# **BC3412 Team 4**

# Final Report Presentation

## **Team members:**

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- ➤ Xu Yinfeng (U2121162B)

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## **Project Background and Problem Statement**

With the assumption and problem statement, we choose to focus on the Energy sector as proof of concept for future work



## **Background and Problem Statement**

Governments worldwide push for the Energy Transition with focus on sustainability and reduced carbon emissions

ESG emerges as a widely acknowledged indicator of corporates' performance in upholding its social responsibilities, used by different stakeholders:

#### Regulators

To assess companies' adherence to guidelines and policies

#### **Insurers and investors**

To assess companies for financial decisionmaking such as insurance underwriting

Companies are under pressure to improve its ESG performance, but are **faced with challenges** in choosing the suitable transition method



Assumption: Better ESG score is associated with reduced business risks

#### Problem statement: How can we

- Identify the main drivers for ESG score?
- ➤ Build models that could **recommend the best transition** pathway for each company, considering its own financial and operational capabilities?
- ➤ How to make the solution **scalable** and **adaptable** to companies regardless of industries or geographical locations

## Industry selection: Energy sector

#### **Macro environment factors**

Companies in the energy sector is well-positioned to lead the Green Energy transition due to external threats and opportunities:

#### **Threats**

- Stringent regulatory pressures
- Growing social pressures
- Main contributor to carbon emissions

## **Opportunities**

- Technological advancements
- Incentives from governments

### **Data availability**

The availability of companies in energy sector in AON's client database enables the models to be tested on a larger data set

The Energy sector is chosen to be proof of concept for analytics and model developments

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## **Analytic Approach and Methodology**

We integrate data from multiple credible sources and created a 2-phase plan to analyze the data and achieve our goals.

**Bloomberg** 

S&P Global

THE WORLD BANK



## **Data Sources and Integration**

#### 1. Bloomberg ESG Data

- SASB-aligned, industry-standard ESG scores
- Covers overall ESG, pillar (E/S/G) scores, and disclosure scores
- · Chosen as target variable for predictive modelling

#### 2. S&P Capital IQ

- Market capitalization and financial data
- Used for company scaling and peer group benchmarking
- Integrates into both prediction and strategy phases

Building on our initial models, we have identified that incorporating ETVI data significantly strengthens our ESG strategy optimization by embedding country-specific risk profiles. This ensures our action plans are tailored to the unique transition readiness of each company's operating environment.

#### 3. Energy Transition Vulnerability Index (ETVI)

- Country-level transition risk profiling (IEA, World Bank, UN data)
- · Measures:
  - Exposure (fossil fuel reliance)
  - Sensitivity (socio-economic vulnerability)
  - Adaptive Capacity (institutional readiness)
- Aggregated into R\_Vulnerability Score for model integration
- Enhances realism with macroeconomic & regulatory alignment

## **Phase 1: Two – Layer Architecture**

#### Layer 1

Use of Random Forest Regressor to study the relationships between variables, hence predicting ESG component scores



#### Layer 2

With the component scores derived from Layer 1, **OLS Regression** is used to predict the final ESG score

**Outcome:** Quantitative ESG baseline to understand current positioning for each company

## **Phase 2: ESG Strategy Optimisation Model**

#### <u>Feature Weightage and</u> Selection

Identify the most influential variables driving ESG outcomes using feature importance analysis from our predictive models.



#### Reinforcement Learning Model

- Incorporates ETVI to model external country-specific risks
- Action Space: 60 actionable ESG initiatives
- Agent learns to balance ESG improvement, cost efficiency, and financial sustainability
- Uses curriculum learning to progressively optimise ESG pathways

#### **Action Stage**

- Practical ESG playbook for companies, supported by data-driven insights and regulatory alignment.
- Customisation ensures global best practices meet local realities.

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# **Data Analytics and Initial Model Development**

Pillar scores alone can predict ESG scores, and Random Forest is the best model for individual Pillar scores.



## **Determining Significant Variables for ESG Score**

#### **Hypothesis**

Dep. Variable: Model:

Df Residuals:

ESG Score is derived from Pillar scores and Disclosure scores

	gression Results	
ESG Score	R-squared (uncentered):	0.
0LS	Adj. R-squared (uncentered):	Θ.
st Squares	F-statistic:	1.695e
3 Apr 2025	Prob (F-statistic):	0
18:54:29	Log-Likelihood:	625

of Model: Covariance Type:	7 nonrobust					
	 C	oef std err	t	P> t	[0.025	0.975]
BESG Environmental Pillar Sco BESG Social Pillar Score BESG Governance Pillar Score ESG Disclosure Score Environmental Disclosure Scori Social Disclosure Score Governance Disclosure Score	0.2 0.2 1.3	920 0.003 371 0.004 460 2.766 486 0.921 476 0.920	-0.487	0.000 0.000 0.627 0.626 0.627 0.626	0.478 0.286 0.229 -4.083 -2.257 -2.254 -2.264	0.491 0.298 0.245 6.775 1.360 1.359
Omnibus: Prob(Omnibus):	516.981 0.000 2.287	Durbin-Watson Jarque-Bera (.		0.570 13041.986		

- [1] R2 is computed without centering (uncentered) since the model does not contain a constant [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 9.4e+04. This might indicate that there are strong multicollinearity or other numerical problems.

850 843

21.636

#### Result:

- High p-values (above 0.6) for **Disclosure** scores → statistically insignificant at 5%. Reanalyze with only Pillar scores
- High  $R^2(0.999) \rightarrow$ Relationship is **linear**

#### OLS Regression Results

Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	Least Squa Thu, 03 Apr 2 23:27	0LS Adj. res F-st 025 Prob :32 Log- 850 AIC: 847 BIC:	F-statistic: Prob (F-statistic):			0.999 0.999 1.949c+95 0.00 622.77 -1240. -1225.		
		coef	std err	t	P> t	[0.025	0.975]	
BESG Environmental BESG Social Pillar BESG Governance Pi	Score	0.4833 0.2907 0.2317	0.002 0.003 0.001	196.467 113.843 159.081	0.000 0.000 0.000	0.479 0.286 0.229	0.488 0.296 0.235	
Omnibus: Prob(Omnibus):	510. 0.		oin-Watson: que-Bera (JE	3):	0.567 12613.919			

Result: R<sup>2</sup> maintain at **0.999** (99.9% of variance in BESG Score explained by Pillar Scores → only Pillar scores necessary to predict ESG score

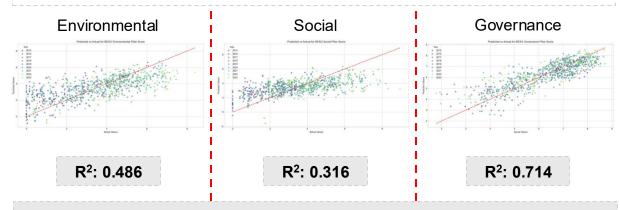
Prob(JB)

2.254

#### **Model Selection for Pillar Scores**

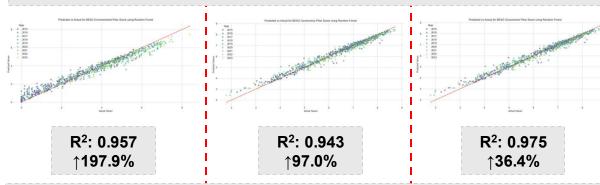
#### **Initial Approach:**

OLS regression for each Pillar score



Problems: Non-linear relationships, clustering, feature interactions, skewed/ bimodal distributions

Solution: Random Forest – more robust compared to linear regression



Big improvements to R<sup>2</sup> → Random Forest model better explains the models for each Pillar Score.

**Data Analytics** Zhi Hao Problem Statement **Project Overview** Insights **Action Plans** 

<sup>[1]</sup> R<sup>2</sup> is computed without centering (uncentered) since the model does not contain a constant

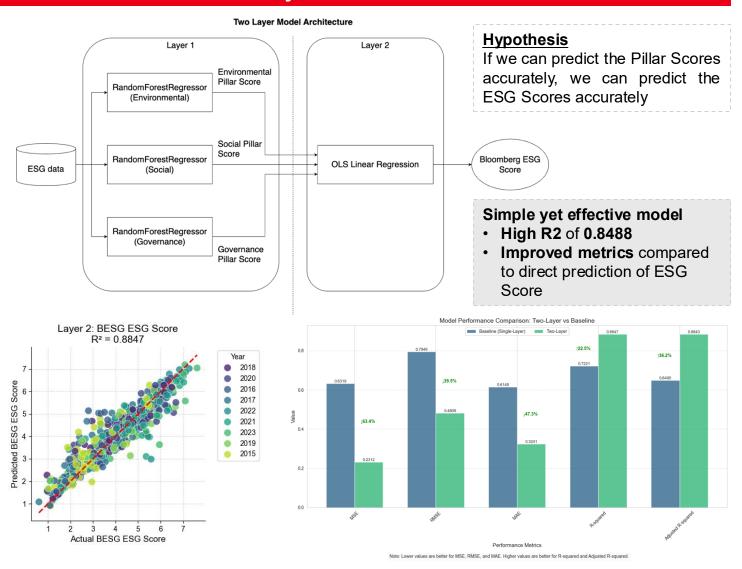
<sup>[2]</sup> Standard Errors assume that the covariance matrix of the errors is correctly specified.

# Phase 1: Two Layer Model – Initial Insights

The model achieved superb predictive results, and the insights gathered were used for further research into ESG transition.



#### **Two Layer Model Architecture**



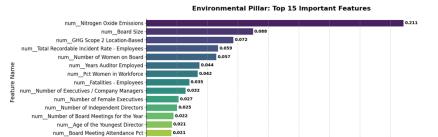
#### **Most important features**

0.020

num Number of Non Executive Directors on Board -

#### Feature Importance Analysis for ESG Pillars

Higher values indicate greater impact on model predictions





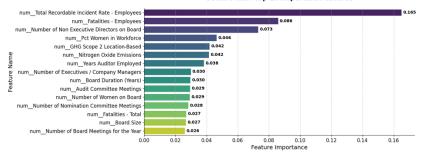
Feature Importance

0.125

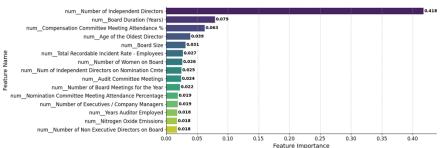
0.150

0.175

0.100



#### Governance Pillar: Top 15 Important Features



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# Phase 2: Reinforcement Learning – Action Plan

The reinforcement learning model outputs in a step-by-step action plan, helping to guide companies in ESG transition.

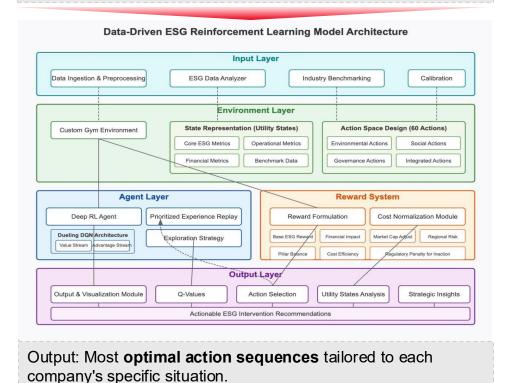


## **Reinforcement Learning Solution**

#### **Problem**

Challenges deciding ESG transition pathway with just the predicted ESG Score and important variables.

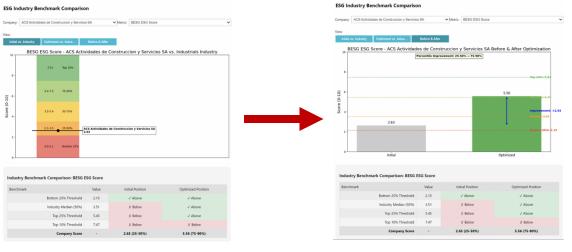
- Which ESG initiatives will deliver the greatest impact?
- In what **sequence** these actions should be implemented?
- How to balance short-term **costs** against long-term **benefits?**



#### **Dashboard Demonstration**



#### **ESG Industry Benchmark Comparison**



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# Thank you!

# OLS Regression with All Pillar Scores and Disclosure Scores



#### OLS Regression Results

Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type:	BESG ESG Scor OL Least Square Thu, 03 Apr 202 18:54:2 85 84	S Adj s F-s 5 Pro 9 Log 0 AIC 3 BIC	tatistic: b (F-statist -Likelihood: :	(uncentered		0.999 0.999 1.695e+05 0.00 625.31 -1237.	
======================================	110111 0bus	-=====	========				=======
		coef	std err	t	P> t	[0.025	0.975]
BESG Environmental BESG Social Pillar BESG Governance Pil ESG Disclosure Scor Environmental Discl Social Disclosure S Governance Disclosu	Score lar Score e osure Score - core -	0.4849 0.2920 0.2371 1.3460 0.4486 0.4476 0.4503	0.003 0.003 0.004 2.766 0.921 0.920 0.924		0.000 0.000 0.000 0.627 0.626 0.627 0.626	0.478 0.286 0.229 -4.083 -2.257 -2.254 -2.264	0.491 0.298 0.245 6.775 1.360 1.359
Omnibus: Prob(Omnibus): Skew: Kurtosis:	516.98 0.00 2.28 21.63	0 Jar 7 Pro	bin-Watson: que-Bera (JE b(JB): d. No.	B):	0.570 13041.986 0.00 9.40e+04		

#### Notes:

- [1] R<sup>2</sup> is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [3] The condition number is large, 9.4e+04. This might indicate that there are strong multicollinearity or other numerical problems.

# OLS Regression with Pillar Scores Only



#### OLS Regression Results

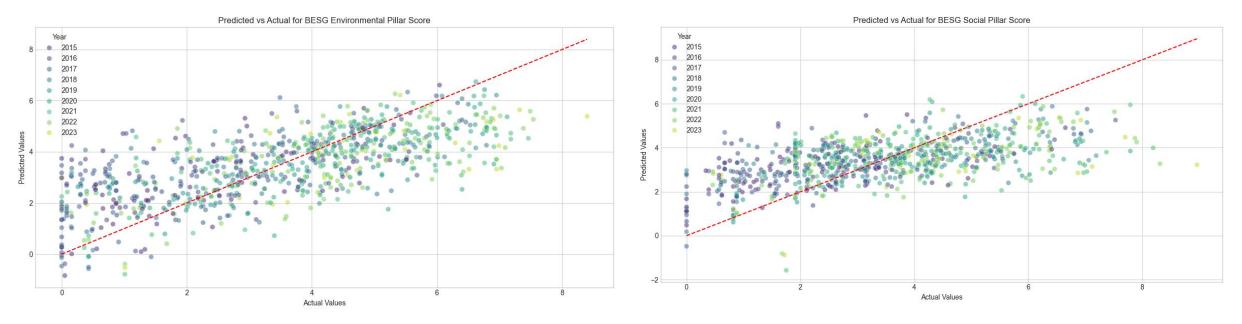
Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model:	BESG ESG Score 0L9 Least Squares Thu, 03 Apr 2025 23:27:32 850 847	Adj F-s Pro Log AIC	tatistic: b (F-statist -Likelihood: :	<pre>(uncentered): ic):</pre>		0.999 0.999 3.949e+05 0.00 622.77 -1240. -1225.	
Covariance Type:	nonrobust	t					
=======================================		coef	std err	t	P> t	[0.025	0.975]
BESG Environmental BESG Social Pillar BESG Governance Pi	Score (	0.4833 0.2907 0.2317	0.002 0.003 0.001	196.467 113.843 159.081	0.000 0.000 0.000	0.479 0.286 0.229	0.488 0.296 0.235
Omnibus: Prob(Omnibus): Skew: Kurtosis:	510.684 0.000 2.254 21.326	Jar Pro	bin-Watson: que-Bera (JB b(JB): d. No.	 ): 	0.567 12613.919 0.00 6.33		

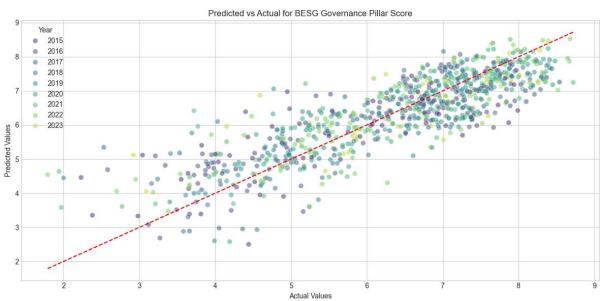
#### Notes:

- [1] R<sup>2</sup> is computed without centering (uncentered) since the model does not contain a constant.
- [2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

# Predicted vs Actual Values for OLS Linear Regression of Pillar Scores

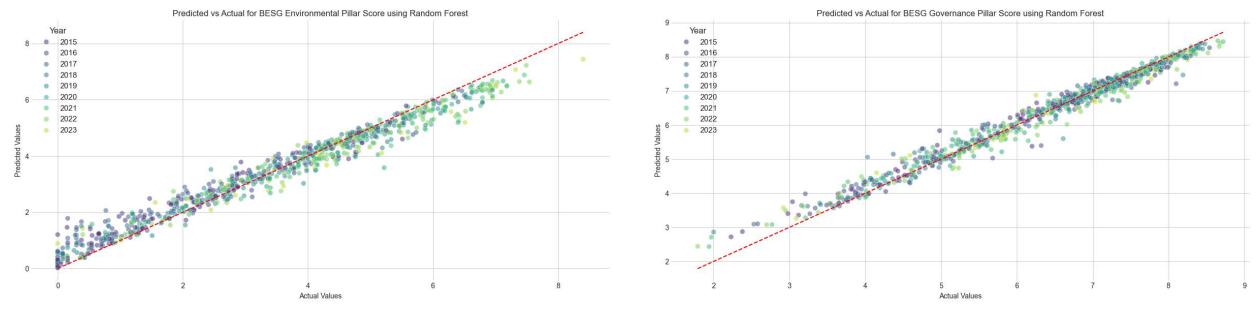


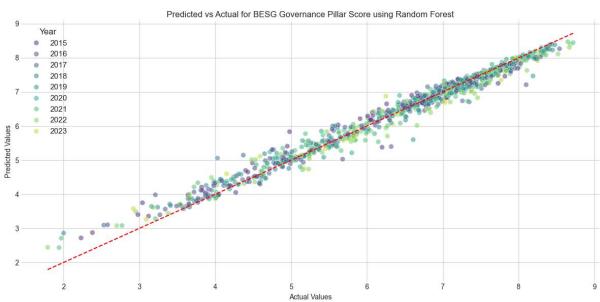




# Predicted vs Actual Values for Random Forest Regression of Pillar Scores

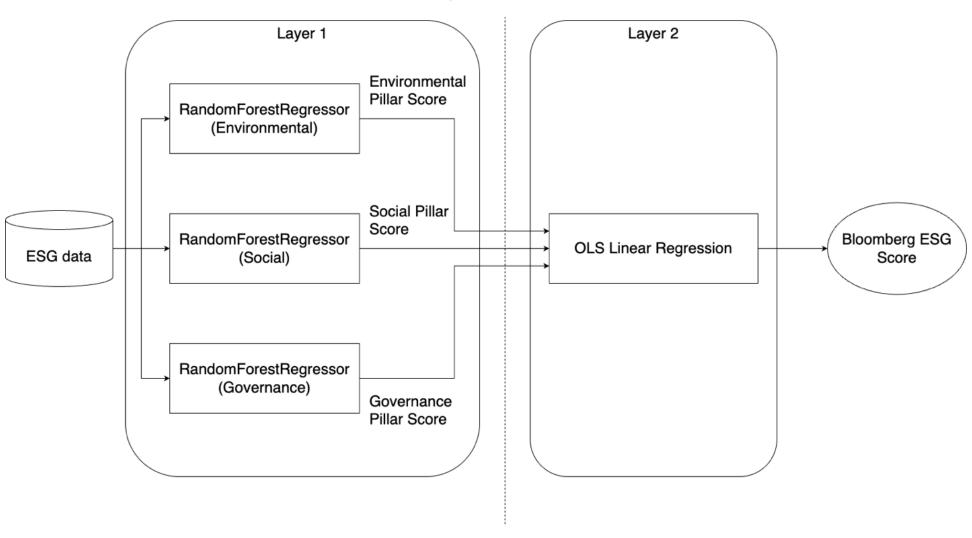






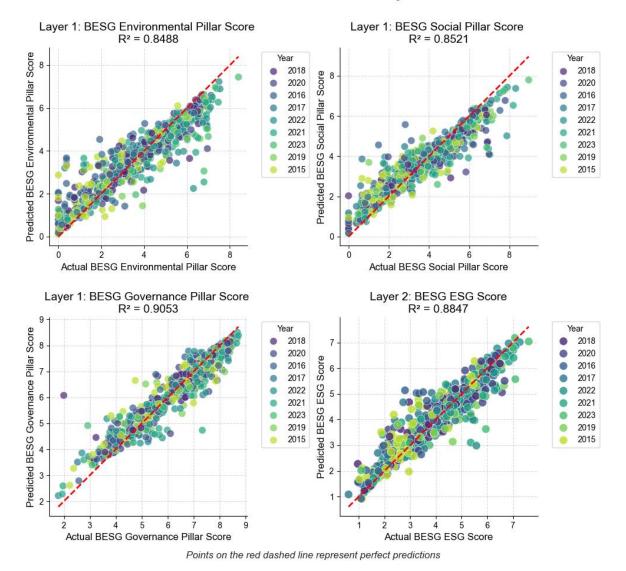


#### **Two Layer Model Architecture**



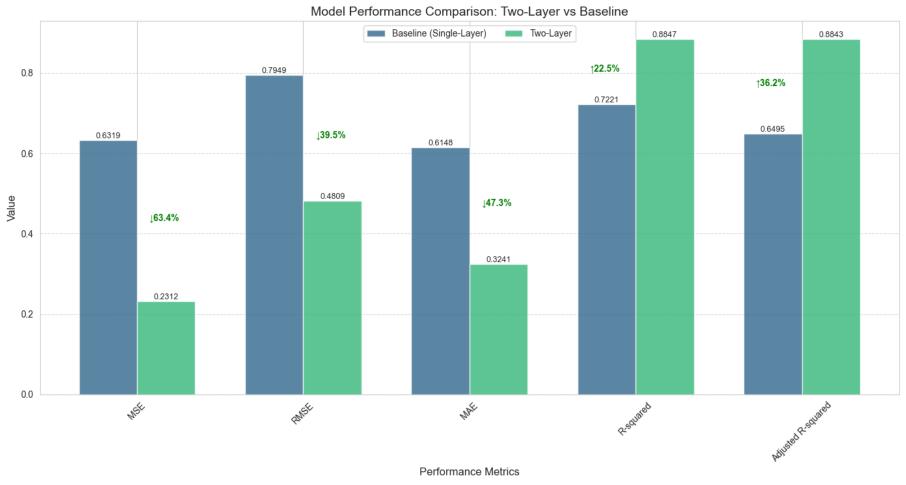


#### Actual vs. Predicted Values for Two-Layer ESG Model



# Model Performance between Two Layer Model and Direct Prediction of ESG Score





Note: Lower values are better for MSE, RMSE, and MAE. Higher values are better for R-squared and Adjusted R-squared.

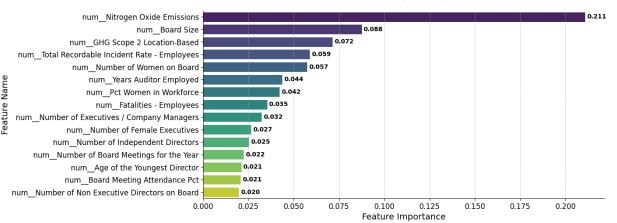
# Feature Importance Analysis for ESG Pillars



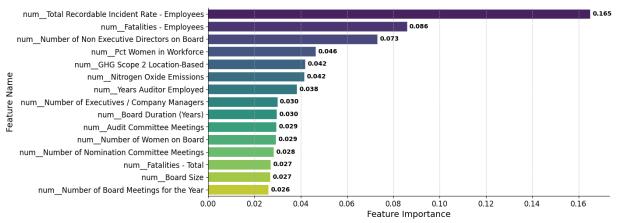
#### Feature Importance Analysis for ESG Pillars

Higher values indicate greater impact on model predictions

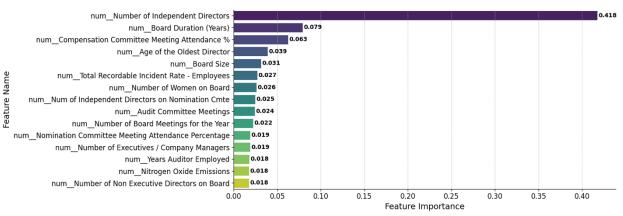
#### **Environmental Pillar: Top 15 Important Features**



#### Social Pillar: Top 15 Important Features

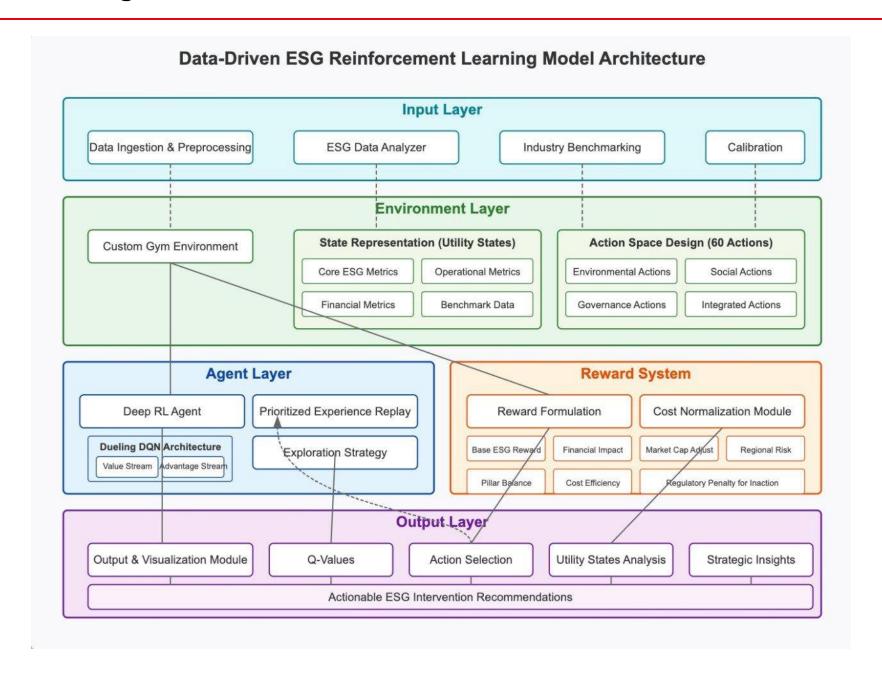


#### Governance Pillar: Top 15 Important Features



# **Reinforcement Learning Model Architecture**







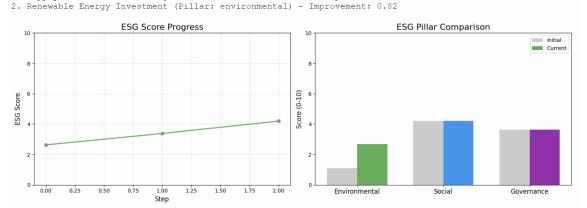
```
# GHG Scope 2 Reduction Actions
30: {'name': 'Scope 2 Reduction: Purchase Voluntary RECs (25% of Consumption)',
     'effects': {'GHG Scope 2 Location-Based': -0.25, 'Renewable Energy Use': 0.25, 'BESG Environmental Pillar Score': 0.05},
     'cost': 10, 'pillar': 'environmental', 'initiative type': 'renewable procurement market'},
31: {'name': 'Scope 2 Reduction: Purchase Compliance RECs (25% of Consumption)',
     'effects': {'GHG Scope 2 Location-Based': -0.25, 'Renewable Energy Use': 0.25, 'BESG Environmental Pillar Score': 0.05},
     'cost': 45, 'pillar': 'environmental', 'initiative type': 'renewable procurement market'},
32: {'name': 'Scope 2 Reduction: Enter Utility Green Tariff (100% of Consumption)',
     'effects': {'GHG Scope 2 Location-Based': -1.0, 'Renewable Energy Use': 1.0, 'BESG Environmental Pillar Score': 0.15},
     'cost': 30, 'pillar': 'environmental', 'initiative_type': 'renewable_procurement_utility'},
33: {'name': 'Scope 2 Reduction: Sign Long-Term PPA (50% of Consumption)',
     'effects': {'GHG Scope 2 Location-Based': -0.50, 'Renewable Energy Use': 0.50, 'BESG Environmental Pillar Score': 0.18},
     'cost': 70, 'pillar': 'environmental', 'initiative_type': 'renewable_procurement_ppa'},
34: {'name': 'Scope 2 Reduction: Install On-site Solar PV (20% of Consumption)',
     'effects': {'GHG Scope 2 Location-Based': -0.20, 'Renewable Energy Use': 0.20, 'BESG Environmental Pillar Score': 0.15},
     'cost': 80, 'pillar': 'environmental', 'initiative_type': 'renewable_generation_onsite'},
# Energy Efficiency Actions
35: {'name': 'Energy Efficiency: LED Lighting Retrofit',
     'effects': {'GHG Scope 2 Location-Based': -0.08, 'BESG Environmental Pillar Score': 0.07},
     'cost': 20, 'pillar': 'environmental', 'initiative_type': 'energy_efficiency_lighting'},
36: {'name': 'Energy Efficiency: HVAC System Upgrade',
     'effects': {'GHG Scope 2 Location-Based': -0.12, 'BESG Environmental Pillar Score': 0.10},
     'cost': 55, 'pillar': 'environmental', 'initiative type': 'energy efficiency hvac'},
37: {'name': 'Energy Efficiency: Building Insulation Improvement',
     'effects': {'GHG Scope 2 Location-Based': -0.05, 'BESG Environmental Pillar Score': 0.05},
     'cost': 30, 'pillar': 'environmental', 'initiative_type': 'energy_efficiency_envelope'},
38: {'name': 'Energy Efficiency: Implement Energy Management System (EMS)',
     'effects': {'GHG Scope 2 Location-Based': -0.10, 'BESG Environmental Pillar Score': 0.08},
     'cost': 40, 'pillar': 'environmental', 'initiative_type': 'energy_efficiency_monitoring'},
39: {'name': 'Energy Efficiency: Industrial Process Optimization',
     'effects': {'GHG Scope 2 Location-Based': -0.15, 'BESG Environmental Pillar Score': 0.12}, # Assumes Scope 2 impact
      'cost': 60, 'pillar': 'environmental', 'initiative_type': 'energy_efficiency_process'},
```

# **ESG Strategy Simulator**

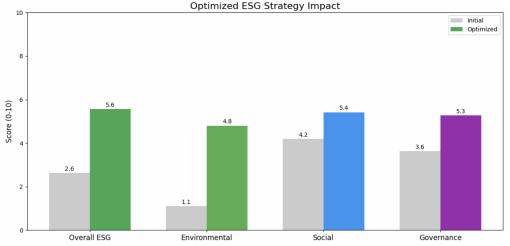


#### **ESG Strategy Simulator**









# **ESG Industry Benchmark Comparison**



