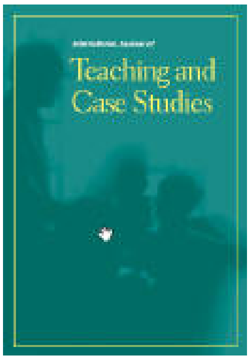

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The impact of artificial intelligence on environmental, social and governance investing: the case of Nexus FrontierTech

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The impact of artificial intelligence on environmental, social and governance investing: the case of Nexus FrontierTech

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Abstract: The finance industry has been rocked by disruptive innovation driven by the rise of environmental, social, and governance (ESG) investing and the growing use of AI-based solutions. Generating accurate ESG ratings for companies is challenging, as such ratings are often based on inaccurate and uncontextualised data. The problem is that little is known about the impact of artificial intelligence on ESG investing and how AI models can overcome obstacles in this process that are impossible for human workers to realistically overcome at a low cost, with speed and error-free. This research addresses the problem through a single-subject, archival case study by presenting the case of Nexus FrontierTech, a company that developed an AI-based tool that automates the ESG reporting and rating process without replacing human analysts' abilities. The results of this study contribute a fresh perspective of scholarly knowledge on applications of AI to ESG investing and reporting.

Keywords: artificial intelligence; AI; environmental; social; and governance; ESG; ESG investing; archival case study; Nexus FrontierTech; fintech; software; asset management; data analytics.

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1 Introduction

ESG factors, by definition, refer to environmental, social, and governance (ESG) issues and are considered essential ingredients for impact and responsible investing (Kulkarni et al., 2023). ESG investing stands for 'environmental, social, and governance' investing. ESG is a framework that helps stakeholders understand how an organisation manages risks and opportunities around sustainability issues (Božić, 2023). There is a growing consensus that ESG factors can be material to financial performance, and considering them can be part of a fiduciary duty (Dixon et al., 2020).

To define ESG initiatives, finance practices and development, and sustainability, researchers have reached a consensus on the factors defining each area (Sheehan et al., 2022). *Environmental (E)* refers to a company's impact on the environment with Factors including carbon footprint or greenhouse gas emissions, waste management, water use, conservation of renewable energy use, impact on biodiversity, and environmental policies and practices. *Social (S)* relates to a company's relationships with its employees, suppliers, customers, and communities where it operates, such as worker rights and conditions, health and safety, diversity and inclusion practices, human rights and child labour practices, impact on local communities and customer satisfaction and product safety. *Governance (G)* relates to a company's leadership, executive pay, audits, internal controls, and shareholder rights, including board structure and diversity, executive compensation, shareholder rights, engagement, transparency, and reporting business ethics and potential conflicts of interest, and cybersecurity risk management (Li et al., 2023; Niemoller, 2021; Saxena et al., 2022).

Fintech has become an ecosystem that various operating areas, such as asset allocation, should rely upon, especially given the increase in progress and innovation in technology applications to the finance industry (Insider Intelligence, 2023). AI's ability to improve financial firm operations stems from machine learning advances. Data analytics – the science of inferring from patterns in data and determining new output values – is enabled by machine learning, in which statistical models and algorithms learn by mimicking how humans learn and thus gradually self-improve their level of accuracy (Dixon et al., 2020). AI has a traceable impact on many areas relevant to asset management, such as credit rating, prediction modelling, and quantitative trading, allowing for the development more efficient operating solutions (Boston Consulting Group, n.d.).

Fitting – the measure of how much a machine learning model generalises to similar data to that on which it was trained – can allow for more interaction efforts and gradually more non-linear thanks to advances in AI (Groth et al., 2023). The measure of the extent to which companies comply with ESG responsibilities can anchor ESG ratings, showing that there are now options to turn away from such customary finance industry practices. Regarding what is considered conventional financial information, in the abovementioned scoring approach, the ESG scores include information notably 'out of sample' (Fluharty-Jaidee and Neidermeyer, 2023). As long as an underlying connection between financial performance in the long run and CSR activities exists, AI can also improve the results of a more traditionally constructed ESG score. A machine learning model that regresses or predicts the variable of long-run market-adjusted return or return on assets would thus determine the significance of ESG indicators. In cases where the relationship between ESG and other variables may be essentially non-linear or cointegrated, elastic net or ridge regressions can also be used to analyse these relationships (Mori and Du, 2023).

Finance scholars identify supervised machine learning as the most efficient method for determining ESG scores because some methods are suited for complex relationships between indicators and predicted outcome variables (Mori and Du, 2023). Nevertheless, questions remain in the literature about how AI can support ESG investing, which led us to explore the state-of-the-art and sketch a tentative picture of what to expect through an archival case study design focusing on one international finance company's activities in linking AI with ESG investing. Researchers recommend illustrating success stories in the scholarly literature that might be replicated to disseminate best practices and lessons learned (Halkias and Neubert, 2020).

2 Background

The advantages of ESG investing have been identified within the finance and sustainable development literature. Firstly, ESG plays a crucial role in risk management. Companies with strong ESG practices may be less exposed to environmental, social, or governance-related risks that could impact their financial performance (Crona and Sundström, 2021). Some studies suggest that companies with better ESG metrics can outperform their peers in the long run, while investors can feel good about investing in companies that align with their personal values (Moodaley and Telukdarie, 2023). ESG investing can also drive positive changes in business practices (Musleh Al-Sartawi et al., 2022).

Over the past few years, ESG investing has gained significant momentum, with many institutional investors, asset managers, and individual investors integrating ESG factors into their investment decisions (Official Monetary and Financial Institutions Forum, & BNY Mellon, 2020). ESG investing is not without challenges identified by finance practitioners and scholarly researchers. A lack of standardisation is one of the critical challenges impeding accurate ESG reporting – a lack of uniform standards for ESG metrics makes comparisons across companies difficult (Tucker and Jones, 2020). Additionally, not all companies disclose ESG data, and the disclosed data might not be complete or accurate. Many organisations also face a trade-off between short-term profits and long-term ESG benefits (UNIDOKH, n.d.).

Integrating Artificial Intelligence (AI) into the measurement and management of ESG factors has opened up significant opportunities for companies, investors, regulators, and other stakeholders (Tominaga, 2022). AI tools can automatically gather and process vast amounts of ESG data from various sources, such as annual reports, sustainability reports, news articles, and social media. With AI's ability to handle big data, it is possible to evaluate global-scale trends and understand the broader impact of ESG issues, making risk assessment more comprehensive (Sestino and De Mauro, 2022). Machine learning algorithms can be trained to identify discrepancies or inaccuracies in data, ensuring that the reported ESG metrics are reliable. AI can also ensure that the standards and metrics used for ESG assessments are consistent across various reports and entities. AI tools can also enable real-time monitoring of ESG-related incidents or developments. For instance, satellite data combined with AI can monitor deforestation, pollution levels, or other environmental concerns in real-time (Saxena et al., 2022).

Using advanced predictive analytics, AI systems can predict potential ESG risks or opportunities based on historical and current data, helping companies and investors make more informed decisions (Minkkinen et al., 2022). Stakeholders, especially investors, often want specific ESG metrics that align with their concerns or criteria. AI can generate tailored, customised reports to meet the unique requirements of different stakeholders (Insider Intelligence, 2023). Natural language processing (NLP), a subset of AI, can analyse stakeholder communications, such as customer feedback or social media comments, to gauge sentiment regarding a company's ESG performance (Haddock and Sirou, 2021). Sensors and IoT devices combined with AI can directly monitor and report environmental metrics like emissions, water usage, or waste management (Božić, 2023).

AI can also streamline due diligence processes, particularly for investors and lenders who want to ensure their investments align with ESG standards. AI can also lower costs and time barriers that might otherwise prevent small and medium-sized enterprises (SMEs) from robust ESG reporting (Antoncic, 2020). Companies and investors can also use AI-driven simulations to assess the potential impact of various ESG-related scenarios on financial performance and resilience. AI systems can also enable responsible sourcing and more sustainable supply chains, which can help monitor and assess suppliers' ESG performance (Musleh Al-Sartawi et al., 2022).

By benchmarking, finance companies can use AI to compare their ESG performance against peers, identifying areas of improvement and best practices (Sheehan et al., 2022). An external benchmark would need to be fitted against holistic ESG scores to provide a crucial source of validity. Market performance in the long run or returns on the firm are always used as the external benchmark in the finance industry (Božić, 2023). It may seem doubtful that a sustainable business could only be counted as company returns or equity price growth because it is implausible that all effects on a business's environment or social context would impact these metrics (Mori and Du, 2023).

While AI offers many opportunities to enhance ESG measurement, it is also crucial to recognise the challenges and ethical considerations associated with AI, such as data privacy, transparency in algorithmic decisions, and potential biases in AI models (Crona and Sundström, 2021). As AI becomes an integral part of ESG measurement and management, stakeholders must ensure its implementation aligns with the principles ESG seeks to uphold. Indeed, even if the ESG scores from different rating agencies can be somewhat combined and standardised to form a coherent overall picture, there remains a need to be able to continuously monitor the ESG developments, compliance, and actions of the companies under observation (Fluharty-Jaidee and Neidermeyer, 2023). Traditionally, these users have relied on the rating and index producers to capture the latest information and news and to incorporate them into their ratings. This, in turn, means that ESG data users lack the opportunities to use their compliance frameworks and have no alternative but to follow those of rating agencies. Moreover, these users' decision-making abilities are limited by the frequency and speed of these agencies in obtaining up-to-date information (Kulkarni et al., 2023).

A cursory inspection of the current body of literature reveals there is only a handful of investigations into the connection between AI and ESG, i.e., Antoncic (2020), Chevalier (2022), Crona and Sundström (2021), and Sætra (2022). This paper aims to fill this wide knowledge gap by providing data on how AI models can impact ESG investing and reporting. Drawing on some of the client-serving experience through our international finance company, *Nexus FrontierTech*, our broader goal is to offer an in-depth description of how to use AI technologies to collect and process ESG data, thereby enabling financial services businesses to make decisions based on their own preferred criteria, requirements, and methodologies.

3 Literature review

3.1 Theoretical/conceptual framework

ESG investing in AI is a relatively new topic in the extant literature, which has not yet allowed the emergence of a reference theoretical model (Kulkarni et al., 2023). Building on the opportunities AI offers rapid and efficient ESG investing and reporting, this case study's theoretical framework is grounded in the classical UTAUT and TAM theories of technological acceptability (Davis, 1989; Silva, 2015), which explain the factors influencing the intersection of AI and ESG investment goals. Our archival case study represents an early attempt to describe the processes of what AI can do to assist international financial services companies in harvesting, organising, and analysing relevant data. This, in turn, enables these companies to overcome some of the current challenges in obtaining ESG-related information and to produce accurate and timely outputs on the ESG developments of their investments (Tucker and Jones, 2020).

The unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) is a valuable tool for scholars and professionals to explain nd sexlore the possibilities of emerging issues in new technologies, information systems, human-computer interaction, and technology adoption. It aids in the formulation and execution of targeted approaches aimed at fostering the adoption and utilisation of technology by employees and customers. UTAUT achieves this by identifying key factors that contribute to both the acceptance and resistance of technology, thereby enabling the development of effective strategies. The primary constructs of UTAUT include performance expectancy (PF), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). *Performance Expectancy* (PE) is the 'degree to which using technology will provide benefits to consumers in performing certain activities'; *effort expectancy* is defined "is the degree of ease associated with consumers' use of technology"; *social influence* refers the "extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology"; *facilitating conditions* are "the consumer perceptions of the resources and support available to perform a behavior" (Venkatesh et al., 2003, 2016).

The technology acceptance model (TAM) (Davis, 1989; Silva, 2015) is recognised as a theoretical framework in information systems and technology adoption research. Its primary objective is to comprehensively understand how consumers embrace and utilise developing technologies and information systems. The model suggests that when users are presented with a new technology, several factors influence their decision about how and when they will use it. While TAM is one of the most influential models used in the studies of technology acceptance and has empirically proved to have high validity, it must be used to a certain extent with caution because, with the internationalisation of companies, there is a growing need to understand how cultural factors can affect the ability of a multinational organisation to adopt and use information technologies (Silva, 2015).

According to Nguyen et al. (2022), scholars and professionals choose between UTAUT and TAM depending on the complexity of the study and the variables involved. TAM is considered a foundational model, while UTAUT offers a more comprehensive framework for comprehending the acceptance and utilisation of technology. This study aims to address the knowledge gap in the current body of research by offering a case study showcasing how AI models can overcome obstacles in ESG investment protocols that are impossible for human workers to realistically overcome at a low cost, with speed, and error-free. This archival case study will use secondary data collection to highlight how an international finance firm utilises algorithms with superior abilities to extract and parse data while human analysts work alongside machines to interpret contextual information. In order to fully leverage the potential of these technologies, it is imperative to address the existing gap in the body of knowledge (Crona and Sundström, 2021; Neubert and Montañez, 2020).

3.2 The intersection of artificial intelligence, business, and social goals

There is no question that digitisation is taking place in all facets of our lives. To adapt to this market landscape, many organisations have deployed new technological means to interact with customers and harness new efficiency enhancement potentials (Marr, 2020). Digital transformation – the use of, for instance, artificial intelligence (AI), the Internet of Things (IoT), cloud computing, and big data – has brought significant changes to business operations, processes, and organisational structures, allowing them to derive competitive products and services to meet new market demand (Kretschmer and Khashabi, 2020). Among the various novel and competitive landscape reforming technologies, AI and the processes that the technology can facilitate are becoming the essential focus of the contemporaneous digital revolution (Correia and Matos, 2021).

While researchers have shown substantial interest in the connections between AI and businesses, there is no shortage of studies on the social problems that AI can potentially introduce (Sestino and De Mauro, 2022). One such area is corporate ethics, such as how companies Facebook (now Meta) deployed AI through Cambridge Analytica to influence voters, interfering with the democratic processes (Miller, 2019). Another significant debate is how AI would eliminate work positions. Ever since the seminal working paper by Frey and Osborne (2017), media and research alike often like to portray how machines will be taking over the jobs currently held by many.

Ford (2015) warns us of the rise of robots that can lead to a potentially jobless future, whereas Kaplan (2015) suggests that humans need not apply as smart machines will win out. Another commonly examined downside of using AI technologies involves injustice and discrimination. Suresh and Guttag (2021) postulate that there are six different types of AI-induced bias, including historical, representation, measurement, measurement, aggregation, and evaluation, with an AI model able to have multiple types of biases present; this demands the establishment of best practices to help design a fair and effective algorithm (Shestakova, 2021).

Nevertheless, like all technologies, AI, when used properly, can also open up new possibilities for creating social benefits. Sestino and De Mauro (2022) have found that prior research mainly concentrated on AI's role in understanding consumer social behaviour and honing marketing strategies; this is surprising as AI technologies can bring social benefits such as sustainability and environmental issues. However, this is not to say that researchers have not examined how AI can advance the sustainability agenda (Crawford, 2021; Nishant et al., 2020). An issue could be that while the literature on this topic is expanding, studies focusing on the relationship between AI and ESG remain few. Additional research in this area is paramount as understanding how technologies can be used to attain ESG goals is crucial for internal decision-makers, markets, and other stakeholders (Sætra, 2022).

In existing research, there appears to be some confusion about what AI is. For example, technology was once defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" [Kaplan and Haenlein, (2019), p.17]. Marr (2020), on the other hand, takes a (perhaps erroneously) even broader view by claiming AI as the ability of machines to act intelligently and 'think' in ways that, until recently, only human beings could.

Our daily work with AI technologies prompted us to find these descriptions lacking accuracy, if not misleading. While AI can be thought of as a simulation of human intelligence processes by machines despite the term 'machine learning', machines are simply incapable to 'learn' or 'think' by themselves, let alone learn and think like humans (Ford, 2015). Instead, modern AI technologies rely on the fact that they raise the accuracy of getting the expected established results with each repeated calculation over time in a process that is controlled and assisted by humans. At least in its current form, AI relies on algorithms to draw inferences from data and performs raw calculations to guess (predict) an outcome (result), often under human guidance (Boston Consulting Group, n.d.). In this sense, AI resembles far more of a powerful calculator with the built-in possibilities for humans to tweak and adjust it to become more effective and much less a smart machine that can 'learn' and 'think' like us (Insider Intelligence, 2023).

3.2.1 ESG investing and reporting

Investments in ESG have fast become an important area of interest. One recent survey indicates that sustainable investments amounted to some $30 trillion in 2018, up 34% from 2016 (Global Sustainable Alliance, 2019). Indeed, investors (and our societies in general) appear to be increasingly keen to understand whether and by what means businesses are being ESG-compliant (UNSDSN, n.d.). Simultaneously, boards and management have become cognizant that ESG is crucial to the long-term survival of their companies (Haddock and Sirou, 2021). All of these perhaps reflect the findings that as much as 90% of investors globally are estimated already to have in place or to have plans to develop specific ESG investment policies (Official Monetary and Financial Institutions Forum, & BNY Mellon, 2020).

Until recently, investors had no natural alternative but to resort to ESG-based rating providers such as MSCI, Bloomberg, and Sustainalytics to glean ESG insights into companies (Tucker and Jones, 2020). Nevertheless, this approach has shown to be, at best, inadequate and, at worst, downright flawed. Consider the example of the UK-based company Boohoo. In June 2020, this pioneer of the ultra-fast-fashion retail phenomenon announced a £150 m planned executive bonus. Even though its 2019 annual report clearly describes a zero-tolerance approach to modern slavery, the company was discovered to be sourcing from a factory in Leicester in which workers were being paid as little as £3.50 an hour (compared to the national living wage of £8.72) (Haill, 2020; Mooney and Nilsson, 2020; Wheeler et al., 2020).

Poor treatment of workers was compounded by improper protective equipment against COVID-19 was not adequately provided (Wheeler et al., 2020). Despite these malpractices, however, Boohoo had received a double A ESG rating from MSCI – the rater's second-highest ranking – while being awarded a far-above industry average score on supply-chain labour standards in its ESG ranking (Mooney and Nilsson, 2020). Indeed, a review of nine other different ratings placed Boohoo in the top 25th percentile of more than 19,000 companies considered worldwide (Haill, 2020). Another example is Wirecard, the disgraced German payment processor and financial services provider. While the company filed for bankruptcy in June 2020 for its string of wrongdoings, in the years of its operations, Wirecard received median-grade ratings from several ESG rating agencies (Nauman et al., 2020).

However, despite these wrongly reached conclusions, investors continue to rely on these raters for ESG insights (Tse et al., 2021). One possible explanation for such reliance is that these investors cannot gather and process ESG-related data themselves

(Tucker and Jones, 2020). Just as challenging to the investors is to compare the ratings of the same company by different rating agencies. To begin with, rating producers and indices deploy their proprietary methodologies and data to analyse companies (Moodaley and Telukdarie, 2023). This results in them using different ESG definitions, compliance measurements, and weightings for different indicators, often leading to scores and verdicts that can be distinctly different from one index to another (Li et al., 2023).

Berg et al. (2022) have found that in a dataset of five ESG rating agencies, correlations between scores on 823 companies were, on average, only 0.61, suggesting that while different rating producers evaluate the same company, their verdicts are usually so differentiated as if they were all rating different companies. It is unsurprising that, in a study of 13,000 messages exchanged by finance professionals from 2017 to 2020, Zeidan (2022) concluded that these professionals still view data quality as one of the overwhelming obstacles to seamlessly integrating ESG into financial portfolios. Such inconsistencies among ratings prompted researchers such as Capizzi et al. (2021) to derive new frameworks to analyse different recommendations, calling for the need to understand what is measured by the ESG rating agencies as well as standardisation and transparency of ESG measurement to favour a more homogeneous set of indicators.

3.3 AI-enabled ESG insights

As the introduction mentions, only a few studies have focused on the linkage between AI and ESG. Moreover, Sætra (2022) points out that none is related to offering a tool for evaluating and disclosing AI-related ESG impacts, an area of research that Minkkinen et al. (2022) urgently call for development. The technology discussed here, and by logical extension, this study answers this call by offering a detailed 'step-by-step' view of how AI technologies extract and process the information needed to meet the investors' ESG metrics. Such algorithms may develop the ability to bring visibility, traceability, and usability to data in real-time (Dixon et al., 2020). In doing so, companies can potentially bypass the rating providers to extract ESG-related information, enabling them to receive first-hand comprehensive data and, therefore, rich insights quickly. AI can help mitigate the information asymmetry problem and perhaps open up new possibilities to invest in ESG (Fluharty-Jaidee and Neidermeyer, 2023). The three steps in the AI-driven approach are presented and explained below as they relate to ESG investing: harvest, organise, and analyse.

3.3.1 Harvest

One of the most significant obstacles to obtaining timely ESG data is collecting a broad spectrum of data (Božić, 2023). Data on these subjects are frequently embedded in sources, including news coverages, messages and mentions in social media, experts' analyses, and reports. Given the number of potential sources, it is impossible to manually pick out all such data. Even if it is possible to have human teams search and collect such a monumental amount of data, it will inevitably require Herculean efforts that are time-consuming, labour-intensive, and highly costly (Musleh Al-Sartawi et al., 2022). Indeed, this is not just a one-time event. A further seemingly unsurmountable challenge is that perpetual monitoring and updating of existing ESG data is needed to ensure the availability of high-quality data for decision-making (Tominaga, 2022).

Moreover, as the ESG-related data universe will inevitably expand, AI technologies most likely represent the only means to gather ESG data speedily and cost-effectively (Li et al., 2023). This is achieved by getting the algorithms to crawl through the Internet and 'scrap' all the data determined to be relevant by ESG data seekers. In the client experience, such 'relevance' varies among financial services companies, each with its requirements (Kulkarni et al., 2023). For example, a fund manager looks for answers to twenty ESG questions to determine whether to include a particular company in its portfolios. In another case, a bank must ensure that a single borrower meets all one hundred ESG compliance criteria before issuing the loan. Hence, depending on the products offered, the nature of the ESG-related queries will vary widely from one firm to another. As a result, only an AI-driven data collection process can satisfy such a broad range of demands (Esposito, 2020; Tse et al., 2019).

3.3.2 Organise

After data collection comes screening and entering extracted data into the database. Traditionally, this entails humans first 'eye-ball' the information and manually input the data, a slow and error-prone process (Crona and Sundström, 2021). It is also mind-numbing for the data entry staff. In contrast, AI technologies can quickly and effectively parse data – turning data from one type into another form fully digestible by different IT setups. Machines can convert a considerable volume of the gathered unstructured data into structured data that is readily usable (Daugherty and Wilson, 2018). As an illustration, one of our clients has 650 borrowing clients, which means not just the need to update the existing ESG data constantly but also cost-effectively parsing such data. This is a very labour-intensive task that machines are best in place to assume. It would take around four to six hours for a senior analyst at a bank to check through a company's ESG performance data and enter it into the system. By contrast, AI technologies could complete the same task in under five minutes, often with fewer mistakes. Indeed, using AI saves the analysts' time and allows them to concentrate on the more intellectually stimulating analytical activities and spend time making decisions (Capizzi et al., 2021).

As mentioned above, different companies look for different ESG data and have different requirements: they all have different investment goals, philosophies, risk appetite, and evaluation criteria (Berg et al., 2022). Consequently, AI allows for extracting the correct data and shaping it to fit these companies' proprietary ESG methodologies perfectly. The latest development in NLP technologies afford investment clients a new capability: the 'questions-answering model' (Dixon et al., 2020). This new information retrieval system looks for answers to queries posed by how we naturally speak. In this case, analysts can ask machines questions in everyday language, such as 'How do the company's targets and climate change strategy compare to peers?' or 'What is the carbon emissions of this company?' Properly trained AI models could 'understand' the query's diffuse context and develop the corresponding answers. This has made it easier for analysts to interrogate the available data and obtain the desired responses quickly and accurately (Antoncic, 2020).

3.3.3 Analyse

The final phase is about discovering and gleaning valuable insights from the structured data on the system (Antoncic, 2020). This involves developing various NLP techniques to classify the collected data to capture the sentimental, contextual, and semantic elements embedded there (Božić, 2023). This is an essential aspect of putting AI to advance the ESG agenda of companies. Consider a report mentioning 'child labour' or 'modern slavery'. These two words carry negative connotations and can be easily categorised as ESG-negative. However, when combined, text can often comprise neutral words with a negative context. In such instances in the past, the only way to discern the tone and sentiment embedded in the information provided is for humans to read through each document and make the appropriate evaluations (Fluharty-Jaidee and Neidermeyer, 2023).

While today's AI technologies have not reached the stage where they can replace humans in playing such a role, they have been progressing fast to improve their abilities to determine whether the text is sentimentally and semantically favourable or unfavourable (Marr, 2020). This is achieved by the concept of 'human-in-the-loop' – the intentional collaboration between human workers and smart machines (Davenport and Miller, 2022; Wu et al., 2022). Several banks in the global market now monitor the ESG developments of their respective clients on an ongoing basis. Both the AI and analysts at these banks would process the same coverage on a company, with the latter assigning a 'positive' or 'negative' tag to it. Subsequently, with the same exercise repeated over time, the algorithm will become increasingly capable of associating the written words and the human input. The result is that machines will raise both the ability and accuracy in predicting if a text is positive or negative in sentiment and context (Božić, 2023).

4 Methodology: the archival case study design

An archival case study design is used in this study to investigate and describe the phenomenon at hand (Yin, 2017). Considering the current gap in the ESG, artificial intelligence, and sustainable investing literature, this archival case study aims to describe how one international finance company designed an AI-based tool that automates the process of generating ESG reports and ratings without replacing the human analyst. In contrast to open-ended surveys or quantitative approaches using secondary data, both of which yield only limited findings, a qualitative approach allows the researchers to gather more in-depth data of a richer nature (Halkias et al., 2022).

The researchers decided to utilise the archival case study design after weighing other qualitative research methods, including document analysis and ethnography, because this study strived to investigate 'how' the tool utilised AI technologies to solve the problem of generating accurate ESG ratings and 'how' it was deployed in a practical context, factors which fulfil the conditions for the ideal archival case study design (Ellet, 2007; Yin, 2017).

Using the case study research design, investigators can rely on archival data to study organisational practices (Halkias and Neubert, 2020). Case study design generally allows the researcher to be more flexible when examining contemporary issues, given that, in this case, the researcher cannot control behavioural events (Halkias and Neubert, 2020).

At the same time, case study design enables the researcher to clarify aspects of the study's social complexities (Yin, 2017).

Archival research methods are defined as a systematic form of knowledge inquiry used to search, analyse, and draw inferences from archival data, answer new research questions, evaluate existing conclusions, discover emerging issues, and strengthen findings' transferability by aggregating archival data from multiple sources (Yin, 2017). In archival studies, data collection sources include company annual reports, historical documents, websites, financial reports, and organisational resources. While interview and observation approaches are commonly applied in qualitative research, a case study design based on archival data offers rich information and valid evidence to support research findings. Thus, a case study design is a valuable research tool, and single-subject cases represent a unique case (Yin, 2017). Unlike group designs, single-case research designs follow an inductive approach, where researchers formulate general principles based on results from particular sets of results and data (Halkias and Neubert, 2020).

5 The case study

5.1 Nexus FrontierTech: intersecting of artificial intelligence and ESG investing

Nexus FrontierTech was founded in 2015 to offer innovative AI solutions to financial services organisations, now also serving other sectors such as government. *Nexus FrontierTech* employs a global team of over 100 researchers to push forward innovations in data management. *Nexus FrontierTech* enables organisations to configure, fine-tune, and deploy AI models into a system using their original proprietary AI platform, Podder. Podder allows many modules to be pluggable and reusable, enhancing scalability with up to 99.5% accuracy and supported by a sturdy security framework. This platform gives *Nexus FrontierTech* capabilities such as NLP, machine learning, computer vision, intelligent document processing, and a ready library of over 50 AI modes.

Nexus FrontierTech's products and services with Podder are based on a five-step data value chain: preparation, extraction, management, analysis, and exchange. Data is acquired from multiple sources during preparation, often in varying qualities and formats. The data is cleaned, filtered, and standardised. Data then moves to the extraction phase, where it is extracted, validated, and digitalised in a structured format, where it is then enriched with external sources and domain knowledge for further validation. During the following management phase, data is organised and stored with metadata. Once the data is structured and accessible, it moves into the analysis phase, where analytical methods combine previously unconnected data to produce conclusions and actionable insights. Finally, during the exchange phase, the data is visualised to reveal patterns and analyse more complex data.

Within this basic framework, *Nexus FrontierTech* has developed various AI solutions to streamline many traditionally cumbersome organisational functions, including operations, regulatory license application processing, financial spreading, wealth management compliance, client onboarding, and more. However, *Nexus FrontierTech*'s growth and success were not only possible because of its innovative use of AI but also because of the input of its human team. *Nexus FrontierTech*'s innovations are all made possible by a diverse team spread across continents, combining expertise from various analysts, business leaders, and researchers with experience in multiple industries. *Nexus FrontierTech*'s tools and solutions are also made to convenience, but not replace, the human user. These tools simplify complicated but necessary operational processes, requiring the human user to interpret and best use the cleaned, organised data each tool generates.

As their success grew in developing solutions for such processes, the *Nexus FrontierTech* team began considering an up-and-coming area where AI could solve a pressing challenge: ESG reporting for investors. ESG data is often highly unstructured, complex, and fragmented, making collecting and analysing this data a significant challenge for investors. This data often exists in large volumes of inconsistent quality, without universal taxonomies and standards against changing and complex regulations.

To address this challenge, the *Nexus FrontierTech* team began developing a hybrid, cloud-based platform that allows clients to automate several key processes around ESG reporting: the search for ESG data in company reports, news sites, and other sources, the extraction, structuring, and visualisation of quantitative and qualitative data, and the identification of critical insights through analytics and benchmarking of comparable companies. The result was the *Nexus FrontierTech* Sustainability Insights-X (SIX), a tool that streamlines the processing of ESG data by automating the creation of ESG ratings and reports via machine learning, following the basic steps of the *Nexus FrontierTech* data value chain.

After receiving input from various sources such as ESG reports, news, social media, experts' analysis, and third-party ratings and data, SIX follows the data value chain in three phases – harvest (ESG data parsing and news monitoring), organise (user-defined framework and reporting heatmap), and analyse (risk dashboards and internal ratings). The final outputs are expert-benchmarked and user-defined ESG ratings with 99% accuracy across 100+ listed companies. The platform also offers recommendations on follow-up actions, such as the level of due diligence for high-risk corporations or individuals. This efficient process offers a 75% reduction in time and effort in producing ESG ratings and reports. The platform is also highly customisable, uses up-to-date regulatory information for its risk assessment models, automates workflows that can be supported with case management, uses built-in audit trails, and makes all key data available to interrogate.

Automating all these processes allows for faster, more accurate results in ESG ratings and reports, ensuring organisations reduce risk in their ESG investment management. Users can also configure their own ESG ratings with a hybrid of user-defined fundamental inputs and automated scoring metrics. SIX also has multi-language capabilities that allow for customisable global frameworks that can be set against internal priorities.

After developing this revolutionary tool, *Nexus FrontierTech* partnered with Chinese asset management firm APS Asset Management to push forward its first and most innovative deployment. ESG investing is growing in popularity among Chinese investors; however, they face challenges in assessing the ESG performance of Chinese companies due to inconsistent reporting standards and a lack of transparency in corporate governance. Asset managers are under particular pressure to follow ESG investing to maximise returns and minimise risks. The *Nexus FrontierTech* team worked with APS to develop ANAFES, an award-winning ESG platform developed as a Proof of Concept (a prototype of a proposed AI solution developed to demonstrate the solutions' feasibility and likelihood of success). The platform gathers data from companies in China, Taiwan, Macau, Singapore, and Hong Kong that issue equity and equity-related securities.

ANAFES was developed as a central portal to manage all ESG frameworks, news, and data, accessible to analysts, portfolio managers, and sustainability managers. The platform followed the basic framework of *Nexus FrontierTech* SIX, emphasising three particular AI models: the ESG Data Parser, News Monitoring, and Investigative AI models. The documents in English and Mandarin analysed by the system include annual reports, third-party reports, sustainability reports, and news headlines and articles of 500 listed Chinese companies selected by APS. 200 ESG data points were gathered from 46 factors mapped against APS's internal ESG framework and Global Reporting Initiative (GRI) standards. The ESG Data Parser accurately traces and extracts ESG data from the input documents, standardisation and mapping it against a user-defined ESG framework. The News Monitoring model aggregates news headlines from public and paid subscription sources, classifying and tagging news based on ESG and company factors and detecting controversial event signals via sentiment analysis. The Investigative AI model then analyses Footnote, Business Term, and Related Party.

No matter how compelling the machine learning behind this smart software was, the *Nexus FrontierTech* team did not forget the value of the human factor in its design. They knew that the final output of the process had to be user-friendly with an interface that was easy to understand and navigate without having to know code or the advanced inner workings of AI. The result was a web application developed with several comprehensive dashboards that can be switched between English and Mandarin outputs. In the application, asset managers can set up their own ESG framework and have the existing ESG database mapped onto it, adjust the scoring methodology and weights of qualitative versus quantitative scores to generate consistent, customised internal ESG scores, and compare and track ESG scores and progress of different watchlists and portfolios. Sector-based ranking tools allow analysts to benchmark qualitative scores quickly and efficiently.

As a result, ANAFES was a resounding success, marking the frontier as a scalable ecosystem service that reduces ESG data analysis time by up to 80% and allows APS to generate nearly 100 internal ESG scores. Beyond just the measurable success of the platform, the *Nexus FrontierTech* team also demonstrated an exemplary case of how AI technologies can be feasibly used to measure ESG data and reduce the company's reliance on uncontextualised external ESG ratings. The platform demonstrates how AI can use global standards such as GRI as a data backbone to map and connect fragmented ESG data and that such a concept can be applied to a cloud-based platform solution with a user-friendly web application interface. This solution can also serve as a data aggregator for asset managers since it is built on an API-ready, modular infrastructure that can be integrated with various service and data providers.

Furthermore, this case also demonstrates how human-computer interaction is necessary to apply AI to business challenges such as ESG reporting. Although the *Nexus FrontierTech* team developed a tool that succeeded in collecting, analysing, and presenting vast amounts of data, including making recommendations about the data, the tool does not supersede the power of its human users. The end user is still responsible for managing and organising the output reports, ratings, and recommendations. The tool complements, rather than replaces, the asset manager's critical knowledge, experience, intuition, and autonomy – a valuable lesson for other actors practicing and researching in the emerging fields of AI and business sustainability.

5.2 Implications for future research directions and conclusions

This paper aims to partially fill the knowledge gap in the current body of research by offering a case study showcasing how AI models can overcome obstacles in ESG investing and reporting that are impossible for human workers to realistically overcome at a low cost, with speed and error-free (Musleh Al-Sartawi et al., 2022). Algorithms possess superior abilities to extract and parse data, while human analysts are far more able to interpret contextual information. This supposition is in line with Brynjolfsson and McAfee (2014) and Tse et al. (2019), who argue that specific tasks are much better to be executed by humans while many other activities machines are much more capable of carrying out. Another key managerial implication from our observations is that the actual business value of AI technologies lies in identifying the right tasks for humans and machines to conduct, striking the right balance, and getting them to collaborate. From this vantage point, we would encourage future studies to follow up on the call by Wu et al. (2022) to conduct more research on the subject of human-in-the-loop.

As illustrated in the prior section, valuable business opportunities are derived from designing the appropriate process to relieve human staff from labour-intensive tasks and let them concentrate on the more intellectually stimulating ones, effectively combining the strengths of humans and machines (Daugherty and Wilson, 2018). Despite its importance, human-in-the-loop is still a relatively new research topic. More studies are needed to broaden our understanding of how AI and human staff can work together to overcome business and social challenges (Davenport and Miller, 2022). Perhaps the most substantial contribution of our work is that it represents a first attempt to illustrate how AI can be deployed to help companies attain ESG goals. We argue that tasking AI to directly harvest, organise, and analyse ESG-related data from a broad range of sources is a far superior alternative to the reliance on rating agencies (Božić, 2023; Fluharty-Jaidee and Neidermeyer, 2023; Kulkarni et al., 2023).

Data seekers can deploy their methodologies supported by updated information, enabling them to make better decisions with greater confidence (Insider Intelligence, 2023). Given the rapid speed of technological developments, we are confident that many technology companies are working on novel solutions to capture better and handle ESG-related data. Future researchers should explore how these technologies could and would work, further helping companies reach their ESG goals (Kulkarni et al., 2023). This should become an area of study as there is no doubt that both technologies and ESG are only playing more and more critical roles in corporate pursuits in the years to come (Crona and Sundström, 2021).

In conclusion, the key to creating value using AI technologies is identifying the tasks machines can best take on, leaving those humans best to undertake to human beings (Brynjolfsson and McAfee, 2014). For example, we are much better at spotting patterns and making sense, whereas computers excel in speedy calculations. Second, to profit the most from using AI technology is to team it up with humans, enabling them to delegate the activities they are less competent at conducting to the other and focus on the tasks they are good at individually. In the words of Daugherty and Wilson (2018), by working collaboratively, machines can effectively augment human capabilities, and humans can also help machines to become better at what they are ordered to do. Whereas humans can be adaptive to various tasks, AI can only perform well-defined and narrow ones. Put differently, AI is essentially a tool that can do only a few things but do them well (Tse et al., 2019).

6 Reflection and conclusions

AI can complement conventional ESG assessment processes while mitigating biases and offering a deeper analysis of ESG ratings; nevertheless, ESG ratings generated by AI systems will not likely replace human analysts (Božić, 2023). There is notable room for AI and ESG to be combined to offer sustainable intelligence beyond ESG ratings, both concepts being two of the most significant disruptors of modern finance (Musleh Al-Sartawi et al., 2022). Other applications of this combination can include AI as a catalyst or trading software for ESG investing. With technology-focused investment platforms garnering broad appeal with younger investors, there is a growing demand for AI software solutions for ESG compliance, with ESG funds increasingly being incorporated in RAs (Tominaga, 2022).

Companies are showing a growing interest in ESG post-pandemic, with some development experts claiming that more global challenges can be addressed if ESG is used to attract private capital (Tse et al., 2021). Current data indicates that the Global North receives most ESG funds (UNSDSN, n.d.). Developing economies, however, are also growing as recipients of ESG funds. More ESG investment in developing economies can aid in fulfilling the UN Sustainable Development Goals (SDGs) (UNIDOKH, n.d.). AI-powered solutions thus have great potential to push forward the potential of ESG in fulfilling the SDGs (Esposito, 2020). Thus, there is a moral imperative for researchers and practitioners to share lessons learned and best practices in this area to benefit not only those directly involved in the realm of investing but also the whole global economy (Sheehan et al., 2022).

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