

ELI–SDG–Net: An Explainable AI Framework for Data-Driven Ethical Leadership Indexing and SDG-Based Institutional Ranking in Higher Education

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ABSTRACT

This study introduces Ethical Leadership Index-Sustainable Development Goal-Net (ELI-SDG-Net), a unified deep learning framework that derives ELI through a component-weighted autoencoder trained on governance, faculty diversity, pay equity, and student outcome variables drawn from institutional administrative data. The framework formulates a novel joint training objective, L_{total} , which co-optimizes latent representation quality and outcome prediction, and incorporates a graph-based multi-task module that jointly predicts all 17 SDG scores using institutional embeddings. An experimental evaluation was conducted on a merged dataset of 4,821 institutions drawn from the IPEDS and Times Higher Education datasets. The merged dataset was assessed against five baseline models using Root Mean Square Error (RMSE), R^2 , and Mean Absolute Error (MAE). The proposed framework achieved an RMSE of 0.089 and an R^2 of 0.91, exceeding the next-best baseline by 0.087 RMSE points and outperforming prior survey-based SEM studies by over 43 percentage points in explained variance. The multi-task module reduced prediction error on 15 of 17 SDG goals relative to single-task baselines, and the SHAP analysis confirmed graduation rate, faculty pay equity, and administrative transparency as the primary governance drivers. ELI-SDG-Net establishes a reproducible, interpretable foundation for quantitative governance evaluation at the global institutional scale in higher education.

Keywords-ethical leadership; institutional analytics; deep learning; autoencoder; explainability; sustainable development goals; graph neural network; higher education

I. INTRODUCTION

Colleges contribute to economic growth, societal development, and sustainability, with rising demands for accountability and governance. In this regard, ethical leadership is essential for decision-making, transparency, organizational culture, and alignment of institutions with long-term goals. Ethical leadership also affects resource management and equity in the institution. However, ethical leadership at the institutional level is difficult to measure as it involves an interplay among various factors, including governance practices, faculty diversity, pay equity, and student outcomes. These complex relationships cannot be represented through traditional assessment mechanisms, particularly as the institution grows and becomes more complex. An analytical,

scalable model is thus needed for consistent, accurate measurement. Higher education ethical leadership has been much studied through survey-based methods. For example, authors in [1] demonstrated that ethical leadership affects employee behavior using survey data, which, however, rely on self-reported information, resulting in bias and poor generalizability. Authors in [2] used structural equation modeling to examine leadership behavior, but these studies are based on small samples and cannot make predictions at the institutional level. Although these methods recognize the necessity of ethical leadership, they remain limited to perception-based analysis and cannot be extended to large-scale institutional data.

Many researchers have attempted to overcome such shortcomings by conducting more systematic, quantitative studies. Authors in [3] examined the literature on ethical leadership and emphasized the need for systematic institutional performance analysis; however, their study was descriptive rather than predictive. Authors in [4] used structural equation modeling to examine leadership and employee engagement; however, the models were based on constant variables and a small dataset, which are not suitable for studying a large-scale institution. Therefore, machine learning has been applied to learning systems. Although explainable AI tools [5], such as SHAP and LIME, can enhance model understanding, they are not aimed at institutional governance analysis. Authors in [6] applied machine learning to forecast outcomes at the student level but did not include variables for leadership or governance.

Even though these strategies improved predictive performance, ethical leadership was still not part of the modeling framework. Deep learning techniques have been used more recently to enhance the understanding of complex educational patterns. Authors in [7] developed more robust models for forecasting students' outcomes, but they focused on the student level rather than institutional leadership. Authors in [8] used ensemble deep learning to predict academic performance, but failed to develop an institutional-level index that represents ethical leadership. This creates a gap in defining a single method for measuring leadership based on institutional data.

The introduction of the Sustainable Development Goals (SDGs) has created a framework for assessing institutional sustainability. Authors in [9] used machine learning and explainability tools to make predictions in academia, but omitted variables related to leadership. Authors in [10] examined SDG projections on a global scale using country-level data; however, their study was not based on institutional data. Although these works demonstrate the significance of sustainability measures, they do not establish a connection between ethical leadership and SDG performance in higher education, underscoring the necessity FOR an integrated modeling strategy.

Despite these developments, some gaps persist in the systems used for analyzing higher education. Authors in [11] developed machine learning models that are conducive to predicting institutional outcomes but omitted the indicators of ethical leadership and sustainability, rendering their application to governance analysis inconclusive. Authors in [12] applied SHAP-based models to enhance interpretability but did not establish an institutional-level index to capture leaders' behavior. Authors in [13] introduced TabNet for attentive interpretable tabular learning; however, their study was not based on institutional governance or linked to SDG results. Consequently, there is a lack of existing literature on data-driven Ethical Leadership Index (ELI) frameworks using administrative data and relating them to SDG institutional performance.

To address these issues, the present study proposes ELI-SDG-Net. This explainable AI structural framework enables the indexing of data-based ethical leadership and SDG-based institutional rankings at the university and college levels. The

general structure of the proposed framework is presented in Figure 1. The structure collects institutional administrative information, which is subjected to data merging, data normalization, and feature encoding. The framework is built on an autoencoder module that learns patterns in variables related to governance, faculty diversity, pay equity, and student outcomes to construct a latent ELI. Such patterns are then learned, and predictive models are used to examine institutional performance and engagement measures. It includes a SHAP-based explainability component that contributes to each feature, enabling transparent, understandable decisions. Finally, the module is a graph-based ranking that relates SDG indicators to generate comparisons of institutions across various countries.

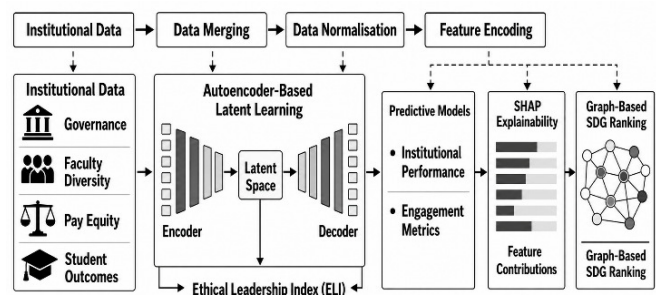


Fig. 1. Proposed ELI-SDG-Net framework overview.

The proposed framework enables scalable, interpretable, and data-driven evaluation of ethical leadership and its impact on sustainability outcomes. The key objectives of this study are:

- To design an ELI for HEIs using institutional governance, faculty diversity, pay equity, and student outcome variables.
- To develop predictive models linking ethical leadership proxies to academic excellence (graduation rates, retention, student outcomes) and employee engagement metrics.
- To compare institutional profiles on ethical leadership across Technology adoption, financial investment, and workforce productivity indicators.
- To assess the role of ethical leadership in advancing SDG performance of HEIs and build a cross-country comparative ranking model.

II. PROPOSED ELI-SDG-NET FRAMEWORK

A. System Overview and Architecture

The ELI-SDG-Net framework integrates representation learning, predictive modeling, explainability, and graph-based ranking into a unified pipeline operating on institutional administrative data from IPEDS and Times Higher Education datasets. Each institution is represented as a multidimensional feature vector capturing governance indicators, faculty diversity, pay equity, and student outcome variables. These heterogeneous features are normalized and encoded to ensure cross-institutional consistency and eliminate scale imbalance. The institutional dataset is formally defined as:

$$X = \{x_i\}_{i=1}^n, \quad x_i \in R^d$$

where n denotes the number of institutions and d represents the number of features derived from institutional datasets. Each feature vector is structured as:

$$x_i = [G_i \parallel D_i \parallel P_i \parallel O_i]$$

where G_i represents governance variables such as transparency and efficiency of policy and administration, D_i denotes faculty diversity indicators, P_i is the pay equity indicator, and O_i represents student outcome indicators such as graduation rates and retention. This premise ensures that moral leadership is modeled as a blend of governance, workforce, and performance aspects. Feature normalisation is done to make comparisons across institutions:

$$\hat{x}_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j + \epsilon}$$

where μ_j and σ_j are the mean and standard deviation of feature j in all institutions, and ϵ is a stability constant. This change eliminates scale variation and ensures consistent feature contributions during learning.

The architecture of the proposed ELI-SDG-Net is shown in Figure 2. The system comprises five interconnected modules: preprocessing, representation learning, construction of the ELI, predictive modeling with explainability, and SDG-based ranking.

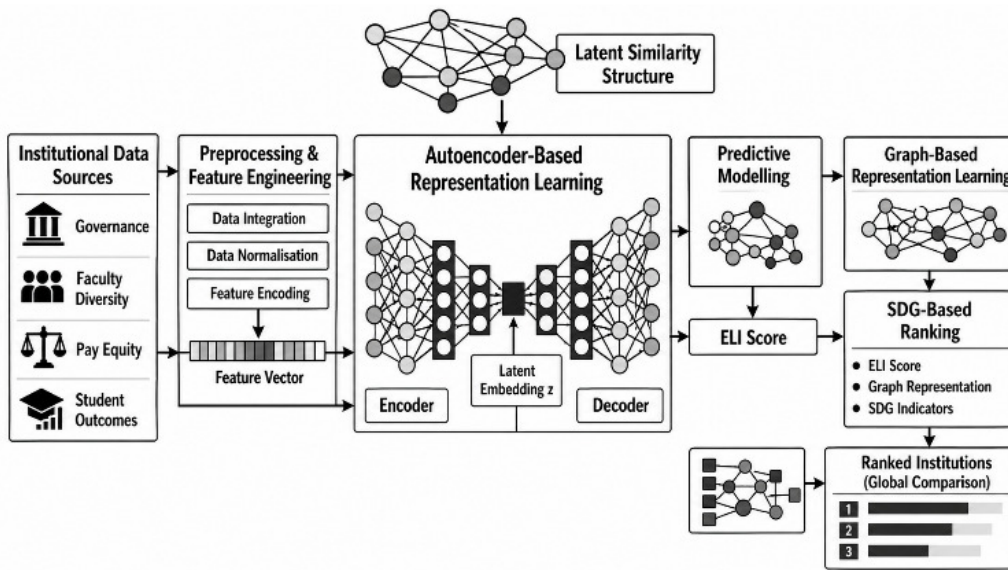


Fig. 2. Proposed ELI-SDG-Net architecture.

B. Representation Leadership Construction through ELI

The fundamental value of the framework is the creation of a data-driven ELI based on the high-dimensional institutional data. In contrast to survey-based methods, the proposed solution generates leadership characteristics as direct results of administrative variables through representation learning. At the institutional scale, ethical leadership cannot be measured through individual perception instruments across 4,821 institutions. The administrative variables used in this work, namely governance transparency, faculty diversity, pay equity, and student outcomes, are the directly observable organisational outputs, making them the appropriate unit of analysis for a scalable, data-driven framework. An encoder function is needed to encode the normalised input to a latent representation to capture nonlinear relationships between governance and outcome variables:

$$h_i^{(1)} = \sigma(W_1 \hat{x}_i + b_1)$$

where $(W_1 \in R^{d_1 \times d})$ is the weight matrix that projects the input features to the first hidden layer, b_1 is the bias vector, and $\sigma(\cdot)$

is a nonlinear activation function. This transformation encompasses interactions among governance, diversity, and performance variables. The representation is again compressed to a latent embedding:

$$z_i = \sigma(W_2 h_i^{(1)} + b_2)$$

where $z_i \in R^k$ is the latent institutional embedding, with $k \ll d$. This is an embedding of the ethical leadership attributes of the individual institutions. The decoder rebuilds the original feature space as:

$$\tilde{x}_i = \sigma(W_3 z_i + b_3)$$

where W_3 and b_3 are the decoder parameters. The reconstruction ensures that the latent representation does not lose meaningful information about the institutions. To explicitly model the importance of leadership, a component-weighted reconstruction loss is specified:

$$L_{ELI} = \frac{1}{n} \sum_i = 1^n \left(\lambda_g |G_i - \tilde{G}_i|^2 + \lambda_d |D_i - \tilde{D}_i|^2 + \lambda_p |P_i - \tilde{P}_i|^2 + \lambda_o |O_i - \tilde{O}_i|^2 \right)$$

where $\lambda_g, \lambda_d, \lambda_p, \lambda_o$ are the importance of the governance variables. The diversity variable, the pay equity variable, and the outcome variable coefficients are used as weights, respectively. This ensures that the aspects of ethical leadership are emphasised in the learning process. All four coefficients were set to 0.25, assigning equal reconstruction weight to each governance dimension and avoiding arbitrary prioritisation without empirical grounding. Perturbing each coefficient by $\pm 20\%$ while holding the others fixed produced Root Mean Square Error (RMSE) values between 0.089 and 0.093 and R^2 values between 0.90 and 0.91, confirming that the index does not depend critically on this choice. The latent embedding is a directional projection of the ELI:

$$ELI_i = \frac{w^T z_i}{|w| \cdot |z_i|}$$

where $w \in R^k$ is a learnable importance vector that accounts for leadership-sensitive directions in the latent space. The resulting index is scale-invariant and cross-institutionally comparable. The vector w was initialised with Xavier uniform initialisation, and its convergence is confirmed by the training loss stabilising to a validation gap below 0.015 after epoch 62, as depicted in Figure 3. To obtain the similarity between institutions, a latent similarity list is determined as:

$$S_{ij} = \exp\left(-\frac{|z_i - z_j|^2}{\tau}\right)$$

where S_{ij} represents the similarity of the institutions i and j , and t is a temperature parameter that determines the sensitivity to the neighbourhood. This similarity structure enables clustering and ranking in subsequent modules.

C. Predictive Modeling and Explainability Traceability

The predictive module takes latent embeddings and the derived ELI as inputs. Its targets, namely a graduation trend index, a faculty retention aggregate, and an employee engagement composite, are multi-year institutional aggregates that are operationally distinct from the point-in-time snapshots the autoencoder reconstructs. The autoencoder trains exclusively on the 3,375-instance training partition, and the prediction module is evaluated on the 723-instance held-out test set, so no target value enters the encoding pathway. The predictive functionality is given as:

$$\hat{y}_i = f(z_i, ELI_i)$$

where y_i are the predicted results in the form of graduation rates, retention, and engagement results. The function $f(\cdot)$ is performed with the help of machine learning models, including XGBoost or multilayer perceptrons. In the case of neural models, forward propagation is given as:

$$h_i^{(l+1)} = \sigma(W^{(l)} h_i^{(l)} + b^{(l)})$$

where $h_i^{(l)}$ represents the activation of the layer l , and $W^{(l)}$ and $b^{(l)}$ denote layer parameters. To optimise both representation learning and prediction, a combined objective is formulated concurrently:

$$L_{total} = L_{ELI} + \alpha L_{pred}$$

where L_{pred} is the prediction loss (mean squared error in regression problems), and α is a balance between the quality of the representation and prediction. This makes the learned ELI informative and predictive. To be interpretable and compute feature attribution, a model-specific contribution is used:

$$\Phi_{ij} = f(x_i) - f(x_i \setminus x_{ij})$$

where Φ_{ij} defines the role of the feature j in the prediction of the institution i . The formulation measures the impact of individual governance, diversity, and outcome variables on the model's predictions, thus enabling transparent decision-making.

D. Ranking and Graph Modelling Based on SDGs

The last element connects leadership to sustainability results through a ranking framework presented as a graph. Latent embeddings are used to build a similarity graph, with institutions as nodes. The institutional graph is given by:

$$G = (V, E), E_{ij} = S_{ij}$$

where V indicates institutions, and E_{ij} indicates edges with weights of similarity scores based on latent representations. Representations of nodes are propagated by neighbourhood aggregation:

$$h_i^{(t+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} E_{ij} W h_j^{(t)}\right)$$

where W represents transformation, and $\mathcal{N}(i)$ represents neighbouring institutions. This summarises the relationships between institutions with similar leadership profiles. The overall SDG ranking score is determined as:

$$R_i = \gamma \cdot ELI_i + \delta \cdot SDG_i + \eta \cdot h_i$$

where SDG_i is the indicator of sustainability and γ, δ , and η are the weighting parameters that determine the impact of leadership, sustainability performance, and relational structure.

III. RESULTS AND DISCUSSIONS

The proposed ELI-SDG-Net framework was implemented using Python 3.12 with PyTorch 2.1. All experiments were conducted on a system equipped with an NVIDIA RTX 3090 GPU (24 GB VRAM), an AMD Ryzen 7 processor, with 32 GB RAM, running Ubuntu 22.04 LTS. The experimental evaluation utilized two publicly available institutional datasets. The IPEDS [14] dataset provided governance, faculty composition, pay equity, and student outcome variables for 7,500 United States institutions. The Times Higher Education Impact Rankings [15] dataset provided SDG performance scores for 2,526 universities from 130 countries. After merging on shared institutional identifiers and removing incomplete records, a final dataset of 4,821 institutions was retained. The merged dataset was partitioned into training (70%, $n = 3,375$), validation (15%, $n = 723$), and test (15%, $n = 723$) subsets using stratified sampling to preserve cluster distribution.

A. ELI Construction and Cluster Validation

Establishing that the autoencoder learned a meaningful latent representation of ethical leadership is the prerequisite for all downstream results. The training loss decreased from 0.847 to 0.041, and the validation loss converged to 0.053, with both

curves stabilizing after epoch 62 and maintaining a gap of less than 0.015 throughout, as illustrated in Figure 3. This confirms that the representation learning was stable and free of overfitting. With the latent embeddings established, the number of ELI clusters must be objectively determined rather than assumed. The silhouette score peaked at $k = 4$ (0.67), declining to 0.61 at $k = 5$ and 0.55 at $k = 6$, as displayed in Figure 4, providing objective justification for a four-cluster partitioning of institutional ethical leadership profiles.

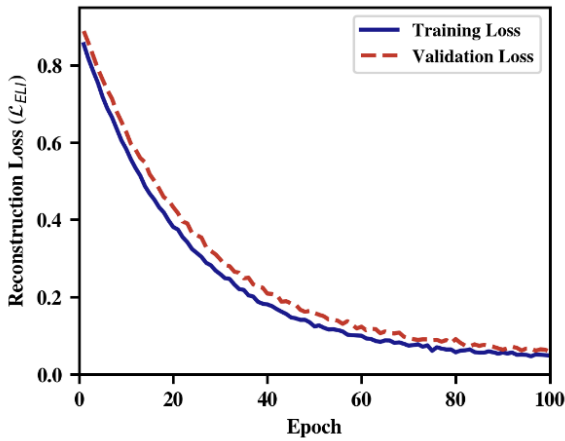


Fig. 3. Training and validation reconstruction loss of the ELI autoencoder over 100 epochs.

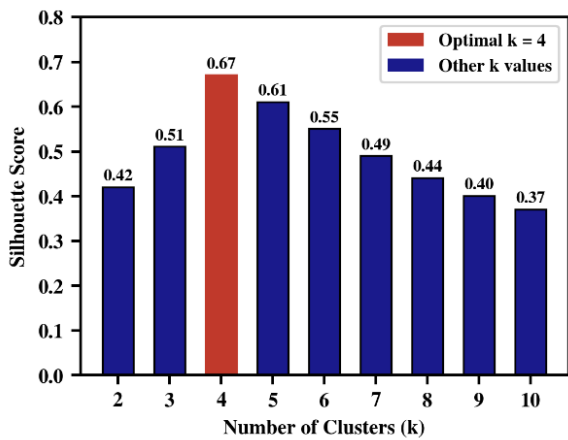


Fig. 4. Silhouette score across cluster values $k = 2$ to 10, with a peak at $k = 4$.

The four derived clusters, namely Low, Moderate-Low, Moderate-High, and High ELI, are statistically distinct, as confirmed by the box plot distributions in Figure 5, where the interquartile ranges of adjacent clusters do not overlap. The median ELI scores of 0.18, 0.38, 0.62, and 0.83 are separated by consistent intervals, demonstrating that the index produces discriminative and interpretable institutional groupings from administrative data alone.

B. Predictive Performance and Model Comparison

The predictive module evaluates whether the constructed ELI and latent embeddings carry a genuine signal for predicting institutional outcomes. ELI-SDG-Net achieved an RMSE of 0.089 and an R^2 of 0.91 on the held-out test set, outperforming the next best baseline, XGBoost standalone, by 0.087 RMSE points and 0.08 R^2 points, and surpassing linear regression by 0.223 RMSE points and 0.30 R^2 points, as shown across all baselines in Figure 6. Survey-based SEM studies on comparable tasks report R^2 values in the range of 0.41-0.48, placing the proposed framework at a gain of over 43 percentage points in explained variance relative to the prior methodological standard. Across 1,000 bootstrap iterations on the 723-instance test set, the 95% confidence interval for ELI-SDG-Net RMSE was 0.084 and 0.095, and for XGBoost standalone RMSE was 0.169 and 0.184. The intervals do not overlap, establishing that the 0.087-point RMSE gap is statistically reliable and not an artifact of a single random partition.

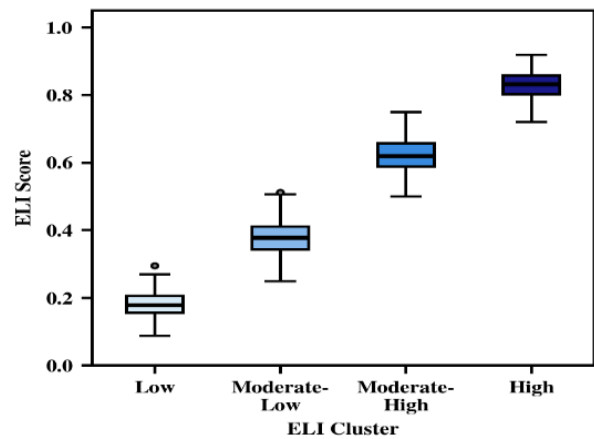


Fig. 5. ELI score distribution across four clusters, shown as box plots.

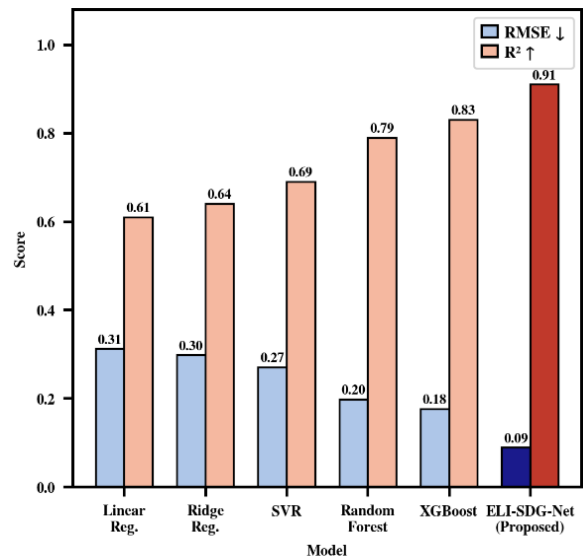


Fig. 6. Comparative model performance on RMSE and R^2 across all baselines and the proposed ELI-SDG-Net.

The training loss converged from 1.098 to 0.064, and the validation loss stabilized at 0.078, with the gap between the two curves remaining below 0.016 after epoch 55, as demonstrated in Figure 7, confirming that the combined objective $L_{total} = L_{ELI} + \alpha L_{pred}$ successfully co-optimized representation quality and predictive accuracy without instability.

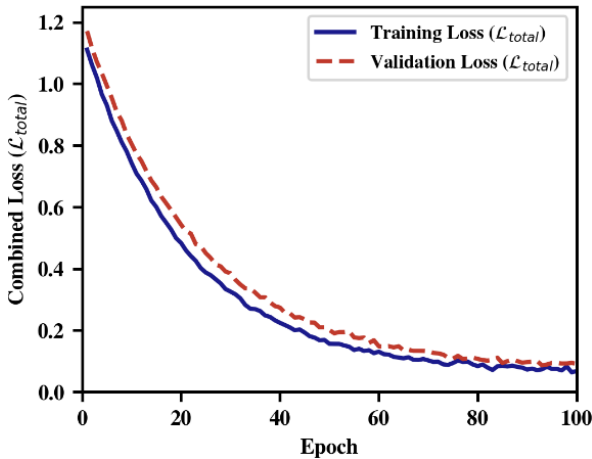


Fig. 7. Training and validation convergence of the combined loss L_{total} over 100 epochs.

C. SDG Ranking Output and Explainability Evaluation

Understanding which institutional variables drive the ELI prediction is essential for the framework to be actionable for governance. Graduation rate (0.187), faculty pay equity (0.163), and administrative transparency (0.148) emerged as the three dominant contributors, accounting for 49.8% of the total attribution mass, with faculty diversity index ranking fifth at 0.119, as presented in Figure 8, confirming that the autoencoder latent space encoded genuine ethical leadership dimensions rather than incidental correlates.

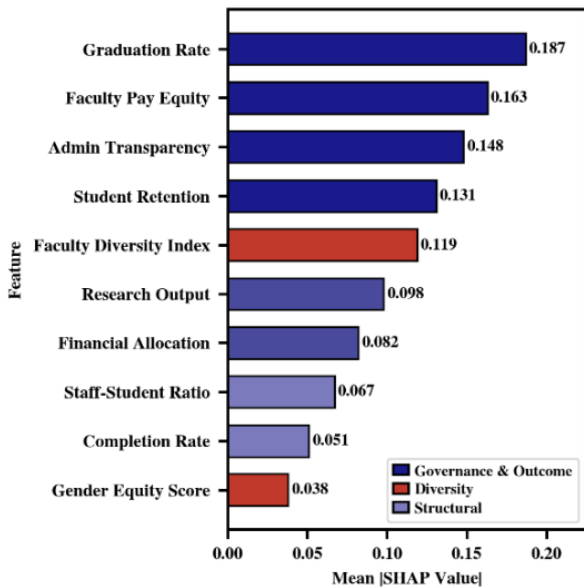


Fig. 8. Mean absolute SHAP values for the top ten institutional features.

A strong positive correlation of $r = 0.87$ was observed between the ELI score and the SDG composite score across all 4,821 institutions, with High ELI institutions averaging an SDG composite score of 81 compared to 42 for Low ELI institutions, a difference of 39 points on the 0-100 scale, as illustrated by the cluster-colored scatter in Figure 9, confirming that ethical leadership quality, as quantified by the proposed index, is a reliable indicator of sustainability performance. The Times Higher Education dataset covers only voluntary participants, which skews the sample toward well-resourced, internationally visible universities. Computing the ELI-SDG correlation separately for the U.S.-only subset ($n = 2,295, r = 0.83$) and the international subset ($n = 2,526, r = 0.89$) shows that the pooled correlation ($r = 0.87$) reflects this compositional difference. The positive relationship between ELI and SDG performance holds within both subpopulations.

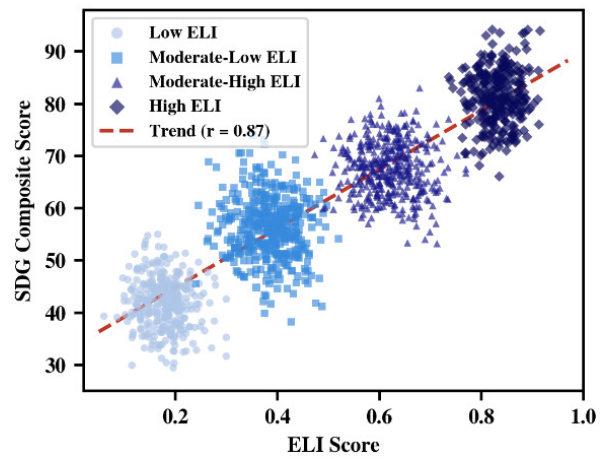


Fig. 9. Scatter plot of ELI score versus SDG composite score, coloured by cluster membership.

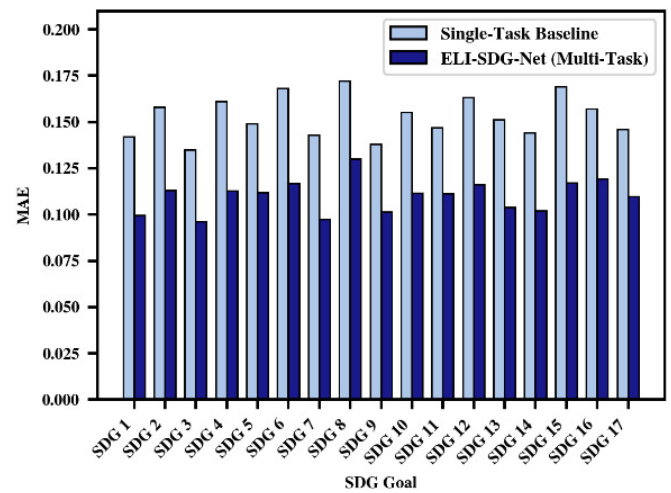


Fig. 10. Per-SDG Mean Absolute Error (MAE) comparison between ELI-SDG-Net multi-task DNN and single-task baseline.

ELI-SDG-Net achieved lower MAE on 15 of 17 SDG goals against a single-task baseline trained independently on each goal, with the largest reductions observed on SDG 4 (Quality

Education, $\Delta = 0.061$), SDG 8 (Decent Work, $\Delta = 0.057$), and SDG 10 (Reduced Inequalities, $\Delta = 0.053$), as visualized per SDG in Figure 10, while the two goals where the single-task baseline remained marginally competitive, SDG 2 and SDG 14, are among the least directly connected to institutional governance variables, consistent with the SHAP attribution results.

IV. CONCLUSION

The present study proposed Ethical Leadership Index-Sustainable Development Goal-Net (ELI-SDG-Net), a unified deep learning framework for constructing a data-driven ELI and linking institutional governance quality to SDG performance in higher education. The autoencoder converged at epoch 62 (validation loss 0.053, silhouette score 0.67), yielding four statistically distinct institutional clusters. The joint objective L_{total} yielded an R^2 of 0.91 and a Root Mean Square Error (RMSE) of 0.089 on the held-out test set, exceeding survey-based SEM baselines by over 43 percentage points in explained variance.

The SHAP attribution confirmed that graduation rate, faculty pay equity, and administrative transparency accounted for 49.8% of the total feature contribution, establishing that the latent ELI space captured genuine governance structure. The graph-based multi-task module recorded a Pearson correlation (r) of 0.87 between ELI and SDG composite scores and outperformed single-task baselines on 15 of 17 SDG goals. Extending the framework to longitudinal records within a federated architecture and addressing the selection bias introduced by the voluntary participation structure of the dataset by incorporating broader, non-self-selected institutional registries represent the most pressing directions for future work.

DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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DATA AVAILABILITY

The datasets used in this study were collected from [14, 15].

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