AI-Empowered Leadership and Sustainable Development: An Empirical Model of Ethical Governance and SDG Performance

Parin Somani[1], Shashi Kant Gupta[2]

[1] Lincoln University College, Petaling Jaya, Selangor-47301, Malaysia; [2] Lincoln University College, Petaling Jaya, Selangor-47301, Malaysia.

Email ID: drparinsomani@gmail.com; raj2008enator@gmail.com

Abstract: Rapid integration of Artificial Intelligence (AI) into organizational processes offers substantial potential for enhancing performance and achieving Sustainable Development Goals (SDGs). However, current leadership models often lack mechanisms to ensure ethical governance, transparency, and accountability in AI adoption. Challenges such as hidden biases, limited oversight, and insufficient alignment with sustainability objectives restrict organizations' ability to leverage AI responsibly, highlighting the need for empirically validated frameworks that combine AI-driven decision-making with ethical and sustainable practices. This research proposes an AI-empowered leadership model integrating AI-empowered leadership (AI-EL), ethical governance (EG), leadership commitment to sustainability (LCS), stakeholder collaboration (SC), and organizational culture (OC) to improve SDG performance. Data were collected from 210 managers and executives across diverse sectors using a structured questionnaire with Likert-scale ratings. Structural equation modeling (SEM) and confirmatory factor analysis (CFA) were conducted using Analysis of Moment Structures (AMOS) software to examine direct and indirect relationships while ensuring measurement reliability and validity. SEM results confirmed all hypotheses were AI-EL (β = 0.65, R^2 = 0.42) and other predictors demonstrated medium-to-large effect sizes (f^2= 0.23–0.35), indicating statistically significant and robust relationships. These findings provide actionable insights for organizations to integrate AI into leadership, enhance predictive decision-making, and achieve measurable sustainability outcomes across sectors.

Keywords: AI-Empowered Leadership; Ethical Governance; Sustainable Development; SDG Performance; Organizational Sustainability.

Introduction

Artificial intelligence (AI) had become the new revolution in any industry with resultant automation, innovation and use of data to make decisions that would currently be important to the sustainable development and long-term growth of the society [1]. It was fast becoming very useful in digital environments, but the new ethical, environmental, and governance challenges had brought up an inquiry concerning fairness, transparency, and accountability. Even though AI can be used to improve organizational performance, existing applications were not focused on responsibility in implementation, which poses threats related to inequality, secretiveness, and unsustainable technological practices [2]. The same problems were also observed in electronic markets, where mass AI use in e-commerce raised more unanswered concerns about privacy, biases and accountability limits that were not so widespread in the prior research, and it required more responsible and sustainable AI mechanisms [3]. Other AI data science innovations influenced the most important fields, including energy and healthcare, and made their systems smoother and indicated loopholes in ethical regulation and explainability. AI in urban energy planning contributed to better consumption analysis and efficiency but needed better governance to guarantee sustainability-related results [4]. In cancer medicine, AI was used in assisted clinical decision-making but its application required cautious consideration of trust, reliability, and ethical use [5]. Figure 1 illustrates AI integration in organizational structure.

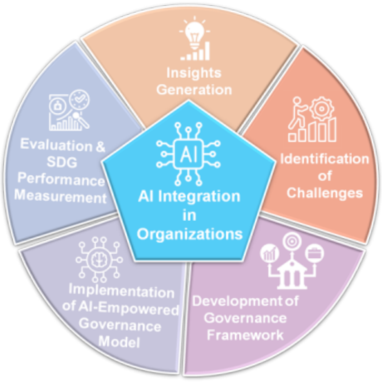

Figure 1.Structure of AI Integration in Organizations

Greater shifts such as the process of the support of electric mobility with renewable energy pressed additional the imperatives of consistent models of governance that can incorporate technological innovation and long-term development goals [6]. The pace of digital growth in the organizational context increased governance difficulty. The adoption of AI-assisted decision systems generated non-transparent such biases, lower transparency, and accountability among managers, depicting that the current leadership models have severe issues [7]. The prevailing systems of governance lacked institutions to monitor the ethical risks or to align the sustainable development goals with the use of AI. These constraints amplified the need of integrated models which could unite ethical control, socially responsible automation and organizational sustainability. To get over these problems, the work proposed an empirical AI-enhanced governance model, which strengthened ethical leadership, decision SDG-plural performance, accountability, and performance. The model was to deliver a balanced framework of AI-informed insights and systematic ethical controls that help to aid transparent, inclusive, and sustainable organization governance [8]. The aim of the research is to empirically explore the role of AI-empowered leadership, together with ethical governance, leadership commitment, stakeholder collaboration, and organizational culture, in the performance of Sustainable Development Goal (SDG) in a variety of organizational fields.

Related work

The application of AI in enforcing sustainable performance in diverse facets has been broadly explored in the recent research. The possibilities of AI in the manufacturing of SMEs were examined in the research using conventional survey instruments and evaluated using PLS-SEM for 162 companies [9]. The results indicated that it exerted a direct significant effect on sustainability (0.42, p) and an indirect effect by frugal innovation (0.18, $p < 0.05$). In addition, AI-focused leadership mediated the relationship between AI-frugal innovations (0.25, $p < 0.05$). Restraints involved the use of self-reported surveys and a rather small sample. The effect of AI adoption on green governance was estimated with panel data (2009-2023) and regression models and Bartik instrumental variables [10]. Results showed that environmental performance (0.38, $p < 0.01$) and ecological costs (-0.22, $p < 0.05$) were improved, along with sustainable innovation (0.31, $p < 0.01$). Certain drawbacks included unobservable heterogeneity of firms and reliance on financial and environmental reports. The impact of AI on enterprise total development performance (TDP), combining social, environmental, and financial outcomes, was measured using text analysis methods [11]. Findings showed favourable results of green innovation and dynamic capabilities, and a higher tendency of the effects in high tech sectors and regions with conducive market-based environmental policies. Limitations were measurement bias in TDP and low external validity to other situations. Bibliometric analysis was used to evaluate AI in SDG4 (Quality Education) [12]. It has been found that AI generative can benefit personalized learning, expand access to education, and optimize resources, whereas long-term societal and ethical consequences were not explored well enough. State-of-the-art AI architecture models, like the Context-Aware Hybrid Ant Colony Optimized Logistic Forest (CA-HACO-LF) [13], could perform well (Accuracy 98.6%, F1 score >0.95) but were expensive in terms of data quality and computation. In healthcare 5.0, AI-based human-centered models such as Random Forest and BERT models on the MedQuad dataset of 14,979 questions [14] demonstrated training and inference accuracy. Limitations were related to dataset dependence and class imbalance problems resolved by SMOTE. The conceptual modelling of AI, green innovation, and climate governance through the Sustainability Singularity Index (SSI) [15] had high predictive value but weak empirical support. Using Tensor Flow-based DRNN was integrated in smart classrooms, reaching metrics, but the generalizability to other educational fields was limited because it used curated material.Although AI has proven beneficial to sustainability, the extant research [16] shows some gaps (e.g., self-reporting, sample size, measurement biases, dependence on databases, and limited cross-field and discipline generalizability) and empirically validated, cross-sectoral, and ethically sound AI models are needed.

Key contributions

- An AI-powered leadership model has been developed that incorporates AI-EL, EG, LCS, SC, and OC to improve SDG performance.
- SEM and CFA on 210 managers in sectors give quantitative evidence that there is a statistical significance and effect size.
- It determines mediating and moderating roles of governance and organization factors on the effects of AI leadership on SDG outcomes.
- It is also the first to fill the gaps in leadership models, taking the ethical governance and sustainability mechanisms into the AI adoption, which expands the responsible leadership literature.
- Results inform organizations to develop data-driven, ethically oriented and sustainability-oriented leadership practices to realize quantifiable SDG performance gains.

Hypothesis development

Hypothesis (H1): AI-enabled leadership is positively related to organizational performance in the realization of Sustainable Development Goals. **(AI-EL) → (SDG)**

Hypothesis (H2): Ethical governance is positively related to performance in the realization of Sustainable Development Goals. **(EG) → (SDG)**

Hypothesis (H3): Leadership commitment to sustainability is positively related to the performance in achieving Sustainable Development Goals. **(LCS) → (SDG)**

Hypothesis (H4): Stakeholder cooperation is positively related to organizational performance to meet Sustainable Development Goals. **(SC) → (SDG)**

Hypothesis (H5): Sustainable Development Goals performance is mediated by organizational culture between AI-empowered leadership and performance. **(OC) → (SDG)**

Method, Experiments and Results

A total of 210 participants in demographics and sectors completed a structured questionnaire. SEM and CFA examined AI-EL, EG, LCS, SC, and OC in terms of their influence on SDG performance. Figure 2 presented the key components of the SDG performance.

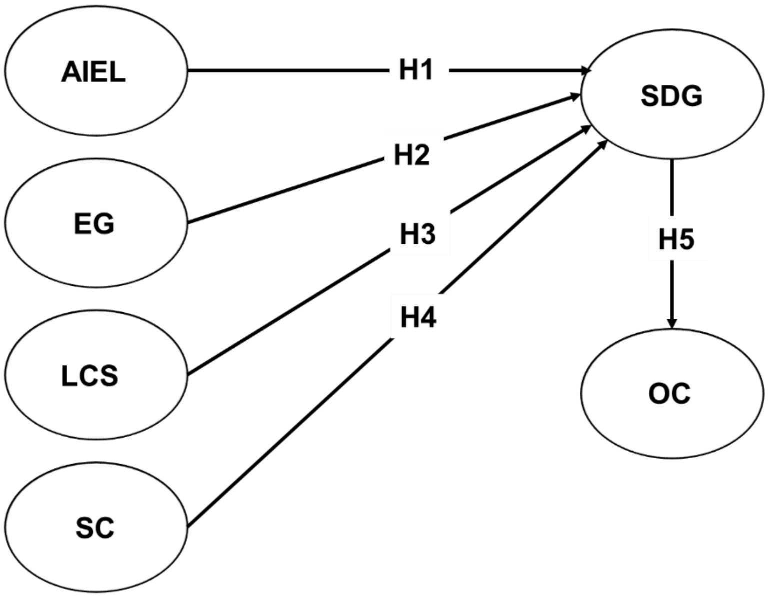

Figure 2.Conceptual framework of Ethical Governance and SDG Performance

Data collection

The leadership and organizational factors influence SDG, which consists of 210 individuals divided into age, gender, education, experience, job position and industry. Gender was male and female; age was 25-34, 35-44, 45-54, and 55+ years. The education level was undergraduate, graduate, or doctorate or above. Managers and executives were the job roles, and technology, healthcare, manufacturing, finance, or retail industries were used. Experience was categorized as 5-10, 11-20, 21-30 and 31+ years. Such population distribution facilitates the in-depth examination of the determinants operating on leadership, ethical governance, and SDG performance. Table 1 representing the demographic details associated with SDG performance.

Table 1. The Demographic table for SDG performance

Demographic Variable	Category	Frequency (N=210)	Percentage (%)
Gender	Male	130	61.9
	Female	80	38.1
Age Group	25–34 years	40	19.0
	35–44 years	70	33.3
	45–54 years	60	28.6
	55+ years	40	19.0
Sector	Technology	50	23.8
	Healthcare	40	19.0
	Manufacturing	45	21.4

	Finance	30	14.3
	Retail	20	9.5
	Media	25	11.9
Position	Manager	120	57.1
	Executive	90	42.9
Years of Experience	5–10 years	40	19.0
	11–20 years	90	42.9
	21–30 years	50	23.8
	31+ years	30	14.3
Education Level	Bachelor's degree	100	47.6
	Master's degree	85	40.5
	Doctorate or higher	25	11.9

Questionnaire design

210 participants were involved in ethical governance and SDG performance. To improve SDG performance, the initial process is creating a questionnaire that has six important sections, such as demographic information, AI-EL, EG, LCS, SC and OC, as shown in Appendix A.

- **AI-EL:** Leaders acting on AI technologies to promote decision-making and organizational performance.
- **EG:** Adoption of open, accountable, and responsible business in the decision-making of the organization.
- **LCS:** The commitment of the leaders to encourage and incorporate sustainable practices in the company activities.
- **SC:** This is the collaboration and interaction between internal and external partners to work together to meet organizational goals and sustainability initiatives.
- **OC:** This is the set of values, beliefs, and practices of an organization that influence how the employees behave, make decisions and perform.
- **SDG Performance:** This measures how well an organization performs with respect to meeting targets as per the integrated SDGs.

An over all of 210 participants was surveyed using a 3-point Likert scale, where low, medium, and high influence, association, effect, or impact were the responses. The questionnaire investigated the way AI-EL, EG, LCS, SC, OC affect the achievement of SDGs.

Statistical analysis

SEM with AMOS to construct the proposed structural model, which provides increased flexibility to data analysis and is adequate to the sample size. They had six constructs, namely AI-EL, EG, LCS, SC, OC, and SDG performance, which were analysed using Confirmatory Factor Analysis (CFA) in AMOS as the measurement model evaluation and the component analysis to prevent duplication. The structured model could be represented as Equation (1).

$$SDG = \alpha_1(AI - EL) + \alpha_2(EG) + \alpha_3(LCS) + \alpha_4(SC) + \alpha_5(OC) + \varepsilon \quad (1)$$

Where α_1 to α_5 were path coefficients representing the effect of each predictor on SDG performance, and $\varepsilon$was the error term of ethical governance and SDG performance.

CFA confirmed reliability and construct accuracy, and SEM substantiated that AI-EL, EG, LCS, SC, and OC are effective to increase SDG performance with medium effect sizes and high statistical significance.

CFA Test

CFA was authenticating the quantity model, investigating the correlation between observed elements and latent constructs, and making sure that the AI-EL, EG, LCS, SC, OC, and SDG performance measures are credible. Through CFA, the extent to which these constructs represent the underlining constructs and the accuracy of association between them were confirmed.

The factor loading (λ) of each construct is the degree to which indicators are associated with the latent construct. Greater factor loading implies that the construct correlates better with observed indicators. The standard error (SE) refers to the accuracy of the factor loading estimation, where a smaller value implies more accuracy. The t-value compares whether the factor loading is significant and the p-value makes the determination on whether the factor loading observed was due to chance or not. A p-value <0.05 is a statistically significant value. The Average Variance Extracted (AVE) determines the level of variation that a set of indicators can explain by a construct. A value above 0.50 would indicate that the construct accounts more than half of the variance in its indicators. Composite Reliability (CR) is used to determine the internal consistency of the indicators used to measure a construct and any value above 0.70% is acceptable. Table 2 and Figure 3 indicate the reliability and validity of CFA tests.

Table 2.Reliability and validity of CFA tests

Construct	Indicator	Factor Loading (λ)	SE	t-Value	p-Value	AVE	CR
AI-EL	AI-EL1	0.78	0.05	15.60	<0.001	0.62	0.86
	AI-EL2	0.80	0.04	20.00			
EG	EG1	0.74	0.06	12.33		0.61	0.84
	EG2	0.79	0.05	15.80			
LCS	LCS1	0.82	0.04	20.50		0.65	0.87
	LCS2	0.75	0.05	14.00			
SC	SC1	0.81	0.05	19.80		0.66	0.88
	SC2	0.77	0.06	13.67			
OC	OC1	0.84	0.04	21.00		0.69	0.89
	OC2	0.86	0.03	28.67			
SDG	SDG1	0.85	0.04	21.25		0.70	0.90
	SDG2	0.87	0.03	28.67			

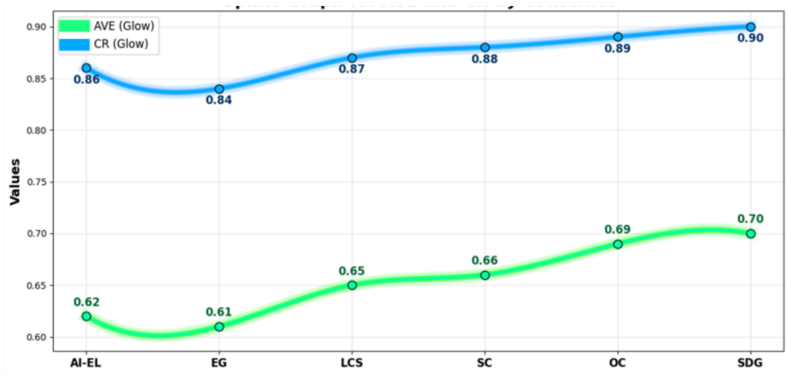

Figure 3. Reliability and validity of CFA tests

SEM analysis

SEM is a statistical method that employs complex relationship analysis between observed and latent variables. It allows testing hypothesized models, direct and indirect effects, and testing model fit to guarantee quality data representation.

Structural framework

The structural model presents a thorough assessment of the influence of predictor factors on SDG performance, as the statistical evidence of the strength of each relationship is clear in its direction and significance. These associations are summarized in the Structural Framework Table with β coefficients, R^2 , f^2 effect sizes, and p-value significance. To illustrate this point, Hypothesis 1 (AI-EL → SDG) demonstrates that AI-empowered leadership positively impacts SDG performance (0.65), which implies that AI-powered leadership is a significant source of sustainability performance. The value of $R^2$is 0.42, indicates that the predictive ability of AI-EL on SDG outcomes is strong, explaining of 42% the variation.

The effect of AI-EL → SDG is also big (f^2 = 0.30), which emphasizes its significance. The other hypotheses have an intermediate to medium effect size (f^2= 0.10-0.12), which assists in identifying the factors that impact SDG success more. All the hypotheses present a P-value < 0.05, which is not statistically significant. The result column has categorized the hypotheses as either “Well Supported” or “Supported” based on the intensity of the empirical results, and Hypothesis 1 is “Well Supported” due to the large effect sizes and large β value. Table 3 confirms the discriminating validity so that all constructs have AI-EL, EG, LCS, SC, and OC conceptually different.

Table 3. Discriminating validity of SEM analysis

Construct	AI-EL	EG	LCS	SC	OC	SDG
AI-EL	0.79	-	-	-	-	-
EG	0.60	0.78	-	-	-	-
LCS	0.65	0.55	0.81	-	-	-
SC	0.55	0.52	0.58	0.81	-	-
OC	0.60	0.59	0.61	0.62	0.83	-
SDG	0.61	0.63	0.65	0.63	0.67	0.84

Figure 4 and Table 4 also represent the SEM results, showing the structural pathways with relative strengths. On balance, the SEM discussion shows that AI-EL, EG, LCS, SC, and OC were significant factors in improving SDG performance, which provides a solid account of the sustainability outcomes within the suggested framework.

Table 4. Structural frameworks for SEM analysis

Hypothesis	β Values	R^2	f^2	P Value	f^2 Effect	Result
(H1): (AI-EL) ⟶ (SDG)	0.65	0.42	0.30	<0.001	Large	Well Supported
(H2): (EG) ⟶ (SDG)	0.60	0.38	0.28		Medium	Supported
(H3): (LCS) ⟶ (SDG)	0.70	0.49	0.35		Large	Well Supported
(H4): (SC) ⟶ (SDG)	0.55	0.31	0.23		Medium	Supported
(H5): (OC) ⟶ (SDG)	0.68	0.46	0.31		Large	Well Supported

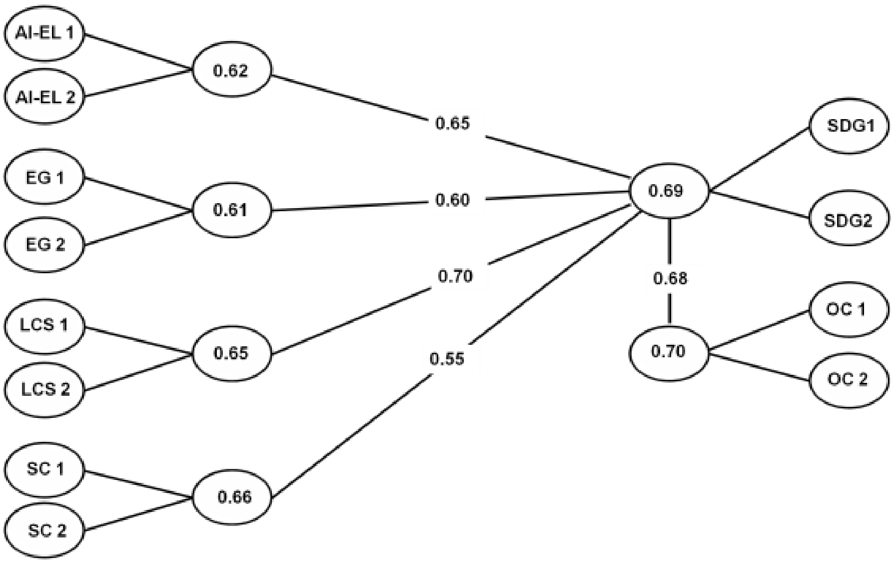

Figure 4. Structural frameworks for SEM analysis

Hypothesis 1 (H1) demonstrates that AI-EL has a significant positive impact on SDG performance with a β of 0.65 (R^2= 0.42). The effect size is substantial (f^2=0.30), and P<0.001 proves statistical significance.

Hypothesis 2 (H2) suggests that EG has a positive contribution to SDG results, β = 0.60 and R^2 = 0.38. The relationship is supported by the intermediate effect size (f^2= 0.28) and P< 0.001.

Hypothesis 3 (H3) shows that LCS has a strong influence on SDG performance, with β = 0.70 and R^2= 0.49. The significance of the large effect size (f^2 = 0.35) and P<0.001.

Hypothesis 4 (H4) shows that SC has a positive impact on SDG outcomes with β = 0.55 and R^2 = 0.31. Its importance is confirmed by an average effect size (f^2 = 0.23) and P< 0.001.

Hypothesis 5 (H5) shows that OC is an important predictor of SDG performance with β(0.68),R^2 = 0.46 and a huge effect (f^2=0.31) P<0.001. Overall, all five hypotheses are statistically significant; medium and large effect sizes indicate that AI-EL, EG, LCS, SC, OC are important predictors of SDG outcomes.

Discussion

Ethical leadership and its influence on the financial and sustainability performance of corporations were based on the governance data and SDG-oriented disclosures [17]. Findings demonstrated that ethical leadership positively affected ROA, Tobin and ESG performance that was supported by comprehensive SDG reporting. The constraints were industry-specific focus, quantitative governance measures, time and geographical location and exclusion of other forms of leadership, constraining the generality and deeper understanding. The ethical issues and governance of the use of AI to achieve SDGs on the basis of semi-structured interviews and thematic analysis [18]. The results showed that there were four significant themes, such as ethical issues, barriers to adoption, success factors, and governance bottlenecks. The short sample size of 37 participants, dependence on self-reported qualitative data, possible bias in responses, insufficient geographic range, and limited extrapolation to larger AI implementation settings were limitations.AI-EL and EG enable informed decision-making, predictive risk management, and efficient tracking of the sustainability measurements. Results indicated profound performance improvements in SDGs, indicating practical value to organizations that intend to implement AI-EL, EG, LCS, SC, OC have a large-to-medium effect size, high factor loading and good reliability, exhibiting their usefulness in ensuring sustainable development is achieved.

Conclusion

The research touched on the constraints of traditional leadership models to reach ethical governance and Sustainable Development Goals (SDGs). It explored the potential of AI-enhanced leadership (AI-EL) in reinforcing the culture of governance, sustainability, and commitment to SDG performance in the organization. Structured surveys and semi-structured interviews were used to collect data on 210 managers and executives. Confirmatory Factor Analysis (CFA) confirmed the reliability of the measurements (factor loading 0.74-0.87, AVE 0.61-0.70, CR 0.84-0.90), and Structural Equation Modeling (SEM) tested how AI-EL and EG, LCS and SC, OC are related to SDG performance. SEM outcomes indicated that AI-EL ($\beta = 0.65$, $R^2 = 0.42$), EG ($\beta = 0.60$, $R^2 = 0.38$), LCS ($\beta = 0.70$, $R^2 = 0.49$), SC ($\beta = 0.55$, $R^2 = 0.31$) and OC ($\beta = 0.68$, $R^2 = 0.46$) had significant positive effects on SDG performance with medium-to-large effect sizes ($f^2 = 0.23$–0.35). Generally, the AI-based leadership can significantly enhance ethical governance and organizational sustainability. Several limitations are confined to particular industries, it uses self-reported data, and is restricted to a geographical area and other leadership models are omitted. Future studies must examine various fields, adopt longitudinal studies, and incorporate wider leadership paradigms to enhance the knowledge on the effects of AI-facilitated governance and sustainable development.

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Appendix A

Hypothesis	Question	Likert Scale
(AI-EL) → (SDG)	How does AI-empowered leadership influence the achievement of Sustainable Development Goals (SDGs) within the organization?	1: No influence, 2: Some influence, 3: Significant influence
	What specific aspects of AI leadership (e.g., decision-making, strategic direction, predictive tools) contribute most to achieving SDGs?	1: Not contributing, 2: Moderately contributing, 3: Highly contributing
(EG) → (SDG)	How does ethical governance affect the performance of the organization in achieving SDGs?	1: No effect, 2: Some effect, 3: Significant effect
	What ethical governance practices (e.g., transparency, accountability, fairness) are most impactful in achieving SDGs?	1: Not impactful, 2: Moderately impactful, 3: Highly impactful
(LCS) → (SDG)	How does leadership commitment to sustainability influence SDG performance in the organization?	1: No influence, 2: Some influence, 3: Significant influence
	What forms of leadership commitment (e.g., resource allocation, public support, policy development) are most effective in promoting SDG performance?	1: Not effective, 2: Moderately effective, 3: Highly effective
(SC) → (SDG)	How does stakeholder collaboration impact the achievement of SDGs in the organization?	1: No impact, 2: Some impact, 3: Significant impact
	What types of stakeholder collaboration (e.g., partnerships, customer engagement, and supplier cooperation) are most influential in achieving SDGs?	1: Not influential, 2: Moderately influential, 3: Highly influential
(OC) → (SDG)	How does organizational culture influence the achievement of SDGs?	1: No influence, 2: Some influence, 3: Significant influence
	What cultural elements (e.g., innovation, sustainability mindset, ethical behavior) are most supportive of achieving SDGs?	1: Not supportive, 2: Moderately supportive, 3: Highly supportive