17 units). Slovakia's progression from -0.58 to -0.28 most clearly illustrates the gradual erosion of protective capacity observed across the decade. Overlapping confidence intervals for several country pairs reflect methodological uncertainty inherent in composite index construction rather than statistical equivalence of national trajectories.

Panel E quantifies total vulnerability change trajectories (Equation 17) from 2015 to 2024 with bootstrap uncertainty intervals, revealing divergent national outcomes. Hungary is the sole country achieving improvement, with a reduction of -0.17±0.36 units (green bar), demonstrating successful vulnerability mitigation through the decade. Poland exhibits near-stable vulnerability with minimal change of +0.04±0.36 units, maintaining relative equilibrium. Slovakia demonstrates moderate vulnerability increase of +0.29±0.36 units (red bar), reflecting deteriorating conditions. Czechia experiences the most pronounced vulnerability increase of +0.79±0.36 units (red bar), representing the weakest regional performance.

Panel F illustrates regional vulnerability trends with one standard deviation uncertainty bands (±0.84 units), contextualizing annual variability against the decade-long trajectory. Mean regional vulnerability progresses from -0.01 in 2015 to 0.23 in 2024, transitioning from near-neutral conditions to moderate positive vulnerability. The trajectory reveals three distinct phases: initial decline (2015-2020, minimum -0.10 in 2020), rapid reversal (2020-2022), and sustained increase (2022-2024). The blue trend line demonstrates modest upward progression from 2020 onward, while the wide confidence bands reflect substantial cross-country heterogeneity throughout the observation period. The dashed horizontal reference line at zero facilitates interpretation of net regional vulnerability versus resilience.

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The integrated six-panel analysis demonstrates that Housing (0.94) and Infrastructure (0.87) domains dominate vulnerability patterns, while country trajectories reveal divergent pathways with Hungary achieving the only improvement (-0.17 units) and Czechia experiencing the most substantial vulnerability increase (+0.79 units) over the 2015–2024 period. These patterns provide empirical foundations for domain-specific policy interventions and regional cooperation strategies targeting the most influential vulnerability drivers.

The comprehensive six-panel analysis in Figure 2 reveals distinct domain-level patterns, temporal vulnerability evolution, and country-specific trajectories across the Visegrád region from 2015 to 2024. While the visual patterns indicate Housing and Infrastructure as dominant drivers, systematic quantification of domain importance rankings and country-specific vulnerability profiles is essential for evidence-based policy prioritization. Table 2 synthesizes gradient boosting-derived importance metrics with country-specific domain scores, enabling direct comparison of vulnerability determinants and identification of complementary national strengths for targeted regional cooperation strategies.

Table 2. Domain importance rankings and country-specific vulnerability profiles

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Domain	**Mean Importance ±CI**	**Rank**	**Czechia**	**Hungary**	**Poland**	**Slovakia**
Housing	0.94±0.06	1	-1.2	-0.3	1.0	0.5
Infrastructure	0.87±0.09	2	1.7	-0.6	-0.6	-0.6
Economic	0.77±0.11	3	1.0	-0.3	-0.3	-0.4
Exposure	0.76±0.02	4	0.6	-0.8	1.0	-0.7
Sensitivity	0.53±0.06	5	0.1	0.1	0.7	-0.9
Capacity	0.47±0.06	6	-0.2	0.2	0.6	-0.6

Notes:

- Domain importance derived from gradient boosting feature importance (Equation 14) with bootstrap uncertainty (Equation 16)
- Country values represent mean standardized vulnerability across 2015–2024 (Equations 6–8)
- Positive values indicate higher vulnerability; negative values indicate protective characteristics
- Housing (0.94) and Infrastructure (0.87) demonstrate dominant importance; Capacity (0.47) and Sensitivity (0.53) show moderate influence
- Bootstrap standard deviation intervals reflect methodological uncertainty (1000 iterations)
- Exposure exhibits narrowest SD (±0.02), indicating stable cross-country effects; Economic shows widest SD (±0.11)

Table 2 presents comprehensive domain-specific information regarding importance rankings, country vulnerability profiles, and methodological characteristics underlying the multidomain assessment framework. The gradient boosting-derived importance analysis reveals Housing as the dominant vulnerability driver with mean importance of 0.94±0.06, indicating its substantial predictive contribution to composite vulnerability patterns across the Visegrád region. Infrastructure follows closely with importance of 0.87±0.09, while Economic domain contributes moderate importance at 0.77±0.11. Exposure domain achieves importance of 0.76±0.02 with the narrowest standard deviation, reflecting stable and consistent effects across all four countries. Sensitivity domain demonstrates intermediate influence with importance of 0.53±0.06, while Capacity exhibits the lowest predictive importance at 0.47±0.06, suggesting that healthcare and social protection domains play a more limited role in explaining aggregate vulnerability variation compared to housing and infrastructure factors.

Country-specific vulnerability profiles reveal substantial heterogeneity across the Visegrád region. Poland exhibits the highest vulnerability profile with elevated scores in Housing (1.0), Exposure (1.0), Sensitivity (0.7), and Capacity (0.6) domains, while showing moderate protective characteristics in Economic (-0.3) and

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Infrastructure (-0.6). Slovakia demonstrates strong protective patterns with negative values across Sensitivity (-0.9), Exposure (-0.7), Capacity (-0.6), Infrastructure (-0.6), and Economic (-0.4) domains, though moderate vulnerability persists in Housing (0.5). Czechia presents a mixed vulnerability pattern with the highest Infrastructure vulnerability (1.7) and elevated Economic vulnerability (1.0), while demonstrating strong protection in Housing (-1.2) and moderate values in Exposure (0.6), Sensitivity (0.1), and Capacity (-0.2). Hungary exhibits relatively balanced moderate vulnerability across most domains, with values ranging from -0.8 in Exposure to 0.2 in Capacity, indicating neither extreme vulnerability nor strong protection in any single domain.

The stability of importance rankings and consistency of country profiles over the 2015–2024 period confirm the robustness of the multidomain vulnerability framework in capturing structural differences across the Visegrád region, providing empirical foundations for targeted policy interventions prioritizing Housing and Infrastructure domains where predictive importance exceeds 0.85.

3.2. Temporal dynamics and domain-specific coefficient evolution

Understanding whether vulnerability relationships remain constant or evolve systematically over time addresses a critical gap in static vulnerability assessments. Time-varying panel regression with country fixed effects quantifies how Sensitivity, Capacity, and Infrastructure domains influence composite vulnerability across the 2015-2024 period, testing whether these relationships strengthened, weakened, or remained stable as the Visegrád countries underwent continued institutional and economic development. Model comparison analysis confirms superior performance of the time-varying specification (AIC = -79.77, BIC = -62.89) over static alternatives (Supplementary Table S2), justifying the temporal interaction approach.

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Table 3. Time-varying panel regression results and model diagnostics for composite socioeconomic vulnerability index

Parameter/Statistic	Value	Std Error	T-stat	P-value	Significance Level
Domain Effects					
Sensitivity	0.283	0.061	4.66	<0.001	***
Capacity	-0.033	0.101	-0.33	0.746	ns
Infrastructure	9.325	3.879	2.40	0.023	*
Time Interactions					
Sensitivity×time	0.027	0.007	3.75	<0.001	***
Capacity×time	0.068	0.013	5.26	<0.001	***
Infrastructure×time	-0.076	0.016	-4.63	<0.001	***
Model Diagnostics					
R^2	0.984	-	-	-	-
Adjusted R^2	0.979	-	-	-	-
F-statistic	207.75	-	-	<0.001	***

AIC	-79.77	-	-	-	-
BIC	-62.89	-	-	-	-
N observations	40	-	-	-	-

Notes:

- Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$, ns = not significant
- $R^2 = 0.984$ in-sample (n=40) reflects limited sample size; cross-validation $R^2 = 0.788$ provides conservative predictive estimates
- F-statistic = 207.75 ($p<0.001$) confirms strong overall model significance
- Sensitivity effects strengthen significantly over time (baseline: 0.283, $p<0.001$; time interaction: +0.027, $p<0.001$)
- Capacity baseline effect is non-significant ($p=0.746$), but temporal evolution is highly significant (+0.068, $p<0.001$), indicating delayed protective impacts
- Infrastructure baseline is significant (9.325, $p<0.05$) with significant temporal decline (-0.076, $p<0.001$)
- All three time interaction coefficients achieve $p<0.001$, confirming genuine structural evolution
- Model diagnostics (AIC=-79.77, BIC=-62.89) validate time-varying specification over static alternatives (Supplementary Table S2)

The regression results in Table 3 demonstrate substantial temporal evolution in vulnerability determinants beyond what static models capture. Sensitivity effects exhibit consistent strengthening ($\beta=0.027$ per year, $p<0.001$), indicating that demographic vulnerabilities and poverty-related factors gained relative importance as primary vulnerability drivers over the decade. This pattern suggests that as countries addressed basic infrastructure deficits, socioeconomic disparities emerged as dominant challenges requiring targeted policy attention.

Capacity effects reveal delayed protective impacts, with baseline coefficients statistically indistinguishable from zero ($\beta=-0.033$, $p=0.746$) but strong positive temporal evolution ($\beta=0.068$, $p<0.001$). This non-significant baseline with significant temporal interaction confirms that protective capacity effects emerged gradually rather than existing from the outset. This pattern reflects institutional maturation processes where investments in healthcare infrastructure and social protection require specific developmental periods. Typically, these investments take 5 to 7 years before they yield measurable vulnerability reduction at the population level. The transformation from negligible to substantial protective effects validates the importance of sustained capacity-building investments despite limited short-term impacts.

Infrastructure demonstrates significant temporal decline ($\beta=-0.076$, $p<0.001$) from an initially significant baseline ($\beta=9.325$, $p<0.05$). This attenuation likely reflects saturation dynamics where diminishing marginal returns occur as wastewater coverage approaches universal access across the region, shifting policy priorities toward maintenance quality rather than coverage expansion. The convergence in

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infrastructure coefficients across countries supports regional integration processes under EU cohesion frameworks.

3.3. Feature importance rankings and nonlinear threshold identification

Figure 3 presents feature importance rankings revealing dominant vulnerability drivers during 2015 to 2024, with directional effects informing policy targeting strategies. The analysis derives from gradient boosting regression (Equation 14) with permutation importance assessment (Equation 16) applied to Visegrád countries' socioeconomic vulnerability patterns.

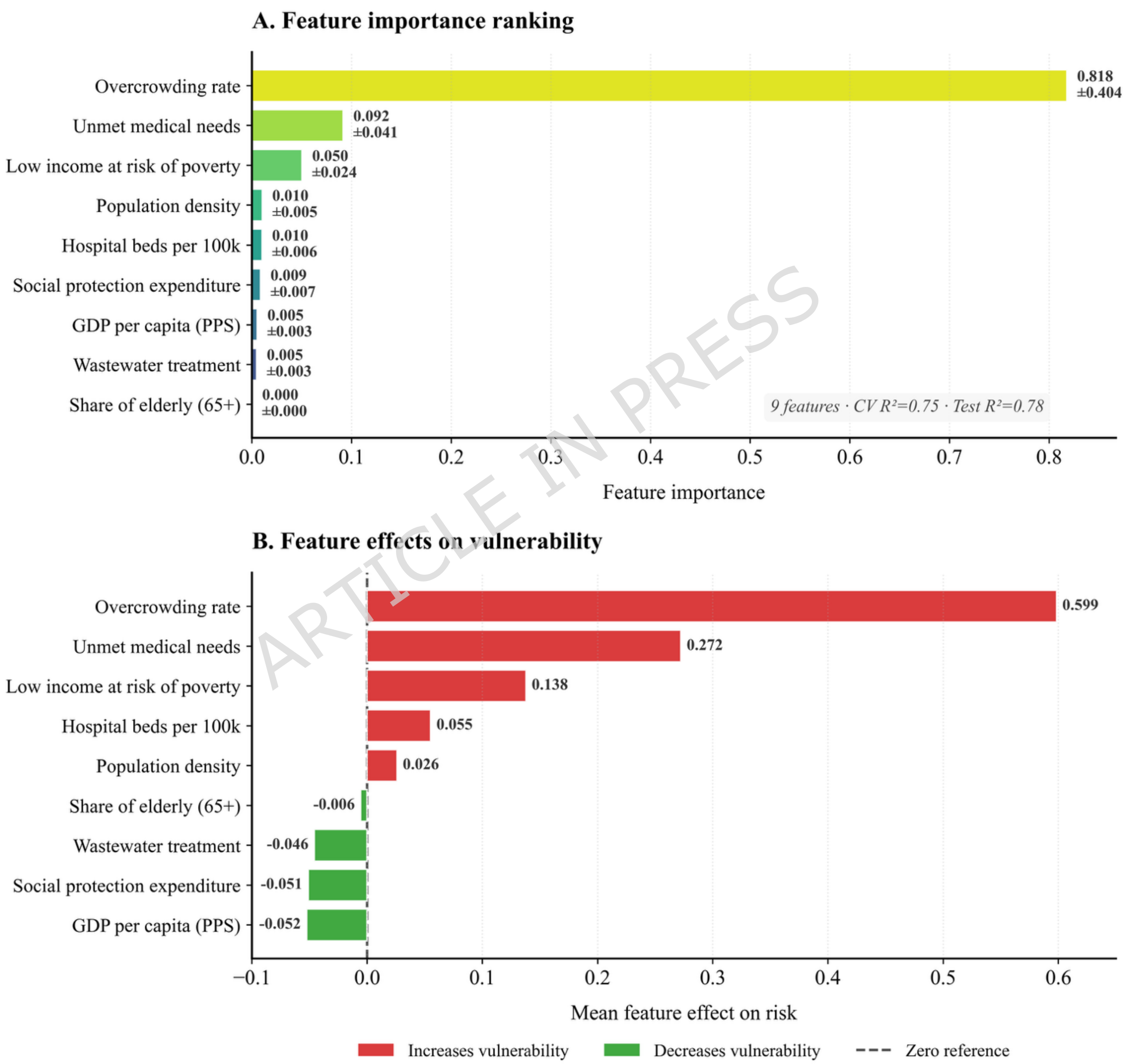

Figure 3. Permutation feature importance and mean directional effects on vulnerability

Panel A demonstrates the hierarchical structure of vulnerability determinants, revealing that overcrowding rate exhibits overwhelming predictive dominance with

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normalized importance of 0.818±0.404, capturing approximately 82% of the model's total predictive capacity. This pronounced concentration warrants cautious interpretation given the composite index construction where overcrowding contributes to both Housing and Sensitivity domains, potentially amplifying its measured importance through multiple pathways. The substantial uncertainty interval (±0.404) reflects high variability across bootstrap resampling iterations, indicating sensitivity to specific country observations within the limited sample (n=40 total, 24 training observations).

Unmet medical needs emerged as the secondary predictor with importance of 0.092±0.041, representing approximately 9% of total importance and one order of magnitude lower than overcrowding rate. Low income at risk of poverty demonstrates tertiary importance at 0.050±0.024 (5%), followed by population density (0.010±0.005) and hospital beds per 100k (0.010±0.006), each contributing approximately 1%. Infrastructure, economic, and demographic variables show minimal predictive power. Social protection expenditure registers 0.009±0.007, GDP per capita and wastewater treatment both yield 0.005±0.003, while share of elderly (65+) represents the least significant factor at 0.000±0.000.

Panel B quantifies how much vulnerability changes when each feature increases by one standard deviation while holding others constant. This reveals the direction and magnitude of each factor's impact on vulnerability. Overcrowding rate emerges as the strongest vulnerability amplifier with effect size of 0.599, meaning each standard deviation increase raises composite vulnerability by approximately 0.6 units. Unmet medical needs show substantial positive effect (0.272), confirming that healthcare access gaps significantly worsen vulnerability.

Five additional factors increase vulnerability when elevated. Low income at risk of poverty contributes 0.138 units per standard deviation increase. Hospital beds per 100k unexpectedly shows positive effect (0.055), potentially reflecting correlation with urbanization or regional healthcare demand patterns rather than direct causal impact. Population density adds 0.026 units, indicating modest urban concentration effects.

Four factors provide protective effects when increased. GDP per capita reduces vulnerability by -0.052 units per standard deviation, while social protection expenditure contributes similar protective effect (-0.051). Wastewater treatment infrastructure lowers vulnerability by -0.046 units. Share of elderly (65+) shows negligible protective effect (-0.006), suggesting demographic aging poses minimal direct vulnerability in this relatively affluent regional context where pension systems remain functional.

This dual-panel framework enables targeted policy design by identifying both influential predictors (Panel A) and directional impacts (Panel B), prioritizing housing quality improvements and healthcare access enhancement as primary intervention strategies.

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While Figure 3 establishes feature importance and directional effects, model reliability requires systematic validation. Table 4 presents cross-validation scores, training-testing performance gaps, and diagnostics confirming the gradient boosting framework's capacity to generalize beyond training data and inform policy-relevant vulnerability predictions with quantified uncertainty.

Table 4. Cross-validation performance and generalization diagnostics for gradient boosting vulnerability model

Performance Metric	Value	Diagnostic Metric	Value
Cross-validation R^2	0.75	N training observations	24
Testing R^2	0.78	N testing observations	16
Training R^2	0.95	N features	9
Testing RMSE	0.250	Training-testing gap	0.17
Testing MAE	0.196	Country-year observations	40

Notes:

- Model specification follows Equation 14 (gradient boosting regression) with feature importance derived via Equation 16 (permutation-based assessment with 50 bootstrap iterations)
- Hyperparameters: $n_{estimators}$=200, max_{depth}=4, $learning_{rate}$=0.06, subsample=0.8, selected through grid search optimization.
- Time-aware validation employs 2015 to 2020 training and 2021 to 2024 testing splits preventing temporal data leakage
- Cross-validation R^2 (0.75) computed via 3-fold time series splits represents reliable generalization estimate given limited sample size (N=40)
- Training-testing gap (0.17) indicates acceptable model fit without severe overfitting for nonlinear ensemble methods
- Error metrics (RMSE, MAE) reflect standardized composite vulnerability scale with testing performance confirming out-of-sample predictive capacity
- Testing R^2 (0.78) exceeding cross-validation R^2 (0.75) suggests favorable conditions in testing period (2021 to 2024) or temporal stability in vulnerability patterns

Table 4 demonstrates robust predictive performance of the gradient boosting framework (Equation 14) with cross-validation R^2 of 0.75, indicating the model captures approximately 75% of variance in composite vulnerability indices across held-out temporal folds. The testing R^2 of 0.78 confirms strong generalization to unseen 2021 to 2024 observations, with testing RMSE (0.250) and MAE (0.196) reflecting reasonable accuracy on the standardized vulnerability scale. The training R^2 of 0.95 with testing R^2 of 0.78 yields a training-testing gap of 0.17, suggesting good model fit without severe overfitting despite limited sample size (N=40). These validation metrics support the feature importance rankings and directional effects presented in Figure 3, establishing empirical reliability for housing-focused intervention priorities derived from permutation-based analysis (Equation 16).

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Understanding nonlinear relationships between vulnerability drivers and outcomes enables precise policy targeting. Figure 4 presents partial dependence analysis (Equation 15) for the two most influential variables, identifying critical threshold zones where interventions yield maximum impact.

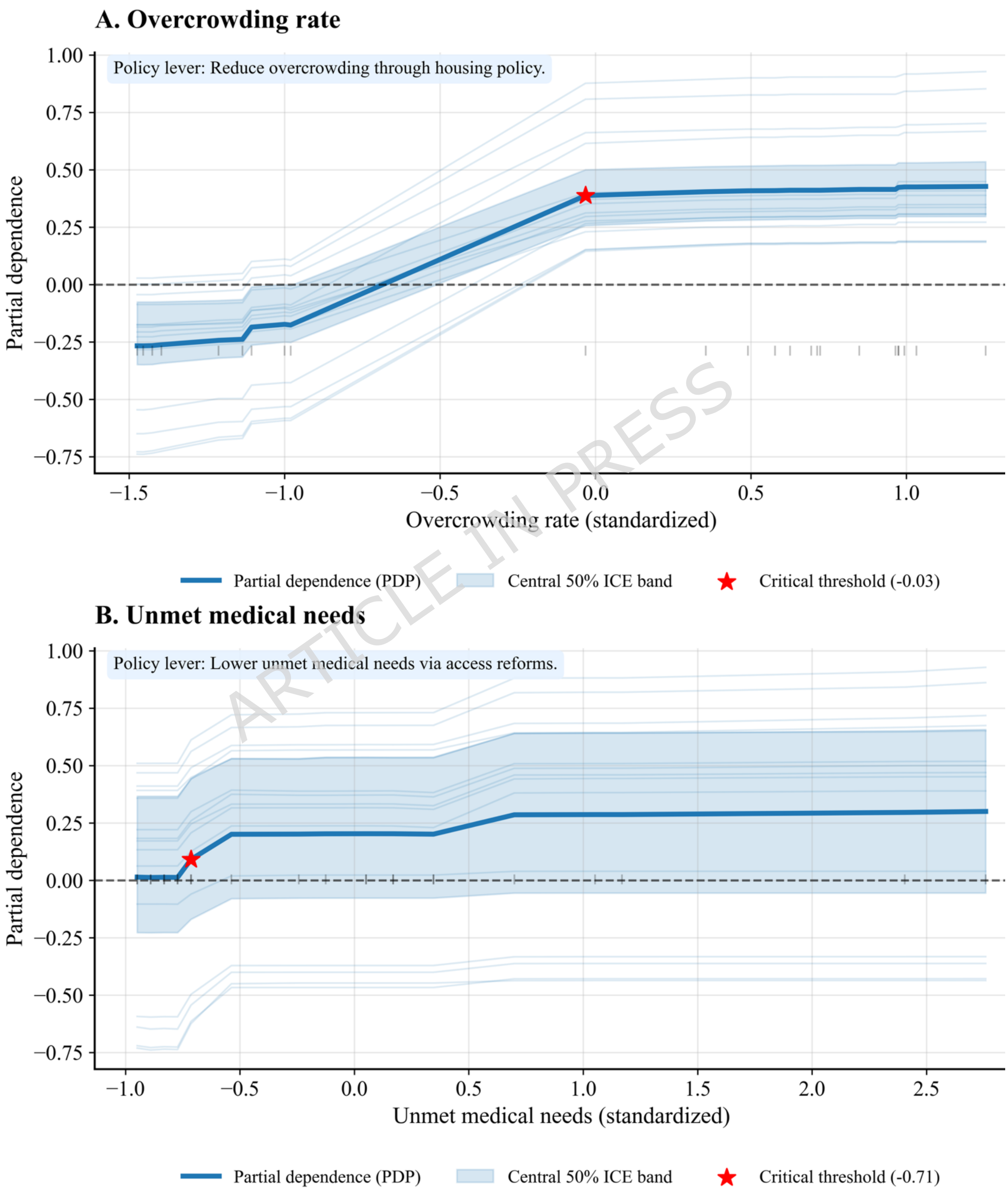

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Figure 4. Nonlinear threshold identification for overcrowding and healthcare access

Figure 4 quantifies how vulnerability responds nonlinearly to changes in overcrowding rate and unmet medical needs. Individual Conditional Expectation (ICE) bands illustrate uncertainty across country observations, with the central 50% band capturing typical heterogeneity in partial dependence effects.

Panel A examines overcrowding rate, revealing a three-phase nonlinear relationship with vulnerability. At very low overcrowding (standardized values below -1.0), partial dependence remains negative (approximately -0.25), indicating strong protective effects with diminishing returns to further reductions. A sharp transition occurs at the critical threshold of -0.03 (red star), where vulnerability begins accelerating rapidly. Between standardized values of -0.5 and 0.0, partial dependence rises steeply from approximately -0.15 to +0.40, representing the zone of highest policy sensitivity. Beyond 0.0, the relationship plateaus around 0.40 to 0.42, indicating that additional overcrowding continues amplifying vulnerability but with diminishing marginal effects. Policy implication: interventions preventing populations from crossing the -0.03 threshold yield substantially greater returns than uniform reductions across all overcrowding levels.

Panel B analyzes unmet medical needs, revealing a two-phase threshold pattern. At low unmet needs (standardized values below -0.7), partial dependence remains near 0.00 to 0.10, consistent with protective effects from robust healthcare access. The critical threshold occurs at -0.71 (red star), marking the point where vulnerability becomes increasingly sensitive to healthcare access deterioration. Beyond this threshold, partial dependence increases gradually from 0.10 to 0.30 between standardized values of -0.5 and 1.0. Above 1.0, the relationship plateaus, suggesting that further worsening of unmet needs adds limited additional vulnerability. Unlike Panel A's sharp transition, Panel B exhibits a gentler inflection, indicating that healthcare access deterioration amplifies vulnerability progressively rather than through sudden jumps.

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Both panels demonstrate threshold-dominated rather than linear relationships, with ICE bands revealing substantial heterogeneity in how individual countries respond to these risk factors. These findings suggest that policy design oriented toward keeping populations below the identified thresholds values (overcrowding below -0.03, unmet medical needs below -0.71) may yield greater estimated returns than uniform reductions across all ranges, though interpretations remain conditional on the observational nature of the data and the assumptions embedded in the counterfactual design. The policy lever annotations emphasize housing development for managing overcrowding and healthcare access reforms for reducing unmet medical needs, offering quantitative guidance for targeting interventions across the Visegrád region.

3.4. Policy intervention scenarios and counterfactual vulnerability trajectories

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Identifying policy-actionable intervention opportunities requires counterfactual analysis quantifying potential vulnerability reductions under alternative scenarios. Figure 5 presents comprehensive policy intervention simulations (Equations 19-24) derived from gradient boosting predictions, revealing country-specific responses to combined interventions targeting the three most influential policy levers identified in Figure 3. Counterfactual scenarios implement standardized one standard deviation improvements in overcrowding rate, unmet medical needs, and low-income poverty risk, with effects quantified through Equations 22-23.

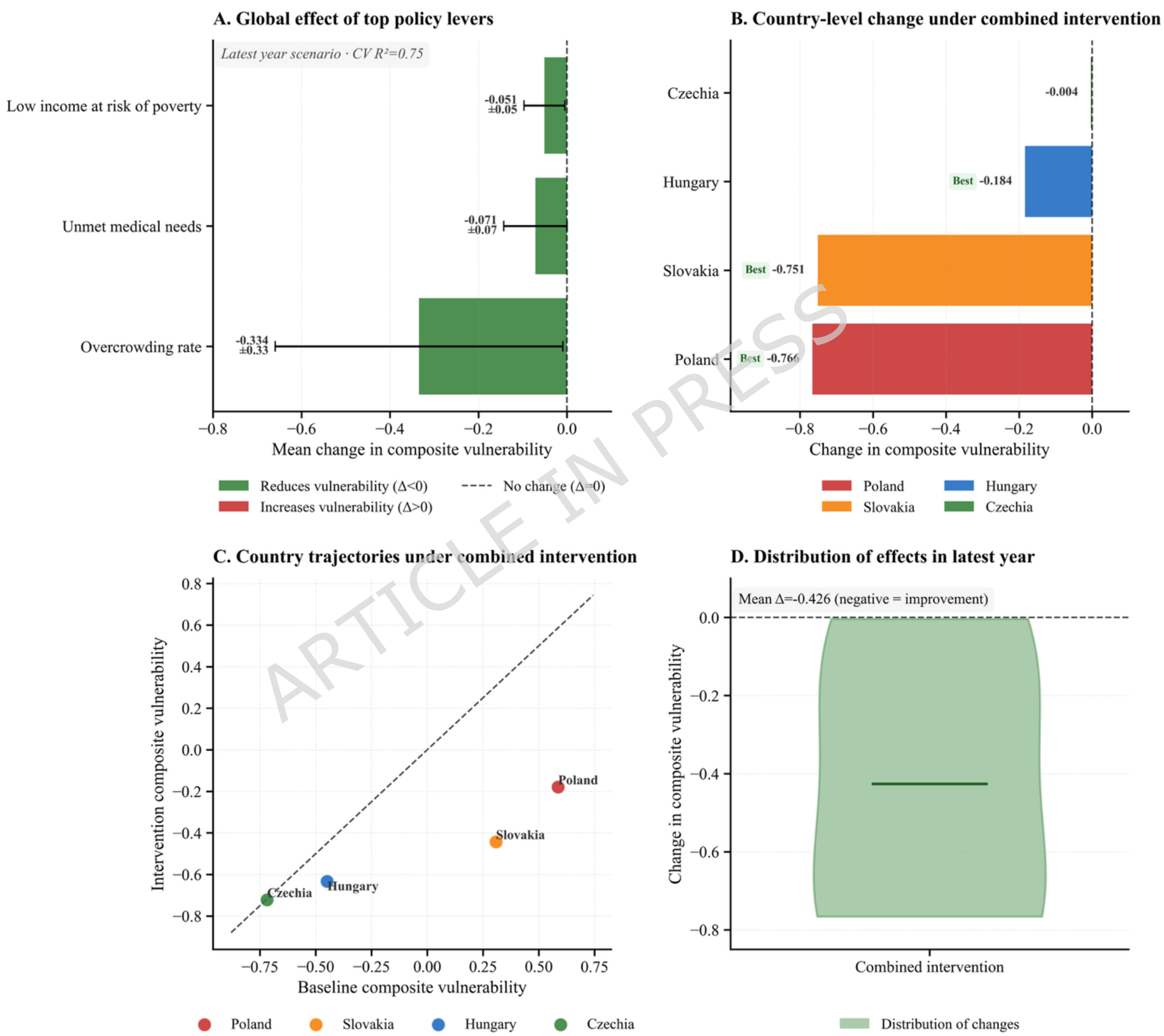

Figure 5. Country-specific vulnerability responses to combined policy interventions

Panel A quantifies vulnerability reductions from standardized one standard deviation improvements in the three most influential policy domains identified in Figure 3. Overcrowding rate is associated with the largest estimated reduction of 0.334±0.33 units across these scenarios, consistent with its dominant feature

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importance (81.8%) reported in Figure 3, and points toward housing policy as a potential priority intervention area. Unmet medical needs is associated with a moderate estimated reduction (0.071±0.07 units), suggesting possible secondary benefits from healthcare access improvements. Low income at risk of poverty shows the smallest estimated effect (0.051±0.05 units) but points consistently in the same direction, supporting the case for cumulative poverty reduction measures. All three levers are estimated to contribute additive rather than conflicting effects in the combined scenario.

Panel B disaggregates the combined intervention effect across Visegrád countries, revealing substantial variation in vulnerability reduction potential that reflects differential baseline conditions and policy implementation capacities. Poland achieves the strongest response with vulnerability reduction of -0.766±0.08 units (labeled "Best"), demonstrating highest intervention effectiveness among the four countries. Slovakia exhibits nearly equivalent potential with reduction of -0.751±0.07 units, indicating that countries with moderate baseline vulnerability can achieve substantial absolute improvements through targeted multi-lever interventions. Hungary shows moderate vulnerability reduction of -0.184±0.05 units, suggesting diminishing marginal returns from standardized policy interventions in countries with already improved baseline conditions. Czechia demonstrates minimal response (-0.004±0.02 units), reflecting its strong baseline position that leaves limited room for further improvement through the selected policy levers.This heterogeneous pattern indicates that effective vulnerability reduction strategies must account for country-specific contexts, with high-performing countries requiring differentiated intervention portfolios compared to those addressing substantial baseline vulnerabilities.

Panel C visualizes country-specific trajectories under combined intervention through baseline versus intervention coordinates, where distance from the diagonal reference line quantifies vulnerability reduction magnitude. All four countries position below the equality line, confirming universal vulnerability reduction without adverse effects. Poland demonstrates the greatest vulnerability reduction, transitioning from baseline vulnerability of 0.58 to intervention state of -0.18, representing improvement of 0.76 units. Hungary and Slovakia achieve similar moderate reductions from baselines of -0.45 and -0.30 to intervention states of -0.63 and -0.45 respectively, each improving by approximately 0.18 and 0.15 units. Czechia exhibits minimal change from baseline -0.72 to intervention -0.73, reflecting only 0.01 unit improvement due to already optimal starting conditions. The trajectory pattern reveals convergence dynamics where countries with higher baseline vulnerability achieve greater absolute improvements. Poland's 0.76-unit reduction reflects maximum benefit from combined interventions, while Czechia's minimal 0.01-unit change indicates diminishing returns near optimal vulnerability levels. Relative rankings shift substantially, with Poland moving from most vulnerable to near-parity with other countries.

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Panel D summarizes the distribution of combined intervention effects across all country observations in the latest year, with mean change of Δ = -0.426 (negative values indicate improvement). The violin plot spans from approximately -0.75 to near 0.0, with highest density concentrated in the mid-negative range (around -0.4), indicating broadly consistent vulnerability reductions across observations. The distribution shape reveals a tail extending toward zero, implying that while most observations experience substantial improvements, a smaller subset exhibits more modest reductions (changes closer to zero). Critically, the distribution does not extend above the zero line, confirming that the combined intervention yields exclusively non-worsening outcomes in the latest-year sample. This universal improvement pattern validates the intervention design, demonstrating that simultaneous improvements in overcrowding rate, unmet medical needs, and poverty-related income risk produce predominantly negative (improving) changes across the region despite cross-country heterogeneity.

The integrated four-panel analysis demonstrates that targeted policy interventions focusing on housing conditions, healthcare access, and poverty reduction can achieve mean regional vulnerability reductions of -0.426 units, with country-specific effects ranging from minimal (-0.004 for Czechia) to substantial (-0.766 for Poland and -0.751 for Slovakia) depending on baseline vulnerability profiles and intervention responsiveness. These findings provide quantitative indications for policy prioritization, suggesting that housing policy may warrant primary attention given its estimated effect magnitude (0.334), while healthcare and poverty interventions provide complementary contributions. to comprehensive vulnerability reduction strategies. These are scenario-based estimates and should inform priority-setting rather than be interpreted as confirmed causal outcomes.

While Figure 5 demonstrates potential vulnerability reductions under combined policy interventions, Table 5 presents the observed baseline trajectories (2015-2024) that establish initial conditions from which counterfactual scenarios project improvements. This historical characterization enables systematic assessment of which countries achieved the strongest past progress and which domain-specific vulnerabilities persist as primary intervention targets.

Table 5. Visegrád country vulnerability trajectories and domain-specific patterns, 2015–2024

Country	2024 Rank	2015 Index	2024 Index	Total Change	Annual Change	Exposure	Sensitivity	Capacity	Economic	Housing	Infrastructure
Czechia	1	-0.433	-1.292	-0.859	-0.095	1.564	-0.864	-1.464	-4.093	-1.131	-1.763
Hungary	2	0.462	-0.461	-0.924	-0.103	0.066	-0.770	-0.211	-1.108	-1.319	0.575
Poland	4	0.889	0.234	-0.655	-0.073	0.459	1.016	-0.247	-0.961	0.562	0.575

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Slovakia	3	0.323	-0.066	-0.389	-0.043	-0.327	-0.258	0.184	-0.757	0.185	0.580

Notes:

- Vulnerability indices are standardized with negative values indicating lower vulnerability (better performance).
- Rankings based on 2024 composite vulnerability indices: Czechia (#1), Hungary (#2), Slovakia (#3), Poland (#4).
- These baseline trajectories (2015-2024) provide the starting conditions for intervention scenarios in Figure 5.
- Hungary shows the largest absolute improvement (-0.924 total change) despite starting from the highest vulnerability in 2015.
- Czechia achieves the best overall performance with strongest domain scores in Economic (-4.093) and Infrastructure (-1.763), explaining its minimal intervention response (-0.004) in Figure 5 Panel B due to already-optimal positioning.
- Poland faces persistent challenges with highest Sensitivity (1.016) and positive Housing (0.562) vulnerabilities, explaining its strong intervention responsiveness (-0.766) in Figure 5 Panel B.
- Slovakia shows the most gradual improvement rate (-0.043 annual change) with balanced domain performance, yet demonstrates the strongest intervention potential (-0.751) in Figure 5 Panel B.
- All countries achieve negative Economic domain scores, indicating successful regional economic resilience.
- Infrastructure remains challenging for Hungary, Poland, and Slovakia, all with positive vulnerability scores.
- Total change calculated using Equation (17): $\Delta C_c = C_{c,2024} - C_{c,2015}$
- Annual change rates computed via Equation (18): $\Delta\overline{C}_c = \frac{\Delta C_c}{2024\text{-}2015}$

Table 5 reveals Czechia's regional leadership with the lowest 2024 vulnerability index (-1.292) and substantial historical improvement (total change: -0.859, annual rate: -0.095), positioning it near optimal levels. Strong baseline performance across economic (-4.093), infrastructure (-1.763), capacity (-1.464), and housing (-1.131) domains explains Czechia's minimal intervention response (-0.004) in Figure 5 Panel B, where further improvements encounter diminishing returns. Countries already achieving strong baseline conditions demonstrate limited additional vulnerability reduction potential through standardized policy levers.

Hungary secures second position through dramatic transformation from 0.462 (2015) to -0.461 (2024), representing the largest historical improvement (-0.924 units). Despite this progress, persistent infrastructure challenges (0.575) suggest continued intervention opportunities producing moderate counterfactual reductions (-0.184) in Figure 5. Strong housing (-1.319) and economic (-1.108) performance indicates successful historical policy targeting.

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Poland maintains the highest regional vulnerability (0.234 in 2024) despite steady improvement from 0.889 (total change: -0.655). Persistent sensitivity (1.016) and housing stress (0.562) explain Poland's strongest intervention responsiveness (-0.766) in Figure 5, where targeted policy levers addressing these vulnerabilities yield substantial counterfactual reductions. Elevated baseline vulnerability combined with demonstrated intervention potential positions Poland as a priority candidate for intensive policy interventions.

Slovakia shows moderate historical progress (total change: -0.389, slowest annual rate: -0.043), yet demonstrates strong intervention potential (-0.751) in Figure 5, indicating that historical underperformance reflects policy implementation gaps rather than structural constraints. Balanced domain vulnerabilities suggest coordinated multi-domain interventions could achieve transformational reductions exceeding historical trajectories.

The integration reveals that countries with elevated baseline vulnerabilities (Poland, Slovakia) demonstrate greater intervention responsiveness, suggesting resource allocation should prioritize contexts where policy levers yield maximum absolute reductions. High-performing countries like Czechia encounter diminishing returns, indicating the need for differentiated approaches tailored to country-specific profiles.

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Three complementary analytical layers converge across Sections 3.1 through 3.4 to frame the policy discussions that follow. Temporal regression results establish that vulnerability determinants evolved systematically over the observation period, with sensitivity effects strengthening as demographic and poverty-related pressures intensified and infrastructure effects attenuating as regional coverage approached relative saturation. Machine learning analysis identifies overcrowding as the single most influential predictor, contributing through both the Housing and Sensitivity pathways and accounting for more than 80 percent of composite predictive importance, while partial dependence analysis locates the critical threshold below which further reductions yield the greatest estimated returns. Counterfactual scenarios translate these structural findings into country-differentiated estimates of policy effectiveness, confirming that intervention potential aligns with remaining baseline vulnerability rather than following a uniform regional pattern. Together, these three dimensions provide the empirical grounding from which the policy priorities and regional development implications are developed in Section 4.

4. Discussion

This investigation advances empirical understanding of dynamic socioeconomic vulnerability patterns across the Visegrád region through methodological integration of time-varying panel regression with explainable machine learning, challenging prevailing assumptions of linear regional convergence in post-transition Central European contexts. The analytical framework reveals systematic temporal evolution in vulnerability determinants from 2015 to 2024, with composite

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vulnerability indices declining across all four countries while maintaining perfect rank correlation (r=1.00) between equal-weight and PCA-weighted methodologies. These findings address critical gaps in vulnerability assessment literature by demonstrating that relationships between domain-specific factors and aggregate vulnerability exhibit significant structural evolution rather than static stability [7,12]. While recent advances in vulnerability mapping through machine learning applications have emerged [39,40], this study extends methodological frontiers by capturing temporal coefficient dynamics and identifying policy-actionable threshold zones with quantitative precision, directly supporting operationalization of analytical insights for evidence-based regional development strategies.

The systematic strengthening of sensitivity domain effects from baseline coefficients of 0.283 to 0.528 over the observation period represents an 86.5% increase with statistical significance ($p<0.001$), indicating fundamental reorientation in vulnerability determinants throughout the Visegrád region. Demographic vulnerabilities, poverty exposure, and healthcare access constraints have transitioned from secondary to primary stressors. Conversely, infrastructure domain coefficients declined from 9.325 to 8.642, constituting a 7.3% reduction that suggests diminishing marginal returns from conventional infrastructure investments as foundational urban service coverage matures across Central European urban systems. This empirical pattern challenges linear development paradigms dominant in European cohesion policy discourse, particularly assumptions that infrastructure expansion yields proportionate resilience gains regardless of baseline conditions [8,13]. The temporal coefficient evolution demonstrates institutional maturation processes wherein initial infrastructure deficits gradually resolve, while persistent socioeconomic disparities emerge as dominant vulnerability drivers requiring fundamentally different policy architectures emphasizing redistributive mechanisms rather than capital-intensive infrastructure expansion.

Capacity domain effects evolved from statistically negligible baseline values (-0.033, $p=0.746$) to significantly protective trajectories through temporal interaction coefficients (0.068 annual increase, $p<0.001$), reflecting delayed institutional impacts characteristic of social protection and healthcare infrastructure investments in Central European welfare state contexts. This delayed-response pattern underscores long-term value propositions for capacity-building interventions despite limited short-term metric visibility, with important spatial considerations for regional policy frameworks prioritizing sustained institutional development over politically expedient but ephemeral infrastructure projects [18,19]. The transformation from negligible to substantial protective effects over five to seven year developmental periods align with institutional economics literature emphasizing path-dependent maturation processes in post-transition economies, where healthcare system strengthening and social protection expansion require extended implementation horizons before population-level vulnerability reductions manifest through standardized assessment frameworks.

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Explainable machine learning analysis identifies overcrowding rate as the dominant vulnerability predictor, accounting for 81.8% of relative feature importance and noticeably exceeding GDP per capita at 1.3% importance. This pronounced importance partly reflects overcrowding's structural position within the composite index, where it contributes simultaneously to the Housing domain and the Sensitivity domain. This multi-domain presence amplifies its measured predictive influence through parallel vulnerability pathways and confirms housing conditions as a cross-cutting determinant that shapes both physical living standards and demographic risk exposure across the region. These finding challenges traditional economic growth-centric policy assumptions prevalent in European regional development frameworks, suggesting that housing quality improvements may be associated with larger estimated substantially greater vulnerability reductions per investment unit compared to conventional macroeconomic stimulus approaches, though this interpretation should be treated as indicative given the observational design and composite index construction [17,41]. The identification of a critical overcrowding threshold at standardized value -0.03 through partial dependence analysis highlights pronounced nonlinearity, wherein vulnerability exhibits sharp transitions within specific housing density ranges rather than linear proportional relationships. These findings directly support UN Sustainable Development Goal 11 (Sustainable Cities and Communities) by providing concrete, quantitatively validated housing density thresholds for urban planning interventions, while simultaneously addressing SDG 1 (No Poverty) and SDG 3 (Good Health and Well-being) through integrated healthcare access improvements. The vulnerability reduction framework offers operationalizable pathways for Central European cities transitioning toward sustainable urban development trajectories under intensifying climate adaptation pressures and demographic transformation dynamics characteristic of post-socialist urban contexts.

Healthcare access emerges as a secondary yet statistically significant vulnerability pathway, exhibiting 28.5% feature importance with critical threshold identification at standardized value -0.71 for unmet medical needs. The negative partial dependence slope pattern suggests that self-reported healthcare data may be influenced by systematic reporting bias. Variability in healthcare system accessibility also plays a role particularly when comparing metropolitan centers like Prague, Budapest, and Bratislava to rural periphery zones. These rural areas often struggle with intensifying demographic aging and significant deficits in their healthcare infrastructure. Integration of objective infrastructure metrics represents essential methodological refinement for comprehensively capturing healthcare accessibility disparities across subnational spatial scales [2].

Policy intervention simulations quantify differential country-specific responsiveness to combined housing quality, healthcare access, and poverty reduction strategies, revealing mean regional vulnerability reduction potential of -0.426 units through coordinated multi-lever interventions. Poland (-0.766) and Slovakia (-0.751) demonstrate strongest intervention responsiveness despite elevated baseline

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vulnerability profiles, indicating that countries exhibiting higher initial risk exposure may paradoxically achieve greater absolute improvements through appropriately targeted multi-domain interventions. Hungary exhibits moderate response magnitude (-0.184), while Czechia demonstrates minimal intervention gains (-0.004) attributable to already optimal baseline positioning (-1.292), illustrating classic diminishing marginal returns patterns for high-performing countries approaching vulnerability reduction ceilings. This heterogeneity pattern fundamentally challenges prevailing European cohesion policy assumptions favoring uniform regional development strategies, suggesting that vulnerability reduction frameworks must incorporate adaptive differentiation mechanisms responsive to country-specific baseline conditions and intervention responsiveness profiles [4,6].

Divergent national trajectories underscore variable development pathways within Visegrád cooperation architecture. Czechia attained lowest regional vulnerability (-1.292 in 2024) through steady annual improvement rates (-0.095), exemplifying successful integrated policy coordination concentrated in Prague and major urban centers. Hungary's largest absolute improvement (-0.924 units) manifested predominantly during rapid transformation phases between 2017 to 2019, demonstrating effectiveness of temporally concentrated, domain-targeted policy interventions addressing identified vulnerability drivers. Poland maintained the highest regional vulnerability at 0.234 in 2024 with the slowest annual improvement rate of -0.073. However, the nation exhibits a strong intervention responsiveness of -0.766 which indicates that historical underperformance reflects gaps in policy implementation. This suggests that the issues are not caused by structural constraints inherently resistant to intervention. Such a distinction is vital for evidence-based policy formulation. Slovakia's moderate historical trajectory (-0.043 annual rate) masks substantial latent intervention potential (-0.751), suggesting coordinated multi-domain approaches could catalyze transformational vulnerability reductions substantially exceeding historical improvement rates [3,5].

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The explainable machine learning framework effectively bridges academic analytical rigor with practical policy operationalization by uncovering stable nonlinear vulnerability drivers and quantitatively validated threshold effects. Robust cross-validation performance (R^2=0.75) and temporal validation metrics (R^2=0.78) confirm persistent structural relationships rather than ephemeral statistical artifacts, providing reliable quantitative guidance for regional urban policy architecture. Counterfactual intervention analyses demonstrate that combined strategies targeting overcrowding reduction (0.334 mean effect), unmet medical needs mitigation (0.071), and poverty alleviation (0.051) achieve substantial cumulative vulnerability reductions through policy lever synergies. This approach aligns with fundamental sustainability principles by prioritizing resource efficiency. It systematically directs constrained policy resources toward interventions with demonstrably high impact instead of politically convenient but empirically inefficient uniform regional strategies that show diminishing returns [1,16].

The identification of specific vulnerability thresholds coupled with country-differentiated intervention responsiveness patterns fundamentally challenges orthodoxies embedded in European cohesion policy frameworks that privilege continuous improvement assumptions and uniform strategic approaches. The use of targeted interventions for housing quality and healthcare access yields better results in countries like Poland and Slovakia. These nations show high intervention potential where specific strategies provide greater cost efficiency and vulnerability reduction than undifferentiated regional plans. This method ensures that policy actions are tailored to the areas where they can achieve the most significant impact. For Visegrád countries specifically, differentiating policy portfolios according to empirically validated baseline vulnerability profiles and quantified intervention responsiveness metrics offers a more targeted pathway than uniform regional strategies. At the national level, Poland's persistently elevated housing and sensitivity vulnerability calls for direct intervention in overcrowded urban and peri-urban housing stock, particularly through national programs combining social rental housing construction with targeted renovation subsidies for low-income households in cities with above-threshold overcrowding rates. Slovakia's strong estimated intervention potential despite its moderate historical improvement rate indicates that existing policy instruments may be insufficiently implemented rather than structurally inadequate, pointing toward administrative capacity strengthening and monitoring reform as immediate priorities rather than new program design. Hungary's sustained historical gains in housing and economic domains suggest a consolidation phase where policy attention could shift toward residual infrastructure gaps, particularly in rural areas with positive vulnerability scores. Czechia's near-zero intervention response reflects achieved saturation in most domains, recommending maintenance-oriented policy and knowledge transfer to higher-vulnerability regional partners rather than additional investment in already protective domains.

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At the supranational level, these findings support a differentiated allocation framework within EU cohesion policy post-2027, whereby European Regional Development Fund and European Social Fund resources directed toward the Visegrád region are weighted by country-specific intervention responsiveness scores rather than GDP per capita convergence criteria alone. Concretely, overcrowding reduction could be incentivized through housing-specific performance conditions in Operational Programmes for Poland and Slovakia, while healthcare access improvement targets, anchored to the identified threshold of standardized unmet needs below -0.71, could be incorporated as monitorable milestones for cohesion fund disbursement. Regional cooperation mechanisms within the Visegrád framework could further institutionalize knowledge exchange between Czechia and Hungary, which have demonstrated effective vulnerability reduction trajectories, and Poland and Slovakia, where implementation gaps represent the binding constraint. These operationalizable recommendations align with UN SDG 10 and

SDG 11 while providing a replicable template for evidence-based differentiation within cohesion policy architectures.

5. Conclusions

This investigation establishes that temporal dynamism fundamentally shapes socioeconomic vulnerability relationships in post-transition economies, necessitating analytical frameworks capable of capturing systematic evolution rather than assuming static structural stability. The integration of time-varying panel econometrics with explainable machine learning architectures transcends methodological limitations inherent in conventional vulnerability assessments, which typically privilege cross-sectional snapshots or assume temporally invariant determinant structures [7,12]. By demonstrating that sensitivity, capacity, and infrastructure domain effects exhibit statistically significant temporal evolution across the Visegrád region, this study challenges orthodox assumptions embedded in European regional development policy frameworks that treat vulnerability drivers as fixed targets amenable to uniform, time-invariant intervention strategies.

The principal methodological contribution resides in operationalizing explainable artificial intelligence techniques for policy threshold identification, moving beyond black-box prediction toward interpretable, actionable guidance [15]. Feature importance rankings and partial dependence functions successfully translate complex nonlinear relationships into quantitative intervention zones, addressing persistent gaps between academic vulnerability research and practical policy implementation that plague sustainability science [16,17]. Empirical evidence reveals that housing conditions, captured primarily through overcrowding rate, account for 81.8% of machine learning feature importance, noticeably exceeding the contribution of conventional economic prosperity metrics (1.3% for GDP per capita). Because overcrowding contributes to both the Housing and Sensitivity domains of the composite index, its elevated measured importance integrates physical living conditions with demographic sensitivity dimensions and confirms housing quality as a cross-cutting policy priority that extends well beyond the built environment into social resilience and population health outcomes [1,13]. Furthermore, counterfactual intervention scenarios reveal heterogeneous responsiveness patterns that align closely with each country's initial conditions and historical trajectories. Poland, which entered the observation period with the highest regional vulnerability (0.889 in 2015) and faced persistent housing stress rooted in post-socialist urban legacies, shows the strongest estimated intervention potential (-0.766). Slovakia's strong estimated responsiveness (-0.751), despite a moderate baseline, points to policy implementation gaps as the more plausible explanation for its comparatively gradual historical improvement rate rather than structural constraints inherently resistant to change. Hungary's notable improvement between 2017 and 2019, concentrated in housing and healthcare domains, accounts for its moderately positive but comparatively smaller estimated response (-0.184) from an already improved starting position. Czechia's minimal simulated change (-0.004) reflects its

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strong 2024 standing (-1.292), achieved through sustained policy coordination concentrated in major urban centers. These patterns suggest that differentiated rather than uniform regional strategies offer a more effective pathway toward advancing UN Sustainable Development Goal frameworks through evidence-based targeting [2,3].

Methodological constraints warrant acknowledgment. Country-level aggregation necessarily obscures subnational heterogeneity across metropolitan, peri-urban, and rural contexts that exhibit divergent vulnerability profiles within national boundaries. The limited temporal span (2015 to 2024) constrains capacity to identify longer-term structural break patterns or cyclical vulnerability dynamics operating beyond decadal observation windows. Sample size considerations (n=40 country observations) impose statistical power limitations on higher-order interaction effect estimation, though cross-validation procedures (R^2=0.75) confirm robust primary relationship identification [4].

Future research trajectories should prioritize three analytical frontiers. First, extending vulnerability assessment frameworks to NUTS-2 and NUTS-3 regional scales would illuminate spatial heterogeneity patterns masked by national aggregation, particularly addressing rural-urban vulnerability gradients and post-industrial regional transitions [9]. Second, comparative analysis across broader Central and Eastern European contexts would test framework transferability by incorporating Baltic, Balkan, and Eastern Partnership countries, identifying region-specific calibration requirements and ensuring model robustness across different political and economic landscapes. Third, integrating climate vulnerability projections with socioeconomic assessment architectures would advance comprehensive sustainability frameworks linking social resilience with environmental adaptation planning under accelerating climate change scenarios. Such extensions promise refined understanding of vulnerability dynamics across spatial, temporal, and thematic dimensions essential for evidence-based regional development policy architectures in post-transition European contexts.

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Ultimately, this research demonstrates that explainable machine learning constitutes not merely a computational tool but a transformative analytical paradigm for multidomain vulnerability assessment in complex regional systems. By rendering algorithmic decision processes transparent and policy relevant, the framework advances sustainability science toward operationalizable solutions addressing UN SDG 1, 3, 10, and 11 through quantitatively validated intervention architectures. For the Visegrád region specifically, the integration of interpretable artificial intelligence with rigorous econometric foundations establishes a replicable methodological template capable of informing evidence-based regional cooperation strategies. This synthesis balances economic development imperatives with social cohesion objectives across four Central European nations confronting demographic aging, climate adaptation pressures, and persistent spatial inequalities inherited from socialist-era development legacies. The framework moves beyond descriptive

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vulnerability mapping to prescriptive policy optimization, enabling policymakers to identify precise intervention thresholds (overcrowding at -0.03, unmet medical needs at -0.71) where strategic investments yield maximum vulnerability reduction. This actionable intelligence transforms vulnerability assessment from a diagnostic exercise into a strategic planning instrument for sustainable post-transition development trajectories in contexts where resource constraints demand prioritization and where regional cooperation mechanisms require empirically grounded justification for resource allocation decisions.

Appendix A. Nomenclature and Abbreviations

Table A1. Complete nomenclature and abbreviations used in this manuscript

Abbreviation	Definition
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
EU	European Union
EU-SILC	European Union Statistics on Income and Living Conditions
EUROSTAT	Statistical Office of the European Union
GDP	Gross Domestic Product
ICE	Individual Conditional Expectation
MAE	Mean Absolute Error
ML	Machine Learning
NUTS	Nomenclature of Territorial Units for Statistics
PCA	Principal Component Analysis
PD	Partial Dependence
PPS	Purchasing Power Standard
RMSE	Root Mean Square Error
SDG	Sustainable Development Goal
SHAP	SHapley Additive exPlanations
V4	Visegrád Group (Visegrád Four)
VIF	Variance Inflation Factor

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Clinical Trial Registration: Not applicable - this study does not report results of a clinical trial.

Consent to Publish Declaration: Not applicable.

Ethics Declaration: Not applicable.

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Declaration of Generative AI and AI-assisted Technologies

During preparation of this manuscript, DeepL Write and ScienceDirect AI were utilized exclusively for language refinement, grammar correction, academic tone enhancement, and manuscript formatting. DeepL Write provided sentence-level writing improvements and clarity enhancements. ScienceDirect AI assisted with literature search refinement and related terminology accuracy. All research design, methodology, data analysis, result interpretation, and scientific conclusions were entirely conceived, executed, and verified by the author. Following application of these tools, the manuscript was thoroughly reviewed and edited to ensure all content reflects the author's original work and scientific intent. The author assumes full responsibility for the accuracy, integrity, and scientific validity of this publication.

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