AI ADOPTION AND ESG PERFORMANCE IN FINANCIAL INSTITUTIONS: EVIDENCE FROM THE US, UK, AND EU

Author: CHIH JOU, KAO
Degree: MSc Investment Banking & Finance, University of Glasgow
Year: 2025

EXECUTIVE SUMMARY

This paper aims to explore whether the application of artificial intelligence (AI) in financial institutions can improve environmental (E), social (S), and governance (G) performance. To clarify whether AI adoption can translate into measurable improvements across all ESG dimensions in the financial sector, some sources were used to analyse in the methodology chapter.

- Main conclusions :
  - AI adoption significantly improves environmental (E) performance: Research results show that AI applications significantly improve environmental performance, which is the area requiring structured analysis. AI helps companies monitor, predict, and mitigate environmental risks, thereby directly improving their environmental scores (E-scores).
  - No significant impact on society (S) and governance (G): AI's impact on social and governance outcomes is less pronounced, reflecting the qualitative and relational complexity of these dimensions. The benefits of AI may be limited to measurable, data-intensive areas such as environmental management, rather than more qualitative or institutional dimensions such as stakeholder relations or governance structures.
  - Different dimensions of performance in EU vs non-EU: EU countries systematically outperform non-EU countries in environmental and social outcomes. However, non-EU companies exhibit stronger governance practices (EU companies have lower governance scores).
  - A gap between ESG weighting and actual performance: Companies that place a higher emphasis on environmental pillars tend to have lower environmental scores, suggesting that a greater formal emphasis on environmental dimensions does not necessarily translate into stronger performance. It may reflect strategic reporting choices or differing regulatory expectations rather than substantive sustainability improvements; meanwhile, it also may reflect disclosure-driven rather than substantive performance.
- Sources:
  - AI adoption → The AI adoption indicator is derived from an analysis of the AI-related keywords' mention frequency. The keywords referred to AI-related reports from the central banks, and they were used to clarify the disclosed reports of financial companies between 2020 and 2024 by a Natural Language Processing (NLP) tool from Insig AI.
  - ESG scores → ESG performance of financial institutions, including ESG pillar scores and weights, is derived from Bloomberg Terminal data in 2025.
  - Sample of data → The final sample includes 138 financial institutions. These institutions are from the financial sector in three indices: S&P 500, FTSE 350, and STOXX 600, located in the European Union, the United States, and the United Kingdom.

METHODOLOGY

- This study designed by a quantitative, and cross-sectional method, in order to assess the relationship between AI adoption and ESG performance. The main analytical method is Ordinary Least Squares (OLS) regression.
- Features :
  - Spanning the US, UK, and EU → Capturing institutional differences, the sample for this paper covers financial institutions across countries, which aims to explore how different regulatory and cultural contexts influence the relationship between AI and ESG performance.
  - Subgroup analysis of ESG pillar weighting → To explore the heterogeneity of companies' sustainability focus, this paper also conducted a subgroup analysis with performed additional regressions based on the weighting of companies' ESG pillars (low, medium, and high). This helps clarify whether the relationship between AI and ESG varies depending on the strategic emphasis companies place on each pillar. Interestingly, Bloomberg gives higher weight to social and governance dimensions in its financial sector scoring methodology.

METHODOLOGY (CONTINUED)

Data Collection

ESG Scores (Bloomberg Terminal, 2025)

- Environmental (E)
- Social (S)
- Governance (G)

AI Adoption (2020–2024)

- Frequency of AI-related keywords in sustainable reports

Regression Model

- log(E_i), log(S_i), log(G_i) = β0 + β1 log(AI_i) + ...
- Controls: size, leverage, governance ...
- Country & industry fixed effects

Findings

- AI ↑ → Environmental ↑
- AI → Social, Governance (no effect)
- Strong E–G interdependence
- EU > Non-EU in E & S, reverse for G
- Pillar weights ≠ actual performance

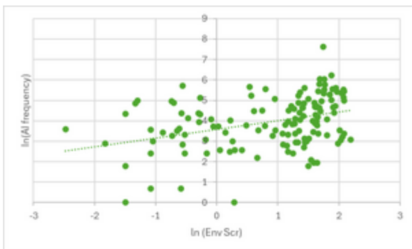
- Variable definition :
  - AI adoption (log AI_i)- The main independent variable is the intensity of AI adoption, measured by counting times of AI-related keywords are mentioned in corporate sustainable reports from 2020 to 2024. Keywords include "Artificial Intelligence", "AI", "Generative AI", "Large Language Models", "Machine Learning", refer to the AI disclosure reports of the central banks. To address data skewness, the count is logarithmically transformed, with higher values indicating higher AI adoption intensity.
  - ESG scores- The dependent variable is the ESG pillar scores from Bloomberg Terminal in 2025. All ESG pillar scores were log-transformed before regression analysis to reduce skewness and ensure the stability of parameter estimates. Scores range from 0-10, with 10 representing best-in-class performance, include:
    - Environment (log E_i): measures climate impact, resource efficiency, and pollution control.
    - Social (log S_i): measures stakeholder relations, workforce development, diversity, and community engagement.
    - Governance (log G_i): assesses board independence, shareholder equity, and disclosure transparency.
  - Control Variables- includes the factors that involve the institution scale, including firm size (total asset), leverage (total debt/ total asset), market value, board independence, country, and industry.

KEY FINDINGS

The empirical results of this study provide several key insights, which can be summarized in the following figures and brief text:

Finding 1: AI improves environmental performance

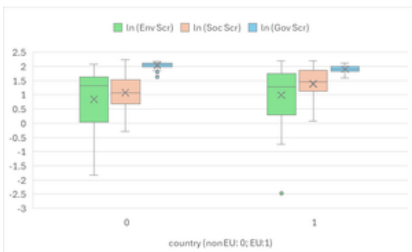
- Regression results show that AI adoption has a significant positive impact on corporate environmental performance, rather than social and governance outcomes. This confirms the core hypothesis of this study that increased AI adoption is associated with higher environmental scores, and suggests that the benefits of AI may be concentrated in measurable, data-intensive areas such as environmental management.



Scatter plot: AI adoption (x-axis) vs Environmental score (y-axis).

Finding 2: EU vs non-EU differences

- Companies in EU countries systematically outperform their non-EU counterparts in terms of environmental performance. This may reflect the more standardized regulatory framework in the EU. However, in terms of governance, non-EU companies show stronger governance outcomes (EU companies have lower governance scores). These differences highlight the significant impact of institutional context and regulatory framework on ESG outcomes.

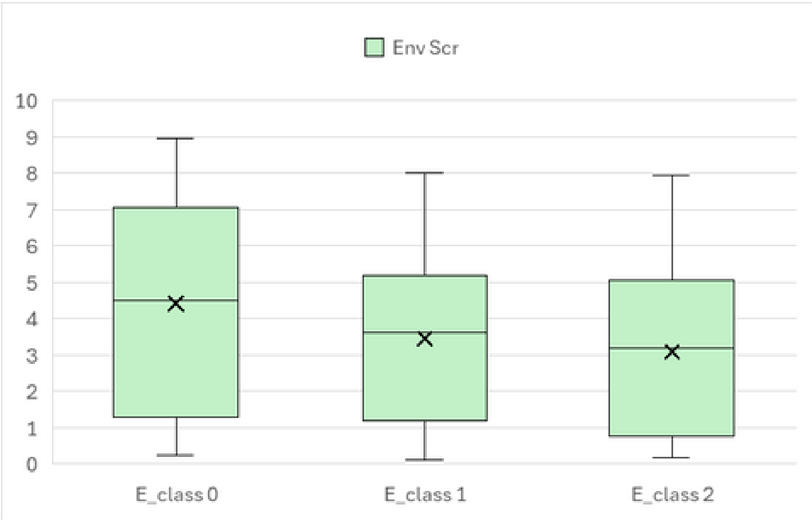


Box analysis: Compare the average performance of EU and non-EU companies in terms of E, S, and G scores.

KEY FINDINGS (CONTINUED)

Finding 3: The paradox of ESG weighting

- This study found a counter-intuitive pattern: companies that assign higher weights to the environmental pillar actually have lower average environmental scores. Specifically, companies classified as medium (E_class 1) and high (E_class 2) in terms of environmental weight have lower environmental scores than the low-weight benchmark group (E_class 0). This finding questions the validity of the environmental pillar weighting as a performance indicator, and suggests that high weights may reflect a company's reporting strategy or emphasis on disclosure rather than actual sustainability performance or genuine environmental improvements.



box analysis: Compare the different environmental weight categories (low, medium, high) with the average of the actual environmental score (E-score).

IMPLICATIONS

- For regulators :
  - There is a need for standardised, adoption-oriented indicators to measure concrete expectations and track dynamic verified emissions reductions or measurable social impact, rather than annual self-reported policy statements.
  - Regulators should move beyond disclosure volume toward adoption-based ESG evaluation, rewarding firms for demonstrable performance improvements rather than symbolic compliance.
  - Regulatory frameworks governing AI in ESG contexts should emphasise transparency, explainability, fairness, and accountability, ensuring that AI-driven assessments remain trustworthy and free from bias, especially for social and governance impact.
  - Independent third-party assurance and data verification mechanisms are essential to mitigate the growing risk of AI-enabled greenwashing, where firms use advanced technologies to enhance the appearance of sustainability without substantive change.
- For financial institutions :
  - AI adoption demonstrably enhances environmental (E) performance, particularly in areas involving measurable data and risk modelling, but it remains insufficient to drive improvements in social (S) and governance (G) outcomes.
  - Firms should leverage AI as a complementary analytical tool, not a substitute for strong governance structures, institutional accountability, or stakeholder engagement.
  - Institutions must be vigilant against greenwashing risks, particularly when using environmental weighting or AI-driven ESG analytics as a legitimacy strategy without corresponding performance progress.
- For investors :
  - Investors should interpret ESG scores with caution, recognising that they may reflect disclosure intensity rather than actual sustainability outcomes. Regional regulatory differences and data limitations significantly affect comparability.
  - The use of AI within ESG assessments is domain-specific: it tends to be highly effective in quantitative, data-driven areas such as environmental monitoring but less reliable in evaluating qualitative aspects like governance or social impact.
  - For non-EU firms, closer scrutiny of disclosure comparability and data reliability is essential; for EU firms, investors should critically assess whether robust governance frameworks translate into tangible environmental and social improvements, rather than compliance-oriented reporting.

NEXT STEPS

- Extended longitudinal analysis (data after 2025): Future studies can address the current limitations of cross-sectional designs in causal inference by adopting longitudinal designs. This will require incorporating AI adoption data and ESG scores beyond 2025 to capture dynamic changes over a longer timeframe.
- Deepen the potential of AI in governance and society: As the impact of AI on social and governance dimensions is not yet clear, future research can adopt qualitative methods to explore in more depth how AI is integrated into governance and social practices.54These dimensions, while not easily quantifiable, are crucial to achieving balanced sustainability.
- Testing a revised model for ESG scoring methodology: addressing the counterintuitive negative relationship between environmental pillar weightings and actual performance. Future research could explore revised ESG scoring methodologies to ensure that scores better reflect actual performance rather than just disclosure strategies.

CONTACT

- Name: CHIH JOU, KAO
- LinkedIn: https://www.linkedin.com/i n/doris-kao/
- GitHub Repo: https://github.com/doriskao922/AI-ESG-Finance-Study.git