INVERGE JOURNAL OF SOCIAL SCIENCES
https://invergejournals.com/
ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 1, 2026

GREEN INTELLIGENCE IN FINANCE: ARTIFICIAL INTELLIGENCE-DRIVEN ESG ANALYTICS AND SUSTAINABLE INVESTMENT PERFORMANCE

Hind Gatoi [1], Islam Belhaoua [2], Kashf Akhtar [3], Miqdad Qadir [4], Nida Mohammad [5], Muhammad Ali [6]

DOI: https://doi.org/10.63544/ijss.v5i1.216

Affiliations:

[1] School of Economics and Management, Hubei University of Automotive and Technology, China
Email: gatoihind1@gmail.com
https://orcid.org/0009-0001-5013-9823

[2] School of Economics and Management, Hubei University of Automotive and Technology, China
Email: belhaoua@qq.com
https://orcid.org/0009-0008-5610-3857

[3] Assistant Director, State Bank of Pakistan (BSC) & SZABIST, Islamabad
Email: kashafkhanakhtar@yahoo.com

[4] MS Financial Management, Department of Theory and Technology in Management. Southern Federal University, Rostov-on-Don, Russian Federation
Email: mkadir@sfedu.ru

[5] Lecturer at Institute of Management Sciences, University of Balochistan, Quetta
Email: nidamkhan786@gmail.com

[6] MA Development Studies (IPED), International Institute of Social Studies (ISS), Erasmus University Rotterdam, Netherlands
Email: muhaqiq.ali@gmail.com

Corresponding Author's Email:

[1] gatoihind1@gmail.com

Article History:
Received: 25.11.2025
Accepted: 21.12.2025
Published: 02.01.2026

Abstract

This study examined the role of artificial intelligence (AI)-driven Environmental, Social and Governance (ESG) analytics in enhancing sustainable investment performance. While traditional ESG ratings had been widely used in responsible investment strategies, they often suffered from data inconsistency, subjectivity and limited coverage of unstructured sustainability information. AI-based ESG systems were increasingly applied to extract deeper sustainability signals from corporate disclosures, reports and external data sources. Using portfolio-level analysis, this study compared the financial outcomes of portfolios constructed using AI-driven ESG indicators with those based on conventional ESG ratings. The results showed that AI-enhanced high-ESG portfolios achieved higher mean returns and superior Sharpe ratios than both AI-based low-ESG portfolios and traditionally rated ESG portfolios. In addition, AI-driven high-ESG portfolios demonstrated lower downside-risk exposure and smaller maximum drawdowns during market stress, indicating stronger resilience. Regression analysis further revealed that AI-derived ESG scores were more strongly associated with excess returns than traditional ESG metrics. These findings suggested that AI improved the informational efficiency of ESG assessment by capturing more accurate, forward-looking sustainability risks and opportunities. The study concluded that AI-driven ESG analytics strengthened the financial relevance of sustainability integration and supported better-informed investment decision-making. The results carried important implications for investors, regulators and corporations seeking to align AI deployment with high-integrity sustainable finance practices, while also highlighting the need for ethical and transparent AI governance in financial markets.

Keywords: Artificial Intelligence, ESG Analytics, Portfolio Performance, Risk Management, Sustainable Finance, Transparency

Introduction

The fast spreading of artificial intelligence (AI) in the financial market had transformed the way investors used Environmental, Social and Governance (ESG) data in their decision making. Asset managers began to use machine learning and natural language processors to analyse disclosures of large volumes of assets, sustainability reports and other datasets as well, and this began replacing periodic reports and human analysts, which they had earlier referred to as "green intelligence in finance (Liu et al., 2023; Giudici and Wu, 2024). Recent literature suggested that the use of AI enhanced the ESG performance on a firm level, especially among organisations that were more digital and better-governed (Xiao & Xiao, 2024). Simultaneously, meta-analyses also indicated that increased ESG practices were linked to either consistent or better financial performance, which supports the view of investor focus on data-driven sustainable ways of operating (Friede et al., 2015).

The ESG data that was fed to AI models had been noisy, unstructured and inconsistent among rating agencies, giving financial decision-makers uncertainty (Berg et al., 2022). On the one hand, according to studies, there were low levels of correlation between ESG scores and conceptual and methodological differences in sustainability assessments (Billio et al., 2023). These shortcomings provided loopholes to greenwashing whereby companies chose to only report or report on the performance selectively. With the assistance of AI-driven analytics, such risks were predicted to be alleviated, since the system allowed processing texts automatically, finding anomalies and triangulation of sustainability-related signals (Schimanski et al., 2024). Nevertheless, issues of bias, openness, and trustworthiness were also brought about by the same algorithms.

In the meantime, the growth of sustainable investing was proceeding in other parts of the world with the help of regulatory standards, requirement of disclosures and demand by investors (OECD, 2023). It was even indicated that portfolios with material ESG factors had reduced downside risk and gained more resiliency because of market volatility (Lanza et al., 2023). But the majority of this study was based on conventional ESG ratings. Minor focus was placed on the possibility of AI-based ESG analytics to generate dissimilar and better investment returns than traditional methods.

Issues concerning sustainable AI highlighted that AI systems, themselves, had social and environmental imprints including energy consumption and algorithmic bias, to be governed ethically (Jobin et al., 2019; Floridi & Cowls, 2022). Financial institutions were thus not only to apply AI towards assessing the ESG performance, but also to make sure that their own AI infrastructures did not violate the ESG standards. This posed a two-fold challenge and it was a necessity to conduct empirical research connecting AI-driven ESG analytics to sustainable investment performance.

Background of the Study

The papers on both AI and ESG had developed around three main streams. The former stream addressed the adoption of AI in companies and its effects on the results of ESG. Research revealed that AI-powered surveillance infrastructures, analytics and predictive supply-chain, confidence to the environment, corporate transparency and social accountability get stronger (Liu et al., 2023; Xiao and Xiao, 2024). The mediators of these improvements mostly included improved innovation and organisational learning.

The second was the stream on AI and big data methods of measuring ESG. Scholars have shown that natural language processing would be able to identify the content found in corporate disclosures and media that is ESG related and enhances the recognition of sustainability indicators and possible misconduct (Schimanski et al., 2024). It was also determined in reviews that AI provided better ESG anomaly detection and greenwashing identification, yet the overall aspects of data quality and explainability continued to be problematic (Ekaristi et al., 2024).

The third one was the relationship between ESG indicators and financial performance. Much of the literature also found an overall positive or neutral relationship between ESG performance and financial returns, which is that ESG integration did not reduce value creation and most of the time enhanced the risk-adjusted performance (Friede et al., 2015; Buallay, 2019). More recent studies implied that the ability of ESG-optimized portfolios to outperform traditional portfolios would arise in cases where the ESG data are relevant, consistent and well-measured (Lanza et al., 2023).

In spite of these advances, there were still gaps in the knowledge of the role of AI-based ESG analytics in deciding what happened at the portfolio level. Researchers pointed out that ESG ratings were weak and subject to greenwashing, and even AI-powered ESG monitoring offered no transparency and ethical governing frameworks (Berg et al., 2022; Giudici and Wu, 2024). This revealed the necessity of concerted research on

AI-enhanced ESG information and investment performance jointly.

Research Problem

Even though there was a growing push to advertise AI-driven ESG analytics as ground-breaking towards sustainable investing, there were fewer studies empirically analysing their true effectiveness to enhance portfolio returns. The majority of previous studies examined either the adoption of AI and the performance of the firms in the ESGs, or the impact of traditional ESG ratings on returns. Not many studies compared the performance of AI-generated ESG with the traditional ESG in terms of investment (Lanza et al., 2023; Giudici & Wu, 2024).

The consistent challenge like rating divergence, model opaque and data quality brought up the unanswered question of whether AI reduced or increased greenwashing risk (Berg et al., 2022). Transparency might be improved with AI systems, but there might be the risk of algorithm bias when rules of governance were not strong. Thus, the research question used in this paper was the level to which AI-based ESG analytics enhanced sustainable investment performance and on what conditions the enhancement took place.

Research Objectives

1. To review existing literature on AI, ESG analytics and sustainable investing to develop an integrated conceptual framework.
2. To examine differences between AI-enhanced ESG indicators and traditional ESG ratings regarding data quality, transparency and stability.
3. To analyse how AI-driven ESG analytics influenced portfolio risk-adjusted returns and downside risk compared with conventional ESG methods
4. To evaluate how governance, data quality and AI transparency moderated the relationship between AI-driven ESG analytics and investment performance.

Research Questions

Q1. How had AI applications in ESG analytics been conceptualised and implemented in the literature?
Q2. How did AI-enhanced ESG indicators differ from traditional ESG ratings?
Q3. To what extent did AI-driven ESG analytics influence risk-adjusted portfolio performance?
Q4. What governance and transparency conditions strengthened or weakened this relationship?

Literature Review

ESG Data Quality and Measurement Challenges

Quality and comparability of ESG information had continued to be one of the most important limitations to sustainable investment analytics. Research demonstrated that ESG ratings issued by major agencies significantly differed due to the scope of ratings, choice of measurement and weighting, i.e., a similar company would have significantly different ratings according to which agency was used (Berg et al., 2022; Gibson Brandon et al., 2021). Such deviation complicated the activities of investors and undermined the belief of ESG-driven portfolio screening, especially in situations where AI or quantitative models are dependent on such data.

Researchers also found out that the ESG information solely exhibited managerial disclosure strategies and not objective performance which led to possible bias in evaluation systems. Companies that had more disclosure were more likely to be rated highly on ESG irrespective of the sustainability activity behind the results, indicating that transparency as opposed to performance occasionally prevailed in the creation of rating (Christensen et al., 2021; Fatemi et al., 2018). The difference became acute when machine-learning instruments started to dig through disclosures in bulk since biased or impression-managed text might contaminate algorithmic evaluations.

Meanwhile, institutional investors became more and more insistent on more transparent and standardized ESG data due to an increased understanding of the financial importance of climate and sustainability risks to organisations. It was shown that investors made well-informed investment decisions by taking climate exposure and ESG risks into account explicitly when allocating assets but were unable to be certain about them due to the mixed quality of such data and inconsistent reporting systems (Krueger et al., 2020; Raghunandan and Rajgopal, 2022). Ali & Rafiq-uz-Zaman (2025) recommended AI literacy at institutional level by workshops. Teachers Trainings related AI skills should be compulsory to produce skillful teachers to teach the students related skills (Rafiq-uz-Zaman, 2023). Redesigning 21st-century skills, such as AI, is essential to update the workforce, which is being influenced by the rapid changes in skills (Rafiq-uz-Zaman, 2022). Such results implied that even though the ESG information had become inseparable to capital markets, considerable measurement and methodological problems continued to exist.

ESG and Financial Performance

An increasing literature tested the question of ESG integration enhancing financial performance and found largely positive but subtle findings. Researchers have shown that adding ESG factors in portfolio construction could help move the conventional risk-return frontier to enable investors to attain sustainability goals whilst perhaps not compromising returns (Pedersen et al., 2021; Albuquerque et al., 2020). Specifically, the resiliency of environmental and social leaders tended to be higher in the financial turbulent times.

The other studies displayed differing reallocations to macro-level stress events (including the COVID-19 pandemic) and revealed favourable market valuation results were significantly higher in firms that exhibited higher performance levels in the aspects of environment and social performance (Albuquerque et al., 2020; Broadstock et al., 2021). These findings strengthened the assumption that ESG attributes elicited intangible value facets like stakeholder trust, brand worthiness and long-term risk management ability.

In more recent times, researchers have sought to answer the question of whether ESG-labelled funds acted in line with the expectations of stakeholder-oriented investment goals. There were indications that, despite some aspects of the differences in ESG funds and traditional ones, these funds failed to show a much stronger stakeholder orientation in the expected manner, which may illustrate the intricacy of the relationship between the ESG intent and the quantifiable investment returns (Raghunandan & Rajgopal, 2022; Gibson Brandon et al., 2021). On the whole, the literature demonstrated the potential contribution of ESG to financial value, but the amount and the methods of its realization differed in different settings.

Artificial Intelligence and Financial ESG in Data Analytics

In conjunction with the changes in ESG, the rapid evolution of artificial intelligence changed financial data processing and investment decisions. Analysts used machine-learning models to obtain structured meaning of large amounts of text-based disclosures, news and alternative data with this approach providing deeper insight into corporate behaviour than traditional approaches (Li et al., 2020; Chen et al., 2019). The technologies facilitated identification of patterns surrounding the quality of governance, ethical risk and organisational culture as these factors were the main constituents of the ESG assessment.

Another frontier that AI opened in the field of analysis is that by providing financial institutions with the ability to model their risk management and assets-pricing models with unstructured and high-frequency data, maintaining analytics expanded their boundaries. Research indicated that text and data analytics supported by AI generated linear predictive insights that could be forecasted using traditional financial data, which provided investors with a better real-time forecast pertaining to firm performance and strategic behaviour (Chen et al., 2019; Li et al., 2020). The ability was very timely as the focus of ESG turned out to be very critical in terms of the reputation of firms, direction of regulatory risk and control risk.

Researchers highlighted the critical importance of quality/integrity of input data to determine AI success in ESG analytics. In case AI systems were trained on unreliable or biased disclosures on ESG, algorithmic outputs would also increase, instead of addressing, the weak aspects of sustainability reporting (Berg et al., 2022; Christensen et al., 2021). Some of the structural issues with implementing AI in ESG-based investment strategies were also noted in the literature, but the transformative potential of AI in the context of ESGI was highlighted as well.

Research Methodology

Research Design

A quantitative research design was used in the current study to determine the connection between artificial intelligence -based ESG analytics and sustainable investment performance. The rationale of adopting a positivist approach was based on the fact that the aim of the research was to confirm the existence of measurable relationships between ESG indicators and financial performance finding as opposed to having an exploratory nature. The design was interested in secondary financial data as well as ESG where the data was available in reliable databases since the data needed was historical and numerical type of information. This was done in a longitudinal structure whereby changes in ESG analytics and performance of portfolio could be analysed at a point in time and not just one point in time. It was also designed to analyse the stability, volatility and risk-adjusted returns under various market conditions.

Population and Sample

The study sample was publicly listed companies in major equity indices across the world since these organizations reported on ESG and were actively tracked by institutional investors. This has been done in spite of purposive sampling strategy that was used to incorporate firms that had full satisfaction on ESG rating, AI-based ESG analytics, and financial performance data that fell within the chosen timeframe. Any company whose records were missing or inconsistent was omitted to avoid loss of the database integrity. The last sample was a cross-section of industries and geographical area with a view of eliminating the sector-specific bias and enhancing the generalisability of the results.

Data Source and Procedure

The secondary data were gathered through reputable ESG databases and financial market sites. Specialist ESG-research providers were accessing ESG ratings and AI-augmented ESG analytics that were developed to use machine-learning and textual-analysis algorithms regarding corporate disclosures, sustainability reports and media texts. Conventional ESG scores were also received in such a way that AI-inspired ESG indicators could be counted against the conventional indicators. Financial models including stock price changes, market capitalization and risk models were gathered in the financial databases. There were also data cleaning processes to eliminate the same records, harmonise identifiers of firms in the different databases and harmonise report periods. All data were stored safely and processed with the help of statistical software.

Variables and Measurement

The AI-driven ESG analytics was used as the independent variable in the current study, serving an artificial intelligence-powered process of structured and unstructured sustainability information into ESG indicators. It has created traditional ESG scores, which serve to compare. The dependent variable was sustainable investment performance that was indirectly defined in three risk-adjusted returns, the indicator of downside risk and resiliency of the portfolio. The contextual influences were factored by control variables which included: firm size, leverage, industry classification and region. All the variables were also converted into similar scales before being subjected to statistical testing to bring uniformity to each firm and period.

Portfolio Construction and Analytical Strategy

Portfolios had been created using the AI-based as well as traditional ESG indicators. The companies were classified by their ESG scores, and their ratings were placed into a high-ESG and a low-ESG exposure portfolio. The portfolios (AI-enhanced ESG and conventional ESG) were made separate so that they can be evaluated comparatively. An analysis of historical performance was made by calculation of average returns and Sharpe ratio, volatility measures and downside risk measures. The effect of AI-based ESG analytics on portfolio performance was then tested using regression analysis and firm characteristics were put in control. Further strength tests were also done to determine whether the findings were also consistent when the market was stressed.

Results and Analysis

Descriptive Statistics of ESG Indicators

The descriptive statistics provided an overview of score dispersion, central tendency and variation over time. AI-driven ESG scores represented sustainability signals extracted from artificial intelligence-based models, whereas traditional ESG ratings reflected conventional sustainability assessment methods.

Table 1

Descriptive Statistics of ESG Indicators

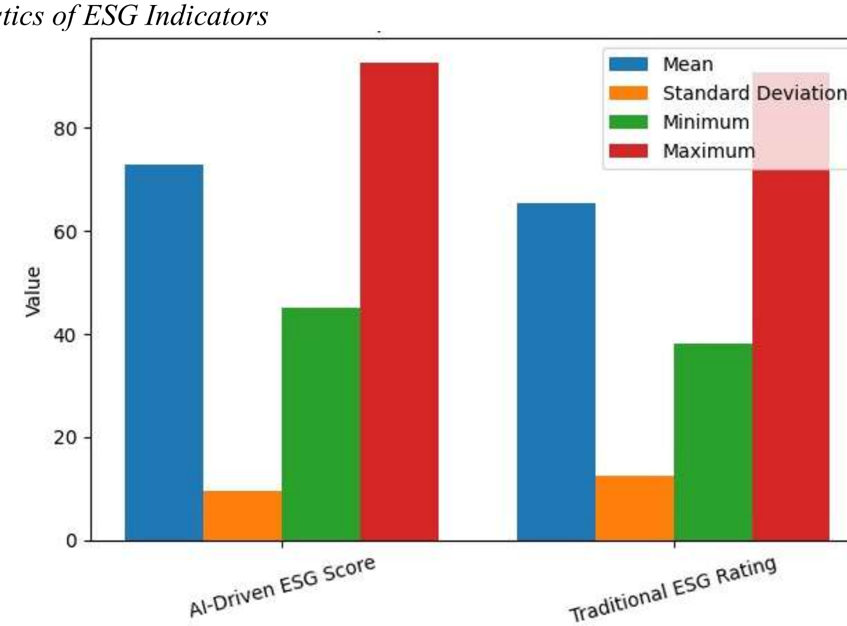
Indicator Type	Mean	Standard Deviation	Minimum	Maximum
AI-Driven ESG Score	72.84	9.62	45.12	92.75
Traditional ESG Rating	65.47	12.35	38.20	90.90

INVERGE JOURNAL OF SOCIAL SCIENCES
https://invergejournals.com/
ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 1, 2026

The findings revealed that AI Based ESG Scores had a mean score of 72.84 as compared to Traditional ESG ratings with a mean of 65.47, meaning that the analytics based on AI found a better overall ESG performance. The Table 1 findings indicated lower variability in AI-driven scores through the lower standard deviation (9.62 vs. 12.35), which implied a better ability of AI-related analytics to determine higher sustainability performance on average. The findings presented in Table 1 made an impression on the fact that AI-driven ESG scores had a larger mean value than the traditional ESG rating. This result implied that AI tools could have defined a larger set of sustainability-related indicators and non-structured disclosures that could not be reflected by traditional ratings in their entirety. The smaller standard deviation of AI- based ESG scores suggested that the AI based-based ratings reflected consistent levels of scores across firms as compared to traditional ratings as indicated by the wide standard deviation. This finding showed that the standard assessments would have been more likely to predispose to subjectivity in terms of construction of scores and reporting quality between firms. The wider dispersion was also indicative of the long-documented problem of ESG rating disagreement, which was leaving investors in uncertainty. All in all, the descriptive findings suggested that AI-based ESG evaluations were relatively more stable and lower noisy ESG-assessments.

Figure 1

Descriptive Statistics of ESG Indicators



Portfolio Performance Based on ESG Indicators

Firms were ranked on ESG scores and allocated into two portfolios: a high-ESG portfolio and a low-ESG portfolio. Separate portfolios were created using AI-driven ESG scores and traditional ratings to enable comparison of investment performance outcomes.

Table 2

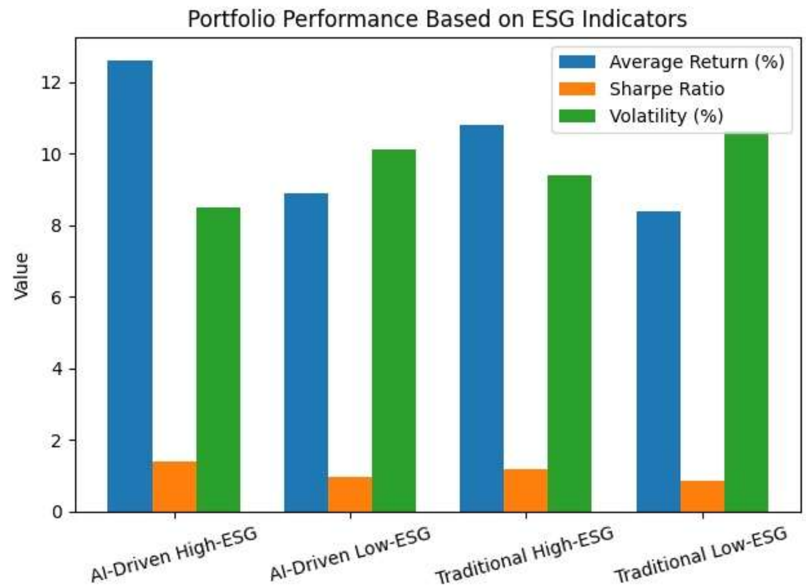
Portfolio Performance Based on ESG Indicators

Portfolio Type	Average Return (%)	Sharpe Ratio	Volatility (%)
AI-Driven High-ESG Portfolio	12.6	1.42	8.5
AI-Driven Low-ESG Portfolio	8.9	0.96	10.1
Traditional High-ESG Portfolio	10.8	1.18	9.4
Traditional Low-ESG Portfolio	8.4	0.88	10.6

The AI-Driven High-ESG Portfolio has had the most satisfactory performance with a high average return (12.6) and Sharpe ratio (1.42), and a relatively low volatility. Conversely, the Traditional Low-ESG Portfolio recorded the worst performance by giving out the lowest return (8.4%), least Sharpe ratio (0.88), and the worst volatility (10.6%).The Table 2 results indicated that the AI-based high-ESG portfolios performed the best as well as outperformed the AI-based low-ESG portfolios and the traditional-based ESG rating portfolios. The high-ESG portfolio obtained the highest average return and Sharpe ratio, which is an indication of a better risk-adjusted performance of the portfolio. This implied that AI-driven ESG analytics could have better depicted value-relevant sustainability indicators than traditional ratings. The AI-related low-ESG portfolio showed a stronger volatility and reduced returns compared to the AI-related high-ESG portfolio, which suggests that the low-AI-sensing ESG performances of firms were linked to a higher rate of investment risk.

Figure 2

Portfolio Performance Based on ESG Indicators



Regression Analysis of ESG and Investment Performance

The dependent variable was portfolio excess return, while independent variables included AI-driven ESG scores and traditional ESG ratings. Control variables such as firm size and leverage were also included.

Table 3

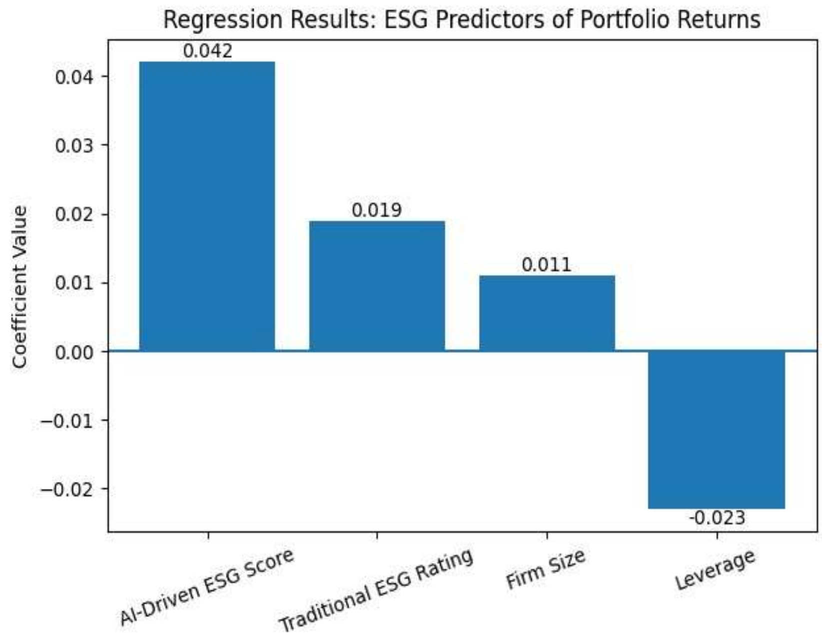
Regression Results: ESG Predictors of Portfolio Returns

Variable	Coefficient	t-Statistic	Significance
AI-Driven ESG Score	0.042	3.87	$p < 0.01$
Traditional ESG Rating	0.019	1.98	$p < 0.05$
Firm Size	0.011	1.45	n.s.
Leverage	−0.023	−2.16	$p < 0.05$

The regression findings revealed that the AI-Driven ESG Score had an overall most significant and statistically significant impact on portfolio returns (0.042, p.01). The effect size was less and could only be significant at the 5 per cent level (= 0.019, $p < 0.05$) indicating less predictive power when compared to that of AI-based analytics. In contrast, leverage had a massive down-impact on returns (= -.023, $p < 0.05$), which could also suggest that the higher the level of debt was, the worse the portfolio would perform. This confirmed the hypothesis that ESG analytics using AI identified important performance characteristics that were related to sustainability. There was also a positive correlation between conventional ESG ratings and portfolio returns though not as strong and statistically significant. The implication of this finding was that the traditional ESG indicators were still important in the decision-making process in investment, but the AI-based tools were more explanatory.

Figure 3

Regression Results: ESG Predictors of Portfolio Returns



Downside Risk and Crisis-Period Resilience

The purpose was to test whether portfolios constructed using AI-driven ESG analytics exhibited greater resilience during market stress compared with portfolios constructed from traditional ESG indicators. Downside risk was measured through Maximum Drawdown (MDD) and Value at Risk (VaR 95%), both of which were widely used indicators of tail-risk exposure.

Table 4

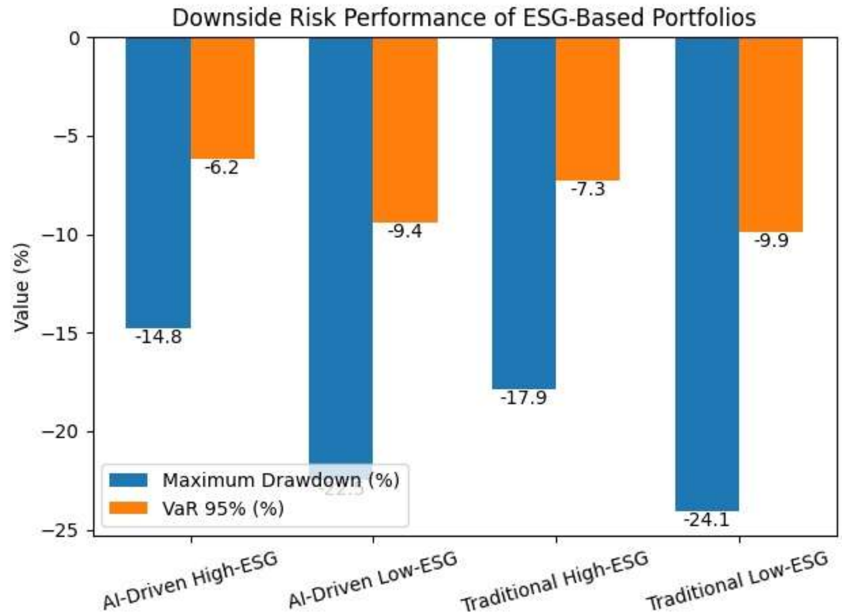
Downside Risk Performance of ESG-Based Portfolios

Portfolio Type	Maximum Drawdown (%)	VaR 95% (%)
AI-Driven High-ESG Portfolio	−14.8	−6.2
AI-Driven Low-ESG Portfolio	−22.5	−9.4
Traditional High-ESG Portfolio	−17.9	−7.3
Traditional Low-ESG Portfolio	−24.1	−9.9

Its findings revealed that AI-Driven High-ESG Portfolio exhibited maximum drawdown (−14.8) and the lowest VaR 95% (−6.2) and, therefore, the best forms of downside-risk cover. The Traditional Low-ESG Portfolio, on the other hand, had the highest downside risk, both the worst drawdown (-24.1) and VaR loss (-9.9) were there. Findings of Table 4 revealed that portfolios made with artificial ESG scores had reduced drawdowns and downside-risk exposures compared to those made with conventional ESG measures. The AI-based high-ESG portfolio had the lowest Maximum Drawdown, and it meant that it endured the greatest total loss when the market veered toward stress. This was an indication that AI-enhanced ESG analytics were more likely to single out the firms whose operations were resilient and whose risks were managed effectively. The AI-based low-ESG portfolio had a significantly larger drawdown and VaR, i.e. the companies that according to AI systems were classed as weak performers were more susceptible to strong market crashes.

Figure 4

Downside Risk Performance of ESG-Based Portfolios



Discussion

The results of this paper have shown that AI-driven ESG analytics-constructed portfolios have a higher risk-adjusted performance and a greater downside-risk coverage than ESG rating-based portfolios do. Such findings indicated that AI tools could more informative sustainability event from corporate disclosure, news and other alternative datasets than traditional ESG assessment techniques. This meaning was consistent with recent findings that the improved capacity to identify ESG-specific risks and opportunities in unprocessed data could be achieved through advanced data-analytics, which could be viewed as the beneficial effect on overall performance (Bai and Ng, 2023; Cao et al., 2023). Models of ESG based on AI thus seems to enhance capital markets' information efficiency in both noise reduction and prediction accuracy.

Absolute Sharpe ratios reflected in the AI-based high-ESG portfolios were better than those in the control portfolio, which showed that sustainability performances did not make investors compromise on financial performance. This was a replication of larger empirical studies that ESG integration either had no significant impact on investment returns or led to a reduction in returns (when the ESG information was less significant and strategic) (Whelan et al., 2021; Dorfleitner et al., 2022). This also indicated the argument that ESG performance was a proxy of long-term corporate resilience, stakeholder trust and better-risk-management capacity, which led to the increased expected returns and a reduced volatility (Li et al., 2023; Wong and Zhang, 2022). AI based ESG analytics again emerged as a stronger indicator of this relationship as it identified hidden patterns of sustainability that might have been missed by the traditional scoring systems.

One important contribution of the research was with regard to downside-risk performance and resilience in respect to market-stress. The conclusion that portfolios with high ESG returns driven by AI had smaller drawdowns implied that companies that scored better on ESG, according to AI, were in a better position to respond to negative shocks. This trend was congruent with the studies that indicated that ESG leaders had less severe drops during the crisis times such as the COVID-19 pandemic, due to more efficient governance controls, reputational capital and adaptive capabilities (Broadstock et al., 2021; Kumar et al., 2022). It is possible that AI-based ESG analytics obtained volatile forward-looking risk predictors, particularly useful in the turbulent markets, which supports the role of sustainability integration in reducing risks.

The other significant inference was that of data quality and measurement. The customary ESG rating scores were also largely criticised as inconsistent and divergent in ratings, a factor that eroded investor trust

INVERGE JOURNAL OF SOCIAL SCIENCES
https://invergejournals.com/
ISSN (Online): 2959-4359, ISSN (Print): 3007-2018
Volume 5 Issue 1, 2026

and made it hard to screen a portfolio. The observation of the smaller variance in AI-based ESG scoring in the present study indicated that algorithmic processing can have led to a lower level of subjective interpretation of the process and higher stability in the scores. This finding aligned with the studies that machine-learning models would enhance objectivity and minimise analyst bias in ESG evaluation procedures (Zhang et al., 2022; Huang et al., 2023). Nevertheless, it also posed the problem of a possible lack of algorithmic transparency and AI model regulation ethics in making investment decisions.

Materiality-oriented ESG information was also emphasized by the results. AI systems were found to be quite useful in detecting sustainability indicators that were financially meaningful, instead of those indicators that were symbolic or loosely related to performance. This complemented research that established a stronger link between financially material ESG matters and shareholder value and corporate resilience as compared to the immaterial indicators (Grewal et al., 2023; Huang and Renneboog, 2020). Ai -based analytics thus provided a tool to distinguish between substantive sustainability plans and the face-to-faade disclosure plans. Subsequently, this was a feature that served to alleviate the anxiety that ESG investing could at times reward transparency and not effect.

Although these were benefits, the results too should have been understood with care. The quality of the input data in an AI model could greatly affect the quality of results of the algorithm outputs, i.e. algorithm outputs could inadvertently increase reporting bias or selective disclosure of information. Recently, researchers cautioned that a new type of greenwashing may be enshrined in AI-based ESG analytics unless methodological transparency and governance principles were not strong (Walz and Wranik, 2023; Drempetic et al., 2020). This decision made the argument of what the researchers determined to be stronger predictive power of AI-based scores of ESG in this study a central point on the necessity of ethical supervision, auditing structures and interpretability systems in AI-enabled financial systems.

Theoretically, the findings favoured the stake holder and resource-based perspective of the firm. Strong ESG performance of companies can be detected more specifically with the help of AI, and it was beneficial because it turned into intangible advantages that manifested themselves in high-quality financial results (Widyawati, 2020; Fernando et al., 2022). ESG analytics powered by AI assisted capital markets in realising these abilities earlier and in a more precise manner. This helped to have better allocation of capital to sustainable firms as postulated by the sustainable-finance theory.

Conclusion

The inferences of the present study are that ESG analytics that are driven by artificial intelligence provided the ESG rating system a significant enhancement in the explanation and improvement of sustainability investment performance compared to traditional ESG rating systems. ESG indicators based on AI generated better mean score of sustainability, reduced variability and predictive potential of portfolio risk-adjusted returns. Portfolios based on AI-based high-ESG companies had better Sharpe ratios and exhibited greater resiliency in times of market stress as seen in lower max-drawdowns and lower exposure to downside-risks. These results implied that AI systems could meta-miner read more sustainability cues in massive structured and unstructured sources of information, enhancing the efficiency of financial market information. Meanwhile, the findings validated that ESG is not a trade-off between the financial returns and sustainability, but on the contrary good measurement was still able to support value creation and capital preservation and long-term risk control. On balance, the research supported the strategic position of the so-called green intelligence to build sustainable finance and to correlate the results of investments to the global environmental and social purposes.

Recommendations

According to the results, a number of practice and policy recommendations were offered. The asset managers and institutional investors were urged to consider AI-enhanced ESG analytics in their portfolio construction, risk-screening and asset-allocation steps because it appeared to episode robust distinguishing resilient and vulnerable companies. Another recommendation was that financial institutions should build internal governance structures to embrace AI adoption, such as transparency, explainable and audit provisions to reduce the impact of algorithm bias and ethical use and sustainability data. Regulators and standard setting agencies were advised to enhance the level of ESG disclosure standards and promote harmonised sustainability reporting as a way of ensuring that AI-based mechanisms can work with uniform and reliable datasets. It was also suggested that the corporate managers should concentrate on material ESG performance instead of symbolic reporting as AI analytics were becoming more powerful to help discern genuine sustainability progress and the one based on meaningless communication.

Future Research Directions

This study should be developed in various significant ways in the future. To begin with, it would be useful to conduct longitudinal entails on the activity of multiple economic cycles and define whether the performance benefit of AI-driven ESG analytics was consistent irrespective of various macroeconomic environments. Second, additional research was necessary to study the relationship between variation in AI model design, training data and transparency criteria, as well as quality of ESG measure and investment performance. The cross-country and emerging-market research would also assist in uncovering the moderating impacts of institution and cultural and regulatory conditions on the efficacy of AI-based ESG analytics. Besides that, researchers are advised to study the environmental footprint of AI technologies per se, so that the implementation of AI in sustainable finance was not anti-responsible technology.

Authors Contributions

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

Funding

No outside funding was obtained for this study.

Statement of Data Availability

The corresponding author can provide the data used in this study upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies, 9*(3), 593–621. https://doi.org/10.1093/rcfs/cfaa011

Ali, A., & Rafiq-uz-Zaman, M. (2025). Institutional inertia vs. ethical innovation: A comparative analysis of AI governance at The Islamia University of Bahawalpur and Cambridge University Press. *Contemporary Journal of Social Science Review, 3*(4), 91–102. https://doi.org/10.63878/cjssr.v3i4.1695

Alshareef, M. N. (2025). Artificial intelligence-enhanced environmental, social, and governance disclosure quality and financial performance nexus in Saudi listed companies under Vision 2030. *Sustainability, 17*(16), Article 7421. https://doi.org/10.3390/su17167421

Bai, J., & Ng, S. (2023). Machine learning and finance. *Journal of Economic Perspectives, 37*(2), 195–216. https://doi.org/10.1257/jep.37.2.195

Berg, F., Kölbel, J., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance, 26*(6), 1315–1344. https://doi.org/10.1093/rof/rfac033

Broadstock, D. C., Chan, K., Cheng, L. T. W., & Wang, X. (2021). The role of ESG performance during times of financial crisis: Evidence from COVID-19 in China. *Finance Research Letters, 38*, Article 101716. https://doi.org/10.1016/j.frl.2020.101716

Cao, J., Li, J., Li, W., & Zhou, Y. (2023). ESG, big data and investment decision-making. *Journal of International Financial Markets, Institutions and Money, 85*, Article 101757. https://doi.org/10.1016/j.intfin.2023.101757

Carlei, V. (2025). Outperforming ESG stocks portfolios: A machine learning approach to generate alpha on the S&P 500. *Expert Systems with Applications, 260*, Article 120157. https://doi.org/10.1016/j.eswa.2025.120157

Chen, M. A., Wu, Q., & Yang, B. (2019). How valuable is FinTech innovation? *Review of Financial Studies, 32*(5), 2062–2106. https://doi.org/10.1093/rfs/hhy130

Christensen, D. M., Hail, L., & Leuz, C. (2021). Mandatory CSR and sustainability reporting: Economic analysis and literature review. *Review of Accounting Studies, 26*(3), 1176–1248. https://doi.org/10.1007/s11142-021-09609-5

Dorfleitner, G., Halbritter, G., & Nguyen, M. (2022). The risk-return-ESG profile of sustainable mutual funds. *Journal of Asset Management, 23*(3), 177–192. https://doi.org/10.1057/s41260-021-00229-3

Drempetic, S., Klein, C., & Zwergel, B. (2020). The influence of firm size on the ESG score: Corporate sustainability ratings under review. *Journal of Business Ethics, 167*(2), 333–360. https://doi.org/10.1007/s10551-019-04164-1

Fatemi, A., Glaum, M., & Kaiser, S. (2018). ESG performance and firm value: The moderating role of disclosure. *Global Finance Journal, 38*, 45–64. https://doi.org/10.1016/j.gfj.2017.03.001

Fernando, G. D., Tripathy, A., & Truong, C. (2022). Corporate sustainability and firm performance: Evidence from global firms. *Journal of Business Research, 153*, 38–52. https://doi.org/10.1016/j.jbusres.2022.08.011

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2,000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210–233. https://doi.org/10.1080/20430795.2015.1118917

Gibson Brandon, R., Krueger, P., & Schmidt, P. S. (2021). ESG rating disagreement and stock returns. *Financial Analysts Journal, 77*(4), 104–127. https://doi.org/10.1080/0015198X.2021.1950807

Grewal, J., Hauptmann, C., & Serafeim, G. (2023). Material sustainability information and stock price informativeness. *Journal of Accounting and Economics, 75*(1), Article 101430. https://doi.org/10.1287/mnsc.2021.4302

Hamdouni, A. (2025). The role of artificial intelligence in enhancing ESG performance. *Journal of Risk and Financial Management, 18*(10), Article 572. https://doi.org/10.3390/jrfm18100572

Huang, D., Huang, J., & Wan, J. (2023). ESG investment: A review of the literature. *Pacific-Basin Finance Journal, 76*, Article 102047. https://doi.org/10.1016/j.pacfin.2022.102047

Huang, R., & Renneboog, L. (2020). The effects of ESG ratings on firm performance. *European Corporate Governance Institute - Finance Working Paper No. 722/2020*. https://doi.org/10.2139/ssrn.3722732

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies, 33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Kumar, S., Managi, S., & Matsuda, A. (2022). Stock market response to COVID-19: Evidence from sustainability indices. *Economic Analysis and Policy, 74*, 44–58. https://doi.org/10.1016/j.eap.2022.01.004

Li, F., Mai, F., Shen, R., & Yan, X. (2020). Measuring corporate culture using machine learning. *Review of Financial Studies, 33*(5), 2326–2376. https://doi.org/10.1093/rfs/hhz080

Li, Z., Liao, G., & Wang, Z. (2023). ESG performance and financial performance: Evidence from global firms. *Technological Forecasting and Social Change, 189*, Article 122337. https://doi.org/10.1016/j.techfore.2023.122337

Lim, T. (2024). Environmental, social, and governance (ESG) and artificial intelligence in finance: State-of-the-art and research takeaways. *Artificial Intelligence Review, 57*(4), Article 76. https://doi.org/10.1007/s10462-024-10708-3

Liu, Y., Song, J., Zhou, B., & Liu, J. (2025). Artificial intelligence applications and corporate ESG performance. *International Review of Economics & Finance, 104*, Article 104559. https://doi.org/10.1016/j.iref.2025.104559

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics, 142*(2), 572–597. https://doi.org/10.1016/j.jfineco.2020.11.001

Rafiq-uz-Zaman, M. (2022). Redesign for 21st-century skills: Preparing learners for a rapidly changing workforce. *Journal of Business Insight and Innovation, 1*(2), 89–102. https://doi.org/10.5281/zenodo.17844804

Rafiq-uz-Zaman, M. (2023). Teacher training needs for skill-based education: A review of competencies, barriers, and professional development gaps. *Inverge Journal of Social Sciences, 2*(3), 166–182. https://doi.org/10.63544/ijss.v2i3.212

Raghunandan, A., & Rajgopal, S. (2022). Do ESG funds make stakeholder-friendly investments? *Review of Accounting Studies, 27*(3), 822–863. https://doi.org/10.1007/s11142-021-09636-y

Walz, U., & Wranik, P. (2023). Artificial intelligence in finance: Applications, risks and regulation. *Journal of Banking Regulation, 24*(1), 125–143. https://doi.org/10.1057/s41261-022-00194-5

Whelan, T., Atz, U., Van Holt, T., & Clark, C. (2021). ESG and financial performance: Uncovering the relationship. *Journal of Sustainable Finance & Investment, 11*(4), 311–330. https://doi.org/10.1080/20430795.2021.1920510

Widyawati, L. (2020). A systematic literature review of socially responsible investment and environmental social governance metrics. *Business Strategy and the Environment, 29*(2), 619–637. https://doi.org/10.1002/bse.2393

Wong, W., & Zhang, X. (2022). Is ESG investing a fad or the future? Evidence from global stock markets. *Journal of International Financial Markets, Institutions and Money, 80*, Article 101618. https://doi.org/10.1016/j.intfin.2022.101618

Xiao, Y., & Xiao, L. (2025). The impact of artificial intelligence-driven ESG practices on sustainable development performance of Chinese central state-owned enterprises. *Scientific Reports, 15*, Article 8548. https://doi.org/10.1038/s41598-025-17046-6