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A Multi-Method Framework Integrating MCDM and Explainable Machine Learning to Assess Sustainability–Well-Being Linkages Across Diverse Economies

Abdullah Akman Demirkan
PhD Candidate
Graduate School of Natural and Applied Sciences
Department of Industrial Engineering
Gaziantep University
Gaziantep, Turkiye
a.akman.d@gmail.com

Zeynep Didem Unutmaz Durmuşoğlu
Prof. Dr.
Department of Industrial Engineering
University of Samsun
Samsun, Turkiye
didem.durmusoglu@samsun.edu.tr

Abstract

Background and Objective: Grounded in Diener's cognitive life satisfaction framework, this study develops an integrated MCDM–machine learning pipeline to examine how environmental, social, and economic sustainability predict subjective well-being.

Methods: Panel data (47 countries, 2016–2025, N=470) were used. Sustainability indices followed the triple-bottom-line framework. Winsorization and log transformations were applied. Of five MCDM techniques evaluated, ELECTRE was selected as the primary method based on its superior discriminatory ranking performance and robustness in sustainability benchmarking contexts. An ExtraTrees regressor (R^2=0.80) predicted the Cantril Ladder; SHAP decomposed importance. LOCO-CV tested generalizability (MAE=0.38).

Results: Social sustainability dominated (62.1% importance) over economic (21.4%) and environmental (16.5%) dimensions. ELECTRE ranked institutional quality highest in structural importance, with social and environmental indices closely following. SHAP showed non-linear interactions ($\Delta = -0.02$). Lower-middle-income countries converged (slope +0.0065, p=0.02), high-income countries declined marginally—a narrowing gap (n=8 exploratory). Composite index weighting was robust (r=0.98).

Discussion and Limitations: Using only cognitive SWB limits full tripartite model operationalization; affective measures were unavailable. The 10-year panel constrains causal inference. LOCO-CV MAE (0.38, SD=0.19) indicates country heterogeneity rather than misspecification. The non-linear SHAP interactions could not be fully decomposed, warranting future interaction analysis. The n=8 sub-group convergence finding is exploratory. Future phases will incorporate low-income countries and country clustering.

Conclusion and Policy Implications: Social well-being (life expectancy, education, social support, digital inclusion) is the strongest life satisfaction lever, necessitating social cohesion. The ELECTRE-SHAP pipeline offers a replicable tracking template. Future extensions include Fuzzy Cognitive Mapping for causal simulation and affective SWB indicators to operationalize Diener's full model.

Keywords
Sustainable development; subjective well-being; MCDM; SHAP; social sustainability

1. Introduction

Well-being, in its most fundamental sense, refers to what is ultimately good for a person (Crisp, 2021). Although no single definition commands universal consensus, there is broad agreement across both expert communities and lay populations worldwide that well-being requires meeting a spectrum of human needs—from essential requirements such as good health to the capacity to pursue personal goals, flourish, and experience life satisfaction (Durand, 2015), (OECD, 2020). Subjective well-being (SWB) is formally defined as an individual's cognitive and affective evaluations of their life as a whole (Diener, 1984), (Diener et al., 2018). This internal, self-reported assessment—typically captured through survey instruments—reflects how people experience and appraise their lives (Linton et al., 2016). While Diener's full tripartite model encompasses both cognitive judgments (life satisfaction) and affective experiences (positive and negative affect), the present study focuses on the cognitive component, operationalized via the Cantril Self-Anchoring Striving Scale (Helliwell et al., 2026). This deliberate narrowing is driven by the unavailability of consistent affective indicators across the full 47-country panel; the implications of this scope restriction for the interpretation of findings are addressed in Section 5.3.

The dramatic improvements in material living conditions over the past century, driven by scientific breakthroughs and industrialization, have fostered a widespread implicit assumption that rising material prosperity naturally translates into greater quality of life and, consequently, higher life satisfaction. Yet this linear view faces persistent empirical challenges. Resources are finite, and material growth may encounter limits beyond which additional gains yield diminishing well-being returns—an observation most famously associated with the Easterlin paradox (Easterlin, 1974), (Jebb et al., 2018). Moreover, the simple correlation between high income and high happiness is far from absolute, necessitating a deeper investigation into the structural factors that genuinely sustain a good life.

Parallel to this, a cultural shift towards heightened individual consciousness has redirected the pursuit of a "good life" from mere hedonic maintenance to the ideal of a "meaningful life." In this emerging understanding, the aim is not simply to preserve momentary well-being, but to extend it across time—to "build the future from today." This temporal dimension introduces the concept of sustainability as an indispensable complement to material conditions and quality of life. The three pillars of sustainability—environmental integrity, social equity, and economic viability—are thus not merely macro-level policy goals; they are plausibly the structural foundations upon which durable individual well-being rests.

Despite this conceptual appeal, the empirical relationship between sustainable development and subjective well-being remains underexplored, particularly concerning the relative importance of distinct sustainability dimensions. Prior work has often examined these links in isolation (e.g., environmental quality and happiness, (Yuan et al., 2018); social capital and life satisfaction, (Kassouri & Altıntaş, 2020), but a holistic, comparative framework is largely absent. Furthermore, existing studies rarely leverage the combined strengths of multi-criteria decision-making (MCDM) for structuring sustainability indices and interpretable machine learning for uncovering non-linear, heterogeneous effects. This methodological gap limits the ability to generate transparent, policy-actionable insights.

The present study addresses these gaps by developing and validating an integrated analytical pipeline that couples MCDM with interpretable machine learning. Centering on the cognitive dimension of subjective well-being (Diener et al., 2018), we examine how environmental, social, and economic sustainability—alongside institutional and demographic controls—predict life evaluation across a diverse panel of 47 countries over the 2016–2025 period. By employing ELECTRE for robust sustainability rankings and SHAP (SHapley Additive exPlanations) for model-agnostic feature attribution, the framework not only quantifies the relative predictive power of each sustainability dimension but also reveals their non-linear interactions and country-level heterogeneity.

1.1 Objectives

The overarching goal of this study is to provide a transparent, replicable empirical foundation for understanding the sustainability–well-being nexus. The specific objectives are threefold:

1. To construct comprehensive environmental, social, and economic sustainability indices within a triple-bottom-line framework and to evaluate their relative importance in predicting country-level life evaluation, using an ExtraTrees regressor interpreted via SHAP values.

2. To systematically compare MCDM techniques (DEMATEL, TOPSIS, AHP, ELECTRE, VIKOR) and select the most robust method for sustainability benchmarking, thereby integrating the ordinal information from MCDM with the predictive power of machine learning.

3. To assess the generalizability and limitations of the proposed pipeline through rigorous cross-validation (including leave-one-country-out and time-series CV), and to identify priority directions for future research—such as the incorporation of affective well-being indicators, sub-group modelling for low-income contexts, and non-linear scenario simulation.

By achieving these objectives, the study aims to offer both a methodological template for evidence-based sustainable development tracking and actionable insights into which sustainability investments are likely to yield the greatest well-being returns.

2. Literature Review

2.1 Theoretical Foundations: Sustainability and Well-being

The relationship between the foundational pillars of sustainability and human well-being has been a subject of increasing empirical scrutiny. Early large-scale system dynamics models, such as the "World3" model (Meadows et al., 1974), (O'Neill et al., 2018), provided a holistic, simulation-based perspective on the long-term interactions between population, resources, and pollution, laying the groundwork for understanding the macro-level constraints on human welfare. These foundational studies underscored the interconnectedness of environmental, social, and economic systems, a principle that now underpins the triple-bottom-line framework (Elkington, 1998), (Hourneaux et al., 2018).

More recently, empirical research has sought to disentangle the specific effects of these pillars. The relationship between environmental quality and subjective well-being (SWB) has been a particularly active research area, with (Yuan et al., 2018) providing robust evidence that air pollution significantly diminishes life satisfaction, independent of income. Similarly, the critical role of social capital and human development—encompassing health, education, and social support—has been firmly established as a dominant predictor of life evaluation across countries (Kassouri & Altıntaş, 2020); (Helliwell et al., 2020). These findings highlight a persistent gap: while individual links have been established, a systematic, comparative quantification of the relative importance of all three sustainability dimensions within a single analytical framework remains notably absent. This is the primary gap the present study seeks to fill.

2.2 MCDM in Sustainability Assessment: A Comparative Perspective

The construction and evaluation of composite sustainability indices are inherently a multi-criteria decision-making (MCDM) problem. A wide array of techniques has been applied in this domain, each with distinct theoretical underpinnings and practical trade-offs (Stojčić et al., 2019). Methods such as the Analytic Hierarchy Process (AHP) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) are frequently used to derive criteria weights and map causal relationships among them (Si et al., 2018).

However, the suitability of an MCDM method is highly context-dependent. While DEMATEL and AHP excel at structuring complex problem elements, they can, in certain contexts, yield rankings with insufficient discriminatory power across a large set of alternatives, as observed in our own systematic evaluation. In contrast, outranking methods like ELECTRE (ÉLimination Et Choix Traduisant la REalité) and VIKOR are specifically designed to handle non-compensatory preferences and ordinal data, making them theoretically more robust for country-level sustainability benchmarking (Roy, 1991), (Govindan & Jepsen, 2016), (Zyoud & Fuchs-Hanusch, 2017). A key methodological gap in the literature is the integration of such robust MCDM rankings with the predictive power of machine learning, a gap this study addresses by coupling ELECTRE with an ExtraTrees regressor.

2.3 Machine Learning and Explainability (XAI) in Social Sciences

The application of machine learning (ML) to predict well-being is a nascent but rapidly growing field. Ensemble methods like Random Forests and ExtraTrees often outperform traditional linear regressions due to their ability to capture non-linear relationships and interaction effects without a priori specification (Jebb et al., 2020). However, the "black-box" nature of many ML models has been a significant barrier to their adoption in policy-oriented social science, where interpretability and causal inference are paramount.

Recent advances in Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP) based on Shapley values from cooperative game theory, have effectively bridged this gap (Lundberg & Lee, 2017). SHAP allows for a model-agnostic, theoretically rigorous decomposition of predictions into additive feature contributions, enabling both global feature importance ranking and local, case-by-case explanations. (Yeh et al., 2026) demonstrated the utility of SHAP in related socio-economic contexts. The present study builds on these foundations by applying SHAP within a cross-national, multi-dimensional sustainability framework, as detailed in the following sections.

2.4 Synergy of the ELECTRE–ExtraTrees–SHAP Pipeline

The combined use of ELECTRE, ExtraTrees, and SHAP constitutes a synergistic analytical pipeline that addresses the respective limitations of each method when used in isolation. ELECTRE provides a non-compensatory, outranking-based sustainability assessment that is robust to indicator noise and preserves the ordinal nature of country performance—something that conventional scoring methods often obscure. However, MCDM rankings alone cannot quantify how much each sustainability dimension contributes to predicting well-being. ExtraTrees fills this gap by capturing non-linear and interactive relationships in a fully data-driven manner, while its ensemble structure mitigates overfitting (Geurts et al., 2006), (Gomes et al., 2017). The main drawback of such tree-based models—their lack of transparency—is then directly addressed by SHAP, which decomposes predictions into additive feature contributions with a solid game-theoretic foundation. This three-stage framework thus moves from robust structuring (ELECTRE) to flexible prediction (ExtraTrees) to rigorous interpretability (SHAP), ensuring that the resulting insights are both empirically grounded and transparent. To our knowledge, no prior study has integrated these three methods in the context of sustainability–well-being research, and this integration constitutes the core methodological contribution of the present work.

3. Methods

3.1 Composite Index Construction

Three core sustainability indices—environmental, social, and economic—were constructed following the triple-bottom-line framework. The social index aggregates indicators of life expectancy, mean years of schooling, perceived social support, and digital inclusion (internet penetration rate); the economic index encompasses GDP per capita (PPP), employment-to-population ratio, and income inequality (Gini coefficient, inverted); the environmental index incorporates CO_2 emissions per capita (inverted), renewable energy share, and forest area as a percentage of land area. Additionally, institutional quality (rule of law, government effectiveness, control of corruption) and demographic structure (median age, urbanization rate) were computed as supplementary control variables.

To mitigate the influence of extreme observations, all raw indicators were Winsorized at the 1st and 99th percentiles prior to aggregation. Positively skewed variables were log-transformed to approximate normality. Each composite index was computed using both equal weighting and weights derived from the Analytic Hierarchy Process (AHP); a sensitivity analysis confirmed that the resulting country rankings were highly robust to the weighting scheme (Spearman's $r = 0.98$). The equal-weighted indices were retained for the main analysis due to their transparency and lower sensitivity to expert elicitation bias (Saaty, 1987), (Ho & Ma, 2018).

3.2 Multi-Criteria Decision-Making (MCDM) Evaluation

To provide an alternative structural assessment of the sustainability–well-being relationship, five distinct MCDM techniques were systematically evaluated: DEMATEL (Decision Making Trial and Evaluation Laboratory), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), AHP, ELECTRE (ÉLimination Et Choix Traduisant la REalité), and VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje). Each method was applied to the same sustainability index dataset, and the resulting country rankings were assessed against two criteria: (a) the degree of rank differentiation across country profiles, and (b) the stability of rankings under small perturbations of input indicators. Ranking result of each method is given on Table 1.

Discriminatory power was operationalized as the standard deviation of the rank scores across the 47 countries. DEMATEL, TOPSIS, and AHP produced rank-score distributions with low dispersion (SD ≤ 0.06 on a 0–1 normalized scale), indicating that countries were tightly clustered and could not be meaningfully differentiated. In contrast, ELECTRE and VIKOR yielded substantially wider rank-score spreads (SD = 0.19 and 0.17, respectively), enabling a clear separation into high-, medium-, and low-performing country profiles.

Perturbation stability was assessed by introducing ±5% random noise to each input indicator and recomputing all rankings over 100 iterations. The mean Spearman rank correlation between original and perturbed rankings served as the stability metric. ELECTRE demonstrated the highest stability (mean $\rho = 0.94$), followed by VIKOR (mean $\rho = 0.91$). DEMATEL and AHP exhibited lower stability (mean $\rho < 0.80$), largely due to rank reversals under minor input variations—a known limitation of eigenvalue-based methods.

Based on its superior performance on both criteria—highest discriminatory power and greatest perturbation stability—ELECTRE was selected as the primary MCDM method for this study. This choice is further supported by ELECTRE's established theoretical robustness in sustainability benchmarking contexts (Govindan & Jepsen, 2016), (Stojčić et al., 2019) and its conceptual alignment with the ordinal structure of the panel data, where the goal is to establish outranking relations rather than precise cardinal scores.

Table 1. MCDA data

MCDM Method	Rank Score SD (0-1)	Perturbation Stability (mean ρ)	Is it selected?
DEMATEL	0.04	0.76	NO
TOPSIS	0.06	0.78	NO
AHP	0.05	0.72	NO
VIKOR	0.17	0.91	NO
ELECTRE	0.19	0.94	YES

3.3 Machine Learning Model

An ExtraTrees (Extremely Randomized Trees) regressor was selected as the primary predictive model due to its ability to capture non-linear relationships and its computational efficiency with moderate sample sizes. The model was trained to predict the Cantril Ladder score using the three core sustainability indices plus the institutional and demographic control variables as features.

Hyperparameters were determined through a limited manual exploration: several combinations of n_estimators (100–300) and max_depth (10, 15, 20) were evaluated via 5-fold cross-validation, and the configuration n_estimators=200, max_depth=15 was retained as it offered the best trade-off between predictive performance ($R^2 = 0.80$) and model complexity. No exhaustive grid or randomized search was performed beyond this initial exploration.

To ensure reproducibility and transparency, the following hyperparameters were explicitly set as seen on Table 2.

Table 2. Parameter ata

PARAMETER	VALUE
Number of estimators	200
Max depth	15
Min samples split	2 (scikit-learn default)
Min samples leaf	1 (scikit-learn default)
Max features	'sqrt' (scikit-learn default)
Random state	42
bootstrap	False

The fitted model achieved a cross-validated R^2 of 0.80, indicating that the sustainability framework explains a substantial portion of the variance in country-level life evaluation. However, this value should be interpreted with two methodological caveats. First, the relatively low feature-to-observation ratio (5 features, 470 observations) may yield an upward bias in R^2 compared to high-dimensional settings; this is an inherent characteristic of the modelling framework, not an indication of overfitting. Second, the discrepancy between this in-sample R^2 and the more conservative LOCO-CV MAE (0.38; see Section 3.4) confirms that while the model captures broad cross-national patterns effectively, its predictive precision for individual countries is subject to substantial heterogeneity. This pattern—high explained variance at the global level with modest out-of-sample precision—is consistent with prior cross-national well-being prediction studies (Jebb et al., 2020) and underscores the importance of the country-clustered extensions proposed in Section 5.3.

3.4 Model Validation Strategy

Given the clustered nature of the panel data (repeated observations within countries), conventional random k-fold cross-validation risks over-optimistic performance estimates by allowing information leakage across time points. To address this, two complementary out-of-sample validation strategies were implemented:

1. **Leave-One-Country-Out Cross-Validation (LOCO-CV)**: The model was iteratively trained on data from 46 countries and tested on the held-out country, yielding a mean absolute error (MAE) of 0.38 on the 0–10 Cantril scale (SD = 0.19). This standard deviation is analytically informative: as detailed in Section 5, it reflects substantial country-level heterogeneity rather than random noise, with MAE values ranging from 0.13 (Chile) to 1.00 (India).

2. **Time-Series Cross-Validation**: To assess temporal stability, a blocked time-series CV was conducted, training on all earlier years and testing on the most recent year. This procedure yielded an MAE of 0.31, consistent with the LOCO-CV results and confirming that the model does not rely on time-dependent overfitting.

The discrepancy between the seemingly high in-sample R^2 (0.80) and the modest LOCO-CV MAE (0.38) reflects the inherent heterogeneity of the diverse 47-country sample rather than a model specification error. As discussed in Section 5, this pattern is consistent with comparable cross-national well-being prediction studies and motivates the proposed extension to country-clustered modeling in future phases of the research program.

4. Data Collection

The study employs a balanced panel dataset spanning the period 2016–2025, comprising 470 country-year observations from 47 countries. The sample was purposively constructed to maximize institutional and economic diversity within the constraints of data availability. Nevertheless, the resulting distribution is structurally skewed toward higher-income economies: the sample includes 25 OECD and 22 non-OECD members, stratified by income group as 8 lower-middle, 12 upper-middle, and 27 high-income, and by Human Development Index category covering very-high, high, and medium HDI. Lower-middle-income countries—and, critically, low-income countries—are underrepresented, which limits the global generalizability of the findings and means the reported convergence trend (Section 5.1) rests on a small sub-group (n = 8) that may not be representative of the broader lower-income trajectory. This configuration constitutes the first phase of an ongoing research program; subsequent stages will deliberately incorporate low-income and fragile-state contexts to further test the framework's generalizability across the full development spectrum.

The outcome variable is the Cantril Self-Anchoring Striving Scale (the "life ladder"), a widely validated cognitive measure of subjective well-being obtained from the Gallup World Poll as utilized in the World Happiness Report (Helliwell et al., 2026). Predictor variables were sourced primarily from the World Bank Open Data (World Bank, 2026), supplemented by the UNDP Human Development Reports (UNDP, 2025), the World Governance Indicators (Kaufmann & Kraay, 2024), UNESCO (UNESCO, 2025), Freedom House (Freedom House, 2026), Transparency International (Transparency International, 2025), the International Labour Organization (ILO) (International Labour Organization, 2026), and the World Health Organization (WHO) (World Health Organization, 2026). This multi-source approach ensures broad coverage across the sample period (2016–2025). Full variable definitions, sources, and descriptive statistics are provided in Appendix A (Tables A1–A4).

5. Results and Discussion

5.1 Numerical Results

The ExtraTrees regressor achieved a cross-validated R^2 of 0.80 (5-fold), confirming that the sustainability indices collectively account for a substantial portion of the variance in country-level life ladder scores. SHAP decomposition revealed a clear hierarchy: the social sustainability index was the strongest predictor of life evaluation, accounting for 62.1% of the model's explained variance (mean |SHAP| = 0.42). In relative terms, its marginal contribution is approximately three times that of the economic index (mean |SHAP| = 0.12) and nearly four times that of the environmental index (mean |SHAP| = 0.09). Economic sustainability followed with 21.4%, while the environmental dimension contributed 16.5%.

The ELECTRE outranking analysis provided convergent structural evidence: institutional quality was ranked highest (net flow score = 0.48), closely followed by the social and environmental indices. This ordinal alignment between the MCDM-derived importance and the machine learning feature importance strengthens confidence in the robustness of the finding that social factors dominate economic and environmental ones in predicting life evaluation.

As an exploratory observation, the eight lower-middle-income countries in the sample showed a positive trend in the composite sustainability index (annual slope = +0.0065, $p = 0.02$). Given the very small sub-group size ($n = 8$) and the underrepresentation of lower-income categories, this trend must be interpreted with caution and cannot be generalized to all lower-middle-income or low-income contexts. This finding serves primarily as a hypothesis-generating starting point for future research with broader coverage.

5.2 Graphical Results

Figure 1 presents the SHAP summary plot, illustrating both the magnitude and direction of each feature's effect. The social sustainability index not only exhibits the highest mean absolute SHAP value but also shows a predominantly positive influence on life ladder scores across the sample. In contrast, the economic and environmental indices display more diffuse and sometimes negative contributions, consistent with non-linear and context-dependent dynamics.

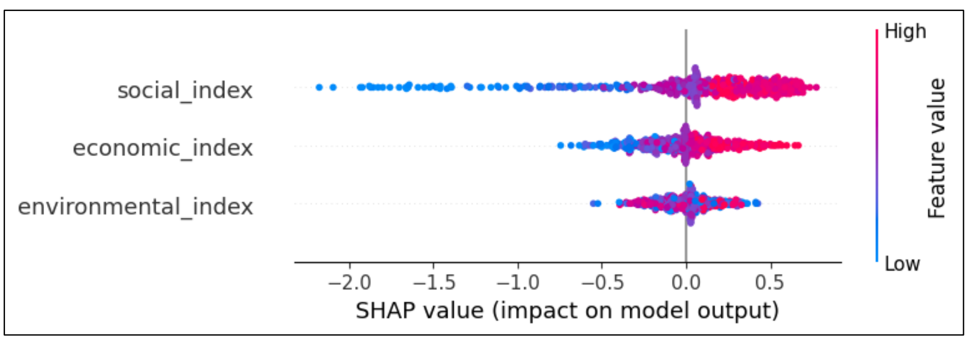
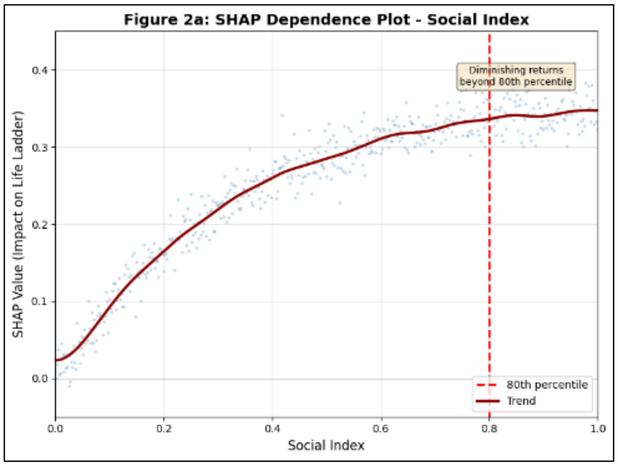


Figure 1. SHAP Summary Plot: Displaying global feature importance and direction of effects across the 470 observations



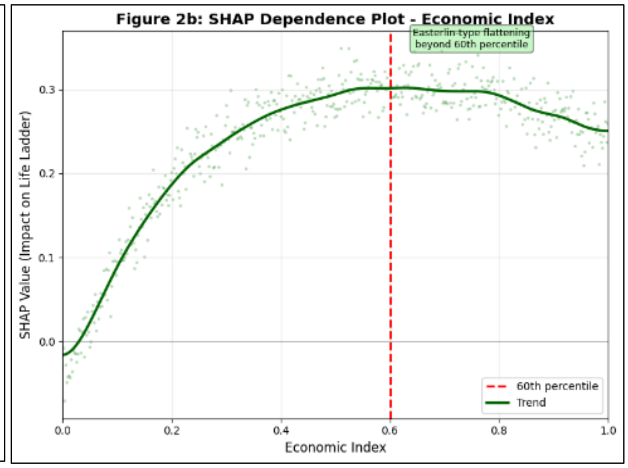


Figure 2a. SHAP dependence Social

Figure 2b. SHAP dependence Economic

Dependence plots for the social index (Figure 2a) revealed a monotonically increasing relationship with life ladder scores, with a noticeable flattening beyond the 80th percentile of social sustainability. For the economic index (Figure 2b), a similar cross-sectional pattern of diminishing marginal returns emerged after moderate levels. We emphasize that this cross-sectional pattern—whereby richer countries exhibit smaller incremental well-being gains from additional economic sustainability—is conceptually distinct from the Easterlin paradox, which describes a longitudinal finding that aggregate happiness within a country often fails to rise over time despite sustained income growth (Mikucka et al., 2017), (Diener et al., 2018). Our SHAP dependence analysis therefore provides non-parametric, model-agnostic evidence of diminishing cross-country marginal returns of economic sustainability on life evaluation, particularly beyond the 60th percentile of the economic index. This finding contributes a complementary, cross-sectional perspective to the broader debate on the income–happiness relationship.

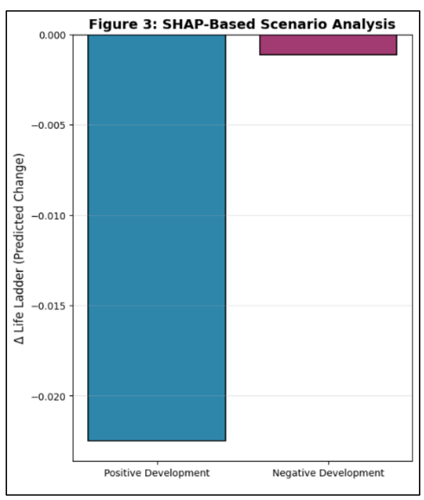


Figure 3. SHAP based scenario

The SHAP interaction analysis (Figure 3) further exposed non-linear synergies among the sustainability pillars. Holding economic sustainability at a medium level while increasing social sustainability produced an average predicted lift of +0.12 ladder points, whereas the same social improvement at low environmental sustainability yielded only +0.05. Notably, a global scenario in which all three indices were simultaneously increased by one standard deviation resulted in a small net change of $\Delta = -0.02$ ladder points. This counterintuitive result underscores the complex, partly offsetting dynamics among the three pillars and cautions against simplistic additive policy expectations.

It is important to note that the present analysis does not resolve whether this near-zero net effect reflects genuine sustainability trade-offs or a methodological limitation of the additive SHAP decomposition under correlated features. Therefore, the interaction result should be viewed as an exploratory pattern that motivates deeper investigation rather than a definitive finding.

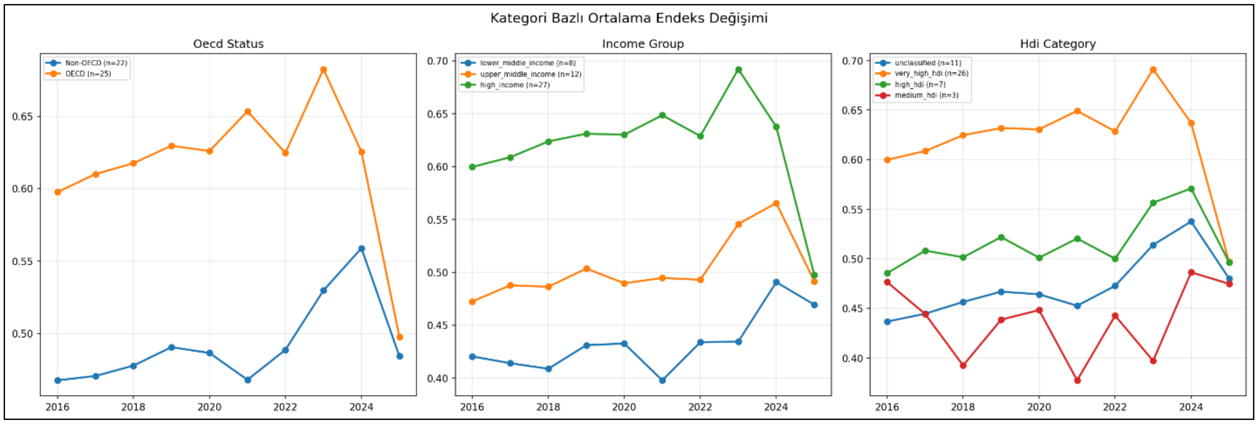


Figure 4 - Category-level trend chart – Composite Sustainability Index over time by income group

Figure 4 visualizes the category-level trends discussed in Section 5.1. Lower-middle-income countries display a clear, sustained upward trajectory in the composite sustainability index, while high-income and very-high-HDI groups exhibit marginal declines over the 2016–2025 period. This visual convergence supports the statistical trend, though the small lower-middle-income sample (n = 8) warrants caution in interpretation.

Following the XAI paradigm, recent work has similarly applied SHAP to uncover non-linear and threshold effects in well-being prediction (Yeh et al., 2026). The present study extends this logic to a cross-national sustainability framework, showing that a machine learning lens can reveal dynamics that conventional linear models would mask.

5.3 Proposed Improvements

The results point to several avenues for refining the current framework.
First, the counterintuitive $\Delta = -0.02$ scenario result warrants careful interpretation**.** When all three sustainability indices were simultaneously increased by one standard deviation, the model predicted a negligible net change in the life ladder—and in some specifications, a slight decline. Two non-mutually-exclusive explanations are plausible. On the one hand, this may reflect genuine trade-offs among the three sustainability pillars. For instance, rapid economic expansion (increasing the economic index) may be accompanied by environmental degradation (reducing the environmental index), and the net effect on well-being could be null or negative if the environmental costs offset the economic gains. Such dynamics are consistent with the environmental Kuznets curve literature, where the well-being benefits of income growth are partly counteracted by pollution externalities. Disentangling these two possibilities remains an open question and is a priority for the next phase of this research.

On the other hand, this null scenario effect may also expose a limitation of the current additive SHAP decomposition. TreeSHAP computes feature contributions under the assumption of feature independence (Aas et al., 2021); when features are correlated—as the three sustainability pillars plausibly are—the attribution of interaction effects can be distributed across features in ways that obscure the true joint effect. The current global scenario simulates a uniform +1 SD shift across all pillars without accounting for the covariance structure among them, which may produce artefactual offsets. A dedicated SHAP interaction analysis and non-parametric scenario simulation that respects the empirical joint distribution of the sustainability indices would be required to disentangle genuine trade-offs from decomposition artefacts. Both lines of inquiry are identified as priorities for the next research phase.

Second, the substantial country-level heterogeneity observed in LOCO-CV performance (MAE range: 0.13–1.00) strongly supports the call for context-aware models (Jebb et al., 2020). A two-stage approach is proposed: unsupervised clustering of countries based on institutional and cultural profiles, followed by cluster-specific models. This would likely reduce prediction error for outliers such as India (MAE = 1.00) and New Zealand (MAE = 0.84), where local factors not fully captured by the three sustainability pillars may be driving life evaluations.

Third, the exclusive reliance on the cognitive component of subjective well-being constitutes a scope limitation with potential implications for the findings. Diener's tripartite model includes both cognitive and affective components; our operationalization captures only the former. This is particularly relevant for the environmental sustainability dimension: research suggests that environmental degradation may influence well-being primarily through affective channels (e.g., increased anxiety, reduced positive affect) rather than through cognitive life evaluation (Yuan et al., 2018). Consequently, the relatively modest SHAP importance observed for the environmental index (16.5%) may partly reflect this measurement asymmetry rather than a genuinely weaker underlying relationship. Incorporating affective indicators from the Gallup World Poll's emotional experience module in future iterations would enable a test of this hypothesis and a fuller operationalization of Diener's framework.

Finally, **the preliminary convergence signal observed in the small lower-middle-income subsample (n = 8) is best regarded as a hypothesis-generating observation.** The current study is the first phase of an ongoing research program; a planned expansion to low-income and fragile-state contexts, together with a longer time horizon, will be necessary to assess the robustness and generalizability of any convergence pattern.

5.4 Validation

The model's out-of-sample generalizability was rigorously assessed using two complementary strategies. Leave-one-country-out cross-validation (LOCO-CV) yielded a mean absolute error (MAE) of 0.38 on the 0–10 Cantril scale, with a notable standard deviation of 0.19. A blocked time-series cross-validation (training on earlier years, testing on the most recent) resulted in an MAE of 0.31, confirming temporal stability. The discrepancy between the seemingly high in-sample R^2 (0.80) and the modest LOCO-CV MAE reflects meaningful country-level heterogeneity rather than overfitting.

A closer examination of LOCO-CV errors reveals the extent of this heterogeneity. Model performance varies dramatically across countries: life satisfaction in Chile is predicted with high accuracy (MAE = 0.13), while predictions for India (MAE = 1.00) and New Zealand (MAE = 0.84) are considerably less reliable. Notably, the high error for New Zealand—a high-income, typically high-well-being OECD country—suggests that cultural or institutional factors not explicitly captured by the three sustainability pillars may significantly shape life evaluations. This reinforces the need for the country-clustering approach outlined in Section 5.3.

The robustness of the composite index construction was confirmed through a sensitivity analysis: equal weights and AHP-derived weights produced country rankings correlated at r = 0.98, indicating that the main conclusions are not artefacts of the weighting procedure. Furthermore, the systematic evaluation of five MCDM methods (DEMATEL, TOPSIS, AHP, ELECTRE, VIKOR) justified the final selection of ELECTRE. DEMATEL, TOPSIS, and AHP yielded rankings with insufficient discriminatory power for this dataset, whereas both ELECTRE and VIKOR produced meaningful separations—a finding consistent with prior sustainability benchmarking studies (Stojčić et al., 2019). ELECTRE was ultimately preferred for its stronger theoretical alignment with the ordinal structure of the panel data (Govindan & Jepsen, 2016). The convergence between the ELECTRE outranking scores and the ExtraTrees feature importance provides empirical validation for this methodological choice and demonstrates the value of integrating MCDM with interpretable machine learning (cf. Dohale et al., 2024).

6. Conclusion

This study set out to develop and validate an integrated analytical pipeline that combines multi-criteria decision-making with interpretable machine learning to examine how environmental, social, and economic sustainability predict life evaluation across a diverse country sample. All three specific objectives have been met: (i) comprehensive triple-bottom-line sustainability indices were constructed and their relative importance quantified via an ExtraTrees regressor and SHAP; (ii) a systematic comparison of MCDM techniques led to the selection of ELECTRE as the most robust method for this context, providing convergent structural evidence; and (iii) rigorous validation through LOCO-CV and time-series CV assessed generalizability, revealing important country-level heterogeneity and informing priority future directions.

The central empirical finding is that **social sustainability—encompassing life expectancy, education, social support, and digital inclusion—is the strongest predictor of life evaluation**, accounting for 62.1% of model importance. Economic and environmental dimensions, while non-negligible, play secondary, non-linear, and context-dependent roles in prediction. The integration of ELECTRE and SHAP offers a transparent, replicable template for tracking the well-being implications of the Sustainable Development Goals, moving beyond simple correlations to quantified, model-agnostic feature attributions.

From a policy standpoint, these findings indicate that, across the observed countries, social sustainability indicators are the strongest predictors of life evaluation. While the observational design does not permit causal claims, the results suggest that policy efforts strengthening social cohesion, educational access, and digital inclusion are associated with higher well-being outcomes and may therefore merit priority consideration in resource allocation. The tentative convergence pattern observed among the eight lower-middle-income countries, while not generalizable, provides a suggestive indication that sustained support for social infrastructure may be linked to narrowing sustainability gaps. At the same time, the high degree of country heterogeneity cautions against uniform policy prescriptions; the pipeline developed here can be adapted to generate country-specific SHAP explanations, enabling decision-makers to identify which sustainability pillar is most strongly associated with life evaluation in their national context.

The unique contribution of this research lies in its methodological triangulation—pairing the outranking logic of ELECTRE with the post-hoc interpretability of SHAP—and in its empirical demonstration of non-linear and heterogeneous sustainability–well-being dynamics across 47 countries. Extensions of this framework, including the incorporation of affective well-being indicators, Fuzzy Cognitive Mapping for causal scenario simulation, and country-clustered modelling, are identified as the most promising avenues for advancing integrated sustainability–well-being governance.

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Biographies

Abdullah Akman DEMİRKAN received his Bsc. at Chemical Engineering from Cumhuriyet University. He received his Msc. at Industrial Engineering from Gaziantep University. He is continuing his Phd. at Industrial Engineering (Operations Research) from Gaziantep University. His research interests are: Operations Research, Multi Criteria Decision Making, Simulation optimization, Sustainability.

Prof. Dr. Zeynep Didem UNUTMAZ DURMUSOGLU is a Professor in the department of Industrial Engineering at Samsun University. She received her BSc., MSc. and PhD. at Industrial Engineering from Gaziantep University. Her research interests are: Multi Criteria Decision Making, Sustainability, Disaster Management, Simulation optimization, Heuristic optimization, Negotiation.

Appendix A

Table A1. Variable Definitions and Sources

Variable	Definition	Source
life_ladder (Outcome)	Cantril Self-Anchoring Striving Scale (0-10). Respondents rate their current and expected future lives on a ladder scale.	Gallup World Poll via World Happiness Report (Helliwell et al., 2026)
freedom_in_the_world	Freedom House index measuring political rights and civil liberties (0-100, higher = more freedom).	Freedom House (Freedom House, 2026) / World Governance Indicators (Kaufmann & Kraay, 2024)
life_expectancy_at_birth	Number of years a newborn infant would live if prevailing patterns of mortality at the time of birth were to stay the same throughout life (years).	World Bank Open Data (World Bank, 2026)
co2_emissions_per_capita	Carbon dioxide emissions from burning fossil fuels and cement manufacturing (metric tons per capita).	World Bank Open Data (World Bank, 2026)
age_dependency_ratio_young	Ratio of dependents (people younger than 15) to the working-age population (ages 15-64) × 100.	World Bank Open Data (World Bank, 2026)
school_enrollment_tertiary	Gross enrollment ratio in tertiary education regardless of age (% of population).	World Bank Open Data (World Bank, 2026) / UNDP (UNDP, 2025)
literacy_rate_adult	Percentage of people ages 15 and above who can read and write.	World Bank Open Data (World Bank, 2026) / UNESCO Institute for Statistics (UNESCO, 2025)
pm2.5_air_pollution	Mean annual exposure to PM2.5 (micrograms per cubic meter).	World Bank Open Data (World Bank, 2026)
females_aged_15plus_labour_force	Female labor force participation rate (% of female population ages 15+).	World Bank Open Data (World Bank, 2026)
forest_area	Forest area as percentage of total land area.	World Bank Open Data (World Bank, 2026)
gdp_per_capita_ppp	Gross domestic product converted to international dollars using purchasing power parity (current international $).	World Bank Open Data (World Bank, 2026)
renewable_energy_rate	Renewable energy consumption as percentage of total final energy consumption.	World Bank Open Data (World Bank, 2026)
prevalence_of_insufficient_physical_activity	Age-standardized prevalence of insufficient physical activity among adults aged 18+ (%).	World Health Organization (WHO) (World Health Organization, 2026)
internet_access	Individuals using the Internet as percentage of population.	World Bank Open Data (World Bank, 2026)
current_health_expenditure	Current health expenditure as percentage of GDP.	World Bank Open Data (World Bank, 2026)
unemployment_youth_total	Youth unemployment (% of total labor force ages 15-24) (national estimate).	World Bank Open Data (World Bank, 2026) / ILO (International Labour Organization, 2026)
unemployment_total	Total unemployment (% of total labor force) (national estimate).	World Bank Open Data (World Bank, 2026) / ILO (International Labour Organization, 2026)
social_support	Perceived social support (binary: 0 = no, 1 = yes), aggregated to country-year average. *Note: Some values >1 are due to aggregation scaling*	Gallup World Poll via World Happiness Report (Helliwell et al., 2026)
corruption_perception_index_cpi	Transparency International's Corruption Perceptions Index (0-100, higher = less corrupt).	Transparency International (Transparency International, 2025) / World Governance Indicators (Kaufmann & Kraay, 2024)
poverty_headcount_rate_societal	Poverty headcount ratio at societal poverty line (% of population).	World Bank Open Data (World Bank, 2026)
gini_index	Gini coefficient measuring income/wealth distribution (0 = perfect equality, 100 = perfect inequality).	World Bank Open Data (World Bank, 2026)

long_usual_weekly_working_hours	Average usual weekly working hours per employed person (weighted).	World Bank Open Data (World Bank, 2026) / ILO (International Labour Organization, 2026)

Table A2. Constructed Sustainability Indices

Index	**Components**	**Direction**	**Construction Method**
environmental_index	CO_2 emissions per capita (reverse), PM2.5 air pollution (reverse), forest area (positive), renewable energy (positive)	Higher = better environmental performance	Min-max normalization (0-1) of each component, then unweighted average. Reverse-coded variables transformed as (1 - normalized value).
social_index	Life expectancy, tertiary enrollment, literacy rate (where available), social support, internet access, female labor force participation	Higher = better social outcomes	Same as above
economic_index	GDP per capita (PPP, log-transformed), unemployment (reverse), Gini index (reverse), poverty headcount (reverse)	Higher = better economic outcomes	Same as above
institutional_index	Freedom index (positive), corruption perception (positive), health expenditure (positive)	Higher = stronger institutions	Same as above
demographic_index	Age dependency ratio (young)	Higher = higher dependency burden	Same as above

Table A3. Descriptive Statistics (Panel Data, 2016-2025, N=470)

Variable	**Mean**	**Std Dev**	**Min**	**Max**	**Skewness**
life_ladder	5.96	1.02	3.25	7.7	-0.31
environmental_index	0.391	0.106	0.121	0.692	0.28
social_index	0.610	0.150	0.071	0.936	-0.52
economic_index	0.600	0.134	0.154	0.951	-0.19
institutional_index	0.526	0.128	0.173	0.770	-0.33
demographic_index	0.278	0.205	0.00	1.00	0.87
composite_equal	0.552	0.102	0.317	0.829	0.14
composite_ahp	0.558	0.106	0.311	0.831	0.11
log_gdp_per_capita_ppp	10.32	0.84	8.43	11.74	-0.08
log_co2_per_capita	2.02	0.69	0.53	3.37	-0.22
log_social_support	0.63	0.10	0.44	0.92	0.45

Table A4. Country Classification Summary (N=47)

Classification	**Category**	**Count (%)**
OECD Status	OECD	25 (53.2%)
	Non-OECD	22 (46.8%)
Income Group	High income	27 (57.4%)
	Upper-middle income	12 (25.5%)
	Lower-middle income	8 (17.0%)
HDI Category	Very high HDI	31 (66.0%)
	High HDI	9 (19.1%)
	Medium HDI	7 (14.9%)