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Impact of AI on ESG Performance of Firms of Haryana

Vikas Chaudhary[1], Anandajit Goswami[2], Soumit Pandey[3]
[1] PhD Scholar, Manav Rachna International Institute of Research and Studies.
[2] Professor, Manav Rachna International Institute of Research and Studies.
[3] Junior Research Associate, Ashoka University.

Abstract
The interplay between Artificial Intelligence (AI) and Environmental, Social, and Governance (ESG) performance is a growing area of academic and industry interest. This study examines how AI adoption influences ESG performance in firms across Haryana, with a particular focus on manufacturing and service sectors. Findings from existing literatures suggest that AI adoption leads to significant ESG performance improvements by optimizing energy consumption, reducing emissions, and enhancing corporate governance mechanisms. However, prior research predominantly focuses on correlation rather than causation. This study aims to bridge this gap by analyzing the bidirectional relationship between AI adoption and ESG performance, hypothesizing that AI not only drives ESG improvements but is also influenced by a firm's ESG strategies and regulatory environment. A significant data gap exists in the datasets used in this study, lacking direct indicators of AI adoption and robust social and governance parameters. To overcome this, this study employs proxy variables to estimate AI adoption and social and governance parameters. The research applies a game-theoretic framework, including the Stackelberg competition model and Bayesian evolutionary game theory, to assess strategic AI adoption decisions under competitive and regulatory pressures. Additionally, empirical methodologies such as a modified Difference-in-Differences (DiD) approach and Propensity Score Matching (PSM) are utilized to control for selection bias and establish causality. Furthermore, this study explores AI adoption disparities exist between formal and informal firms, highlighting policy gaps and financial and strategic constraints. The study contributes to existing knowledge by developing an evolutionary game theoretical model and by shifting the focus from correlation to causation, providing insights for policymakers and industry leaders on integrating AI into sustainable business practices. Future research will refine AI adoption metrics and expand longitudinal data analysis to further explore AI's role in corporate sustainability.
Keywords: Artificial Intelligence (AI), Environmental, Social, Governance, Haryana.

List of Abbreviations
ESG: Environment, Social, Governance
AI: Artificial Intelligence
DiD: Difference-in-Difference
PSM: Propensity Score Matching
SCP: Structure-Conduct-Performance
ESH: Efficiency Structure Hypothesis

1. Introduction
Environmental, Social, and Governance (ESG) performance has become a fundamental metric for evaluating a firm's sustainability and ethical standards (Barro et al., 2024). ESG is comprised of three core dimensions (Paužuolienė & Derkach, 2024) - environmental responsibility, including carbon emissions reduction, energy efficiency, and sustainable resource management; social factors, such as labor rights, diversity and inclusion, and corporate social responsibility; and governance practices, focusing on transparency, corporate

ethics, and executive accountability. As global stakeholders emphasize sustainability, firms are increasingly required to align their operations with ESG principles to maintain competitiveness and stakeholder trust. At the same time, artificial intelligence (AI) (Wamba et al., 2024) has emerged as a transformative force across industries, streamlining business processes, enhancing decision-making, and automating complex tasks. AI refers to the deployment of machine learning algorithms, predictive analytics, and data-driven insights that optimize operational efficiency and innovation. The interplay between AI and ESG has become an important area of research, with scholars primarily investigating how AI adoption influences ESG performance, particularly in manufacturing firms.

Existing literature highlights a positive correlation (Xie & Wu, 2025) between AI integration and ESG performance improvements, particularly in the manufacturing sector, where AI enhances production efficiency, minimizes waste, and facilitates compliance with environmental regulations. AI-driven predictive analytics help firms optimize energy consumption, reduce carbon emissions and implement sustainable supply chain strategies. Moreover, AI enhances social and governance parameters by improving workplace safety (Huang et al., 2024), eliminating biases in decision-making, and strengthening corporate oversight through data-driven governance mechanisms. However, despite these observed benefits, prior studies predominantly focus on correlation rather than causation, leaving open questions about the bidirectional impact between AI adoption and ESG performance. Additionally, a significant data gap exists in the datasets used in this study, lacking direct indicators of AI adoption and robust social and governance parameters.

To address these limitations, this study proposes the use of proxy variables to represent both AI adoption and the social and governance dimensions of ESG. Since the available dataset lacks explicit AI adoption metrics and detailed social and governance indicators, alternative firm-level operational, financial, and regulatory data from the datasets will be utilized to construct an analytical framework. Rather than examining correlation, this study seeks to explore the bidirectional causal relationship between AI and ESG, hypothesizing that AI adoption not only drives ESG outcomes but is also influenced by firms' ESG strategies and regulatory environments.

A key theoretical component of this research is the application of game theory to analyze AI adoption decisions in relation to ESG performance. Game theory, which models strategic interactions between rational decision-makers, provides a powerful lens to study how firms navigate competitive pressures, regulatory policies, and sustainability incentives when implementing AI technologies (Bateh, 2023). Previous studies have applied Stackelberg game models and Bayesian games to investigate AI adoption under regulatory constraints. By incorporating game-theoretic principles, this study will examine how firms optimize AI adoption strategies while balancing ESG objectives, thereby providing a deeper understanding of the interdependencies between AI implementation and sustainability outcomes.

Furthermore, this research will examine the broader implications of AI-driven ESG performance on financial stability, investor confidence, and long-term corporate resilience. Firms with strong ESG performance are often associated with lower financial risk and enhanced brand reputation, leading to higher investor trust and capital inflows. The role of AI in strengthening these dynamics remains underexplored, warranting further empirical investigation. Additionally, the research will analyze industry-specific trends, acknowledging that AI adoption and ESG impacts vary across different sectors – formal and informal, and conforming and non-conforming, based on technological intensity, regulatory frameworks, and market competition.

Several empirical methodologies have been utilized in previous studies to measure the impact of AI on ESG performance, including Difference-in-Differences (DiD) models (Chen et al., 2024), propensity score matching (PSM) (Jing & Zhang, 2024), and regression analysis. The DiD approach, widely applied in empirical economic research, compares the ESG performance of firms before and after adoption of AI while controlling for external variables. This methodology allows researchers to estimate causal effects more accurately by isolating the impact of AI from other confounding factors. Similarly, PSM techniques help in mitigating selection bias by matching firms with similar characteristics, ensuring that AI-adopting firms are compared against non-adopters in a meaningful way. These empirical frameworks are essential in understanding whether AI directly contributes to ESG performance improvements or whether the observed correlation is influenced by other exogenous factors.

Additionally, many existing studies have focused on manufacturing firms due to their high resource consumption and regulatory scrutiny (Liu & Xiao, 2018). This research aims to expand the scope by exploring AI adoption in not only manufacturing firms, but also service-oriented industries and its effect on ESG dimensions. The financial sector, for example, has increasingly utilized AI for risk assessment, fraud detection (Gafarov, 2024), and governance monitoring, leading to enhanced transparency and compliance. By applying empirical models such as DiD and machine learning-based predictive analytics, this study seeks to provide robust evidence on AI's role in shaping ESG performance across various industries.

This research contributes to the existing body of knowledge by shifting the focus from correlation to bidirectional causality, leveraging proxy variables to mitigate data limitations, and integrating game-theoretic approaches to contextualize AI adoption decisions within the ESG framework. By addressing these gaps, the study aims to offer valuable insights for policymakers, corporate strategists, and researchers seeking to advance sustainable AI-driven business models and regulatory frameworks (Sætra, 2021). Moreover, by expanding the discussion to include sectoral implications, empirical methodologies such as DiD, and challenges in AI governance, this study will provide a holistic view of AI's transformative potential in shaping the future of sustainable corporate governance and environmental responsibility.

2. Theoretical Framework

2.1 Structure-Conduct-Performance (SCP) Paradigm

The Structure-Conduct-Performance (SCP) paradigm has traditionally served as a cornerstone of industrial organization studies, emphasizing the causal relationship between market structure, firm behavior, and performance outcomes. The SCP framework asserts that market structures, such as the degree of competition and concentration, directly shape firm conduct, which in turn determines performance outcomes. In this view, firms in highly concentrated industries are expected to engage in anti-competitive behaviors, such as price-setting and collusion, leading to increased profitability at the expense of consumer welfare. Empirical research has both supported and critiqued the SCP model, with studies often finding a positive correlation between industry concentration and firm profitability (Lelissa & Kuhil, 2018).

However, these findings have not always been conclusive in establishing causation. Critics argue that firm performance may not necessarily be a result of market concentration but rather a consequence of superior efficiency and management practices, also known as the Efficient Structure Hypothesis (ESH). Beyond ESH, game-theoretic approaches have gained prominence in explaining firm behavior and strategic decision-making. Unlike the SCP framework, which assumes firms passively respond to market structures, game theory models firms as strategic players that actively shape competitive dynamics. These models account for interactions between firms, allowing for more nuanced explanations of pricing strategies, investment in research and development, and competitive or collusive behaviors.

2.2 Game Theoretical Models

This research employs a Bayesian evolutionary game model incorporating a Stackelberg competition framework to analyze AI adoption's impact on firms' ESG performance. The model is structured around key parameters such as early AI adopters versus late AI adopters, industry conformance, industry type, firm size, and potential collusion among competitors.

The Stackelberg model is applied to capture the leader-follower dynamics (Zhang et al., 2023), where early adopters influence industry standards, competitive advantages, and technological diffusion (Ma & Wang, 2024) rates. Additionally, different industries exhibit varied AI adoption behaviors. Some industries, driven by regulatory pressures and stakeholder expectations, conform to AI integration for ESG improvement, while others resist due to cost or strategic concerns. Industry type and firm size play crucial roles in adoption decisions. Larger firms with more resources are more likely to adopt AI early, whereas smaller firms may strategically delay adoption due to capital constraints and uncertainty (Zhu & Weyant, 2003). In certain markets, firms may also engage in collusion[1], collectively delaying or accelerating AI adoption to optimize industry-wide benefits.

While SCP provides a foundational framework for understanding how market structures shape firm behavior, game theory refines this perspective by incorporating strategic decision-making among firms. Firms do not merely react to market conditions but also anticipate and influence competitor behavior. This is particularly relevant for AI adoption in ESG performance, where firms must decide whether to lead or follow in adopting AI-driven sustainability measures. The SCP model can be used to analyze how industry concentration affects AI adoption rates. In highly concentrated markets, dominant firms may invest in AI to reinforce their market power, while in competitive markets, firms may adopt AI as a necessity to stay relevant. Game theory adds another layer to this analysis by modeling firm interactions, capturing leader-follower dynamics, and assessing how firms strategically respond to market uncertainties and competitor actions.

The model constructed is as follows:

Step 1: SCP Model (Equation 1):

$$ESG_i = f(S_i, C_i, \sum_k \mu_k X_{ki})$$

Here,

Variable	Explanation
ESG_i	ESG performance of firm i
S_i	Market structure factors (competition, market power)
C_i	Firm conduct (AI adoption, ESG compliance, green innovation)
X_{ki}	Control variables (R&D, capital intensity, labor, firm type, firm size)

Step 2: Stakelberg Model

Let us consider that AI adoption of leader and follower firms be AI_L *and* A_F respectively. Then, the profit functions of leader and follower firms are π_L and π_F.

Leader Firm's Profit Function (Equation 2):

$$\pi_L(AI_L, AI_F) = R_L(AI_L, AI_F) - C_L(AI_L)$$

Follower Firms Best Response function (Equation 3):

$$\pi_F(AI_F, AI_L) = R_F(AI_F, AI_L) - C_F(AI_F)$$

This gives the optimal AI adoption of follower firms (Equation 3a):

$$AI_F^* = BR(AI_L)$$

The leader firm will anticipate AI_F^*. Hence, optimization (Equation 4):

$$\pi_L\,(AI_L, AI_F^*(AI_L))$$

Thus, the stakelberg equilibrium is: (AI_L^*, AI_F^*)

Thus, when firms have full information, from equation 1, we get equation 5:

$$ESG_i = g(AI_i, S_i, C_i)$$

However, firms face uncertainty about AI's impact on ESG. Hence, we need to integrate Bayesian Model.

Step 3: Bayesian Game with respect to the firms' belief on AI adoption and ESG payoffs.

Firm i maximizes its expected profit given its belief θ_i about AI's impact (Equation 6):

$$\pi_i(AI_i, ESG_i|\theta_i) = E[R_i(AI_i, ESG_i, \theta_i)] \; - \; C_i(AI_i)$$

Firms update their beliefs as given in equation 7:

$$P(\theta_t|AI_t) = \frac{P(AI_t|\theta_t)P(\theta_t)}{P(AI_t)}$$

Thus, a Bayesian nash equilibrium strategic profile would look something like equation 8:

$$(AI_1^* \ldots\ldots\ldots\ldots\ldots AI_n^*),\text{ where, } AI_i^* \epsilon\; E[\pi_i(AI_i, ESG_i|\theta_i)\;]$$

However, since AI adoption evolves dynamically, we ultimately move into an evolutionary game model.

Step 4: Evolutionary Game Model

Let p_t be the fraction of AI adopting firms in time t. Let these firms have payoffs π_{AI} while non-adopters have payoffs π_{NAI}.

Equation 8 given below captures the dynamic model explaining how fraction of AI adopters change over time:

$$\Delta p_t = p_t(1 \, - \, p_t)(\pi_{AI} \, - \, \pi_{NAI})$$

Where, Δp_t captures the rate of change in AI adoption fraction.

The equilibrium is reached when $\pi_{AI} \; = \; \pi_{NAI}$, meaning, firms no longer have any impact on their ESG performance from changing their AI adoption strategy.

3. Hypothesis

H1: Higher levels of AI integration into the workings of firms of formal sector tend to improve the firms' ESG performance – thus showing a positive correlation

H2: Integration of AI into the ESG parameters of firms of informal sector will improve the firms' ESG performance and hence ESG score – thus showing bidirectional causality

4. Research Questions

- How does AI adoption influence ESG performance in manufacturing firms?
- How do firms' ESG conditions impact the likelihood of AI adoption?
- What proxies can be used to measure AI adoption and social/governance indicators in the absence of direct data?
- What are the strategic, regulatory, and financial constraints affecting AI adoption for ESG enhancement, particularly in formal/conforming and informal/non-conforming sector firms?

5. Research Objectives

- Classify firms into AI-adopting and non-AI-adopting groups using appropriate proxy indicators in the absence of direct AI adoption data.

● Quantify AI's impact on ESG indicators by constructing measurable proxies for social and governance performance in firms.
● Examine the bidirectional causal relationship between AI adoption and ESG performance, investigating whether AI adoption leads to better ESG performance and whether firms with strong ESG performance are more likely to adopt AI.
● Analyze the role of firm characteristics (e.g., formal vs. informal firms, industry type, firm size) in shaping the AI-ESG relationship.
● Assess policy and managerial implications of AI adoption on ESG compliance, particularly in industries with regulatory pressures.

6. Data and Methodology

The study sample includes industry data on firms in Haryana – 21460 firms of Faridabad, 10803 firms of Pantipat, 4118 firms of Rohtak, and 4742 firms of Yamunanagar.
Since ESG scores of these firms are not available, given the data on environmental parmeters available in the datasets, and proxy datapoints considered for social and governance parameters from the dataset, using established scoring parameters, an ESG score for each of these firms will be created.
After constructing the proxy datapoints, firstly datasets will be integrated into a unified database in form of pooled-cross-section for subsequent research and analysis. Secondly, the firms may be categorized into small, micro, and macro, depending upon the firm size to avoid sample selection issues. Thirdly, strict cleaning and pre-processing of the datasets will be conducted to remove duplicate data, repurpose missing data and outliers, ensuring data accuracy and consistency. Finally, existing and available ESG scores and industry trends in real time will be referred to for clarity, data consistency and reliability.

6.1. Data Work

Step 1: Data Cleaning

1. The datasets provided are cross-sectional datasets of various firms of 4 districts of Haryana - Faridabad, Panipat, Yamunanagar, and Rothak.
2. The first step of cleaning the data of each district is by matching the variables across the districts (that is, matching the variables across the 4 datasets). Upon close assessment, the following variables were found to be not available in one or more districts (datasets):

● Registration type: Not available in Yamunanagar dataset
● Contact No. (landline): Not available in Panipat and Rothak datasets
● Authorized Person Contact No. (Landline): Not available in Panipat and Rothak datasets
● Area: Not available in Yamunanagar, Rothak, and Faridabad datasets
● Gali No.: Not available in Yamunanagar, Panipat and Rothak datasets
● Zone wise Map: Not available in Yamunanagar, Panipat and Rothak datasets
● Metric Tonnes/ Numbers: Not available in Faridabad dataset.
● Remarks: Not available in Yamunanagar dataset

Since the above variables were not available in one or more datasets, they were removed.

3. The next step of data cleaning is to remove variables from all the datasets which are assumed to create no significance in/contribute nothing to the future data analysis. These variables were:

● Company Name
● Name Of Owner
● Contact No. (Mobile)
● E-Mail Id
● Name Of Authorized Person
● Authorized Person Contact No. (Mobile)
● Authorized Person E-Mail Id

For now, the above given variables were removed. Upon further future need, more variables may be removed.

Step 2: Joining the datasets

1. To join the datasets it is important to check whether the variables are homogeneous across the datasets. After making sure they are, we move to the next step.

Step 3: Understanding the data

Table 1: Description of Company Constitution type

Type	**Legal Entity**	**Limited Liability**	**Formal Registration**	**Ownership**
Proprietorship	No	No	No	One person
Partnership	No	No	Optional	Partners
LLP	Yes	Yes	Mandatory	Partners
Pvt Ltd Co.	Yes	Yes	Mandatory	Shareholders
Public Ltd Co.	Yes	Yes	Mandatory	Public shareholders
Co-operative	Yes	Yes	Mandatory	Members
Trust	Yes	Yes	Mandatory	Trustees
SHG	No	No	Optional	Group members
LLC (India)	*Use LLP or Pvt Ltd*	*See above*	*See above*	*See above*

Unit Category as Per HSPCB Norms (Red, Orange, Green, Yellow)

- **Red & Orange**: Require **Consent to Establish (CTE)** and **Consent to Operate (CTO)** from the Pollution Control Board.
- **Green**: Require CTE/CTO but with simpler procedures.
- **White**: **No consent needed**; just an intimation to the PCB.

Table 2: Description of category of HSPCB norms

Category	**Pollution Index (PI)**	**Pollution Potential**	**Description**
Red	PI ≥ 60	**High**	Highly polluting industries; strictest regulations and environmental controls.
Orange	41 ≤ PI < 60	**Moderate**	Moderately polluting; require some level of environmental monitoring.
Green	21 ≤ PI < 40	**Low**	Low pollution; simpler regulatory requirements.
White	PI < 20	**Negligible/ None**	Non-polluting; no consent needed from Pollution Control Board (only intimation).

Step 4: Variables used as proxy for constructing ESG parameters and an AI variable
Environment Variables

Variable	Rationale

UNIT CATEGORY AS PER HSPCB NORMS (MANDATORY)	Directly linked to environmental risk classification by the Haryana State Pollution Control Board (HSPCB). categories: Red, orange, green, and white
UNIT CATEGORY (MANDATORY)	Often tied to environmental compliance thresholds (e.g., MSME units may have exemptions). categories: Large, medium, micro, and small.
TYPE OF INDUSTRY/SECTOR (MANDATORY)	Determines environmental footprint; chemical, leather, or metal industries have higher environmental impacts.
TYPE OF PRODUCT (MANDATORY)	Some products have larger ecological footprints than others (e.g. plastic vs textiles).
TOTAL PLOT AREA in sqmtrs (MANDATORY)	Larger units often have higher potential for pollution and resource consumption.
BUILDING PLAN (MANDATORY)	Indicates formal land use planning and zoning compliance (a land use environmental governance factor). Formal land use planning compliance means better for the environment.
CLU OBTAINED (MANDATORY)	Change of Land Use clearance is required to convert agricultural land to industrial, often assessed for environmental impacts. Higher the CLU higher is the environmental impact.
LATITUDE / LONGITUDE	Enables geo-mapping of units near protected areas, water bodies, or pollution hotspots. Can help in spatial environmental analysis. Closer to the water bodies, protected areas, higher is the environmental impact.

Social Variables

Variable	Rationale
TOTAL CONTRACTUAL EMPLOYEES (OPTIONAL)	Reflects labor intensity and workforce welfare issues (e.g., job security).
CONTRACTUAL EMPLOYEES WITH/WITHOUT HARYANA DOMICILE (OPTIONAL)	Inclusion of local workforce is key to social equity and local employment generation.
CAUSUAL EMPLOYEES DAILY WAGES (OPTIONAL)	Captures informal sector presence and potential for wage exploitation.
TOTAL REGULAR EMPLOYEES (MANDATORY)	Indicates stable employment generation, contributing to local livelihoods.
REGULAR EMPLOYEES WITH/WITHOUT HARYANA DOMICILE (OPTIONAL)	Local vs. migrant employment balance is a key social issue.
INVESTMENT IN BUILDING (OPTIONAL)	Implies infrastructure development with potential local economic impact.
ANNUAL PRODUCTION and ANNUAL TURNOVER	Reflects economic contribution to the region, indirectly tied to job creation and value generation.

Governance Parameters

Variable	Rationale

REGISTRATION NO. (MANDATORY)	Indicates formal registration and traceability.
UNIT (FUNCTIONING OR CLOSED) (MANDATORY)	Tracks operational status and regulatory updating.
COMPANY CONSTITUTION TYPE (OPTIONAL)	Helps distinguish between proprietorships, LLPs, or companies — varying governance implications.
GST NUMBER (OPTIONAL)	Tax compliance is a hallmark of good governance.
PLOT OWNERSHIP (MANDATORY)	Ownership vs. lease reflects long-term commitment and regulatory reliability.
ELECTRIC ACCOUNT NO (OPTIONAL)	Indicates formal electricity access and billing — key to formal governance.
START DATE OF COMMERCIAL PRODUCTION	Helps assess operational maturity and regulatory history.
BIP NO (OPTIONAL) and FACTORIES ACT COVERAGE	Legal compliance with factory labor norms.
TYPE OF CONNECTION (MANDATORY)	May indicate the category of industrial consumption — which has regulatory implications.

AI variables

Variable	Rationale
INVESTMENT IN PLANT & MACHINERY (OPTIONAL)	High capital expenditure is often associated with automation and AI-enabled processes.
INSTALLED PRODUCTION CAPACITY	High capacity suggests mechanization, likely tied to tech or AI-enabled systems.
CONNECTED ELECTRICAL LOAD	Advanced machinery and AI systems consume more electricity. High load may suggest tech usage.
TYPE OF INDUSTRY/SECTOR	Sectors like IT, electronics, precision manufacturing, or logistics are more likely to adopt AI.

6.2 Regression Model

AI adoption of firms is not clear in the datasets, leading to taking proxy datapoints from the datasets to construct AI adoption parameter of each firm. After creating the proxy, firms present in the datasets can be divided into two categories – Firms with AI adoption, and Firms with no AI adoption. Correlation analysis will be conducted to see correlation between ESG score and AI adoption of firms. To check for multicollinearity, Variance Inflation Factor (VIF) method will be employed.

To analyze the bidirectional causal relationship between AI adoption and ESG performance, we will employ a modified DiD model since our dataset lacks pre-adoption AI data. Traditional DiD relies on pre- and post-treatment observations, but in the absence of such data, we have to adopt a pseudo-DiD approach by leveraging industry trends as an external benchmark. This will allow us to estimate the ESG impact by comparing AI-adopting and non-AI-adopting firms, assuming that industry trends serve as a counterfactual for non-adopters. Additionally, we will use PSM to mitigate selection bias, ensuring that firms in both groups share similar observable characteristics.

The **DiD model** is given below:

$$Y_{it} = \beta_0 + \beta_1 AI_i + \beta_2 Post_t + \beta_3 (AI_i \times Post_t) + \sum X_{it} + e_{it}$$

Where,

Variables	Explanation
Y_{it}	Constructed ESG performance for firm i at time, from proxies, serving as the dependent variable.
AI_i	Binary indicator (Dummy) taking the value 1 if the firm adopts AI and 0 otherwise.
$Post_t$	Indicator for the post-AI adoption period (approximated using industry trends, since direct pre-adoption data is unavailable).
$AI_i \times Post_t$	Interaction term that captures the effect of AI adoption on ESG performance, leveraging industry trends as an external benchmark.
X_{it}	Vector of control variables, including firm size, sector, investment levels, and whether the firm belongs to the formal or informal sector.
e_{it}	Error term

7. Conclusion and Insights

The study provides valuable insights into the intricate relationship between AI adoption and ESG performance, particularly in the context of manufacturing firms. By leveraging proxy variables to address data limitations and employing a game-theoretic approach, the research moves beyond simple correlation analyses to explore bidirectional causality. The findings highlight that AI integration enhances ESG outcomes by improving energy efficiency, reducing carbon emissions, and streamlining corporate governance. At the same time, firms with strong ESG frameworks are more likely to invest in AI, reinforcing a mutually beneficial cycle.

A key takeaway from the study is the role of industry dynamics in shaping AI adoption strategies. Larger firms with greater resources are more likely to be early adopters, influencing industry standards and regulatory frameworks. The game-theoretic modeling, particularly through the Stackelberg competition framework, illustrates how firms strategically respond to competitive pressures and regulatory environments when implementing AI for ESG improvements. The Bayesian model and ultimately evolutionary game model further refines this analysis by incorporating firms' evolving beliefs about AI's impact on sustainability outcomes. Another critical insight is the disparity between formal and informal sector firms. While formal firms are more inclined to adopt AI-driven ESG practices due to regulatory compliance and investor expectations, informal firms face barriers such as financial constraints and lack of policy incentives. This highlights the need for targeted policy interventions to promote AI adoption across diverse industrial landscapes.

Methodologically, the study makes a significant contribution by employing a modified Difference-in-Differences (DiD) approach to estimate AI's impact on ESG performance in the absence of pre-adoption data. By using industry trends as an external benchmark and applying Propensity Score Matching (PSM) to control for selection bias, the research ensures a more robust causal analysis. These empirical techniques provide a clearer understanding of how AI adoption influences ESG performance over time.

In conclusion, the study gives a narrative and theoretical background to AI's transformative potential in driving sustainable business practices. However, it also emphasizes the need for careful policy design, industry-specific strategies, and equitable access to AI technologies to maximize ESG benefits across different sectors. Future research will expand on these findings by incorporating analysis on the longitudinal database and refining AI adoption metrics to further enhance the understanding of AI's role in corporate sustainability.

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