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The Integration of Artificial Intelligence (AI) in ESG Investment Evaluation

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Abstract

This paper examines how Artificial Intelligence (AI) is reshaping the way ESG (Environmental, Social, and Governance) investments are evaluated, and what that means for investor behaviour. While ESG investing has grown significantly in prominence, the evaluation methods underpinning it have long struggled with inconsistency, subjectivity, and reliance on outdated, static data. AI-driven tools offer a compelling alternative, capable of processing large and varied datasets in ways that manual approaches simply cannot match. Drawing on survey responses from 105 investors and financial industry professionals, we investigated how three dimensions of AI engagement — perceived effectiveness, usage frequency, and familiarity — relate to investor confidence, portfolio allocation decisions, and perceived transparency. Our findings suggest that AI's effectiveness and investors' familiarity with it meaningfully strengthen confidence and perceptions of transparency, while the relationship between usage frequency and investment allocation is more complex than initially anticipated.

Keywords: Artificial Intelligence, ESG Investing, Investor Confidence, Portfolio Allocation, Transparency

1. Introduction

ESG factors have moved from the periphery of financial analysis to the centre of investment strategy. Across asset classes and geographies, investors and asset managers have come to recognise that how a company manages its environmental footprint, social relationships, and governance structures is closely tied to its long-term financial health. What was once framed as 'values-based' investing has steadily matured into a mainstream risk management and value-creation discipline.

Yet the mechanisms used to evaluate ESG performance have not kept pace with this growing importance. Conventional ESG assessments have historically depended on company self-disclosures, analyst-driven manual reviews, and static scoring frameworks that are updated infrequently. This creates a disconnect: investors are asking increasingly sophisticated questions about sustainability risks, but the tools available to answer them have been slow, inconsistent, and difficult to compare across providers. The sheer volume of relevant data — spanning annual reports, sustainability disclosures, regulatory filings, news coverage, and social media signals — makes it near-impossible for human analysts alone to form a complete, timely picture of a company's ESG standing.

Artificial Intelligence has emerged as a technology with genuine potential to address these structural weaknesses. Machine learning algorithms, natural language processing, and big data analytics together enable the systematic processing of both structured and unstructured information at a scale and speed no human team could replicate. Satellite imagery, real-time news feeds, regulatory databases, and sustainability reports can all be integrated into a dynamic assessment, surfacing risks and opportunities that might otherwise go undetected.

The potential benefits are meaningful. AI can reduce the subjectivity that dogs manual ESG scoring, deliver near-real-time intelligence to investors, and support forward-looking risk predictions that reactive, backward-looking models cannot. These capabilities matter especially now, as investors navigate a landscape shaped by tightening regulation, accelerating climate risk, and heightened stakeholder scrutiny.

This study sets out to examine those possibilities — and their limits — through a quantitative lens. We focus specifically on how AI integration affects investment decision-making in ESG contexts, looking at the experiences and perceptions of practitioners currently engaged with these tools. The goal is to produce insights that are actionable for investors, asset managers, policymakers, and regulators working to align financial performance with sustainable development in an increasingly data-driven world.

1.1 Research Gap

Despite the momentum behind ESG investing, the field's foundational evaluation infrastructure remains fragile. Inconsistent rating methodologies, fragmented data sources, and subjective interpretation processes mean that two investors looking at the same company can arrive at very different ESG conclusions. AI has shown real promise in addressing these problems — its ability to process diverse, high-volume data streams is well-documented — but important questions remain unanswered. How much does AI's perceived effectiveness actually shift investor confidence? Does the frequency with which investors use AI tools translate into different allocation behaviours? And does greater familiarity with AI genuinely improve perceptions of transparency in ESG evaluation? These specific behavioural dimensions have received limited empirical attention, and this study aims to contribute to that gap.

1.2 Problem Statement

The core tension this research addresses is this: AI holds considerable promise for improving the objectivity, speed, and predictive power of ESG evaluation, but its effective integration depends on trust, transparency, and methodological coherence — all of which remain works in progress. Investors' willingness to rely on AI-generated ESG reports, and their preparedness to adjust portfolios on the basis of those reports, is not simply a function of how capable the technology is. It also depends on how effective they perceive it to be, how familiar they are with how it works, and how often they use it. Unpacking these relationships — and understanding where they are strong, where they are weak, and what might be done to strengthen them — is the central task of this study.

2. Literature Review

The body of research at the intersection of AI and ESG investment has grown rapidly, though it remains unevenly developed across different questions.

There is now a well-established empirical foundation showing that ESG performance and financial performance are positively linked. Friede, Busch, and Bassen (2015) synthesised evidence across a large number of studies and found consistent associations between strong ESG practices and reduced financial risk and higher profitability. Eccles, Ioannou, and Serafeim (2014) reached comparable conclusions at the firm level, while Clark, Feiner, and Viehs (2015) demonstrated similar patterns at the portfolio level, lending further support to the case for integrating ESG factors into mainstream investment analysis.

What is less settled is whether the ESG ratings that operationalise these factors are reliable. Berg, Kölbel, and Rigobon (2022) documented surprisingly low correlations between ESG scores produced by different rating agencies, attributing this to divergence in how providers define, measure, and weight ESG criteria. Chatterji et al. (2016) found similarly low agreement across providers, suggesting that the problem runs deep rather than reflecting easily correctable technical differences. These findings raise genuine questions about whether ESG ratings, as currently constructed, are fit for purpose in risk management.

AI-based approaches have been proposed as a way to address this inconsistency. Bollen (2021) highlighted the capacity of machine learning to process text-based information — news sentiment, social media signals, analyst commentary — that traditional models typically ignore. Dorfleitner, Halbritter, and Nguyen (2021) similarly demonstrated that machine learning models can deliver more granular and dynamic ESG assessments than conventional rating frameworks, particularly when trained on diverse, real-time data sources.

The case for real-time monitoring is developed further by Krueger, Sautner, and Starks (2020), who showed that institutional investors increasingly want to track climate and governance risks as they evolve rather than receiving periodic snapshots. Bolton and Kacperczyk (2021) extended this line of argument, linking proactive risk monitoring to improved portfolio-level outcomes over time.

Several challenges, however, temper this optimism. Mittelstadt et al. (2016) raised concerns about algorithmic bias, noting that AI models trained on historically uneven data can reproduce or amplify geographic and sectoral disparities in ESG coverage. Guidotti et al. (2018) and the OECD (2021) drew attention to the 'black box' problem: when investors cannot understand how an ESG score was generated, their ability to scrutinise, challenge, or trust that score is materially diminished. Amel-Zadeh and Serafeim (2018) and the IFRS Foundation (2021) both pointed to the absence of standardised ESG reporting frameworks as a structural constraint on AI's effectiveness, suggesting that the technology's benefits will remain partial until data inputs are more consistent.

Taken together, the literature supports cautious optimism: AI has genuine capacity to improve ESG evaluation, but its integration raises real questions about bias, transparency, and governance that require deliberate attention (European Commission, 2020; Serafeim, 2020).

3. Research Methodology

This study utilizes a quantitative approach in investigating the use of Artificial Intelligence (AI) in the evaluation of Environmental, Social, and Governance (ESG) investment evaluation. This approach will help assess the effect of the effectiveness of AI on investors' confidence levels, the association between the frequency of AI tool utilization and investment allocation decisions, and the association between the level of familiarity with AI and the level of transparency in ESG evaluation.

3.1 Sample Size and Sampling Technique

The study drew on responses from 105 participants — investors and asset managers who are actively engaged in ESG investing and have direct experience using AI tools within that context. Participants were selected to ensure that respondents could speak from practice rather than in the abstract

3.2 Data Collection

Data were collected through a structured questionnaire designed to capture both attitudes and behaviours related to AI use in ESG evaluation. The questionnaire covered the following dimensions:

- Familiarity with AI technologies used in ESG evaluation
- Frequency of AI tool usage in investment-related workflows
- Perceived effectiveness of AI in monitoring ESG regulatory compliance
- Confidence in reports generated by AI-based ESG evaluation systems
- Perceived transparency enhancement attributable to AI tools
- The extent to which AI-driven evaluations influenced portfolio allocation decisions

3.3 Data Analysis

The analysis combined descriptive statistics, correlation analysis, and multiple regression modelling to test each of the three hypotheses set out below. Regression coefficients, standard errors, and significance levels are reported for each model.

Hypothesis 1: Perceived effectiveness of AI in regulatory compliance monitoring and familiarity with AI both significantly and positively influence investor confidence in AI-generated ESG reports.

The regression results (Table 3) supported this hypothesis. Effectiveness was the stronger predictor ($\beta = 0.488$, $p < 0.001$), with familiarity also showing a significant positive effect ($\beta = 0.232$, $p < 0.001$). Both predictors met the threshold for statistical significance, and the null hypothesis was rejected.

Hypothesis 2: Usage frequency of AI tools significantly predicts the degree to which AI evaluations influence portfolio allocation decisions.

Results here were more nuanced (Table 4). Usage frequency showed a negative coefficient that approached but did not reach conventional significance (β = −0.078, $p = 0.058$). The perceived importance of AI in risk identification, however, was a significant negative predictor of portfolio allocation (β = −0.113, $p = 0.004$). Hypothesis 2 was therefore only partially supported.

Hypothesis 3: Familiarity with AI in ESG evaluation significantly predicts the perception that AI enhances transparency.

Familiarity proved to be a strong and significant predictor of perceived transparency (β = 0.417, $p < 0.001$), while usage frequency was not statistically significant at the 5% level (β = 0.163, $p = 0.093$). Hypothesis 3 was supported with respect to familiarity, but not usage frequency.

3.4 Ethical Considerations

Participant confidentiality and anonymity were maintained throughout the research process. All participants provided informed consent prior to completing the questionnaire, and no personally identifying information was retained in the dataset.

4. Research Objectives

This study was organised around three core objectives:

1. To determine how the perceived effectiveness of AI in ESG regulatory compliance monitoring shapes investor confidence in AI-generated evaluation reports.
2. To examine whether the frequency with which investors use AI tools predicts the degree to which those tools influence their portfolio allocation decisions.
3. To assess the extent to which familiarity with AI technologies in ESG evaluation relates to perceived transparency in the investment evaluation process.

4.1 Hypotheses

The investigation aimed to test the following null H_0 and alternative H_1 hypotheses:

Hypothesis 1 H_1:

Perceived effectiveness of AI in monitoring regulatory compliance and familiarity significantly and positively influences investors' confidence in AI-generated ESG reports.

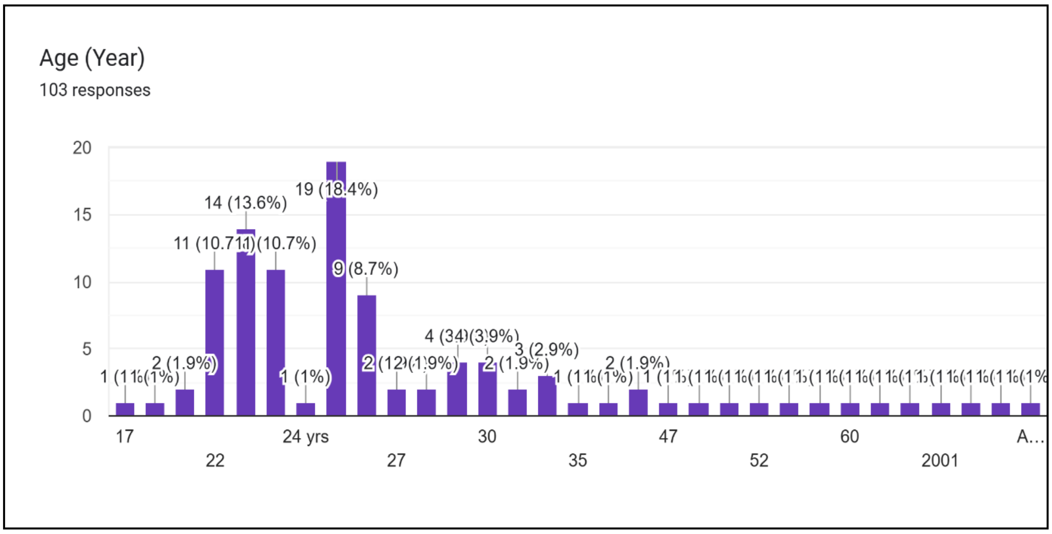
Hypothesis 2 H_1:

Frequency of usage significantly predicts the extent to which AI evaluations influence investment portfolio allocation.

Hypothesis 3 H_1:

Familiarity with AI in ESG evaluation significantly predicts the extent to which AI enhances the transparency in the investment evaluation process

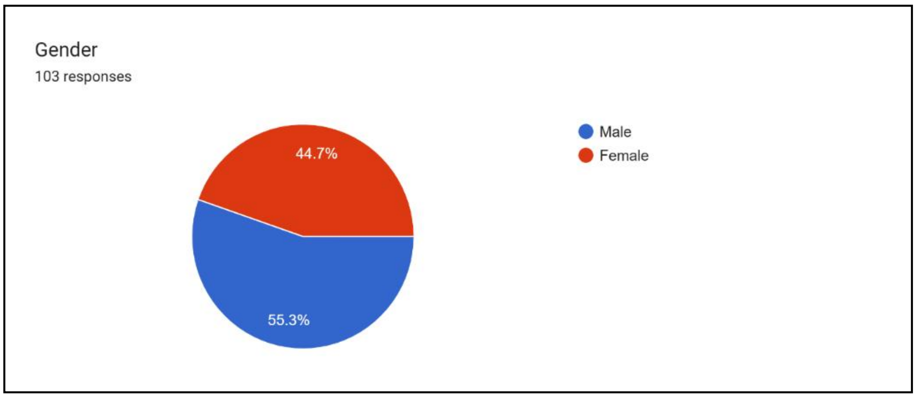
4.2 Demographic Variables



Graph 4.2.1

Interpretation

- A majority of respondents are within the 22-26 years age range, but the highest concentration of respondents falls within the 24-25 years range, i.e., 18.4%.
- A very small number of respondents fall within the range of less than 20 years or more than 35 years, which indicates that the sample population of the research lies within a range of young people in early careers or students.
- The curve appears to be skewed to one side, which indicates that the research findings are based on a sample population of young adults rather than a diversified age range.

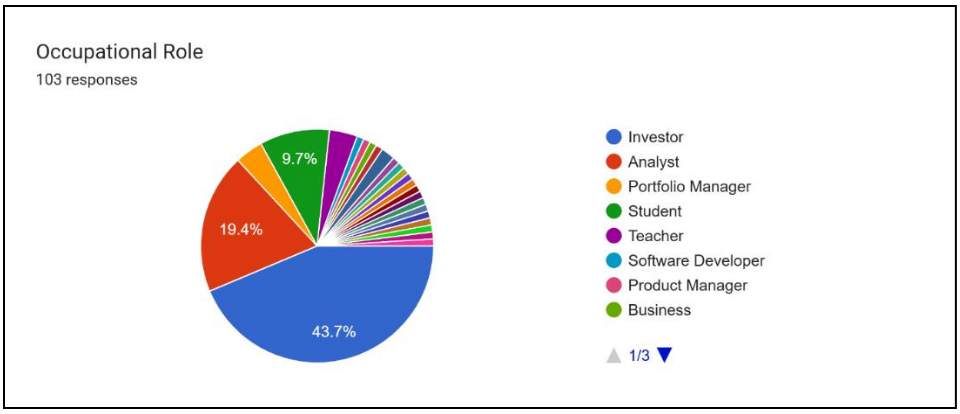


Graph 4.2.2

Interpretation

- From the distribution chart, there are slightly more males than females, with a percentage distribution of 55.3% for males and 44.7% for females. This shows that there is a moderately balanced composition.
- Even though there are more males than females, the gap between the two groups is not very significant. This shows that there are opinions from both genders in the survey in fairly proportional numbers.

- The fact that there is a near-balanced composition in the distribution chart shows that the results are reliable, as there are no major opinions from a particular gender group.



Graph 4.2.3

Interpretation

- The majority of respondents belong to the Investors group (43.7%), followed by Analysts (19.4%). This indicates that the survey has mainly focused on the viewpoints of finance and investment professionals.
- Students make up 9.7%, while other professional groups such as Portfolio Managers, Teachers, Software Developers, and Business professionals make up a smaller percentage of respondents.
- The dominance of investors and analysts indicates that the survey results might be more in favor of market-oriented and investment-based viewpoints rather than the general public's opinion.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev	Min	Max
Familiarity with AI	2.39	1.52	0	5
AI Tool Usage Frequency	2.57	1.13	1	5
Perceived Risk Identification Importance	3.11	1.19	1	5
Effectiveness in Compliance Monitoring	3.3	1.09	1	5
Confidence in AI ESG Reports	3.05	1.1	1	5
Agreement: AI Enhances Transparency	3.22	1.16	1	5
Influence on Portfolio Allocation	1.24	0.43	1	2

This table provides the mean, standard deviation, and range for the key survey metrics.

Table 2: Correlation Matrix

The matrix shows the strength and direction of the relationships between variables (r values).

Variable	Familiarity	Frequency	Confidence	Transparency
Familiarity	1	0.38	0.61	0.64
Frequency	0.38	1	0.27	0.25
Confidence	0.61	0.27	1	0.75
Transparency	0.64	0.25	0.75	1

Table 3: Regression Results (Hypothesis 1)

Dependent Variable: Confidence in AI Reports

Independent Variable	Coefficient (β)	Std. Error	t-value	p-value
(Constant)	0.883	0.243	3.638	< 0.001
Effectiveness (Compliance)	0.488	0.088	5.575	< 0.001
Familiarity with AI	0.232	0.063	3.706	< 0.001

Interpretation (Hypothesis 1):

- Effectiveness (Compliance) has a significant impact on confidence in AI reports, with a high β value of 0.488 and a p-value of <0.001. This suggests that the more effective the AI reports, the higher the confidence, and it is the most significant predictor.
- Familiarity with AI also has a significant impact on confidence, with a β value of 0.232 and a p-value of <0.001. This suggests that the more familiar a person is with AI, the higher their confidence in AI reports.
- Both variables have a p-value of <0.001, which is significant, so the null hypothesis is rejected, and Hypothesis 1 is supported.

Table 4: Regression Results (Hypothesis 2)

Dependent Variable: Influence on Portfolio Allocation

Independent Variable	Coefficient (β)	Std. Error	t-value	p-value
(Constant)	1.792	0.112	16.02	< 0.001
Usage Frequency	-0.078	0.041	-1.917	0.058
Importance in Risk ID	-0.113	0.039	-2.921	0.004

Interpretation (Hypothesis 2):

- Importance in Risk Identification is a crucial aspect in Risk Identification, which influences portfolio allocation (β = –0.113, p = 0.004). A negative coefficient was found, showing that an increase in the importance of AI in risk identification is related to a decrease in portfolio allocation, and this is statistically significant.
- There is no statistically significant effect of Usage Frequency on portfolio allocation (β = –0.078, p = 0.058). As the p-value is larger than 0.05, it is evident that there is no significant effect, though it is close to significance at a 10% confidence level.

- Hypothesis 2 is partially supported based on the p-value of the data, where only one of the variables, namely, importance in risk identification, shows a significant effect, while there is no strong evidence of a significant effect of usage frequency on portfolio allocation.

Table 5: Regression Results (Hypothesis 3)

Dependent Variable: Perception that AI Enhances Transparency

Independent Variable	Coefficient (β)	Std. Error	t-value	p-value
(Constant)	1.804	0.216	8.334	< 0.001
Familiarity with AI	0.417	0.071	5.833	< 0.001
Usage Frequency	0.163	0.096	1.697	0.093

Interpretation (Hypothesis 3):

- Familiarity with AI has a strong and statistically significant positive influence on the perception that AI improves transparency ($\beta = 0.417$, $p < 0.001$). This means that the more familiar people are with AI, the higher the likelihood that they will perceive AI as improving transparency.
- On the other hand, Usage Frequency is not statistically significant at the 5% level ($\beta = 0.163$, $p = 0.093$). Although the coefficient is positive, the p-value is higher than 0.05, indicating weak and marginal evidence at the 10% significance level.
- Thus, Hypothesis 3 is supported to some extent. Familiarity with AI is significant, whereas usage frequency is not statistically significant.

5.Findings

The analysis produced five principal findings:

First, both the perceived effectiveness of AI and investors' familiarity with the technology emerged as significant positive drivers of confidence in AI-generated ESG reports. Investors who believe AI tools work well, and who understand how they work, are considerably more likely to trust what those tools produce.

Second, investors appear to value the role AI plays in providing objective, timely compliance-related information. This signal — that AI can be relied upon for regulatory monitoring — appears to matter to confidence independently of broader questions about the technology's general capabilities.

Third, the relationship between AI usage frequency and portfolio allocation decisions was not straightforward. The near-significant negative coefficient suggests that more frequent AI users may become more cautious rather than more decisive in their portfolio adjustments — possibly because greater exposure to AI outputs also brings greater awareness of their limitations.

Fourth, the perceived importance of AI in risk identification was a significant negative predictor of portfolio allocation. This counter-intuitive finding may reflect investors' discomfort with acting on AI-generated risk signals before they feel they fully understand them — a trust gap that better explainability could help close.

Fifth, familiarity with AI had a strong positive association with perceived transparency. Investors who are more comfortable with AI technology are more likely to see it as making ESG evaluation more transparent rather than less, suggesting that education and exposure are important levers for building trust.

Alongside these findings, it is worth acknowledging the barriers that remain. Data bias, algorithmic opacity, and the absence of standardised ESG reporting frameworks continue to constrain the full integration of AI into ESG investment workflows.

Recommendations

Drawing on the findings above, we offer the following recommendations for practitioners, organisations, and policymakers working in this space:

1. Invest in investor education.

The link between familiarity and both confidence and perceived transparency suggests that training and education programmes could yield meaningful returns. Investors who understand what AI can and cannot do are better equipped to use it well and to scrutinise its outputs critically. Asset managers and financial institutions would do well to build AI literacy into their professional development offerings.

2. Prioritise explain ability in AI design.

The 'black box' problem identified in the literature is not merely theoretical. Our findings suggest it has real consequences for investor behaviour. AI systems used in ESG evaluation should be designed with interpretability as a core requirement, not an optional feature. Regulators and standard-setters can play a role here by setting minimum explain ability standards for AI tools used in regulated investment contexts.

3. Work toward standardised ESG data and reporting.

AI is only as good as the data it is trained on. The fragmented state of ESG reporting standards creates inconsistencies that propagate through AI-generated evaluations and ultimately undermine investor confidence. Regulatory bodies and industry organisations should accelerate work on common ESG definitions, metrics, and disclosure formats that can serve as a reliable foundation for AI systems.

4. Address data quality and bias systematically.

Organisations deploying AI for ESG evaluation should implement robust data validation procedures and actively monitor their models for signs of geographic or sectoral bias. Diverse training datasets and regular audits are practical steps toward more equitable and accurate ESG assessments.

5. Maintain meaningful human oversight.

AI performs best as a complement to human judgement, not a replacement for it. Hybrid workflows that combine AI's data-processing capabilities with human contextual expertise and ethical reasoning are likely to produce more reliable ESG evaluations than either approach alone. This is particularly important for assessments involving contested or emerging sustainability issues where algorithmic certainty may be misplaced.

6. Leverage AI for real-time risk tracking.

One of AI's most distinctive advantages is its capacity to monitor ESG-relevant developments continuously rather than periodically. Organisations should make more active use of this capability, particularly in relation to regulatory compliance monitoring and early identification of emerging risks — precisely the functions that our respondents found most confidence-building.

Conclusion

This study has explored how AI integration shapes the way investors engage with ESG evaluation — and the conditions under which it tends to strengthen or complicate that engagement. The clearest message from our data is that investor confidence and perceptions of transparency are closely tied to how effective and how familiar investors find the AI tools they use. These are not fixed properties of the technology itself; they can be actively cultivated through better tool design, stronger explainability, and deliberate investment in user education.

At the same time, the results around portfolio allocation and usage frequency caution against assuming that more AI automatically means better decisions. The relationship between AI use and investment behaviour is mediated by trust, and trust is not built simply by increasing the frequency of exposure. It requires meaningful understanding, which in turn requires transparency about how AI systems work and what their limitations are.

The challenges ahead — data bias, algorithmic opacity, fragmented reporting standards — are real, but they are not insurmountable. The trajectory of AI in sustainable finance is broadly positive, and this study adds to the growing body of evidence that the technology, deployed thoughtfully and governed carefully, can genuinely strengthen ESG evaluation and contribute to more informed, more sustainable investment decisions.

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