

ESG and AI: the Role of a new Player in the Sustainability's Game

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Abstract

The study explores the relationship between AI adoption and ESG performance, addressing a gap in literature. AI enhances sustainability by improving environmental monitoring, optimizing resource allocation, and fostering circular economy initiatives. Socially, AI promotes diversity and workplace well-being through advanced algorithms, while in governance, it strengthens oversight, risk assessment, and compliance. Using Bloomberg data on U.S. and Western European companies, the study tests whether ethical AI policies impact ESG scores. The results confirm a significant positive effect, suggesting that responsible AI adoption strengthens corporate transparency, investor trust, and decision-making.

Keywords: AI, ESG, Listed companies, USA and Western Europe

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1. Introduction

This study aims to explore the interconnection between artificial intelligence (AI) and environmental, social, and governance (ESG) practices. Despite the broad academic interest in both fields, few studies directly analyze this relationship (Zhang & Yang, 2024). Our research aims to fill this gap by investigating whether companies' adoption of AI impacts their sustainability performance (ESG). Moreover, we want analyse if the adoption of ethical guidelines and policies related to the use, design, and development of Artificial Intelligence (AI) has a positive and significant impact on sustainability performance as measured by the ESG Score.

ESG practices are now central to many companies, given the growing awareness of sustainability issues and regulatory and social pressure (Bifulco et al., 2023). On the other hand, AI represents one of the most promising technologies for transforming and improving business processes and strategic decisions. However, as Nishant et al. (2020) and Vinuesa et al. (2020) point out, the intersection between AI and ESG is not yet fully understood, despite its potential to revolutionize how companies approach sustainability.

The study examines the impact of ethical policies on AI use on ESG performance, using Bloomberg data on 348 companies in the US and Western Europe. The analysis shows that companies with ethical AI guidelines achieve significantly higher ESG Scores. The regression model indicates a positive and significant coefficient, confirmed even when including control variables such as company size and financial performance. This suggests that adopting responsible AI practices enhances corporate sustainability, strengthens stakeholder trust, and optimizes strategic decision-making related to ESG objectives.

2. Literature review and hypothesis development

The convergence of technological innovation and sustainability goals creates significant opportunities to study how AI influences ESG practices. According to recent studies, ESG practices are widely disseminated through digital platforms (Niccolò et al., 2025; Niccolò et al., 2022; Raimo et al., 2024). Technology, and increasingly emerging AI technologies, are being applied in ESG practices, previous studies show that AI technologies contribute to and support Sustainable Development Goals (SDGs) (Brescia et al., 2025). From an environmental perspective, advanced AI technologies improve ecological monitoring, optimize resource allocation, and support circular economy initiatives (Vinuesa et al., 2020). In the social context, AI helps promote diversity and workplace well-being through advanced selection algorithms and personalized professional development programs (Tamburri, 2020). Concerning governance, AI strengthens organizational oversight mechanisms, improving risk assessments and compliance procedures (Felício et al., 2016). However, the role of AI in influencing such results through improving ESG practices remains largely unexplored. As Adeoye et al. (2024) and Chiaramonte et al. (2022), financial institutions that use AI to assess ESG achieve superior returns on investments, suggesting a promising link between technology and sustainability.

Overall, implementing AI in companies offers numerous benefits, including increased transparency and improved decision-making effectiveness (Davenport & Ronanki, 2018; Degregori et al., 2025). For example, advanced AI-based analytics improve the accuracy and timeliness of ESG reports,

strengthening stakeholder trust (Pappas et al., 2018). Furthermore, AI applications optimize industrial energy consumption, helping to reduce carbon emissions (Nishant et al., 2020).

Qi Yudong et al. (2024) identified a strong synergy between the adoption of digital technologies and ESG performance, demonstrating their combined positive impact on firm performance, though with variations across regions. Similarly, Zhou Hailing and Liu Ji (2023) found a significant positive correlation between ICT and corporate ESG performance, emphasizing the crucial role of energy efficiency in achieving ESG objectives. Lastly, Xie and Wu (2025) show how companies adopting ethical guidelines for AI achieve higher ESG scores, highlighting how the responsible integration of AI is positively perceived by stakeholders, strengthening both corporate sustainability and investor trust.

From a regulatory standpoint, however, the governance of Artificial Intelligence reveals marked differences across regions, particularly between the European Union and the United States. The EU has already adopted a principle-based prescriptive model centered on the AI Act, which establishes binding obligations grounded in risk classification, transparency, and human oversight (Olimid, 2024; Radanliev, 2025; Golpayegani et al., 2025). This approach aligns technological innovation with ethical compliance and fundamental rights protection. Conversely, the U.S. framework remains decentralized and market-driven, relying mainly on voluntary standards and self-regulation, such as the NIST¹ AI Risk Management Framework and state-level initiatives (DePaula et al., 2025; Norton, 2024). In this context, firms assume a primary role in defining internal AI ethics policies as instruments of self-governance, although such autonomy may lead to fragmented accountability and uneven compliance (Luckett, 2023).

Despite these opportunities, significant challenges also emerge. AI infrastructure, for example, entails significant environmental costs related to energy consumption (Truby, 2020). Therefore, it is necessary to develop sustainable systems that balance technological efficiency and environmental impact and, as highlighted by Rahwan et al. (2019), harmonize AI capabilities with social values to ensure a positive impact on communities.

The relationship between AI adoption and ESG performance is complex and potentially indirect. A crucial role in this relationship is played by absorptive capability, defined as an organization's ability to recognize, assimilate, and apply new external knowledge (Cohen & Levinthal, 1990). This concept acts as a bridge, enabling companies to leverage AI technologies for sustainable practices effectively. Zahra and George (2002) further developed the notion by distinguishing between potential absorptive

¹ National Institute of Standards and Technology (NIST)

capability, which involves acquiring and assimilating knowledge. They realized absorptive capability, which involves transforming and applying that knowledge.

Some research, such as Xie et al. (2019), shows that absorptive capability positively moderates the relationship between green technological innovation and firm performance. Gomez-Mejia et al. (2019) further highlight that companies with greater absorptive capacity respond better to stakeholder demands for sustainable practices, translating such pressures into improved ESG outcomes.

Considering those assumptions, we develop the following hypothesis

HP: The adoption of ethical guidelines and policies related to the use, design, and development of Artificial Intelligence (AI) has a positive and significant impact on sustainability performance as measured by the ESG Score.

3. Sample and method

To develop our analysis, the reference dataset was constructed exclusively referring to Bloomberg as data provider. The sampling procedure for corporate observations was carried out using Bloomberg's equity screening function (EQS), querying the terminal about the following criteria:

- Trade status: active;
- Equity attributes: primary company stock only;
- Country: US and Western EU;
- Industry sector: communications, consumer cyclical and non-cyclical, energy, financial, technology and industrial.

Sampling was specifically limited to those companies (so-called equity tickers) for which the Bloomberg data provider guarantees data availability with respect to the “AI_ETH_PLCY” field. Indeed, this field indicates whether the observed company has implemented ethical guidelines and/or undertaken compliance activities related to the use, design, and development of Artificial Intelligence (AI). A value of “Y” (1) indicates the company's commitment to adopting AI practices aimed at minimizing disparities and promoting inclusive representation. Otherwise, Bloomberg returns “N” (0). The ESG Score assigned by Bloomberg, along with the scores for each pillar (Environmental Score, Social Score, and Governance Score), was collected for each equity ticker in the sample.

Additionally, avoiding multicollinearity problems, the dataset was enriched with the following control variables: total assets and total revenues (both expressed as natural logarithms), EBIT (expressed as a natural logarithm), EPS, ROE, ROA, ROIC, and the Tobin's Q ratio.

The table below (Table 1) provides a description of the variables included in the dataset used for the analysis.

The variables include the dummy variable identifying whether firms have adopted ethical policies on artificial intelligence, the ESG Scores, financial and economic metrics.

Table 1: List and description of the variables.

List of variables	Description
ARTFCIL_INTLLIGENCE_ETH_PLCY (Dummy Variable)	Artificial Intelligence Ethical Policy (ARTFCIL_INTLLIGENCE_ETH_PLCY) Indicates whether the company has adopted ethical guidelines and/or alignment activities for the designed and developed Artificial Intelligence (AI). 1 indicates the company is committed to AI that minimizes gaps and promotes inclusive representation.
ESG_SCORE	ESG Score (ESG_SCORE) Provides the Bloomberg score assessing the company's overall ESG performance. The score is a generalized weighted average (power) of the Pillar scores, where weights are determined by the pillar priority ranking. Values range from 0 to 10; 10 is best.
ENVIRONMENTAL_SCORE	Environmental Pillar Score (ENVIRONMENTAL_SCORE) Provides the Bloomberg score assessing the company's overall environmental performance. The pillar score is a generalized weighted average (power) of issue scores, where weights are determined by the issue priority ranking. Values range from 0 to 10; 10 is best.
SOCIAL_SCORE	Social Pillar Score (SOCIAL_SCORE) Provides the Bloomberg score assessing the company's overall social performance. The pillar score is a generalized weighted average (power) of issue scores, where weights are determined by the issue priority ranking. Values range from 0 to 10; 10 is best.
GOVERNANCE_SCORE	Governance Pillar Score (GOVERNANCE_SCORE) Provides the Bloomberg score assessing the company's overall governance performance. The pillar score is a generalized weighted average (power) of theme scores, where weights are determined by the theme priority ranking. Values range from 0 to 10; 10 is best.
BS_TOT_ASSET	Total Assets (BS_TOT_ASSET) Total assets: The total of short- and long-term assets as reported on the balance sheet. For “Financials”, Total assets: Sum of cash and equivalents, short-term investments and securities inventory, net receivables, total long-term investments, net fixed assets, and other

List of variables	Description
	assets. BS_TOT_ASSETLN is expressed as a natural logarithm.
SALES_REV_TURN	Revenues (SALES_REV_TURN) The amount of sales generated by a company after deducting returns, allowances, discounts, and sales-based taxes. Includes revenue from financial subsidiaries in industrial companies if consolidated. For “financials”, refers to gross revenue from any operating activity. Total revenue is the sum of income from interest, trading profit (loss), commissions, earned fees, and other operating income. SALES_REV_TURNLN is expressed as a natural logarithm.
IS_EPS	Earnings per Share (IS_EPS) Earnings per Share (EPS) is the portion of a company’s profit allocated to each shareholder. It is calculated based on net income available to common shareholders divided by the weighted average shares outstanding.
EBIT	EBIT (EBIT) Earnings before interest and taxes. For “Financials”: Operating profit + Interest expenses. Data expressed in millions. EBITLN is expressed as a natural logarithm.
RETURN_COM_EQY	Return on Common Equity (RETURN_COM_EQY) Measures a company’s profitability, highlighting profit generated with the money shareholders have invested, expressed as a percentage. Calculated as: (T12 Net income available to common shareholders / Average total common shares) * 100
RETURN_ON_ASSET	Return on Assets (RETURN_ON_ASSET) Measures a company’s profitability relative to its total assets, in percentage. Weighted asset return gives an idea of management efficiency in using assets to generate earnings.
OPERATING_ROIC	Operating Return on Invested Capital (OPERATING_ROIC) Indicates the efficient use of capital sources through the company’s activities. Unit: Effective. Calculated as: [Operating income last 12 months / (Beginning total invested capital + Ending total invested capital) / 2] * 100
TOBIN_Q_RATIO	Tobin’s Q Ratio (TOBIN_Q_RATIO) Ratio of a company’s market value to the replacement cost of its assets. The Q ratio is useful for company valuation. Based on the hypothesis that in the long term, a company’s market value should approximately equal the replacement cost of its assets. Calculated as: (Market cap + Total liabilities + Preferred shares + Minority interests) / Total assets

The dataset used for the analysis consists of 371 observations, each of which corresponds to a listed company for which information regarding the adoption of ethical policies related to artificial intelligence (AI) is available.

From a geographical perspective, the sample includes companies headquartered both in the United States and Europe, with a distribution of 64% and 36% respectively. In terms of industry classification, the majority of firms in the dataset operates within the technology sector, accounting for approximately 56% of the total sample. Other represented sectors include consumer goods (cyclical and non-cyclical), industrial, communications, financial services, and energy.

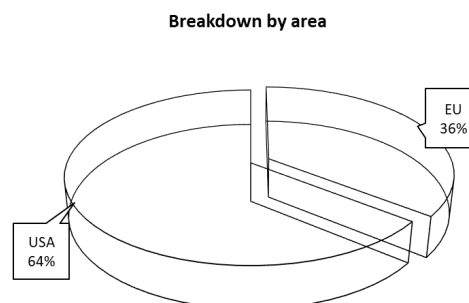
As stated, the dataset comprises both firms that have adopted ethical AI policies and those that have not, as identified by a binary (dummy) variable. This structure enables a comparative analysis of ESG performance between adopters and non-adopters, which constitutes the core of investigation.

The figure below (figure 1) shows the geographical and sectoral distribution of firms within the scope of the dataset.

Geographical and Sectoral Distribution of Firms with Available Data on AI Ethics Policy

Breakdown of the 371 companies included in the dataset by region (USA vs. EU) and industry sector, based on the availability of data on the adoption of ethical AI policies.

Heat Map DB AI_ETHPLCY Equity Ticker	USA	EU	Total
Technology	141	67	208
Consumer, Cyclical	20	16	36
Consumer, Non-cyclical	25	11	36
Industrial	16	19	35
Communications	20	10	30
Financial	13	9	22
Energy	4	-	4
Total DB by sector	239	132	371



Green: strong concentration of firms in the given area-sector combination. Yellow: medium values. Orange: low to medium values. Red very low or zero values (no companies represented).

Figure 1: Geographical and Sectoral Distribution of Firms in Dataset (Heat Map).

The structure of the dataset allows for a robust comparative analysis across firms operating in different sectors and exhibiting heterogeneous size characteristics, due to the inclusion of variables capturing geographical, sectoral, financial, and sustainability dimensions.

Below (Table 2) are the descriptive statistics of the variables included in the database. The data reveals a significant degree of heterogeneity among firms, particularly with respect to economic

indicators such as total assets, revenues, and profitability. ESG-related variables show relatively moderate distributions, with governance scores appearing more stable compared to the environmental and social dimensions. Measures of corporate performance (such as ROE, ROA, and ROIC) also display substantial variability, suggesting the presence of firms with markedly different economic profiles.

Table 2: Descriptive statistics of the variables.

Descriptive Statistics	Count	Mean	Sd	Min	Max
ARTFCIL_INTLLIGENCE_ETH_PLCY	371	0.12	0.32	0.00	1.00
ESG_SCORE	348	3.34	1.52	0.66	7.74
ENVIRONMENTAL_SCORE	348	2.68	2.49	0.00	8.80
SOCIAL_SCORE	348	2.32	1.82	0.00	10.00
GOVERNANCE_SCORE	348	6.41	1.11	2.41	9.06
BS_TOT_ASSET	371	21555.42	119537.63	7.09	1797062.00
BS_TOT_ASSETLN	371	7.91	1.70	1.96	14.40
SALES_REV_TURN	371	9689.97	53975.45	0.21	800125.00
SALES_REV_TURNLN	371	7.27	1.74	-1.55	13.59
IS_EPS	369	2.08	7.96	-27.54	87.92
EBIT	364	725.05	3637.04	-20450.00	36852.00
EBITLN	246	5.31	1.85	-0.04	10.51
RETURN_COM_EQY	342	10.37	71.50	-182.18	1168.54
RETURN_ON_ASSET	366	1.50	14.60	-139.02	84.01
OPERATING_ROIC	360	5.50	21.26	-157.84	132.70
TOBIN_Q_RATIO	367	3.10	3.10	0.65	29.16
Observations	371				

Moreover, the descriptive statistics reveal a substantial degree of cross-sectional heterogeneity among the sampled firms, both in terms of scale and financial performance. The wide dispersion in total assets (SD = 119,537.63) and revenues (SD = 53,975.45) indicates the coexistence of very large multinational corporations and smaller entities within the dataset. Such variability justifies the use of logarithmic transformations for these variables—BS_TOT_ASSETLN and SALES_REV_TURNLN—which yield more balanced distributions (mean values of 7.91 and 7.27, respectively) and reduce the risk of distortion in the subsequent econometric estimations. Profitability indicators exhibit similar heterogeneity: the high standard deviations and broad ranges observed for EPS, EBIT, ROE, and ROA confirm the inclusion of firms operating under markedly different financial conditions. In particular, the extreme values of ROE (from −182.18 to 1168.54) and ROA (from −139.02 to 84.01) suggest the presence of outliers and asymmetric distributions, typical of multi-sector datasets. This dispersion provides a realistic representation of the listed corporate landscape, encompassing firms at different stages of maturity, capitalization, and profitability.

Regarding sustainability performance, ESG-related indicators display a more moderate but still significant variability. The mean overall ESG score (3.34) suggests that most firms attain intermediate levels of sustainability commitment, whereas the Environmental and Social pillars show wider dispersion ($SD = 2.49$ and $SD = 1.82$, respectively). The Environmental Score, in particular, ranges from 0 to 8.8, highlighting a polarized distribution consistent with sectoral differences in environmental exposure and technological intensity. Conversely, the Governance pillar presents the lowest variance ($SD = 1.11$), pointing to a higher degree of homogeneity likely stemming from the widespread standardization of governance structures, disclosure frameworks, and compliance mechanisms across listed companies.

Taken together, these descriptive insights delineate a heterogeneous and well-balanced sample, representative of diverse economic and sustainability profiles. Such heterogeneity strengthens the reliability and external validity of the empirical analysis, ensuring that the regression models are able to capture meaningful structural differences in firms' ESG performance and in their propensity to adopt ethical AI policies. This statistical variability thus constitutes an essential premise for interpreting the estimated coefficients as reflective of substantive differences in firm behavior rather than sample-specific effects.

This variability enhances the robustness and external validity of the empirical analysis, allowing the regression models to capture meaningful differences in firms' ESG performance as a function of their adoption of ethical AI policies, while also highlighting the importance of controlling for firm size, profitability, and market valuation in the subsequent econometric estimations. Ultimately, such heterogeneity ensures that the estimated relationships reflect genuine structural patterns rather than sample-specific anomalies, thereby reinforcing the credibility and interpretative depth of the empirical results.

The accompanying graphical evidence (Figure 2) provides a visual synthesis of the descriptive findings and offers preliminary insights into the relationship between AI ethics policies and firms' ESG performance. The left panel presents the scatter plot of ESG scores against the binary variable capturing the presence of an ethical AI policy, while the right panel reports the boxplots disaggregated by geographical area (United States and European Union). The scatter plot clearly illustrates the binary nature of the explanatory variable and suggests a visible concentration of firms adopting AI ethics policies ("1") in the upper range of ESG scores, whereas non-adopters ("0") exhibit a broader and more dispersed distribution around lower values.

The boxplot analysis further enriches this descriptive perspective by displaying the median and variability of ESG scores across regions and policy adoption categories. Firms reporting the implementation of ethical AI guidelines tend to exhibit higher central values and less dispersion, indicating greater consistency in sustainability performance. This pattern emerges in both the U.S. and European samples, although European firms show slightly higher median scores and a narrower interquartile range, potentially reflecting regional differences in regulatory orientation and stakeholder expectations regarding ethical and sustainable practices.

Overall, these graphical representations provide an initial, data-driven indication of heterogeneity in ESG outcomes associated with the presence of AI ethical policies, supporting the relevance of investigating this relationship through subsequent econometric analysis.

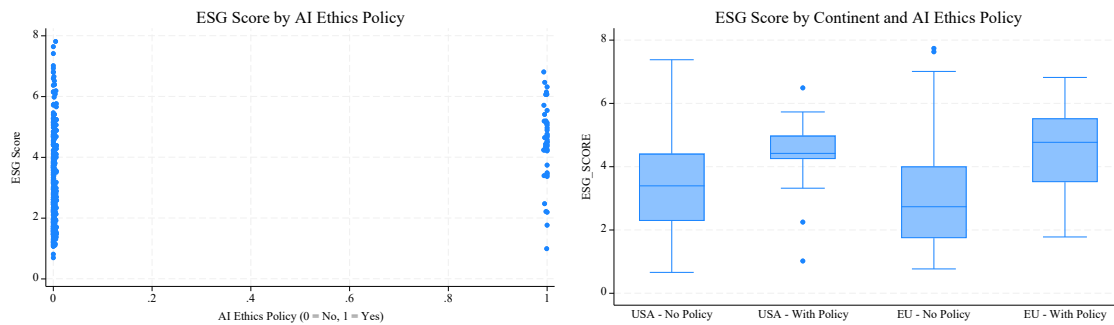


Figure 2: ESG Score by AI Ethics Policy and Continent (Left: Scatter Plot; Right: Boxplot Comparison).

To test our hypothesis (HP), we first used a linear regression model:

$$ESG_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + \varepsilon_i$$

Where:

- ESG_Score_i is the dependent variable (the ESG score given to the firm_i by Bloomberg).
- α is the intercept, (mean value of ESG_Score_i when $AI_ETH_PLCY_dum_i = 0$);
- $AI_ETH_PLCY_dum_i$ is the independent variable dummy (1 for companies with ethical policies on AI, 0 otherwise).
- ε_i is the residual error.

Then to further test our analyses, we included control variables measuring firm size and financial economic performance in the model.

Specifically:

$$ESG_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i$$

- Where $X_i'\beta$ expresses the vector of control variables, which includes total assets and total revenues (both expressed in natural logarithm), EBIT (expressed in natural logarithm), EPS, ROE, ROA, ROIC, and Tobin's Q ratio.

The estimation was carried out using Ordinary Least Squares (OLS). The analysis is based on cross-sectional data referring to the year 2024, due to the nature and availability of the variables, particularly the AI policy dummy variable. The choice of an OLS regression model applied to cross-sectional data is justified by the structure and availability of the data. This approach allows us to evaluate the associative relationship between the presence of ethical AI policies and ESG performance in a statistically consistent and interpretable framework.

Unfortunately, the absence of data for previous years - particularly with respect to the availability of the key explanatory variable concerning AI ethical policies - excluded the use of panel data models with fixed or random effects.

Such models would have enabled a more robust causal inference by controlling for unobserved firm-specific heterogeneity over time. However, due to the cross-sectional nature of the available dataset, the use of an OLS model on cross-sectional data remains the most suitable methodological approach under the current constraints.

This methodological choice is also consistent with the current stage of diffusion of AI ethics policies, which represents an emerging and still early-stage phenomenon within corporate sustainability practices. As a result, the cross-sectional design constitutes the only viable framework for empirical investigation at this stage, allowing for the observation of contemporaneous associations between ethical AI adoption and ESG performance across firms. Future longitudinal analyses may become feasible as the disclosure and standardization of AI-related ethical data improve over time, enabling the transition toward more dynamic panel-based approaches once the phenomenon reaches greater maturity and data coverage expands.

Then, to further explore the impact of ethical AI policies on the individual components of corporate sustainability, we developed three additional econometric models, each referring to one of the ESG pillars — Environmental, Social, and Governance. This disaggregated approach allows for a more granular assessment of how AI ethics influences the specific dimensions that jointly determine the overall ESG performance.

Specifically:

$$E_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i'\beta + \varepsilon_i$$

$$S_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i$$

$$G_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i$$

4. Results

Our H_p , predicts that β_1 is positive and significant, implying that companies that adopt ethical policies on AI score, on average, higher ESG scores, and that this relationship is robust and not random. The results allowed us to test our hypothesis (see Table 3): the β_1 coefficient is 1.30, and the p-value associated with the coefficient shows that this positive relationship is robust and statistically significant ($p < 0.01$).

Table 3: OLS n.1 - $ESG_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + \varepsilon_i$.

OLS n.1	ESG_SCORE
AI_ETH_PLCY dum	1.302*** (0.241)
_cons	3.188*** (0.0838)
N	348

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To further test our analyses, we included control variables measuring firm size and financial economic performance in the model.

Specifically:

$$ESG_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i$$

Where $X_i' \beta$ expresses the vector of control variables, which includes total assets and total revenues (both expressed in natural logarithm), EBIT (expressed in natural logarithm), EPS, ROE, ROA, ROIC, and Tobin's Q ratio. Even following the use of the control variables (see Table 4), the value of the β_1 coefficient results positive and statistically significant (0.65 with a $p < 0.05$).

Table 4: OLS n.2 - $ESG_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i$.

OLS n.2.	ESG_SCORE
ARTFCIL_INTLLIGENCE_ETH_PLCY dum	0.648** (0.277)
BS_TOT_ASSETLN	0.401** (0.173)
SALES_REV_TURNLN	-0.176 (0.161)

OLS n.2.	ESG_SCORE
IS_EPS	-0.0123 (0.0113)
EBITLN	0.244** (0.110)
RETURN_COM_EQY	0.00151 (0.00113)
RETURN_ON_ASSET	0.00518 (0.0244)
OPERATING_ROIC	-0.00785 (0.0146)
TOBIN_Q_RATIO	0.0528 (0.0487)
_cons	0.157 (0.604)
N	218

Standard errors in parentheses
** p < 0.10, ** p < 0.05, *** p < 0.01*

The results of the estimated linear regression indicate that the adoption of ethical guidelines and policies related to the use, design, and development of Artificial Intelligence (AI) – captured by the binary dependent variable ARTFCIL_INTLLIGENCE_ETH_PLCY – is positively and significantly associated with firms' ESG scores. In the baseline model (OLS n.1, see Table 3), which does not include control variables, the coefficient associated with the AI ethics policy dummy is 1.30, statistically significant at the 1% level, suggesting that companies that adopt ethical AI policies tend to have significantly higher ESG scores on average compared to those that do not.

To assess the robustness of this result and account for potential confounding factors—that is, variables that may influence both the dependent and independent variables, and which, if omitted, could bias the estimated effect—a second model was estimated, including a set of firm-level control variables (OLS n.2, see Table 4).

These controls include firm size (BS_TOT_ASSETLN), revenues (SALES_REV_TURNLN), profitability metrics (IS_EPS, +RETURN_COM_EQY, RETURN_ON_ASSET, OPERATING_ROIC, EBITLN), and market valuation (TOBIN_Q_RATIO).

In this extended model, the coefficient associated with the adoption of AI ethics policies remains positive and statistically significant (0.648, significant at the 5% level), confirming the robustness of the observed association. The inclusion of control variables is crucial to isolate the net effect of the

main explanatory variable, reducing the risk that the observed relationship is merely driven by structural characteristics of the firms, such as size, economic performance, or industry.

Among the control variables, both firm size (BS_TOT_ASSETLN) and operating profitability (EBITLN) are also statistically significant, suggesting that larger and more profitable firms are more likely to exhibit higher ESG scores.

The accompanying graphical analysis (see Figure 3) presents the coefficient estimates of the OLS regression model, providing a visual representation of the relative impact and significance of the explanatory variables—most notably the positive association between AI ethical policies and firms' ESG scores.

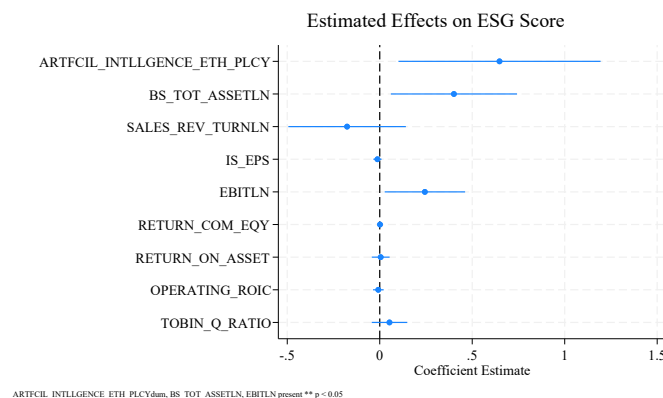


Figure 3: AI Ethic Policy Estimated effect on ESG Score. Visual Evidence.

In summary, the empirical evidence suggests that the adoption of ethical policies on artificial intelligence is associated with better ESG performance. This relationship holds even after controlling key firm-level characteristics, reinforcing the hypothesis that such policies may serve as a signal of a company's concrete commitment to sustainability.

Conducting the analysis for each individual pillar that composes the aggregated ESG score provides further insight into the specific dimensions through which the adoption of ethical policies on Artificial Intelligence (AI) exerts its influence. The results of the three Ordinary Least Squares (OLS) regressions, estimated with the same specification as Model n.2, are the following ones:

$$\begin{aligned}
 (3) \ E_Score_i &= \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i \\
 (4) \ S_Score_i &= \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i \\
 (5) \ G_Score_i &= \alpha + \beta_1 * AI_ETH_PLCY_dum_i + X_i' \beta + \varepsilon_i
 \end{aligned}$$

*Table 5 OLS n.3-4-5 - $E-S-G_Score_i = \alpha + \beta_1 * AI_ETH_PLCY_dumi + X_i' \beta + \varepsilon_i$ (ESG Pillars)*

OLS 3-4-5	(3) ENVIRONMENTAL_SCORE	(4) SOCIAL_SCORE	(5) GOVERNANCE_SCORE
ARTFCIL_INTLLIGENCE_ETH_PLCY dum	1.604*** (0.462)	0.349 (0.372)	0.00311 (0.230)
BS_TOT_ASSETLN	0.556* (0.289)	0.167 (0.232)	0.400*** (0.143)
SALES_REV_TURNLN	-0.298 (0.269)	-0.0613 (0.216)	-0.168 (0.134)
IS_EPS	-0.0311* (0.0188)	-0.00840 (0.0151)	-0.00481 (0.00934)
EBITLN	0.352* (0.184)	0.365** (0.148)	0.0173 (0.0915)
RETURN_COM_EQY	0.00373** (0.00188)	-0.00112 (0.00151)	0.00233** (0.000937)
RETURN_ON_ASSET	-0.0129 (0.0408)	0.0237 (0.0328)	-0.00356 (0.0203)
OPERATING_ROIC	0.0202 (0.0244)	-0.0264 (0.0196)	-0.0145 (0.0121)
TOBIN_Q_RATIO	0.0243 (0.0812)	0.0305 (0.0653)	0.0829** (0.0404)
_cons	-1.670* (1.008)	-0.180 (0.810)	4.375*** (0.501)
N	218	218	218

*Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

The results indicate a heterogeneous impact across the Environmental, Social, and Governance dimensions. Specifically, the coefficient associated with the AI ethical policy dummy variable (ARTFCIL_INTLLIGENCE_ETH_PLCY) is positive and highly significant for the Environmental Score ($\beta = 1.604$, $p < 0.01$), positive but not statistically significant for the Social Score ($\beta = 0.349$, n.s.), and practically null for the Governance Score ($\beta = 0.003$, n.s.).

Conversely, the absence of statistically significant effects for the social and governance pillars reveals that the integration of ethical AI principles does not yet translate into measurable improvements in these dimensions. The limited impact on the social pillar may reflect the inherent difficulty in capturing the heterogeneity of social indicators—such as diversity, workplace well-being, and inclusion—across sectors and corporate cultures. Similarly, the non-significant relationship with the governance pillar suggests that ethical AI policies, while signaling corporate responsibility, are not directly embedded in formal governance structures, which typically depend on institutional arrangements, board composition, and disclosure mechanisms. Nonetheless, the positive and

significant association of Tobin's Q and return on equity (ROE) with the governance pillar indicates that the market tends to reward sound governance practices independently of AI-related policies.

Control variables behave coherently with theoretical expectations: firm size (BS_TOT_ASSETLN) exerts a positive and significant effect, particularly on the environmental and governance dimensions, confirming that larger firms—due to greater resources and stakeholder exposure—tend to achieve higher ESG-related outcomes. Operating profitability (EBITLN) also shows a positive and significant association with both environmental and social scores, suggesting that more profitable firms are better positioned to implement sustainability-oriented strategies.

Overall, the disaggregated evidence reinforces the robustness of the main results, showing that the adoption of ethical AI policies operates primarily as an environmental driver within the ESG framework, with more limited effects on the social and governance dimensions. These findings underline the role of AI ethics not only as a signal of corporate commitment to sustainability but also as a potential catalyst for environmental innovation and efficiency.

5. Discussion and conclusions

The study examines how AI adoption influences ESG (Environmental, Social, and Governance) performance, highlighting both opportunities and challenges. AI adoption enhances environmental sustainability through advanced monitoring, resource optimization, and circular economy initiatives (Vinuesa et al., 2020; Nishant et al., 2020), while also promoting diversity, workplace well-being, and improved governance through algorithmic oversight (Tamburri, 2020; Felício et al., 2016).

While previous research has shown a strong correlation between ESG performance and financial results, the specific role of AI in this relationship remains underexplored. Studies suggest that financial institutions using AI for ESG assessments achieve higher investment returns, pointing to a promising link between AI adoption and sustainability.

The study uses a dataset from Bloomberg covering 348 U.S. and Western European companies across various industries. A linear regression model tests the hypothesis that ethical AI policies positively impact ESG performance.

The result confirms the positive effect already observed, even in the presence of the control variables. The positivity and significance of the coefficient highlights that the implementation of ethical guidelines related to the use, design, and development of AI is perceived as an adding value by ESG evaluators. The implementation of ethical policies on AI is a tangible signal of commitment to the principles of sustainability and social responsibility. Moreover, such practices can increase the trust

of stakeholders, including investors and regulators, as they demonstrate the company's willingness to adopt technologies responsibly and to proactively manage the ethical risks associated with AI.

These findings suggest that the positive association between AI ethics and overall ESG performance observed in the aggregate model is predominantly driven by the environmental dimension. Firms that have implemented ethical guidelines for the design and use of AI exhibit, on average, higher environmental scores, pointing to a consistent alignment between responsible technological innovation and environmental sustainability practices. This result is coherent with the theoretical framework proposed by Vinuesa et al. (2020) and Nishant et al. (2020), according to which AI acts as an enabling technology for the ecological transition—enhancing energy efficiency, resource optimization, and environmental monitoring. Similarly, Brescia et al. (2025) emphasize how AI supports the Sustainable Development Goals by driving resource-efficient processes, confirming the environmental leverage identified in our analysis.

From a policy perspective, this evidence highlights how the promotion of ethical AI standards can generate environmental co-benefits, contributing to the broader objectives of sustainable technological transformation.

While the environmental pillar exhibits a strong and significant relationship, the social dimension shows weaker statistical evidence, consistent with the view that social outcomes of AI ethics adoption require longer organizational and cultural adjustments to emerge (Tamburri, 2020). Moreover, the absence of significant effects for the governance pillar aligns with the findings of Felício et al. (2016), who point out that governance indicators often depend on formal institutional arrangements and disclosure frameworks that evolve over time rather than on single policy adoptions.

6. Limitations, contributions and future research

The overall pattern supports prior literature linking AI and sustainability, particularly the positive association between digitalization, energy efficiency, and ESG performance discussed by Qi Yudong et al. (2024) and Zhou & Liu (2023). The evidence that AI-ethics adoption enhances transparency and operational efficiency also resonates with Pappas et al. (2018) and Davenport & Ronanki (2018), who highlight that AI-based analytics improve ESG data quality and decision-making effectiveness.

However, several limitations should be acknowledged when interpreting these findings. First, the analysis relies on cross-sectional data referring to the year 2024, as historical and longitudinal

information on the adoption of ethical AI policies is currently unavailable. Consequently, the model does not allow for causal inference or the identification of potential reverse causality between ESG performance and AI ethics adoption. Nevertheless, this constraint is consistent with the exploratory nature of the research, which aims to provide preliminary empirical evidence on a phenomenon still in its early stage of diffusion.

Second, the relatively limited sample size prevents the estimation of separate models for U.S. and European firms, which would have allowed for a deeper appreciation of the institutional differences arising from the distinct regulatory frameworks governing AI governance in the two regions. The European Union's prescriptive and principle-based AI Act framework contrasts with the United States' decentralized and market-driven approach, as discussed by Radanliev (2025), DePaula et al. (2025), and Norton (2024). Such regulatory asymmetry may help explain regional heterogeneity in the strength of the observed relationships.

Likewise, the number of observations does not permit robust analyses by industry sector, which could have revealed sector-specific dynamics in the interaction between AI ethics and ESG performance—especially relevant given evidence from Adeoye et al. (2024) and Chiaramonte et al. (2022) showing that financial and technologically intensive sectors respond differently to AI-driven sustainability innovations.

Finally, as noted by Truby (2020), AI infrastructure itself entails non-negligible environmental costs related to computational energy demand. While our results reveal a net environmental premium associated with AI ethics, future studies should integrate these costs to fully assess the environmental balance of AI adoption.

This study highlights the need to delve deeper into the relationship between AI and ESG, providing basis for developing new measurement frameworks that assess the contribution of AI to corporate sustainability. Although the existing literature provides valuable insights, research exploring the overall impact of AI on ESG performance in different economic contexts is lacking. Our study focuses on these aspects to provide policymakers, companies and technology developers with a reference framework for defining the best strategies to support business processes.

This aspect is particularly timely also in light of the very recent initiatives announced by the European Commission (2025) for the creation of AI gigafactories (AI Gigafactories) and the development of a strategy for applied AI (Apply AI) in order to guide the development and adoption of AI in key industrial sectors.

These limitations also represent valuable directions for future research. As the availability of AI-related data expands and longitudinal series become accessible, future studies should employ panel data models to capture the dynamic and potentially causal link between ethical AI adoption and ESG performance. Building on the concepts of absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002), future research could also investigate how firms' ability to acquire and apply external knowledge mediates the effectiveness of AI ethics policies on sustainability outcomes.

Comparative analyses across regions and industries would further illuminate how institutional pressures and regulatory heterogeneity shape corporate behavior—especially considering the evidence provided by Radanliev (2025) and Olimid (2024) on the EU's rights-based framework, and by Luckett (2023) on the self-regulatory orientation of U.S. firms. Finally, cross-sectoral studies could integrate behavioral and organizational perspectives, exploring how factors such as managerial incentives, stakeholder expectations, and firm capabilities (Gomez-Mejia et al., 2019; Xie et al., 2019) influence the translation of AI-ethics adoption into

Ethics declaration

This study did not involve procedures requiring ethical clearance, and no ethical approval was necessary for the research conducted.

AI declaration

The authors confirm that no artificial intelligence tools were used in the preparation or production of this paper.

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