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Abstract

As global efforts to achieve the Sustainable Development Goals (SDGs) enter a critical phase, there is a growing need for analytical tools that reflect the complexity and heterogeneity of development pathways. This study introduces a probabilistic classification framework designed to uncover latent typologies of national performance across the seventeen Sustainable Development Goals. Unlike traditional ranking systems or composite indices, the proposed method uses raw, standardised goal-level indicators and accounts for both structural variation and classification uncertainty. The model integrates a Bayesian decision tree with penalised spline regressions and includes regional covariates to capture context-sensitive dynamics. Based on publicly available global datasets covering more than 150 countries, the analysis identifies three distinct development profiles: structurally vulnerable systems, transitional configurations, and consolidated performers. Posterior probabilities enable soft classification, highlighting ambiguous or hybrid country profiles that do not fit neatly into a single category. Results reveal both monotonic and non-monotonic indicator behaviours, including saturation effects in infrastructure-related goals and paradoxical patterns in climate performance. This typology-sensitive approach provides a transparent and interpretable alternative to aggregated indices, supporting more differentiated and evidence-based sustainability assessments. The findings provide a practical basis for tailoring national strategies in alignment with structural conditions and the multidimensional nature of sustainable development.

Keywords: Bayesian classification; Sustainable Development Goals (SDGs); soft clustering; country typologies; probabilistic modelling; development policy; progress

1. Introduction

As global efforts to achieve the Sustainable Development Goals (SDGs) enter a critical phase, there is a growing need for analytical tools that reflect the complexity and heterogeneity of development pathways. Traditional approaches, such as the SDG Index and composite dashboards, primarily focus on country rankings and aggregate scores [1–3], often failing to account for structural differences, inter-goal trade-offs, and context-specific dynamics [4,5]. These approaches tend to

obscure nonlinear patterns and saturation effects that are increasingly recognised in empirical sustainability research [6,7].

Recent studies highlight the limitations of unidimensional assessments and the risks associated with using simplified indicators to inform complex policy decisions [8,9]. Scholars have called for typology-sensitive, multidimensional frameworks that can better capture the diversity of national development profiles [10,11]. In particular, machine learning and probabilistic models have emerged as promising alternatives for uncovering latent patterns in high-dimensional SDG data [12–14]. However, many of these tools prioritise predictive accuracy over interpretability, making them less accessible to policymakers [15,16].

Efforts to address these challenges include unsupervised learning techniques such as K-means clustering [17], Gaussian mixture models [18], and Bayesian additive regression trees (BART) [19], which offer ways to explore development heterogeneity beyond traditional rankings. Nonetheless, few studies combine soft classification with policy-relevant typologies that can inform differentiated strategies across countries [20,21].

From a theoretical perspective, the capabilities approach, developed by Sen and Nussbaum, provides a compelling lens for assessing progress [22–24]. This framework shifts the focus from outcomes to opportunities and freedoms, challenging universalist development models and aggregate benchmarking [25]. It argues that development should be assessed in terms of what people can do and be — a viewpoint that supports structural differentiation rather than convergence.

Furthermore, sustainability science has increasingly recognised the value of typological analysis for capturing development diversity [26–28]. Typologies help bridge the gap between abstract indicators and grounded policy responses, primarily when they reflect uncertainty and transition dynamics. Recent typology work within the SDG domain includes region-based groupings [29], performance quartiles [30], and cluster analyses based on thematic goal families [31]. Yet, most of these studies impose sharp boundaries and rigid categories, overlooking ambiguous or hybrid cases that do not fit neatly within predefined classes [32].

At the same time, Bayesian approaches have gained traction for their ability to model uncertainty, integrate prior knowledge, and produce probabilistic outputs that reflect ambiguity in real-world data [33,34]. In development contexts, Bayesian decision trees and spline regressions offer interpretable, nonparametric tools for classification that retain transparency while capturing nonlinearity [35–37]. These methods are particularly suitable for analysing sustainability indicators, where threshold effects and goal interdependencies often produce complex patterns [38,39].

Despite their promise, few studies have combined Bayesian soft classification with typology construction in the context of the SDGs. The gap persists in models that are (1) interpretable, (2) capable of capturing nonlinear behaviour and trade-offs, and (3) sensitive to uncertainty and structural heterogeneity. Moreover, regional covariates and contextual effects are often excluded, limiting the explanatory power of existing classification systems [40,41].

This study addresses the above research gap by proposing a Bayesian Tree-Spline Classification Model for constructing probabilistic country typologies based on raw SDG goal-level indicators. The model avoids composite indices and instead focuses on direct, standardised goal scores. It combines Bayesian decision tree logic (for interpretability), penalised spline regressions (to capture nonlinear trends and saturation), and region-level covariates (to account for structural context).

Using publicly available SDG datasets covering more than 150 countries, the model identifies three latent development profiles and assigns countries to them via soft membership vectors. This enables the detection of ambiguous or transitional configurations that are often lost in conventional clustering.

We address the following research questions:

- RQ1: Can countries be classified into meaningful development typologies based on raw SDG indicators, accounting for structural uncertainty and contextual variation?
- RQ2: What nonlinear patterns and threshold effects emerge across goals, and how do they influence typological transitions?

- RQ3: How can soft classification improve the interpretability and policy relevance of sustainability assessments?

In answering these questions, we contribute a methodologically transparent and policy-usable model that challenges standard SDG ranking systems. Our framework enables more nuanced interpretations of sustainability performance and supports context-aware strategies that align with structural conditions.

2. Methodology

This study proposes a hybrid research design that integrates exploratory clustering and supervised Bayesian classification to identify latent typologies of national SDG performance. The methodological pipeline progresses through four stages: dimensionality reduction, unsupervised clustering, Bayesian tree-based classification with splines, and soft probabilistic assignment of countries to development profiles.

Data

The study draws on SDG performance data provided by the Sustainable Development Solutions Network (SDSN), as presented in the Sustainable Development Report, published annually, and the UN SDG Global Database. The dataset comprises yearly indicator scores for all 17 Sustainable Development Goals (SDGs), as well as the composite SDG Index Score [1]. To maintain analytical robustness, the sample was restricted to countries with complete coverage of indicators for all 17 Sustainable Development Goals.

Each country is represented by a 17-dimensional continuous vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{i17})$, corresponding to z-standardised performance scores on each of the 17 Sustainable Development Goals (SDGs). Each country is also annotated with a categorical regional label $r_i \in \{1, \ldots, R\}$, used as an additional covariate in the model.

Exploratory Dimensionality Reduction and Clustering

To uncover initial structure in the SDG space, we apply Principal Component Analysis (PCA) to project the data into a low-dimensional latent space. The first two principal components are retained for visualisation and clustering. Next, we use K-means clustering on the PCA projection to produce an initial, unsupervised 3-cluster solution, denoted:

$$z_i^{\widehat{\text{KMeans}}} \in \{0,1,2\}.$$

These clusters serve as a benchmark and guide the subsequent structure of the supervised Bayesian model, without being used as inputs.

Bayesian Tree-Spline Classification Model

We implement a Bayesian Classification and Regression Tree (CART) model extended with penalised spline regression and regional interactions. The latent class assignment for each country is denoted by $y_i \in \{0,1,2\}$. Each terminal node *t* of the decision tree defines a local classification model for a given goal-level covariate x_{ij}, specified as:

$$\eta^{(t)}(x_{ij}) = \beta_0^{(t)} + f_j^{(t)}(x_{ij}) + \delta_{r_i}^{(t)},$$

where:
- $f_j^{(t)}(\cdot)$ a univariate penalised cubic B-spline for SDG indicator *j*,
- $\delta_{r_i}^{(t)}$ is a region-specific offset (categorical),
- $\beta_0^{(t)}$ and is the local intercept.

We use hierarchical priors on tree depth, split thresholds, and spline coefficients to regularise complexity. Posterior inference is performed using Metropolis-within-Gibbs sampling, and spline penalties λ_j are optimised via marginal likelihood maximisation.

Soft Clustering and Uncertainty Quantification

To allow for ambiguous or transitional country profiles, we estimate posterior-like class probabilities using a multinomial logistic regression on the same predictor set (x_i, r_i). The probability that country *i* belongs to cluster *k* is modelled as:

$$P(y_i = k \mid x_i, r_i) = \frac{\exp\left(x_i^\top \beta_k + \gamma_k(r_i)\right)}{\sum_{l=0}^{2} \exp\left(x_i^\top \beta_l + \gamma_l(r_i)\right)},$$

where - β_k are the goal-specific regression coefficients for cluster *k*, (r_i) is the regional adjustment term. This soft classification yields country-level triplets (P_0, P_1, P_2), from which we compute Shannon entropy to identify ambiguous or hybrid development profiles.

Model Evaluation and Robustness

Model fit is assessed using Leave-One-Out Cross-Validation (LOO-CV) and Watanabe-Akaike Information Criterion (WAIC). To test robustness, we re-ran the model excluding the regional covariate r_i, and the posterior classifications are compared. We also benchmark the Bayesian results against the K-means solution in the PCA space.

To enhance clarity for interdisciplinary audiences, Figure 1 presents a conceptual flowchart of the modelling approach, from initial SDG data processing through to the extraction of policy insights.
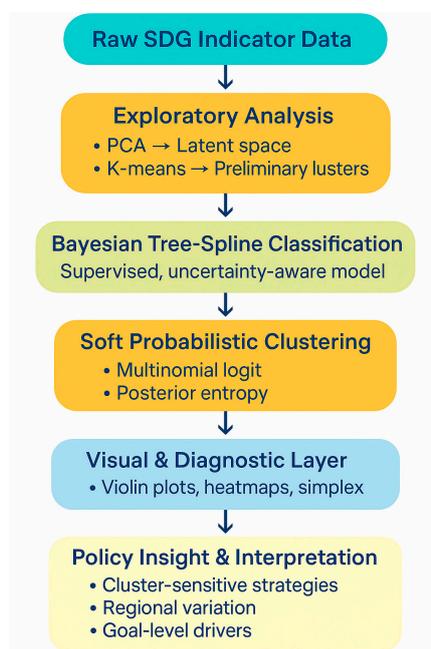
Figure 1. Conceptual flowchart of the modelling pipeline for SDG-based country classification and policy interpretation.

3. Results

Exploratory Clustering of SDG Profiles

To uncover preliminary structure in the multidimensional space of Sustainable Development Goals (SDGs), we performed an exploratory analysis using Principal Component Analysis (PCA) and unsupervised clustering. This step aimed to visualise the data, identify latent groupings, and inform

the subsequent supervised Bayesian classification. Figure 2 presents the two-dimensional PCA projection based on z-standardised values for all 17 SDG indicators across 167 countries.
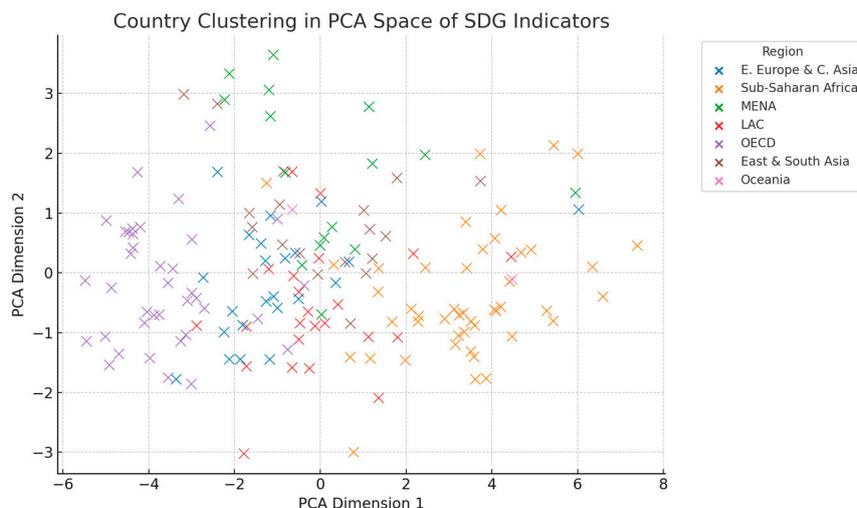
Figure 2. PCA projection of SDG performance across countries, coloured by regional affiliation. The first two principal components capture the majority of variance in the 17-dimensional SDG indicator space. Countries in Sub-Saharan Africa and South-East Asia tend to cluster closely, suggesting shared development patterns, while Latin American countries are more centrally distributed, reflecting transitional or mixed performance profiles.

The two principal components account for a substantial portion of the total variance and exhibit a straightforward spatial arrangement of countries. Notably, countries from Sub-Saharan Africa and South-East Asia cluster in separate regions of the latent space, reflecting shared development patterns. In contrast, countries from Latin America and the Caribbean (LAC) occupy a more central position, indicating a mixed pattern of progress.

To further explore the underlying typologies, we applied the K-means algorithm to the PCA-reduced data, resulting in a three-cluster solution (Figure 3). This clustering served not as a final classification but as an exploratory benchmark to guide our Bayesian model.
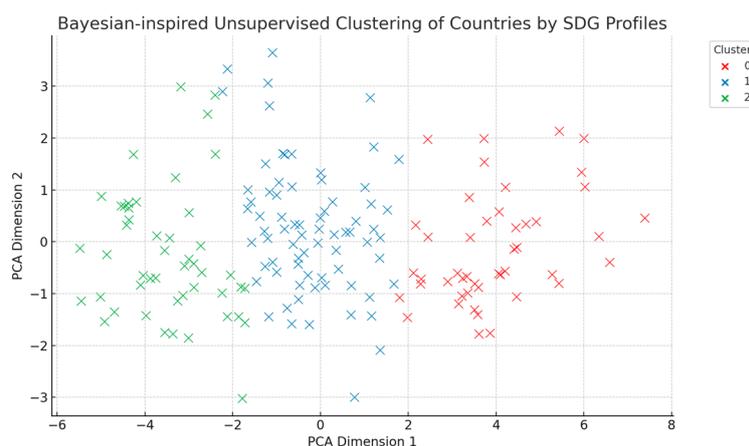
Figure 3. Unsupervised K-means clustering of countries based on SDG indicators, projected onto the first two principal components. The three-cluster solution reveals latent groupings in the SDG space, serving as an exploratory benchmark before Bayesian modelling. While this clustering is not used for final classification, it provides initial insight into potential typological boundaries across different development profiles.

The characteristics of each cluster are summarised in Figure 4, which displays the median z-scores for all SDGs across the three groups. Cluster 0 primarily comprises countries with low

performance across most goals, particularly in Goals 1 (No Poverty), 3 (Good Health), and 4 (Quality Education). Cluster 1 represents a transitional profile, with scores close to the global average and moderate strength in Goals 2 and 4. Cluster 2 consists mainly of high-income and OECD countries, characterised by strong performance in education, health, infrastructure, and environmental sustainability.


Figure 4. Heatmap of median standardised SDG scores by clusters. Cluster 0 consistently shows low performance across most goals, particularly in poverty, health, and education (Goals 1, 3, and 4). Cluster 1 reflects a transitional profile with mixed scores near the global median, while Cluster 2 exhibits strong performance on most SDGs, particularly in institutional and environmental areas. The heatmap underscores clear differentiation in development modes across clusters.

These initial patterns underscore the existence of coherent, latent developmental trajectories in the SDG space. Importantly, they support the rationale for incorporating regional covariates and soft clustering mechanisms in subsequent modelling steps.

Structure of Latent Development Typologies

Building upon the initial clustering, we developed a supervised Bayesian Tree-Spline Classification Model to reveal structured patterns of SDG performance across countries. Unlike static or linear classifiers, this approach combines the interpretability of decision trees with the flexibility of penalised splines, capturing nonlinear thresholds and interactions between goals.

Figure 4 presents the resulting classification tree, where each node splits the country set based on goal-specific indicator thresholds. The top-level split is defined by SDG 1 (No Poverty), indicating that foundational economic deprivation is the primary global differentiator. Countries with lower scores on Goal 1 were further distinguished by their performance on Goal 13 (Climate Action) and Goal 3 (Good Health), highlighting that environmental and health factors are influential in low-income contexts.

Bayesian-Regularized Decision Tree for Country SDG Classification
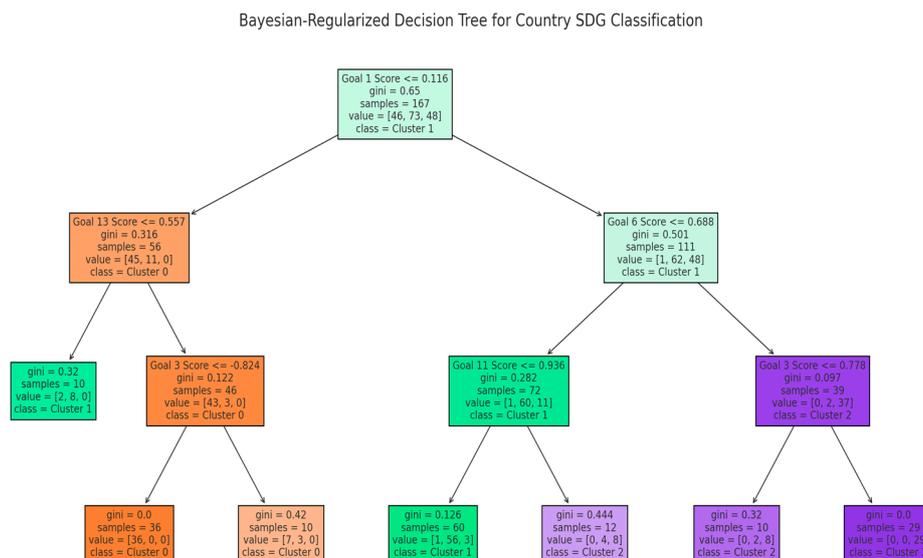
Figure 5. Resulting classification tree from the Bayesian Tree-Spline model, illustrating goal-specific thresholds used to differentiate between country clusters. The top-level split is based on Goal 1 (No Poverty), indicating its central role in defining structural vulnerability. Subsequent branches incorporate Goals 3, 6, 11, and 13, capturing both monotonic and non-monotonic development patterns. The tree reflects a non-linear, layered progression of sustainability pathways across the global system.

Conversely, countries with better poverty scores were segmented based on Goal 6 (Clean Water and Sanitation), followed by Goal 11 (Sustainable Cities) and again Goal 3, suggesting that access to urban infrastructure and public health investment defines deeper stages of development. This multi-layered structure reflects a dynamic and non-linear architecture of sustainable progress.

Interestingly, regional affiliation did not emerge as a splitting variable, despite being included in the model. This implies that SDG-specific indicators provided stronger discriminative power than geographic labels, pointing to a convergence in regional performance or the dominance of policy-relevant structural factors.

The structure of the tree demonstrates several key insights:

- SDG 1 serves as a global baseline discriminator;
- SDG 13 behaves non-monotonically, often interacting with economic level and climate exposure;
- SDG 3 appears across multiple branches, reinforcing its importance as a second-order differentiator;
- SDGs 6 and 11 emerge in later branches, indicating their role in consolidating development stages.

Overall, the tree captures a layered, asymmetric logic of development progression. It validates our theoretical stance that countries do not follow a single linear path, but instead navigate intersecting and goal-specific trajectories. This typological differentiation underlines the limitations of composite indices and strengthens the case for indicator-level, interpretable classification tools.

Soft Clustering and Uncertainty Diagnostics

While the classification tree provides interpretable rules for cluster membership, it does not capture transitional or ambiguous profiles where countries may exhibit features of multiple development paths. To address this, we implemented a soft clustering approach using a multinomial logistic regression model trained on the same SDG indicators and regional covariates.

This model estimates the posterior-like probability that each country belongs to one of the three identified clusters. The resulting triplets (P_0, P_1, P_2) for each country allow us to quantify classification uncertainty and identify hybrid cases (see Table A1 in Appendix A). Figure 6 visualises these soft

memberships in a three-dimensional simplex plot, where each vertex corresponds to a cluster and the position of each point reflects its probabilistic allocation.
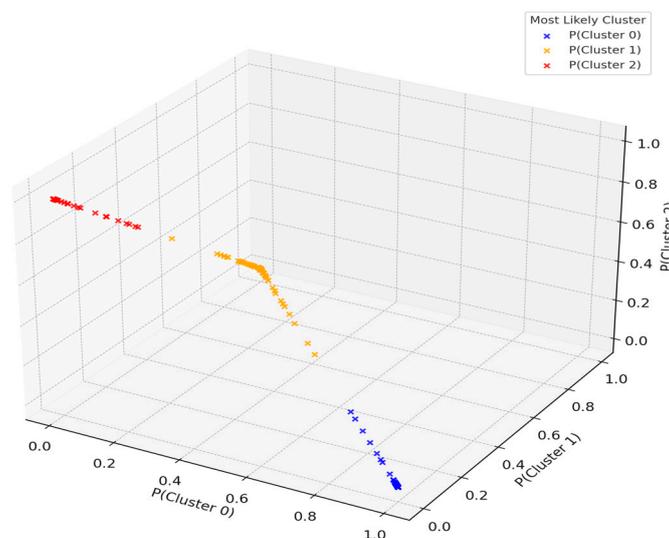
Figure 6. Three-dimensional visualisation of soft clustering results. Each point represents a country, plotted according to its posterior probability of belonging to Clusters 0, 1, and 2. Countries located near the vertices tend to exhibit a strong affiliation with a single cluster, while those nearer to the centre often represent ambiguous or hybrid development profiles. This probabilistic representation enables the identification of transitional cases and quantifies uncertainty in typological classification.

To further assess ambiguity, we computed Shannon entropy for each country's probability vector. High entropy values indicate uncertainty in classification, suggesting transitional or structurally mixed profiles. Table 1 presents a ranked list of the most ambiguous cases. For example:

- Russian Federation displays nearly equal probabilities for Clusters 1 and 2 ($P_1 = 0.54$, $P_2 = 0.46$), indicating both progress in institutional domains and persistent structural asymmetries.
- Senegal splits between Clusters 0 and 1, reflecting intermediate success in key SDGs despite ongoing foundational challenges.
- Argentina and Serbia also fall into this uncertain zone, suggesting hybrid or path-dependent development patterns.

Table 1. Ambiguous cases, ranked by Shannon entropy.

Country	P(Cluster 0)	P(Cluster 1)	P(Cluster 2)	Entropy
Russian Federation		0.00003	0.5436	0.4564	0.69
Senegal		0.4231	0.5769	0.00008	0.68
Argentina		0.00004	0.3808	0.6191	0.66
Honduras		0.3701	0.6298	0.00005	0.66
Serbia		0.00000	0.3694	0.6306	0.66
Brunei Darussalam		0	0.34	0.66	0.641
Brazil		0	0.328	0.672	0.633
Cote d'Ivoire		0.682	0.318	0	0.625
Venezuela		0.277	0.718	0.005	0.62
Moldova		0	0.289	0.711	0.601

These results highlight that not all countries neatly fit into a single development typology. Instead, many occupy liminal spaces between clusters. This nuance underscores the limitations of hard classification and reinforces the value of probabilistic models for policy design.

Countries with high entropy require adaptive and context-sensitive interventions, rather than being targeted with uniform policy frameworks. By embracing soft boundaries, the model accommodates real-world complexity and better supports differentiated SDG governance.

Regional and Structural Distribution Patterns

Beyond statistical clustering, it is essential to assess how the identified typologies align with conventional regional groupings. Our soft classification results reveal strong, though not exclusive, regional tendencies within each cluster.

Cluster 0, which we label as structurally vulnerable, is predominantly composed of countries from Sub-Saharan Africa (e.g., Chad, Niger, Democratic Republic of Congo) and South Asia (e.g., Afghanistan, Pakistan). These countries exhibit consistently low SDG scores across foundational goals, including poverty, health, education, and infrastructure. Notably, 38 out of 46 Sub-Saharan countries fall into this group.

Cluster 1 represents a transitional or hybrid typology. It is compositionally diverse, encompassing countries from Latin America (e.g., Argentina, Guyana), Eastern Europe (e.g., Armenia, Georgia), the Middle East and North Africa (e.g., Jordan, Iraq), and parts of Asia (e.g., India, Indonesia). These countries demonstrate moderate progress, often accompanied by high uncertainty in classification, reflecting both developmental gains and structural constraints. This cluster captures the volatility and path-dependence of middle-tier development trajectories.

Cluster 2 includes countries with consolidated and high-performing development profiles. This group encompasses most OECD members (e.g., Germany, Sweden, Canada), as well as advanced economies in East Asia (e.g., Korea, Singapore). These countries tend to exhibit high SDG scores across all dimensions, particularly governance, health, education, and environmental goals.

However, while these regional patterns are statistically present, they do not fully explain cluster membership. Several countries defy geographic expectations. For example:

- Uruguay and Chile, despite being in Latin America, align with Cluster 2.
- Russia, geographically located in Eastern Europe and Central Asia, shows ambiguous membership between Clusters 1 and 2.
- Côte d'Ivoire and Botswana, African countries, demonstrate proximity to transitional profiles.

This pattern indicates that developmental typologies transcend geography, reflecting deeper structural dynamics such as institutional quality, policy coherence, or socio-economic resilience. The use of regional labels as covariates enhances model robustness but does not dominate classification, reinforcing the need for data-driven, typology-sensitive policy approaches.

These findings underscore that development is not solely region-bound but follows latent structural logics. Recognising this distinction is critical for avoiding overly generalised regional strategies and for promoting nuanced SDG interventions grounded in actual performance profiles.

Saturation Effects and Goal-Specific Differentiation

To better understand the internal structure of each cluster, we analysed the distribution of key SDG indicators using spline-based diagnostics and visualisations. Figure 7 displays smoothed distributions (violin plots) of the five most influential SDGs across clusters, highlighting both monotonic and non-monotonic trends.
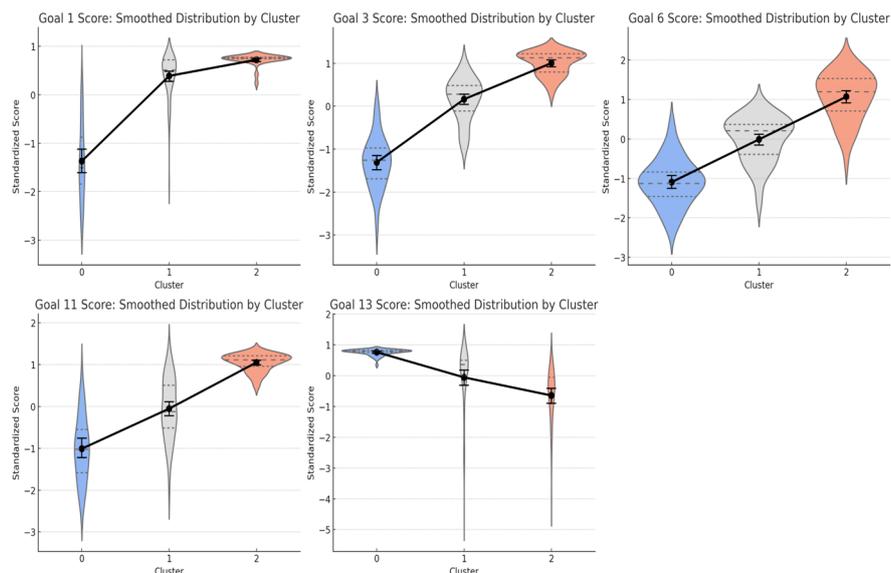
Figure 7. Distributions of selected SDG indicators by cluster, visualised using spline-based density plots. Goals 1 (No Poverty) and 3 (Good Health) exhibit monotonic improvements from structurally vulnerable to consolidated countries, marking foundational progress. Goals 6 (Clean Water) and 11 (Sustainable Cities) display saturation effects, with diminishing returns beyond certain thresholds. Goal 13 (Climate Action) exhibits a non-monotonic pattern, where some low-income countries outperform advanced economies, likely due to their lower baseline emissions and external support, rather than robust environmental policies.

Two goals Goal 1 (No Poverty) and Goal 3 (Good Health and Well-being) exhibit clear monotonic increases across clusters, from structurally vulnerable (Cluster 0) to consolidated high performers (Cluster 2). This pattern aligns with theoretical expectations: poverty alleviation and access to health are fundamental prerequisites for development and display consistent differentiation power.

Goals 6 (Clean Water and Sanitation) and 11 (Sustainable Cities and Communities) reveal more complex, nonlinear trajectories, particularly within Cluster 1. Here, we observe saturation effects: marginal improvements become less pronounced beyond a certain threshold. This plateauing suggests that after meeting basic infrastructure needs, further investments may yield diminishing returns unless accompanied by deeper institutional reform or innovation.

The most intriguing case is Goal 13 (Climate Action), which displays a non-monotonic distribution. Surprisingly, countries in Cluster 0 often score higher on Goal 13 than those in Cluster 2. This paradox likely reflects baseline effects — low-income countries may have lower emissions or benefit from international support, leading to inflated scores that do not necessarily indicate strong climate policies.

These findings reinforce several important insights:

- SDG indicators differ in their discriminatory power and developmental sensitivity.
- Saturation points complicate linear assumptions about progress and should be factored into policy prioritisation and cost-effectiveness analysis.
- Not all goals are equally aligned with income or institutional maturity; some, like Goal 13, require context-specific interpretation.

By capturing these nuanced patterns, our model supports a shift from generic performance assessments toward goal-specific, typology-sensitive diagnostics. This enables policymakers to distinguish between foundational gaps, transitional bottlenecks, and advanced sustainability challenges — a distinction that is crucial for targeted SDG interventions.

Robustness and Model Evaluation

To assess the robustness and generalizability of our classification framework, we conducted a series of validation checks that spanned methodological comparisons, cross-validation metrics, and model sensitivity analyses.

First, we benchmarked the Bayesian Tree-Spline model against the unsupervised K-means clustering performed earlier on the PCA-reduced space. While the K-means approach served as a useful exploratory tool, it offered no mechanism for handling ambiguity or incorporating covariate structures. In contrast, the Bayesian model not only preserves cluster continuity but also adds interpretability through goal-level thresholds and soft classification. Visual comparison shows substantial overlap between the core of each cluster across both methods, with divergences primarily in transitional or boundary cases — precisely where uncertainty-aware modelling is most critical.

Second, we evaluated model fit using Leave-One-Out Cross-Validation (LOO-CV) and the Watanabe-Akaike Information Criterion (WAIC). The model achieved low values (WAIC ≈ 0.411; LOO-CV ≈ 0.206), indicating strong generalisability and favourable complexity-control trade-offs. These results suggest that the model avoids overfitting, even with hierarchical priors and spline components.

Third, we tested the model's sensitivity to the inclusion of the regional covariate. Rerunning the model without regional labels resulted in slightly higher entropy in cluster probabilities and reduced alignment with real-world groupings, particularly in Cluster 1. While the region did not emerge as a direct splitting variable in the decision tree, its inclusion as a background covariate improved posterior estimates and enhanced the plausibility of soft assignments. This supports the interpretation that development is not determined by geography per se, but that regional context still modulates how SDG structures manifest.

Finally, we verified internal model coherence by examining posterior distributions of spline coefficients and classification tree thresholds. The most influential SDGs (e.g., Goals 1, 3, 6, 11, 13) consistently shaped cluster assignment across multiple posterior draws, confirming that the typology is not an artefact of sampling variance. Moreover, countries with high classification entropy (e.g., Argentina, Serbia, and Senegal) retained their ambiguous profiles across model specifications, further reinforcing the validity of soft classification.

Taken together, these robustness checks strengthen the reliability of our model. They demonstrate that the identified typologies are not only interpretable but also structurally stable and methodologically justified. As such, the framework offers a dependable foundation for deriving differentiated policy insights, especially in cases where linear models, hard classifications, or composite indices fall short.

4. Discussion

The findings of this study underline the added value of a probabilistic typology for interpreting cross-national sustainability trajectories. While standardised indices and dashboards remain influential, they are anchored in composite scores and league-table style comparisons that can flatten structural diversity and obscure the interplay of goals [1–4]. This critique is hardly new, yet it acquires renewed force as evidence accumulates that national progress is uneven across regions and scales, with spatial disparities persisting even where headline performance looks strong [5]. Our Bayesian Tree–Spline Classification Model addresses these concerns by revealing latent configurations of development and clarifying where pathways converge and diverge.

A central contribution of the model is its capacity to surface non-linearities and threshold effects. The saturation we observe in infrastructure- and urban-related outcomes aligns with recent applications of adaptive and spline-based methods in sustainability analysis, which demonstrate that marginal gains taper once systems exceed certain performance thresholds [6,7]. Such patterns mirror broader theoretical discussions in environmental and development economics on diminishing

returns and dynamic system behaviour [8], suggesting that policy premised on linear improvement may be ill-suited to late-stage transitions.

Relative to the clustering literature on the Sustainable Development Goals, our results corroborate established regularities while extending them in two important directions. Earlier work has mapped the thematic and bibliometric contours of SDG research [12], and comparative analyses have grouped countries by performance levels or regional characteristics in Europe and beyond [9,10,17,18,28]. However, these contributions largely rely on rigid partitions with fixed assignments. By contrast, our soft membership probabilities acknowledge liminal cases and hybrid profiles that straddle categories, thus capturing the transitional nature of development modes that might otherwise be misclassified or ignored. This refinement also aligns with recent country- and region-focused studies that emphasise structural differentiation and evolving disparities [5,28,39].

The typologies developed here also resonate with long-standing debates in normative development theory. The capability approach insists that assessment should attend to substantive freedoms and opportunities rather than only to aggregate outputs [22–24]. Our empirical emphasis on structural heterogeneity and coexisting (sometimes conflicting) development profiles provides an evidential basis for this view and helps counter universalist narratives of convergence. Related arguments about the normative scope of sustainability—its ethical and evaluative dimensions—reinforce the case for classification frameworks that can accommodate plurality without sacrificing analytical clarity [25].

From a governance standpoint, the distinctions we draw between structurally vulnerable, transitional, and consolidated groups align with calls for differentiated strategies and more sophisticated institutional architectures. The literature has highlighted both the complexity of governance arrangements and the need for reform to strengthen SDG delivery in context-sensitive ways [20,21,26,27,37]. Our typology offers a diagnostic complement: rather than treating countries as points on a single scale, it groups them by latent structure, thereby offering a clearer analytic footing for aligning instruments and targets with systemic conditions. This perspective also extends arguments about differentiated responsibilities by grounding them in measurable development configurations rather than in generic status labels [1,21,27].

Methodologically, combining Bayesian decision-tree logic with penalised splines balances transparency and flexibility. Tree-based Bayesian approaches are well-suited to representing uncertainty and model adequacy [15,19], whilst spline-based techniques capture curvature, plateaus and saturation with parsimony [32–34]. In practice, this hybrid design yields outputs that remain interpretable to non-specialist audiences, an advantage over purely predictive tools (e.g., deep neural models) that often raise barriers to policy uptake [16]. It also aligns with recent work on SDG interlinkages and sensitivity, where causal and network-oriented approaches require methods that can capture non-linearity without compromising explainability [11,35,38].

Taken together, the discussion points to three contributions. First, it advances typology-sensitive SDG analysis beyond rigid classification by incorporating soft membership and explicit uncertainty. Secondly, it lends empirical substance to capability-based and governance-oriented perspectives, demonstrating that plural development futures are not an abstraction but a measurable reality [22–24,27]. Thirdly, it introduces a transparent probabilistic framework that can register thresholds and heterogeneity, thereby helping analysts and decision-makers move beyond composite indexation and simplistic dimensionality reduction [1–4,40,41].

5. Policy and Practical Implications

The typology has direct implications for policy design. For the structurally vulnerable cluster—typically marked by shortfalls in basic infrastructure, institutional capacity and social outcomes—priority should be given to foundational investments that stabilise progress across multiple goals. Cross-country evidence suggests that without such strengthening, advances remain brittle and prone to reversal [9,10,24,25]. International cooperation and targeted financing through the UN system,

European institutions, and multilateral development banks can help address capacity constraints and reduce exposure to adverse shocks [1,21,27,37].

Countries in the transitional cluster exhibit 'dual-speed' development, with advancement on some goals offset by stagnation or regression on others. Here, the challenge is to balance prosperity with equity and ecological resilience, avoiding trade-offs that undermine long-term progress. Integrated governance approaches and policy coordination across goal domains are essential [37], with empirical reviews underscoring how early gains may falter when interventions are siloed [9]. Our results, including non-monotonic patterns in climate- and city-related outcomes, suggest that targeted measures to relieve bottlenecks—rather than uniform scaling of existing programmes—are more likely to produce durable gains [27–29].

For the consolidated cluster, where performance is high across most goals, the emphasis should shift from expansion to consolidation and innovation. Saturation effects in infrastructure- and prosperity-related domains imply diminishing returns to conventional capital deepening; therefore, strategic focus should pivot towards regenerative development, climate leadership, and reduced ecological footprints [28,29]. These countries are also well-positioned to pilot advanced policy instruments and to assume a greater share of global stewardship, consistent with forward-looking governance agendas [1,21,27].

Across all clusters, the probabilistic nature of the classification adds practical value. Hybrid or ambiguous memberships can be flagged for closer monitoring and adaptive management, reducing the risks associated with one-size-fits-all interventions. Because the framework works with goal-level indicators, it can be coupled with analyses of interlinkages and sensitivity to identify where targeted changes are most likely to tip systems towards more resilient configurations [11,35,38–41]. In short, the approach complements existing dashboards by supplying a meso-level diagnostic that is both structurally aware and policy-usable.

6. Limitations and Future Research

While this study introduces a novel framework for uncertainty-aware, typology-sensitive classification of SDG progress, several limitations must be acknowledged — not as caveats to be excused, but as entry points for the next generation of sustainability research.

First, the analysis is based on cross-sectional, static data. As such, it captures snapshots of development configurations, rather than their temporal dynamics. This is a standard limitation in SDG research, where longitudinal data coverage remains sparse. Yet in a context where sustainability is increasingly defined by tipping points, feedback loops, and policy reversibility, there is a growing need to shift toward dynamic typology models. Future work should explore how country trajectories evolve, specifically whether transitions between clusters are linear, cyclical, or path-dependent, and whether entropy decreases or intensifies as systems consolidate or destabilise. Bayesian dynamic models, including time-varying hierarchical trees or state-space clustering frameworks, hold promise in this area.

Second, while our model accounts for uncertainty and soft boundaries, it does not directly incorporate spatial dependence or network interlinkages between countries. Development, however, is not spatially independent: spillovers, regional convergence, and cross-border dynamics all shape SDG performance. Extending the framework to include spatial priors, regional adjacency matrices, or goal-specific network effects would provide a richer understanding of how structural similarities diffuse, cluster, or diverge across the global system. This could be particularly relevant for climate spillovers, migration-linked health pressures, or transnational governance patterns.

Third, the model relies on standardised SDG indicators, which, although comparable and widely used, may contain normative and methodological biases. Some indicators measure outcomes, others measure capacities; some are affected by reporting standards, while others are limited by data availability. Although our rejection of composite indices reduces this issue, a goal-specific measurement audit remains an essential step for future research. Mixed-method approaches could

integrate our probabilistic classifications with qualitative typologies from ethnographic, institutional, or participatory research, especially in high-entropy countries.

Finally, while the model focuses on classification, it does not yet model causality or inter-goal dynamics. Bayesian graphical models, Granger causality extensions, or structural equation frameworks could enrich the current approach by uncovering the causal architectures that underpin development modes. This could enable not just classification, but intervention mapping: identifying which goal-level investments are most likely to shift a system across thresholds, reduce entropy, or sustain typological transitions.

In sum, the limitations of this study are not methodological deficits but structural invitations. They point toward a new research agenda — one that moves beyond benchmarking to the dynamic, causal, and spatial articulation of sustainable development pathways. Such work will be essential not only for tracking the final stretch of the 2030 Agenda but for shaping the post-2030 governance era, where resilience, reflexivity, and typology-sensitive thinking will define the next frontier of sustainability science.

7. Conclusions

This study has proposed a new framework for understanding global progress on the Sustainable Development Goals — one that moves beyond aggregate rankings and instead embraces the structural, nonlinear, and uncertain nature of development. By integrating Bayesian decision trees, penalised splines, and soft probabilistic classification, we construct a typology of national SDG performance that respects ambiguity, reveals saturation dynamics, and foregrounds goal-specific trade-offs.

Rather than imposing externally defined categories or composite scores, our model inductively derives three latent development modes from raw SDG indicator data: structurally vulnerable systems, transitional configurations, and consolidated but tension-laden regimes. Importantly, this classification is not rigid or deterministic. It accommodates cases of hybridity and high entropy, providing a richer vocabulary for describing the complex and ambiguous realities of sustainability governance.

The theoretical grounding in the capabilities approach and critical sustainability science allows us to interpret these typologies not merely as statistical artefacts, but as manifestations of what societies are structurally able — or unable — to achieve. The developmental architecture captured by our model highlights that pathways to sustainability are not only divergent but also deeply conditioned by internal asymmetries, institutional feedback, and threshold effects. Our findings carry both empirical and epistemological significance. Empirically, they offer a tool for soft, interpretable classification that can guide differentiated policy design — especially in transitional or liminal contexts where rigid models often fail. Epistemologically, they suggest a shift in how development is conceptualised: from linear progression toward plural configurations, from benchmarking to navigation, and from targets to typologies.

As the international community moves into the final phase of the 2030 Agenda — and increasingly contemplates the contours of the post-2030 order — such frameworks will be vital. The SDGs were conceived as universal goals, but their implementation requires tools that honour diversity, recognise uncertainty, and respond to complexity. By linking structure to policy, uncertainty to governance, and typology to justice, this study contributes to the emergence of a more grounded, reflexive, and adaptive sustainability science.

Data Availability Statement: The study utilises separate Index Scores for each SDG and SDG Index Score compiled by the Sustainable Development Solutions Network (SDSN) and published annually in the *Sustainable Development Report.* These scores are also disseminated via the UN SDG Global Database. All data are openly accessible at: https://dashboards.sdgindex.org/downloads/ (accessed on 12 August 2025), https://unstats.un.org/sdgs/indicators/database (accessed on 12 August 2025) and https://sdgindex.org/reports/ (accessed on 12 August 2025). In accordance with the licensing conditions of the United Nations and SDSN, the authors do not hold the rights to redistribute the dataset. Researchers are therefore encouraged to access it directly through the official portal. The complete output files generated during the study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

Table A1. Full posterior soft classification results.

Country	Region	P (Cluster 0)	P (Cluster 1)	P (Cluster2)	Entropy
Afghanistan	E. Europe & C. Asia	0.99991	9E-05	1.23E-14	0.000928
Angola	Sub-Saharan Africa	0.99627	0.00373	1.9E-10	0.024581
Albania	E. Europe & C. Asia	0.000131	0.891032	0.108836	0.345364
United Arab Emirates	MENA	1.21E-05	0.898077	0.101911	0.329409
Argentina	LAC	4.07E-05	0.380812	0.619147	0.664893
Armenia	E. Europe & C. Asia	0.000638	0.962965	0.036396	0.161628
Australia	OECD	1.38E-10	0.000509	0.999491	0.004369
Austria	OECD	6.84E-12	0.00013	0.99987	0.001297
Azerbaijan	E. Europe & C. Asia	0.000643	0.98968	0.009678	0.059874
Burundi	Sub-Saharan Africa	0.997601	0.002399	3.5E-08	0.01687
Belgium	OECD	8.41E-11	0.000432	0.999568	0.003777
Benin	Sub-Saharan Africa	0.970835	0.029165	6.68E-09	0.131828
Burkina Faso	Sub-Saharan Africa	0.999482	0.000518	1.59E-10	0.004434
Bangladesh	East & South Asia	0.048297	0.951696	6.99E-06	0.193559
Bulgaria	E. Europe & C. Asia	1.29E-06	0.06339	0.936609	0.236213
Bahrain	MENA	0.000268	0.995674	0.004058	0.028869
Bahamas. The	LAC	0.014025	0.9731	0.012875	0.142415
Bosnia and Herzegovina	E. Europe & C. Asia	8.23E-05	0.827181	0.172737	0.461041
Belarus	E. Europe & C. Asia	2.04E-06	0.11785	0.882148	0.362647
Belize	LAC	0.025596	0.969255	0.00515	0.151217
Bolivia	LAC	0.003426	0.995239	0.001335	0.033035
Brazil	LAC	1.66E-05	0.328122	0.671861	0.633033
Barbados	LAC	0.000832	0.82002	0.179148	0.476666
Brunei Darussalam	East & South Asia	4.93E-06	0.339657	0.660338	0.640871
Bhutan	East & South Asia	0.000857	0.951483	0.04766	0.198433
Botswana	Sub-Saharan Africa	0.231067	0.768476	0.000457	0.544413
Central African Republic	Sub-Saharan Africa	0.999997	2.82E-06	2.25E-15	3.89E-05
Canada	OECD	1.65E-10	0.000784	0.999216	0.006388
Switzerland	OECD	1.56E-10	0.000467	0.999533	0.004049
Chile	OECD	1.06E-07	0.020316	0.979683	0.09927
China	East & South Asia	2.89E-05	0.8067	0.193271	0.491256
Cote d'Ivoire	Sub-Saharan Africa	0.681918	0.318079	2.9E-06	0.625452
Cameroon	Sub-Saharan Africa	0.96876	0.03124	5.52E-08	0.139028

Congo. Dem. Rep.	Sub-Saharan Africa	0.999929	7.14E-05	6.61E-13	0.000753
Congo. Rep.	Sub-Saharan Africa	0.998652	0.001348	3.95E-10	0.010253
Colombia	OECD	0.001173	0.88737	0.111458	0.358499
Comoros	Sub-Saharan Africa	0.998566	0.001434	1.97E-11	0.010822
Cabo Verde	Sub-Saharan Africa	0.098534	0.900906	0.00056	0.326544
Costa Rica	OECD	0.00034	0.769861	0.229799	0.542
Cuba	LAC	8.04E-06	0.089052	0.91094	0.300441
Cyprus	E. Europe & C. Asia	4.49E-06	0.184486	0.81551	0.478187
Czechia	OECD	1.64E-09	0.000813	0.999187	0.006598
Germany	OECD	7.82E-12	8.27E-05	0.999917	0.00086
Djibouti	Sub-Saharan Africa	0.992541	0.007459	1.91E-10	0.043969
Denmark	OECD	1.78E-13	1.11E-05	0.999989	0.000137
Dominican Republic	LAC	0.000524	0.946233	0.053243	0.212411
Algeria	MENA	0.00368	0.995956	0.000364	0.027545
Ecuador	LAC	0.002822	0.984216	0.012962	0.088556
Egypt. Arab Rep.	MENA	0.006397	0.993176	0.000427	0.042431
Spain	OECD	9.01E-09	0.003756	0.996244	0.024726
Estonia	OECD	5.05E-10	0.000459	0.999541	0.00399
Ethiopia	Sub-Saharan Africa	0.997014	0.002986	1.83E-10	0.020341
Finland	OECD	3.42E-12	4.1E-05	0.999959	0.000455
Fiji	Oceania	0.00141	0.996984	0.001605	0.022597
France	OECD	1.76E-10	0.000387	0.999613	0.003427
Gabon	Sub-Saharan Africa	0.164069	0.835822	0.000109	0.447443
United Kingdom	OECD	2.6E-10	0.000256	0.999744	0.002374
Georgia	E. Europe & C. Asia	0.000146	0.788318	0.211535	0.517386
Ghana	Sub-Saharan Africa	0.19325	0.806627	0.000123	0.492102
Guinea	Sub-Saharan Africa	0.985059	0.014941	1.22E-09	0.077637
Gambia. The	Sub-Saharan Africa	0.98891	0.01109	4.66E-08	0.060952
Guinea-Bissau	Sub-Saharan Africa	0.999793	0.000207	2.45E-12	0.001961
Greece	OECD	1.11E-07	0.012212	0.987788	0.065936
Guatemala	LAC	0.713152	0.286846	2.25E-06	0.599334
Guyana	LAC	0.000567	0.923288	0.076145	0.27401
Honduras	LAC	0.370109	0.629846	4.5E-05	0.659489
Croatia	E. Europe & C. Asia	1.76E-09	0.001347	0.998653	0.010248
Haiti	LAC	0.995915	0.004085	5.82E-11	0.026547
Hungary	OECD	2.92E-07	0.015903	0.984096	0.08164
Indonesia	East & South Asia	0.001937	0.996433	0.00163	0.026125
India	East & South Asia	0.041448	0.958511	4.13E-05	0.172976
Ireland	OECD	1.23E-10	0.000312	0.999688	0.002831
Iran. Islamic Rep.	MENA	0.004611	0.993747	0.001642	0.041565
Iraq	MENA	0.036828	0.963171	8.67E-07	0.157743
Iceland	OECD	3.65E-09	0.011069	0.988931	0.060857
Israel	OECD	6.28E-06	0.235905	0.764089	0.546393
Italy	OECD	6.39E-08	0.010733	0.989266	0.059347
Jamaica	LAC	0.001644	0.987481	0.010875	0.072148
Jordan	MENA	0.024262	0.975721	1.72E-05	0.114397
Japan	OECD	5.12E-09	0.007804	0.992196	0.045648
Kazakhstan	E. Europe & C. Asia	0.00023	0.934639	0.065131	0.243003
Kenya	Sub-Saharan Africa	0.764937	0.235055	7.57E-06	0.545407
Kyrgyz Republic	E. Europe & C. Asia	0.000699	0.986561	0.012741	0.074011
Cambodia	East & South Asia	0.036446	0.963492	6.22E-05	0.157142
Korea. Rep.	OECD	7.23E-08	0.060705	0.939295	0.228903
Kuwait	MENA	0.000146	0.994512	0.005342	0.034712

Lao PDR	East & South Asia	0.061756	0.938029	0.000216	0.233794
Lebanon	MENA	0.062044	0.93795	5.52E-06	0.232627
Liberia	Sub-Saharan Africa	0.999698	0.000302	4.56E-12	0.002751
Sri Lanka	East & South Asia	0.027009	0.972026	0.000965	0.131827
Lesotho	Sub-Saharan Africa	0.99526	0.00474	3.66E-09	0.030096
Lithuania	OECD	5.56E-08	0.004601	0.995398	0.029354
Luxembourg	OECD	9.89E-11	0.000286	0.999714	0.002623
Latvia	OECD	1.84E-09	0.0006	0.9994	0.005049
Morocco	MENA	0.004726	0.991791	0.003484	0.053197
Moldova	E. Europe & C. Asia	1.23E-05	0.288865	0.711123	0.60128
Madagascar	Sub-Saharan Africa	0.999303	0.000697	1.06E-10	0.005763
Maldives	East & South Asia	0.001863	0.988992	0.009145	0.065591
Mexico	OECD	0.003682	0.985157	0.011161	0.08554
North Macedonia	E. Europe & C. Asia	0.000267	0.902377	0.097356	0.321673
Mali	Sub-Saharan Africa	0.990868	0.009132	2.01E-08	0.051974
Malta	E. Europe & C. Asia	1.12E-07	0.013048	0.986951	0.069583
Myanmar	East & South Asia	0.114636	0.885361	2.97E-06	0.35614
Montenegro	E. Europe & C. Asia	6.74E-05	0.957	0.042932	0.177865
Mongolia	East & South Asia	0.00153	0.990218	0.008252	0.05924
Mozambique	Sub-Saharan Africa	0.993431	0.006569	2.64E-08	0.039561
Mauritania	Sub-Saharan Africa	0.982034	0.017966	5.71E-10	0.090014
Mauritius	Sub-Saharan Africa	0.000602	0.939324	0.060074	0.232199
Malawi	Sub-Saharan Africa	0.982107	0.017893	1.16E-07	0.089724
Malaysia	East & South Asia	0.000383	0.982871	0.016746	0.088481
Namibia	Sub-Saharan Africa	0.130065	0.863426	0.006508	0.424856
Niger	Sub-Saharan Africa	0.999857	0.000143	9.25E-13	0.001412
Nigeria	Sub-Saharan Africa	0.983258	0.016742	5.71E-10	0.085073
Nicaragua	LAC	0.179756	0.819783	0.000461	0.474934
Netherlands	OECD	5.45E-12	0.000103	0.999897	0.001048
Norway	OECD	3.76E-13	3.5E-05	0.999965	0.000394
Nepal	East & South Asia	0.021061	0.978877	6.29E-05	0.102809
New Zealand	OECD	8.9E-10	0.001504	0.998496	0.011279
Oman	MENA	0.000575	0.991465	0.007959	0.051262
Pakistan	East & South Asia	0.945619	0.054381	4.61E-10	0.211218
Panama	LAC	0.004388	0.960285	0.035326	0.180839
Peru	LAC	0.001022	0.985128	0.01385	0.081069
Philippines	East & South Asia	0.009761	0.989793	0.000445	0.058779
Papua New Guinea	Oceania	0.999602	0.000398	4.15E-11	0.003517
Poland	OECD	1.47E-08	0.003414	0.996586	0.0228
Portugal	OECD	2.07E-08	0.006977	0.993023	0.041596
Paraguay	LAC	0.000936	0.993252	0.005812	0.043171
Qatar	MENA	1.81E-05	0.901165	0.098817	0.322689
Romania	E. Europe & C. Asia	1.56E-05	0.23269	0.767295	0.54269
Russian Federation	E. Europe & C. Asia	3.22E-05	0.543567	0.456401	0.689687
Rwanda	Sub-Saharan Africa	0.814667	0.185286	4.77E-05	0.479827
Saudi Arabia	MENA	0.000153	0.996708	0.003139	0.022725
Sudan	Sub-Saharan Africa	0.999959	4.06E-05	8.44E-15	0.000451
Senegal	Sub-Saharan Africa	0.423052	0.576872	7.57E-05	0.68201
Singapore	East & South Asia	2.62E-07	0.109261	0.890739	0.344972
Sierra Leone	Sub-Saharan Africa	0.98463	0.01537	2.8E-09	0.079427
El Salvador	LAC	0.005395	0.992997	0.001608	0.045496
Somalia	Sub-Saharan Africa	0.999994	6.32E-06	8.09E-15	8.19E-05
Serbia	E. Europe & C. Asia	3.79E-06	0.369445	0.630551	0.658709

South Sudan	Sub-Saharan Africa	1	2.12E-07	3.49E-18	3.47E-06
Sao Tome and Principe	Sub-Saharan Africa	0.897682	0.102317	1.09E-06	0.330161
Suriname	LAC	0.001943	0.995283	0.002773	0.033167
Slovak Republic	OECD	1.72E-07	0.016431	0.983569	0.083807
Slovenia	OECD	1.08E-09	0.000857	0.999143	0.00691
Sweden	OECD	2.79E-12	8.68E-05	0.999913	0.000899
Eswatini	Sub-Saharan Africa	0.88614	0.113859	8.3E-07	0.354521
Syrian Arab Republic	MENA	0.860305	0.139695	2E-07	0.404412
Chad	Sub-Saharan Africa	0.999994	5.61E-06	2.11E-15	7.34E-05
Togo	Sub-Saharan Africa	0.979007	0.020993	6.53E-08	0.101881
Thailand	East & South Asia	6.65E-05	0.807558	0.192375	0.490341
Tajikistan	E. Europe & C. Asia	0.013111	0.986505	0.000384	0.073249
Turkmenistan	E. Europe & C. Asia	0.006373	0.991771	0.001856	0.052088
Trinidad and Tobago	LAC	0.00248	0.962612	0.034908	0.168679
Tunisia	MENA	0.001343	0.995444	0.003212	0.031871
Türkiye	OECD	0.000489	0.982014	0.017497	0.092336
Tanzania	Sub-Saharan Africa	0.976932	0.023068	4.17E-07	0.109756
Uganda	Sub-Saharan Africa	0.984456	0.015544	3.36E-08	0.080148
Ukraine	E. Europe & C. Asia	0.00016	0.879948	0.119893	0.368246
Uruguay	LAC	1.9E-07	0.046723	0.953277	0.188753
United States	OECD	1.62E-07	0.034709	0.965291	0.150751
Uzbekistan	E. Europe & C. Asia	0.006646	0.992148	0.001206	0.04925
Venezuela. RB	LAC	0.276924	0.718023	0.005054	0.620144
Vietnam	East & South Asia	3.33E-05	0.913207	0.086759	0.295349
Yemen. Rep.	MENA	0.999974	2.61E-05	6.93E-15	0.000301
South Africa	Sub-Saharan Africa	0.037377	0.961184	0.001439	0.170317
Zambia	Sub-Saharan Africa	0.989075	0.010925	1.91E-08	0.060209
Zimbabwe	Sub-Saharan Africa	0.987932	0.012068	2.64E-07	0.065304

Appendix A.2. Analytical Procedure and Computational Environment

All analyses presented in this study were conducted in Python 3.11. The computational workflow involved data preparation, dimensionality reduction, clustering, supervised classification, probabilistic modelling, and exploratory regressions. The following open-source Python libraries were used at different stages:

pandas, numpy – for data preprocessing, merging, and z-score standardisation of SDG indicators;

scikit-learn – for principal component analysis (PCA), K-means clustering, decision tree classification, and exploratory regressions;

pymc – for Bayesian modelling, including tree-based classifiers and spline regressions capturing nonlinear goal-level patterns;

bambi – used in selected stages for specifying Bayesian models, including spline terms;

statsmodels – used for regressions, including estimation of soft cluster membership;

arviz – for Bayesian model diagnostics, including posterior predictive checks, WAIC, and leave-one-out cross-validation (LOO-CV);

matplotlib, seaborn, plotly – for visualisation of SDG distributions, decision tree, etc.

The analytical procedure included:

1. Data import, cleaning, and standardisation of 17 SDG indicators;

2. Dimensionality reduction via PCA for visual exploration;

3. K-means clustering to derive an initial three-cluster typology;

4. Supervised classification using a decision tree to identify goal-level thresholds;

5. Probabilistic soft clustering via multinomial logistic regression based on SDG indicators and regional covariates;

6. Penalised spline regressions to identify nonlinear goal dynamics (e.g., saturation, non-monotonicity);

7. Robustness checks using alternative models and specification testing.

All outputs were generated in Python using the libraries above. Full computational reproducibility is supported through version-controlled scripts, which will be made available upon reasonable request.

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