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AI and Robotic Engagement as Catalysts for Mining Industry Sustainability Performance

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ABSTRACT

This study examines the impact of carbon emission reduction, green behaviour, and green economic value on sustainability performance, highlighting artificial intelligence (AI) and robotic engagement as distinct instruments in the Society 5.0 era among Indonesian mining firms during 2022-2025. A quantitative panel data approach is applied using secondary data with purposive sampling, employing the best fit model (CEM, FEM, or REM), supported by classical assumption tests and robust multiple regression standard errors. The results show that carbon reduction, green income, and AI significantly enhance sustainability performance. AI strengthens the effects of carbon reduction and green income, but weakens the role of green employee behaviour. In contrast, robotic engagement has a negative and insignificant moderating effect, leading to the rejection of related hypotheses. This study extends sustainability literature through the Resource-Based View (RBV) by positioning AI as a strategic resource and distinguishing it from robotic engagement. Practically, it suggests firms prioritize AI driven strategies while aligning them with human behaviour to achieve sustainable performance. The novelty lies in a modified proxy model and the separation of AI and robotics as distinct constructs.

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1. INTRODUCTION

The mining industry faces increasing pressure to align financial performance with sustainability accountability in the Industry 5.0 era, where accounting practices are expected to capture not only economic outcomes but also environmental and social impacts. This issue is particularly relevant within the domain of sustainability accounting, which emphasizes the measurement, recognition, and disclosure of non-financial performance alongside traditional financial metrics. Empirical research in accounting that specifically examines the role of artificial intelligence (AI) and robotics in sustainability remains limited, indicating a gap in the scientific development of accounting knowledge. Sustainability reporting has not fully integrated digital technologies in an ethical and transparent manner for stakeholders, creating a discrepancy between operational reality and disclosed information. As a resource- and energy-intensive sector, mining activities generate high carbon emissions, hazardous waste, and land degradation that remain difficult to mitigate and consistently measure within accounting systems (Midde and Rao, 2023). At the same time, the adoption of artificial intelligence (AI) and robotics is transforming industrial processes through autonomous systems, predictive analytics, and precision-based operations, enhancing efficiency and safety (Deloitte, 2023; PwC, 2025). Empirical evidence shows that AI-driven monitoring and robotic automation can reduce energy consumption and workplace risks (Meng and Okwara, 2025; Du et al., 2025). Within the Triple Bottom Line (TBL) framework, these developments relate closely to green income, emission reduction, and green employee behavior as key drivers of sustainability performance (Gómez Gandía et al., 2025; Baltezarević, 2025; Rahim et al., 2025; Singh et al., 2023).

Prior findings remain inconclusive. Some studies confirm that carbon reduction and green innovation improve sustainability performance (Ibishova et al., 2024; Seroka-Stolka, 2023), while others report insignificant effects due to high costs and technological readiness constraints (Acemoglu and Restrepo, 2018; Amoujavadi and Nemati, 2024). The role of green employee behavior is also conditional on organizational support and digital infrastructure (Arshad et al., 2025; Kutaula et al., 2025). These inconsistencies highlight the need for stronger theoretical grounding. This study is anchored in the Natural Resource-Based View (Hart, 1995), which explains how environmental capabilities create competitive advantage; stakeholder theory (Freeman, 1994), which emphasizes responsiveness to stakeholder expectations Baroroh et al., (2025); and legitimacy theory (Dowling and Pfeffer, 1975), which underscores the importance of aligning corporate actions with societal norms. These theories provide a comprehensive lens for understanding how sustainability performance is shaped by environmental actions, economic incentives, and social legitimacy amid digital transformation.

Most prior studies treat AI and robotics as a unified construct, overlooking the distinction between algorithmic intelligence and physical automation (Yang et al., 2024; Yu et al., 2025). This creates a limitation in accounting-based sustainability analysis, particularly in understanding how digital technologies are measured, reported, and linked to firm performance. In addition, prior research predominantly measures environmental, social, and economic aspects using disclosure indices, which often reflect reporting completeness rather than actual sustainability performance. This creates a critical gap, as high disclosure scores do not necessarily indicate real improvements in emission reduction, environmental impact, or economic sustainability outcomes.

Gap of this study develops an integrated framework grounded in the Natural Resource-Based View (Hart, 1995), stakeholder theory (Freeman, 1994), legitimacy theory (Dowling and Pfeffer, 1975), and the Theory of Planned Behavior (Ajzen, 1991). It conceptualizes AI as an intangible strategic resource that enhances data-driven sustainability decisions, while robotic engagement represents tangible operational capabilities. Unlike prior studies relying on perception-based data, this research constructs quantitative proxies for carbon reduction, green income, and robotic engagement using secondary data, thereby strengthening the reliability of sustainability measurement (Dhiman et al., 2024; Song et al., 2025).

Indonesia's mining sector provides a relevant context due to its high environmental exposure and increasing digital transformation (Baltezarević, 2025; World Economic Forum, 2024). Accordingly, this study aims to examine whether AI and robotic technologies can drive the Triple Bottom Line dimensions, environmental, social, and economic, to enhance sustainability performance. The study contributes to the applied accounting literature by providing empirical evidence on how digital technologies can be integrated into sustainability accounting practices and reporting. Furthermore, it offers a conceptual foundation for future research to extend the framework toward a four-bottom line, where technology becomes an integral dimension of sustainability measurement and reporting.

2. METHODS

This study adopts a quantitative research design using panel data to investigate the effects of carbon reduction rate, green employee behavior, and green income on corporate sustainability performance, as well as the moderating roles of sustainable artificial intelligence (EAI) and robotic engagement. The framework is grounded in the Triple Bottom Line perspective, integrating environmental, social, and economic dimensions. Secondary data were collected from annual reports, sustainability reports, ESG disclosures, and financial statements of mining companies listed on the Indonesia Stock Exchange (IDX) for the period 2022-2025. Additional ESG data were obtained from the Katadata ESG Index to ensure consistency and comparability. Purposive sampling was applied based on three criteria: (1) mining firms listed on the IDX during 2022-2025; (2) companies consistently included in the Katadata ESG Index; and (3) firms that did not report negative gross profit during the observation period. Of the 65 listed mining companies, 13 were excluded because they were not included in ESG indices, resulting in a final sample of 52 firms and 208 firm-year observations.

Carbon reduction rate is measured following Yin et al. (2023), modified to capture annual emission reduction progress, calculated as the change in total carbon emissions from year t-1 to year t divided by total emissions in year t. Green employee behavior is proxied using certification levels from the Green Building Council Indonesia (GBCI, 2024), scored from 0 (non-certified) to 4 (Platinum), reflecting structured environmental engagement within the organization. Green income is adapted from Jawadi et al. (2025) and measured as the growth in economic value from year t-1 to year t, divided by the economic value distributed in year t, indicating sustainable economic value creation. Sustainable artificial intelligence is assessed using a text-mining approach adapted from Yu et al. (2025), employing an AI-related keyword dictionary processed with AntConc (2024 version); keyword frequencies are transformed using ln(1 + frequency) to construct a continuous EAI index. Robotic engagement follows Xie et al. (2025) and is calculated using the robotic-to-human ratio derived from corporate disclosures. Sustainability performance is measured using a composite ESG score adapted from the Katadata ESG Index and Damtoft et al. (2025), weighted across environmental (50%), social (20%), and governance and economic (30%) dimensions as suggested by Putryanda and Purnamasari (2025).

Panel regression analysis was conducted using the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). Model selection was performed sequentially through the Chow Test (CEM vs. FEM) and the Hausman Test (FEM vs. REM), followed by the Lagrange Multiplier (LM) Test when REM was indicated. The use of multiple panel estimation models aims to identify the most appropriate specification and to minimize bias arising from unobserved heterogeneity across firms. Classical assumption tests were applied prior to hypothesis testing to ensure the validity of the estimator. To enhance robustness and ensure that results remain

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consistent across different specifications, three additional estimation strategies were employed: (1) robust standard error estimation using heteroskedasticity consistent (White) corrections to address potential variance bias; (2) lagged independent variable estimation to mitigate reverse causality and short-term endogeneity concerns; and (3) alternative variable operationalization by substituting the composite ESG score with its environmental sub-index to verify consistency across sustainability dimensions. These approaches are intended to confirm that the empirical results reported by Griep et al. (2025) and Kan (2025), including the moderating interaction effects of EAI and robotic engagement, are stable, reliable, and not sensitive to model selection or measurement variation. Furthermore, the methodological design and proxy measurements developed in this study provide a practical reference for future researchers employing quantitative approaches with secondary data, particularly in examining sustainability performance and digital technology integration across different sectors and contexts. The table is shown in **Table 1**.

Table.1 Variables measures

Variable	Measurements and Scale	Source
Carbon Reduction Rate	**Ratio** $ERD\ (\%) = \frac{(Emission_{t-1}) - (Emission_t)}{(Emission_t)}$	(Yin et al., 2023)
Green Employee Behaviour	**Ordinal** Score of 4 denotes a Platinum Trophy Score of 3 denotes a Gold Trophy Score of 2 denotes a Silver Trophy Score of 1 denotes a Bronze Trophy	(Valor et al., 2024)
Green Income	**Ratio** $GIC = \frac{(Economic\ \ Generated_t) - (Economic\ \ Generated_{t-1})}{(Economic\ \ Distributed_t)}$	(Jawadi et al., 2025)
Sustainable Artificial Intelligence	**Nominal** $EAI = In(1 + Total\ AI\ Keyword\ Frequency)$	(Yu et al., 2025)
Robotic Engagement	**Ratio** $RBE = \frac{Total\ Number\ of\ Robots\ or\ NonHuman\ Equipment}{Total\ Human\ Workers}$	(Xie et al., 2025)
Sustainability Performance	**Nominal** $Indicator\ Reverse\ Score_{ESG} = 100 - [\left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right) 100]$ $SPR = 50\% Environmental + 20\% Social + 20\% Governance$	(Putryanda and Purnamasari, 2025)

3. RESULTS AND DISCUSSION

3.1. Statistic Descriptive

Based on the results of the data processed of the total amount of samples, the analysis with multiple linear regression using EViews13, in general, the 2 descriptive statistics can be seen in **Table 2**.

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Table 2. Statistic descriptive summary

Variables	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis
SPR	5.897	5.952	8.158	3.579	9.913	-0.271	2.690
ERD	0.039	0.043	0.083	0.012	0.013	0.298	3.038
GEB	3.129	3.000	4.000	1.000	0.796	-0.622	2.858
GIC	2.137	1.290	8.400	0.540	2.334	1.333	3.550
AIE	1.248	1.255	1.681	0.778	0.209	-0.059	2.266
RBE	0.011	0.009	0.040	0.001	0.007	1.092	4.665
Observations					208		

Source: Processed Data

Note: SPR: Sustainability Performance; ERD: Carbon Reduction Rate; GEB: Green Employee Behavior; GIC: Green Income; AIR: Sustainable Artificial Intelligence; RBE: Robotic Engagement

The sustainability performance (SPR) variable, serving as the dependent variable, recorded a minimum value of 3.579 for PT Super Energy Tbk and PT Ifishdeco Tbk in 2022. This result reflects weak sustainability performance, characterized by low operational efficiency, high environmental impact, and limited social contribution. Conversely, the maximum value of 8.158 was achieved by PT Bukit Asam Tbk in 2022, a state-owned coal mining company demonstrating outstanding sustainability performance through energy and water efficiency, implementation of the 3R program (reduce, reuse, recycle) in waste management, biodiversity conservation, and recognition with the Gold Rank Award by Indonesia's Ministry of Environment and Forestry.

The mean SPR value was 5.897, indicating that the majority (81%) of mining companies in the sample exhibit good sustainability implementation: 100 observations scored above 50, and only 24 scored below 50. The skewness value of -0.271 indicates a left-skewed distribution, suggesting slightly more firms with above-average scores, while the kurtosis of 2.690 (close to 3) denotes a near-normal distribution that is neither too peaked nor too flat. The standard deviation of 9.913, which is lower than the mean (58.970), indicates that the data are relatively homogeneous, with low variation across firms.

For the carbon reduction rate variable, which acts as an independent variable, the minimum value of 0.012 was found for PT Golden Energy Mines Tbk in 2023, due to limited progress in the clean energy transition, as operations remained heavily dependent on large-scale coal production and combustion. The maximum value of 0.083 (8.3%) was achieved by PT Super Energy Tbk in 2024, attributed to enhanced operational efficiency and expanded use of gas and renewable energy sources. The mean of 0.039 suggests that carbon-reduction levels among Indonesian mining firms remain relatively low, with a standard deviation of 0.013, indicating homogeneity in emission-reduction performance. The skewness of 0.298 (right-skewed) indicates that a few companies achieved higher-than-average reduction rates, while the kurtosis of 3.038 indicates a leptokurtic distribution that is still near-normal.

Regarding the green employee behavior (GEB) variable, the minimum score of 1.000 was recorded by PT Resources Alam Indonesia Tbk, PT RMK Energy Tbk, PT Cita Mineral Investindo Tbk, and PT Kapuas Prima Coal Tbk in 2022, all of which obtained a Bronze rating from the Green Building Council Indonesia (GBCI). This reflects the absence of strategic internal policies supporting green workplace behavior at that time. The maximum score of 4.000 was achieved by 44 observations (35.4%) representing companies with Platinum certification between 2022 and 2025. The mean value of 3.129 indicates a generally good level of employee environmental awareness and engagement, with 56 samples achieving a Gold rating. The standard deviation of 0.796, lower than the mean, suggests data homogeneity. The skewness value of -0.622 (left-skewed) indicates that

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most companies scored high on GEB, while the kurtosis of 2.858 (close to 3) denotes an approximately normal distribution.

For the green income (GIC) variable, the minimum value of 0.540 was observed in PT Super Energy Tbk (2022), corresponding to a green income of IDR 709 billion, whereas the maximum value of 8.400 was recorded for PT Bumi Resources Tbk (2022), which achieved a green income of IDR 84 trillion. The mean value of 2.137 indicates that most companies have begun to realize economic benefits from sustainable initiatives. The relatively high standard deviation (2.334) indicates greater variability across firms. The positive skewness (1.333) reveals a right-skewed distribution, suggesting that most companies have low GIC values while a few have very high ones. The kurtosis value of 3.550 (>3) indicates a leptokurtic distribution with some extreme observations, although still within the acceptable range of normality.

The sustainable artificial intelligence (AIE) variable ranges from 0.778 for PT Kapuas Prima Coal Tbk (2022) to 1.681 for PT Indika Energy Tbk (2025). The latter company demonstrated stronger AI integration within its operational and sustainability strategies, while the former remained in the early stages of digital transformation with limited infrastructure for AI adoption. The mean value of 1.248 indicates a relatively high and stable level of AI adoption across the sample, supported by a low standard deviation (0.209), implying homogeneity in AI disclosure. The skewness of -0.059 suggests a slightly left-skewed distribution, while the kurtosis of 2.266 indicates a platykurtic distribution, flatter and more evenly spread, with few extreme values.

The robotic engagement (RBE) variable recorded a minimum value of 0.001 for PT Darma Henwa Tbk (2022), indicating minimal robotic integration due to a high reliance on manual labor. Conversely, the maximum value of 0.040 was found for PT Super Energy Tbk (2025), which had significantly advanced automation initiatives, employing approximately 8-10 robotic units with a relatively small workforce (200 employees). The mean value of 0.011 indicates that the average level of robotic adoption remains low within Indonesia's mining sector. The relatively high standard deviation (0.007) compared to the mean (0.011) denotes moderate variation in adoption levels. The positive skewness (1.092) shows that most companies have low robotic engagement, while a few have high levels of adoption. The kurtosis of 4.665 (>3) indicates a leptokurtic distribution with a sharp peak and extreme outliers, suggesting substantial disparities in robotic technology implementation across mining firms.

3.2. Model Selected Test

Robust model selection is conducted using panel data procedures. The Chow test is first applied to compare the Common Effect Model (CEM) and the Fixed Effect Model (FEM). If FEM is preferred, the Hausman test is subsequently employed to determine whether FEM or the Random Effect Model (REM) is more appropriate. A Hausman significance value below 0.05 indicates that FEM is consistent and selected, whereas a value above 0.05 supports the use of REM. To ensure robustness, three estimation models are specified.

1st Estimate → $SPR = \alpha + \beta1ERD + \beta2GEB + \beta3GIC + \beta4EAI + \varepsilon$

2nd Estimate → $SPR = \alpha + \beta1ERD + \beta2GEB + \beta3GIC + \beta4RBE + \varepsilon$

3rd Estimate → $SPR = \alpha + \beta1ERD + \beta2GEB + \beta3GIC + \beta4EAI + \beta5RBE + \beta6ERD \times EAI \times \beta7GEB \times EAI + \beta8GIC \times EAI + \beta9ERD \times RBE + \beta10GEB \times RBE + \beta11GIC \times RBE + \varepsilon$

The Chow test results are shown in **Table 3**.

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Table.3 Chow test

Estimate	Effects Test	Statistic	d.f	Prob	Interpretation
1st	Cross-section F	11.675909	(30,89)	0.0000	Fixed Effect Model
	Cross-section Chi-square	195.965312	30	0.0000	(FEM) is selected
2nd	Cross-section F	12.410393	(30,89)	0.0000	Fixed Effect Model
	Cross-section Chi-square	204.034286	30	0.0000	(FEM) is selected
3rd	Cross-section F	10.483396	(30,82)	0.0000	Fixed Effect Model
	Cross-section Chi-square	195.419233	30	0.0000	(FEM) is selected

Source: Processed Data

The results of the Chow test indicate that the p-values for all models (p-value = 0.0000 < 0.05) indicate a significant difference across entities (companies) in the panel data. Therefore, the Fixed Effect Model (FEM) is more appropriate than the Common Effect Model (CEM), as FEM can capture the influence of unobserved heterogeneity and the unique characteristics specific to each company that cannot be directly observed. This finding suggests that each firm possesses a distinct intercept, which significantly affects the relationship between the independent and dependent variables. The table is shown in **Table 4**.

Table.4 Housman test

Estimate	Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f	Prob	Interpretation
1st	Cross-section random	20.664710	4	0.0004	Fixed Effect Model (FEM) is selected
2nd	Cross-section random	26.626953	4	0.0000	Fixed Effect Model (FEM) is selected
3rd	Cross-section random	27.201304	11	0.0043	Fixed Effect Model (FEM) is selected

Source: Processed Data

The results of the Hausman test reveal a Chi-square value of 20.6647 with 4 degrees of freedom (d.f.) and a probability value of 0.0004 for Model 1, a Chi-square value of 26.6269 with 4 (d.f.) and a probability value of 0.0000 for Model 2, and a Chi-square value of 27.2013 with 11 (d.f.) and a probability value of 0.0043 for Model 3 (combined model). All probability values are below the 0.05 significance threshold, indicating a systematic difference between the coefficients of the Fixed Effect Model (FEM) and the Random Effect Model (REM). The Fixed Effect Model (FEM) is deemed the most appropriate estimation approach, as it effectively captures unobserved heterogeneity across firms and yields consistent parameter estimates. This result implies that firm-specific effects are correlated with the explanatory variables, confirming that the FEM is the most suitable model for panel data analysis in this study, particularly within the combined Model 3 framework used to test the research hypotheses.

3.3. Classical Assumption Test

This study conducted a series of classical assumption tests, including normality, heteroskedasticity, multicollinearity, and autocorrelation tests, prior to hypothesis testing. The purpose of these diagnostic tests is to ensure that the dataset satisfies the regression model assumptions and that the estimated parameters are reliable, unbiased, and efficient. The results of these tests are summarized in **Table 5**.

Table.5 Classical assumption test

Tests	Standard		Results	Summary
Normality Test (Jarque-Bera)	Probability value > 0.05		0.642	Normally distributed
Autocorrelation Test (Durbin-Watson)	dL<dU<DW<4-dU<4-dL		1.806	Autocorrelation Free
Multicollinearity Test (Variance Inflation Factor)	Centered VIF < 10	ERD	1.250	Multicollinearity Free
		GEB	5.770	
		GIC	5.887	
		EAI	8.249	
		RBE	6.183	
		ERD*EAI	7.047	
		GEB*EAI	4.602	
		GIC*EAI	3.486	
		ERD*RBE	4.794	
		GEB*RBE	7.686	
		GIC*RBE	4.641	
Heteroscedasticity test (Breusch Pegan Godfrey)	Prob Chi-Square (110 < 0.05		0.747	Heteroscedasticity Free

Source: Processed Data

The normality test using the Jarque-Bera method yielded a test statistic of 0.884877 and a p-value of 0.642468, both of which are greater than the significance level of 0.05. This result indicates that the residuals are normally distributed, meaning the regression model satisfies the normality assumption. Consequently, the residuals are random and exhibit no systematic pattern, ensuring that the parameter estimates are valid for subsequent hypothesis testing.

The Durbin-Watson statistic of 1.806, which lies within the acceptable range of 1.6240 < 1.7914 < 1.806 < 2.208 < 2.376, indicates that the regression model is free from autocorrelation. This suggests that the residuals across periods are random and independent, thus confirming the model's suitability for further hypothesis testing.

The multicollinearity test results show that all independent variables have Centered Variance Inflation Factor (VIF) values below 10, ranging from 1.25 to 8.25. These values fall within the acceptable tolerance threshold (VIF < 10), indicating no serious multicollinearity issues among the independent variables. Hence, each independent variable uniquely explains variations in sustainability performance without excessive mutual influence, implying that the regression model satisfies the independence assumption and can be used for valid hypothesis testing.

The heteroskedasticity test results reveal that the Prob. F (0.4006), Prob. Chi-Square (Obs*R-squared = 0.3878), and Prob. Scaled Explained SS (0.7473) values all exceed the 0.05 significance level. This finding indicates that the model does not suffer from heteroskedasticity, meaning the residual variance is homogeneous across observations. Therefore, the model satisfies the homoskedasticity assumption, ensuring that the estimated parameters are efficient and unbiased.

3.4. Hypothesis Test

The results of the hypothesis test using the fixed-effect model indicate that the independent variables, when examined simultaneously, have a significant influence on corporate sustainability performance, as shown in the following analysis.

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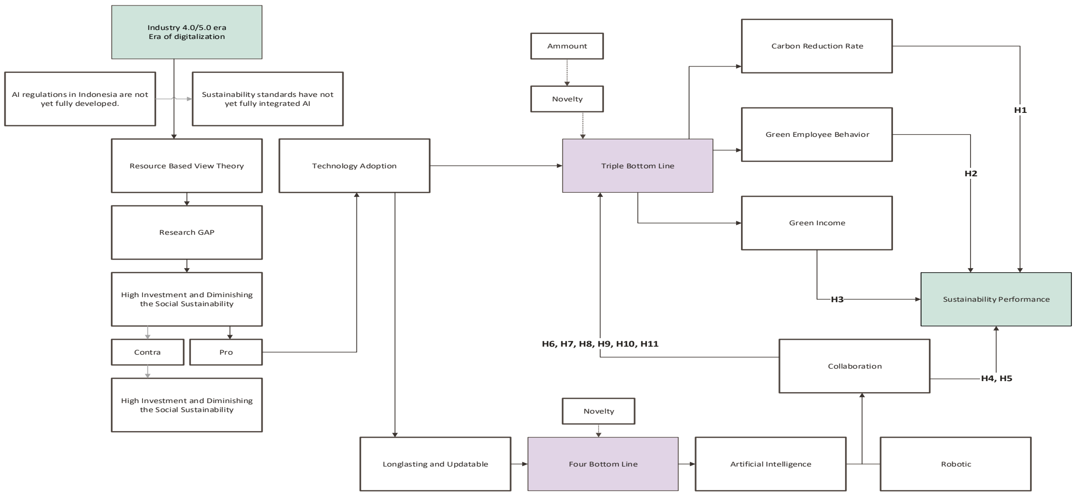
The conceptual framework posits that Artificial Intelligence (AI) adoption serves as a strategic capability enabling banks to enhance operational efficiency, data-driven decision-making, risk management, and innovation capacity. These improvements are expected to strengthen sustainability performance across the four dimensions of the Four Bottom Line (4BL): profit, people, planet, and technology. AI contributes to sustainable economic value creation through greater efficiency and financial performance (profit), supports workforce productivity and human capital development (people), promotes resource optimization and environmental responsibility (planet), and reinforces continuous innovation and digital transformation capabilities (technology). This study argues that AI functions not merely as an operational tool but as a distinct sustainability pillar that generates multidimensional value. By positioning technology as an independent dimension alongside economic, social, and environmental objectives, the framework extends the traditional Triple Bottom Line perspective toward a Four Bottom Line approach that better reflects the sustainability challenges and opportunities of the digital era. The integrated framework is illustrated in **Figure 1**.



Source: Author Design by Ms. Visio

Figure 1. Integrated Framework of Research Findings

Table 6. Hypothesis test

One Tailed	Variable	Coef	Std. Error	t-Statistic	Prob.	Result
H1	ERD →SPR	85.03205	42.13935	2.017878	0.0234*	Supported
H2	GEB → SPR	-1.142527	1.535067	-0.744285	0.2294	Reject
H3	GIC → SPR	0.882355	0.397293	2.220917	0.0145*	Supported
H4a	EAI → SPR	82.32268	35.03576	2.349676	0.0106*	Supported
H4b	RBE → SPR	-39.61794	15.88780	-2.493609	0.0073*	Contradict
H5a	ERD*EAI → SPR	613.3026	183.4907	3.342418	0.0006*	Supported
H6a	GEB*EAI → SPR	-8.209380	4.889395	-1.679018	0.0485*	Contradict
H7a	GIC*EAI → SPR	0.034449	0.300636	0.114586	0.0451*	Supported
H5b	ERD*RBE → SPR	2324.940	4202.259	0.553260	0.2908	Reject
H6b	GEB*RBE → SPR	-3.628368	3.383179	-1.072473	0.0286*	Contradict
H7b	GIC*RBE → SPR	-20.40040	22.07043	-0.924332	0.0358*	Contradict
	Adjusted R-squared				0.8783	
	Prob (F-statistic)				0.0000	

Source: Processed Data

Note: SPR: Sustainability Performance; ERD: Carbon Reduction Rate; GEB: Green Employee Behavior; GIC: Green Income; AIR: Sustainable Artificial Intelligence; RBE: Robotic Engagement

Based on the results in **Table 6**, The findings demonstrate that sustainability performance is shaped by the interaction of environmental effectiveness, economic value creation, and digital technological capabilities within an integrated sustainability framework. Carbon reduction rate shows a positive and significant effect on sustainability performance, Meiyanti and Adhariani, (2025) confirming that measurable emission reduction constitutes a substantive driver of sustainability rather than symbolic disclosure. This result reinforces the natural resource-based view (Hart, 1995), which holds that environmental capabilities are strategic assets that enhance long-term competitiveness (Singh et al., 2023; Seroka-Stolka, 2023). Empirical evidence indicates that firms achieving higher levels of emission reduction simultaneously strengthen operational efficiency, regulatory compliance, and reputational capital. Legitimacy theory (Dowling and Pfeffer, 1975) and stakeholder theory (Freeman, 1994) provide additional explanatory power, as emission reduction strengthens societal acceptance and stakeholder trust, which subsequently translate into improved sustainability outcomes (Arogundade et al., 2023; Baltezarević, 2025; Sharaf-Addin, 2024). These findings reject the notion that disclosure-based sustainability proxies adequately represent real environmental performance, emphasizing the importance of outcome-based measurement.

Green employee behavior exhibits no significant influence on sustainability performance, reflecting a structural disconnect between individual-level pro-environmental actions and organizational-level outcomes. The theory of planned behavior (Ajzen, 1991) conceptualizes behavior as a function of intention, subjective norms, and perceived control (Tang et al., 2023), yet empirical results indicate that behavioral intention alone lacks sufficient power to influence sustainability performance without institutional reinforcement. Organizational mechanisms such as governance systems, performance incentives, and sustainability-oriented culture determine the extent to which individual behavior can be translated into measurable outcomes (Arshad et al., 2025; Valor et al., 2025; Pratiwi et al., 2025). This finding highlights a critical limitation within prior literature that overemphasizes behavioral dimensions while underestimating structural enablers. Sustainability performance emerges from systemic alignment rather than isolated behavioral initiatives.

Green income demonstrates a positive and significant effect on sustainability performance, indicating that economic value Rari Dwi et al., (2025) derived from environmentally oriented activities contributes directly to sustainability achievements. This evidence positions sustainability as a value-generating mechanism rather than a compliance cost. Stakeholder theory (Freeman, 1994) explains that market responses to green products and services strengthen legitimacy and reinforce sustainable strategies (Alsayegh et al., 2020; Cuong et al., 2025; Rahman et al., 2025). Efficient allocation of environmentally related financial resources enhances both economic and environmental outcomes, supporting the argument that sustainability integration improves resource optimization and long-term value creation. This finding addresses inconsistencies in prior studies by demonstrating that the effectiveness of green income depends on its strategic management and alignment with sustainability objectives (Kumar et al., 2025; Meng and Okwara, 2025).

Sustainable artificial intelligence emerges as a central driver of sustainability performance, exerting a positive, significant direct effect while strengthening relationships between environmental and economic variables. AI functions as a digital capability that enhances emission monitoring, energy optimization, and decision-making accuracy through data-driven processes (Dhiman et al., 2024; Bolón-Canedo et al., 2024; Song et al., 2025). The integration of AI extends the natural resource-based view by incorporating digital resources as critical strategic assets. The significant interaction between AI and carbon reduction confirms that digital technologies amplify environmental effectiveness, while the interaction with green income indicates improved economic optimization within sustainability initiatives. A negative interaction between AI and green employee

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behavior reveals a misalignment between technological systems and human capability. Limited digital competence, insufficient training, and weak integration frameworks reduce the effectiveness of behavioral contributions (Pratiwi et al., 2025; Arshad et al., 2025). These findings indicate that technological capability requires complementary human and organizational readiness to generate optimal sustainability outcomes.

Robotic engagement has a negative, significant effect on sustainability performance and weakens the influence of sustainability drivers. This result challenges deterministic assumptions regarding the positive role of automation in sustainability. Empirical evidence indicates that robotic implementation often prioritizes operational efficiency over environmental and social objectives, leading to unintended negative consequences (Acemoglu and Restrepo, 2018; Du et al., 2025). Stakeholder resistance, workforce displacement concerns, and high implementation costs reduce legitimacy and weaken sustainability outcomes (Cheng, 2025; Midde and Rao, 2023). The negative moderation effects suggest that excessive automation reduces the contribution of human-centered sustainability practices and diminishes the economic benefits derived from green income. Theoretical perspectives emphasize that technological adoption must align with stakeholder expectations and organizational readiness to generate positive outcomes (Dowling and Pfeffer, 1975; Freeman, 1994). Robotics, therefore, represents a contingent factor whose impact depends on strategic alignment, social acceptance, and sustainability-oriented implementation.

These findings collectively support a conceptual transition from the traditional triple bottom line to a four-bottom-line framework. Economic, environmental, and social dimensions remain fundamental, while technology emerges as an embedded and inseparable component of sustainability. Technology functions not as an external enabler but as an internalized dimension that reshapes sustainability processes, measurement systems, and performance evaluation. The four-bottom-line framework reflects the structural transformation of sustainability in the digital era, where technological capability determines the effectiveness of sustainability integration (Yang et al., 2024).

The implications for the accounting discipline are substantial (Kurniawati, 2025). The expansion of digital technologies has generated concerns regarding the displacement of accounting functions. Empirical evidence from this study demonstrates an alternative trajectory characterized by adaptation rather than substitution. Accounting evolves into an integrative information system that incorporates financial, environmental, social, and technological data within a unified reporting structure. The presence of artificial intelligence enhances data processing capacity, improves measurement accuracy, and enables real-time sustainability reporting. These developments strengthen the relevance of accounting by expanding its analytical scope and decision-support capabilities.

Technology serves as a collaborative tool in accounting. Artificial intelligence, data analytics, and digital systems support the identification, measurement, and disclosure of sustainability performance without eliminating the foundational principles of accounting (Kutaula et al., 2025). The integration of technology within the four bottom line framework positions accounting as a central mechanism for translating complex sustainability phenomena into structured and decision-useful information. This transformation reinforces accounting as an adaptive discipline capable of responding to technological disruption while maintaining its core epistemological foundation.

The continuity of accounting knowledge depends on its ability to integrate technological advancements into its conceptual and practical frameworks. Adaptation replaces displacement as the dominant paradigm. Accounting maintains its relevance by incorporating digital capabilities that enhance transparency, accountability, and sustainability measurement. The discipline retains its foundational role in supporting economic decision-making while expanding its scope to address environmental and social challenges within a technologically embedded context.

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The Adjusted R-squared value of 0.8783 indicates that 87.83% of the variation in corporate sustainability performance is explained by the independent variables in the model. This demonstrates that the model possesses strong explanatory power, while the remaining 12.17% of the variation is attributed to other factors not captured in this study, such as government policies, global market pressures, or non-digital innovations. Moreover, the Prob (F-statistic) value of 0.0000 (< 0.05) confirms that the regression model is statistically significant as a whole, meaning that all independent variables jointly exert a significant influence on sustainability performance. Therefore, the model exhibits a high level of goodness-of-fit and provides strong empirical relevance in explaining the relationship between digital sustainability drivers (artificial intelligence and robotic engagement) and corporate sustainability performance.

4. CONCLUSION

This study demonstrates that carbon emission reduction and green income are key determinants of sustainability performance, supported by their positive and significant effects. Artificial intelligence (AI) strengthens these relationships by improving monitoring accuracy, resource efficiency, and environmental decision-making. AI acts as a strategic enabler, amplifying the effectiveness of carbon reduction and green income. In contrast, green employee behavior does not significantly influence sustainability performance, suggesting that individual initiatives require robust organizational systems to yield measurable outcomes. Robotic engagement shows a negative direct effect, weakening the contribution of sustainability drivers, suggesting that its current implementation remains efficiency-oriented rather than sustainability-driven.

The findings indicate that sustainability improvement depends on effective collaboration between AI and robotics to reduce carbon emissions and enhance sustainability performance. Both technologies contribute to emission reduction and green income. However, robotics may increase emissions when not properly managed or aligned with environmental objectives. The presence of AI and robotics does not, in itself, automatically strengthen green employee behavior without robust environmental management. Integrated governance is required to align technology with sustainability goals. Regulatory frameworks become the primary driver, emphasizing the need for ethical standards on AI and robotic use. The Global Reporting Initiative (GRI) should expand reporting standards by incorporating technological dimensions within the four bottom lines. This study is limited by inconsistent sustainability disclosures and its focus on the mining sector. Future research should expand cross-sector samples, develop the four bottom line framework, and apply more robust methods, including endogeneity testing.

REFERENCES

Acemoglu, D., and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Alsayegh, M. F., Rahman, R. A., and Homayoun, S. (2020). Corporate economic, environmental, and social sustainability performance transformation through ESG disclosure. *Sustainability (Switzerland)*, *12*(9). https://doi.org/10.3390/su12093910

Amoujavadi, S., and Nemati, A. (2024). Developing sustainability, resiliency, agility, and security criteria for cloud service providers' viability assessment: A comprehensive hierarchical structure. *Sustainable Futures*, *7*. https://doi.org/10.1016/j.sftr.2024.100219

DOI: https://doi.org/10.17509/jaset.v18i1
p- ISSN 2086-2563 e- ISSN 2541-0342

Arogundade, S., Dulaimi, M., and Ajayi, S. (2023). Holistic review of construction process carbon-reduction measures: A Systematic Literature Review Approach. *Buildings*, *13*(7). https://doi.org/10.3390/buildings13071780

Arshad, M., Zhang, K., Khan, M., Khan, M. S., and Sulaiman, R. (2025). Fostering employee green behavior through inclusive leadership: Roles of sustainable HRM practices and commitment to organizational change. *Journal of Organizational Change Managemen, 38*(5), 983-1001. https://doi.org/10.1108/JOCM-10-2024-0650

Baltezarević, R. (2025). AI robotics' contribution to sustainable development. *Bilsel International Ahlat Scientific Researches*. https://bilselkongreleri.com/

Baroroh, N., Yanto, H., Intan Pertiwi, M., Widya Ningrum, M., and Fikri Luthfi, M. (2025). The impacts of stakeholder pressure, profitability, and audit committee on the quality of sustainability reports. *Jurnal ASET (Akuntansi Riset)*, *1*(17), 001–014. https://doi.org/10.17509/jaset.v17i1.75264

Bolón-Canedo, V., Morán-Fernández, L., Cancela, B., and Alonso-Betanzos, A. (2024). A review of green artificial intelligence: Towards a more sustainable future. *Neurocomputing, 599*. https://doi.org/10.1016/j.neucom.2024.128096

Cheng, C.-F. (2025). Love–hate tango: Exploring the efficacy of human–machine interaction in service robots. *Journal of Intellectual Capital*, *27*(2),353-371. https://doi.org/10.1108/jic-01-2025-0020

Cuong, T., Minh, D. H., and Chinh, T. T. Q. (2025). Does stakeholder pressure enhance sustainable performance? Mediating role of corporate social responsibility, circular economy practices, and Sustainable Supply Chain Management. *WSEAS Transactions on Business and Economics*, *22*, 962–978. https://doi.org/10.37394/23207.2025.22.80

Damtoft, N. F., van Liempd, D., & Lueg, R. (2025). Sustainability performance measurement – a framework for context-specific applications. *Journal of Global Responsibility*, *16*(1), 162–201. https://doi.org/10.1108/JGR-05-2023-0082

Deloitte. (2023): The top 10 issues transforming the future of mining. *Deloitte Insights*. https://www2.deloitte.com

Dhiman, R., Miteff, S., Wang, Y., Ma, S.-C., Amirikas, R., and Fabian, B. (2024). Artificial intelligence and sustainability – A review. *MDPI*, *3*(1), 140–162. https://doi.org/10.20944/preprints202312.2117.v1

Dowling, J., and Pfeffer, J. (1975). Organizational legitimacy: Social values and organizational behavior. *The Pacific Sociological Review*, *18*(1), 122–136. https://doi.org/10.2307/1388226

Du, H., Chan, L., Tong, J., Raad, R., Naghdy, F., Guo, Q., Yu, Y., Islam, M. R., Tubbal, F., Ros, M., Li, Z., and Ritz, C. (2025). Industrial progress of robotic automation in mining applications: A survey. *In Mining, Metallurgy and Exploration, 42*(2), 537-556. https://doi.org/10.1007/s42461-025-01219-y

Freeman, R. E. (1994). The politics of stakeholder theory: Some future directions. *Business Ethics Quarterly, 4*(4), 409–421. https://doi.org/10.2307/3857340

Gómez Gandía, J. A., Gavrila Gavrila, S., de Lucas Ancillo, A., and del Val Núñez, M. T. (2025). Towards sustainable business in the automation era: Exploring its transformative impact from top management and employee perspective. *Technological Forecasting and Social Change, 210*. https://doi.org/10.1016/j.techfore.2024.123908

Griep, Y., Hansen, S. D., Kraak, J. M., Sherman, U., and Bankins, S. (2025). Sustainable human resource management: The good, the bad, and making it work. *Organizational Dynamics*, *54(2)*. https://doi.org/10.1016/j.orgdyn.2024.101112

Hart, S. L. (1995). A natural-resource-based view of the firm. *The Academy of Management Review, 20*(4), *986–1014*. https://doi.org/10.2307/258963

Ibishova, B., Misund, B., and Tveterås, R. (2024). Driving green: Financial benefits of carbon emission reduction in companies. *International Review of Financial Analysis, 96*. https://doi.org/10.1016/j.irfa.2024.103757

Jawadi, F., Pondie, T. M., and Cheffou, A. I. (2025). New challenges for green finance and sustainable industrialization in developing countries: A panel data analysis. *Energy Economics, 142.* https://doi.org/10.1016/j.eneco.2024.108120

Kumar, P., Kaur, R., Radulescu, M., Kalaš, B., and Hagiu, A. (2025). Drivers of environmental sustainability, economic growth, and inequality: A study of economic complexity, FDI, and human development role in BRICS+ nations. *Sustainability (Switzerland), 17*(9). https://doi.org/10.3390/su17094180

Kan, Y. (2025). AI for environmental sustainability: Advances, challenges, and future directions. *International Journal of Artificial Intelligence for Science (IJAI4S)*, *1*(1). https://doi.org/10.63619/ijais.v1i1.006

Kurniawati, A. D. (2025). Revealing sustainability performance: A content analysis of sustainability reporting from big four indonesian banking institutions*, In Proceedings of the 12th Gadjah Mada International Conference on Economics and Business (GAMAICEB 2024)* (pp. 46–60). Atlantis Press. https://doi.org/10.2991/978-94-6463-692-5_4

Kutaula, S., Chowdhury, S., Gillani, A., Budhwar, P. S., and Dey, P. K. (2025). Linking HRM with sustainability performance through sustainability practices: Unlocking the black box. *British Journal of Management, 36*(2), 615–632. https://doi.org/10.1111/1467-8551.12861

Meiyanti, F., and Adhariani, D. (2025). ESG reputation risk, corporate risk-taking, and climate impact in southeast asia. *Jurnal ASET (Akuntansi Riset), 2*(17), 313–324. https://doi.org/10.17509/jaset.v17i2

Meng, Q., and Okwara, U. K. (2025). Sustainable provider selection for artificial intelligence-powered robotic systems: A framework and evaluating methodology. *Business Process Management Journal*. https://doi.org/10.1108/BPMJ-03-2025-0290

Midde, S., and Rao, G. V. V. J. (2023). The Role of Robotics Technology for a Future Sustainability. *International Journal of Creative Research Thoughts (IJCRT), 11*, 607. https:// www.ijcrt.org

Pratiwi, I., Saefudin, A., Sari, G. I., Maliki, B. I., Fauzi, Soenyono, Basrowi, and Nuryanto, U. W. (2025). Green human capital and organizational performance: The role of employee environmental awareness and sustainable innovation in achieving organizational sustainability. *Innovation and Green Development, 4*(3). https://doi.org/10.1016/j.igd.2025.100244

PricewaterhouseCoopers (PwC). (2025). Mine 2025: The era of intelligent mining. *PwC Global Mining Report*. https://www.pwc.com/mine2025

Putryanda, and Purnamasari, F. (2025). *Katadata ESG index 2025.* Katadata Corporate Sustainability Index Summary Report. https://databoks.katadata.co.id/publikasi/2025/09/09/katadata-esg-index-2025

Rahim, A., Rosid, M. H. O., and Islam, M. F. (2025). Conceptualizing the drivers of sustainable competitive advantage: a qualitative exploration on fintech adoption, sustainability performance and employee green behavior. *Qualitative Research in Financial Markets*. https://doi.org/10.1108/QRFM-09-2024-0261

Rahman, M. A., Shaon, S. H., and Islam, S. (2025). Trust over ease? Examining the mediated effects of profitability on AI adoption in accounting. *Technological Sustainability*, *4*(4), 402–423. https://doi.org/10.1108/techs-05-2025-0098

Rari Dwi, D. R., Mulyani Azis, Y., and Heryana, T. (2025). Does Green Finance Influence the Relationship Between Sustainability Disclosure and Firm Performance? *Jurnal ASET (Akuntansi Riset)*, *2*(17), 379–388. https://doi.org/10.17509/jaset.v17i2

Seroka-Stolka, O. (2023). Enhancing environmental sustainability: Stakeholder pressure and corporate CO2-related performance an examination of the mediating and moderating effects of corporate decarbonization strategies. *Sustainability (Switzerland), 15*(19). https://doi.org/10.3390/su151914257

Sharaf-Addin, H. H. (2024). Towards net-zero carbon emissions: A systematic review of carbon sustainability reporting based on GHG protocol framework. *In Environmental and Sustainability Indicators, 24.* https://doi.org/10.1016/j.indic.2024.100516

Singh, N., Sharma, R. L., and Yadav, K. (2023). Sustainable development by carbon emission reduction and its quantification: An overview of current methods and best practices. *Asian Journal of Civil Engineering, 24*(8), 3797–3822. https://doi.org/10.1007/s42107-023-00732-z

Song, Y., Mi, L., Bian, Z., Tu, W., and He, J. (2025). How does artificial intelligence impact corporate ESG performance? The catching up effect of digital technological innovation. *Journal of Innovation and Knowledge, 10*(6), 100843. https://doi.org/10.1016/j.jik.2025.100843

Tang, G., Ren, S., Wang, M., Li, Y., and Zhang, S. (2023). Employee green behaviour: A review and recommendations for future research. *International Journal of Management Reviews, 25*(2), 297–317. https://doi.org/10.1111/ijmr.12328

Valor, C., Redondo, R., and Carrero, I. (2025). Workplace greenery and employee green behavior: a moderated-mediation model. *Management Research Review, 48*(5), 726–745. https://doi.org/10.1108/MRR-07-2024-0562

World Economic Forum (WEF). (2024). Mining and metals in a sustainable world 2050. *World Economic Forum.* https://www.weforum.org/reports/mining-and-metals-in-a-sustainable-world

Xie, Y., Zhao, L., Zhang, Y., and Wang, Z. (2025). How do robot applications affect corporate sustainability?—An analysis based on environmental, social, and governance performance. *Sustainability (Switzerland), 17*(5). https://doi.org/10.3390/su17051822

Yang, X., Ren, Z., and Xie, Y. (2024). The effect of artificial intelligence technology on corporate greenwashing level: Evidence from chinese listed enterprises*. Transactions on Economics, Business and Management Research, 9,* 2960–2254. https://doi.org/10.62051/j74rpn53

Yin, F., Xiao, Y., Cao, R., & Zhang, J. (2023). Impacts of ESG Disclosure on Corporate Carbon Performance: Empirical Evidence from Listed Companies in Heavy Pollution Industries. *Sustainability (Switzerland)*, *15*(21). https://doi.org/10.3390/su152115296

Yu, X., Fan, L., and Yu, Y. (2025). Artificial intelligence and corporate ESG performance: A mechanism analysis based on corporate efficiency and external environment. *Sustainability (Switzerland), 17*(9). https://doi.org/10.3390/su17093819

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