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Environmental, social, and governance (ESG) and artificial intelligence in finance: State-of-the-art and research takeaways

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Citation

Environmental, social, and governance (ESG) and artificial intelligence in finance: State-of-the-art and research takeaways

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Abstract

The rapidly growing research landscape in finance, encompassing environmental, social, and governance (ESG) topics and associated Artificial Intelligence (AI) applications, presents challenges for both new researchers and seasoned practitioners. This study aims to systematically map the research area, identify knowledge gaps, and examine potential research areas for researchers and practitioners. The investigation focuses on three primary research questions: the main research themes concerning ESG and AI in finance, the evolution of research intensity and interest in these areas, and the application and evolution of AI techniques specifically in research studies within the ESG and AI in finance domain. Eight archetypical research domains were identified: (i) Trading and Investment, (ii) ESG Disclosure, Measurement and Governance, (iii) Firm Governance, (iv) Financial Markets and Instruments, (v) Risk Management, (vi) Forecasting and Valuation, (vii) Data, and (viii) Responsible Use of AI. Distinctive AI techniques were found to be employed across these archetypes. The study contributes to consolidating knowledge on the intersection of ESG, AI, and finance, offering an ontological inquiry and key takeaways for practitioners and researchers. Important insights include the popularity and crowding of the Trading and Investment domain, the growth potential of the Data archetype, and the high potential of Responsible Use of AI, despite its low publication count. By understanding the nuances of different research archetypes, researchers and practitioners can better navigate this complex landscape and contribute to a more sustainable and responsible financial sector.

Keywords Environmental, social, and governance (ESG) · Sustainable finance · Artificial intelligence in finance · Systematic literature mapping · Literature survey and review · Trends

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1 Introduction

Within the realm of finance, the research landscape that investigates broad environmental, social, and governance (ESG)-related issues and the associated Artificial Intelligence (AI) applications that underlie the discourse are highly diversified and growing fast. Studies deliberating on ESG considerations straddle economic-financial areas from trading and investments to corporate governance and risk management, supported by a myriad of AI tools and resources (Abdalmuttaleb et al. 2022; Stanley 2023). This erects a favorable barrier-to-entry for incumbents; a new researcher looking to enter the field may be overwhelmed by the notion of where to start reading. This said, a seasoned practitioner may also be uncertain about the diversity and evolution of this field.

The overarching goal of this study is to illuminate the intricate web of research themes, track the intensity of research efforts, and understand the diverse AI techniques employed within these domains through a systematic literature mapping approach. Kumar et al. (2022) examined AI's role in sustainable finance using bibliometric analysis, a method that, despite its merits, overlooks a detailed examination of thematic content and methodological evolution. Conversely, Burnaev et al. (2023) explored practical AI applications in ESG studies but did not extend this into the finance domain. Our objective is to address a distinct gap in the literature: the unavailability of a comprehensive resource that coherently unifies the themes, evolution, and AI methodologies within ESG, AI, and finance, a shortfall evident to both emerging researchers and established academics in this broad and evolving domain (Kumar et al. 2022; Burnaev et al. 2023).

The objective of this study is to review this landscape through a systematic literature mapping approach. The systematic literature mapping study is the "*study concerned with the mapping and structuring of a topical research area, the identification of gaps in knowledge, and the examination of possible research topics*" (Petersen et al. 2015; Lim et al. 2023). Mappings help trace concurrent developments across lineages of research and provide the basis of systemized reviews, as a best form of evidential synthesis towards a methodological thematic scoping of a research landscape. The notable lack of research covering holistic ESG-related finance areas and the use of extensive AI techniques provide the research novelty and value to this work.

The following research questions were investigated:

RQ1: What are the key research themes that outline the research scape for ESG and AI in finance?
Utilizing topic modeling and network analysis, this question aimed to discern specific archetypical research domains prevalent in current studies. In every identified thematic area, the study, when possible, also sought to pinpoint well-defined research sub-themes supported by existing literature. This analysis offers a structured categorization and overview of the current research landscape.
RQ2: How has research intensity and interest in various archetypical domains evolved over time?
This question aimed to discern the research intensity and interest by examining publication and citation counts within each archetypical research domain, and to explore their progression over recent years. This analysis offers a perspective on the scale and trajectory of pivotal research endeavors and their relevance in the research landscape.
RQ3: Which AI techniques have been employed in studies across the archetypical domains, and how have their usages changed over time?

This question sought to pinpoint unique trends in the application of AI techniques across each archetypical research domain and to track the progression of these techniques over time. This analysis sheds light on the variety and development of primary AI methods employed in the research landscape.

Results of this study found eight archetypical research domains within the field, namely: (i) *Trading and Investment*, (ii) *ESG Disclosure, Measurement and Governance*, (iii) *Firm Governance*, (iv) *Financial Markets and Instruments*, (v) *Risk Management*, (vi) *Forecasting and Valuation*, (vii) *Data*, and (viii) *Responsible Use of AI*. Research identified *Trading and Investment* as the archetype generating the highest research publications, while *Risk Management* and *Responsible Use of AI* were the archetypes exhibiting high citation impacts. Further, while the AI techniques were dominated, on an overall basis, by multivariate regression and natural language processing, research in each archetype engaged distinctive AI techniques, ranging from ensemble and deep learning methods for the *Forecasting and Valuation* archetype, to generative AI for the *Data* archetype.

The significance of this study is to: (i) understand and consolidate knowledge pertaining to what was previously explored in research straddling the intersection of ESG, AI and finance, (ii) provide an ontological inquiry into the research scape to understand the nuances of different research archetypes, and (iii) identify key takeaways for practitioners and researchers. By categorizing and analyzing the vast body of work in this domain, we not only consolidate existing knowledge but also spotlight areas that have been underexplored, paving the way for future research endeavors.

Our findings offer tangible benefits to a broad spectrum of stakeholders. For researchers, this study provides a consolidated foundation, highlighting areas ripe for further exploration. Policymakers can glean insights into the evolving dynamics of ESG and AI in finance, informing more robust and future-ready policy frameworks. Practitioners, on the other hand, can harness the synthesized knowledge to drive innovative strategies and solutions in their respective domains. Moreover, other stakeholders, such as investors and industry leaders, can leverage the insights to make informed decisions, ensuring alignment with both technological advancements and ESG considerations.

The reminder of this paper is organized as follows: (i) the *Background and Literature Review* section introduces research that straddles the intersection of ESG, AI and finance through a survey of existing literature; (ii) the *Methodology* section explains the systematic literature mapping protocol, describes the tools and AI techniques utilized, discusses research validity issues and highlights limitations to the study; (iii) the *Findings* section presents the ontological and time-series results from topic modeling, network analyses and full paper reviews, (iv) the *Discussion* section looks to summarize the results into actionable insights that can be utilized by researchers and practitioners, and (v) the *Conclusion* section provides a closing, and proposes future work that can be undertaken by researchers and practitioners.

2 Background and literature review

2.1 AI in finance

Artificial intelligence refers to the use of algorithms and other computational techniques to automate or augment decision-making processes. In finance, AI is used to analyze large data

sets, identify patterns and insights, and make predictions based on historical data. Generative AI, a subset of AI, has emerged as a powerful tool that can generate new data instances, simulate financial scenarios, and even propose innovative financial strategies by learning from vast amounts of data. Advances in AI have transformed how modern financial and economic entities operate, interact, transact and collaborate with the environment and participants (e.g., regulators, markets and consumers).

It has effected a slew of changes to existing economic-financial systems and services, creating new innovations and opportunities in economic-financial models, efficient infrastructure and intelligent mechanisms, personalized products and user-friendly real-time services, and new assets and secure cost-effective transactions, among others.

AI in finance is defined as the machine mimicry of human-like behavior and consciousness to achieve financial objectives, through the utilization of technological tools and resources that allows digital systems to perform tasks commonly associated with intelligent beings. Generative AI, in this context, can be seen as a method to simulate potential financial market movements, generate synthetic financial data for backtesting, or even create hypothetical financial products. The term '*AI in finance*' is often used interchangeably with the terms '*machine learning in finance*', '*data mining in finance*', '*data science in finance*', '*data analytics in finance*', and sometimes '*deep learning in finance*', '*reinforcement learning in finance*', and their variants. This said, there exists distinct differences between the terms.

AI as a superset, comprises machine learning, and in turn, deep learning and reinforcement learning as subsets. Researchers in the machine learning field of inquiry look to understand and design computing methods that can enable instrumentalized and automated learning through data-driven decisions. Deep learning utilizes a specific class of machine learning methods, or neural networks, to make out representation elements of a dataset, to learn features and perform tasks. Reinforcement learning is where machine learning methods are utilized for intelligent agents to perform an action, such that some notion of reward is optimized in a pre-specified environment. The remainder three concepts—data science in finance, data mining in finance, and data analytics in finance—are related but distinct concepts that lie within the broader field of AI in finance. Data science in finance refers to the application of advanced analytics, machine learning, and statistical modeling techniques to financial data in order to gain insights, make predictions, and improve decision-making in financial services. This involves collecting, storing, processing, and analyzing large and complex data sets from various sources such as financial markets, customer behavior, and economic indicators. Data mining in finance is a subset of data science that specifically focuses on the extraction of patterns and insights from financial data using techniques such as clustering, classification, and association rule mining. The goal of data mining in finance is to discover hidden relationships and patterns that can inform investment decisions, risk management, and other financial activities. Data analytics in finance involves the use of statistical and quantitative methods to analyze and interpret financial data in order to identify trends, patterns, and insights. This includes techniques such as regression analysis, time series analysis, and hypothesis testing. The goal of data analytics in finance is to provide a clear understanding of financial performance and to inform decision-making.

2.2 Convergence of ESG and AI in finance research

ESG is defined as the "*environmental, social or governance matters that may have a positive or negative impact on the financial performance or solvency of an entity, sovereign or individual*" (EBA 2021). ESG is commonly used interchangeably with the term

'*sustainable finance*', which is defined as "*process of taking ESG considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects*" (European Commission 2021). ESG was first mentioned in an influential report "*Who Cares Wins: Connecting Financial Markets to a Changing World*" in 2004, where the United Nations encouraged the integration of ESG considerations into the financial industry, including security brokerage services, asset management and associated research functions (The Global Compact 2004). Since then, a wealth of ESG research has emerged in finance literature. Tabulation of publication from Google Scholar indicated a six-times growth from 2460 in the 5 years between 2004 and 2008, to 18,000 in the years between 2018 and 2022. ESG research efforts are known to be inundated by large data volume; it was not surprising that ESG research efforts in finance literature that were supported by artificial intelligence (AI) techniques, stood to represent about one-fifth of the publications on ESG in finance in the latter five years. The integration of ESG considerations and artificial intelligence in finance has broader implications for the finance industry and society as a whole.

For instance, one area where ESG and AI can have a significant impact is in risk management. Generative AI can be employed to simulate various ESG scenarios, helping financial institutions to visualize potential future landscapes and adjust their strategies accordingly. By using AI-powered risk assessment tools that integrate ESG considerations, financial institutions can identify and mitigate potential risks associated with environmental and social factors, such as climate change, labor practices, and human rights violations (e.g., Yang and Broby 2020; Ranta and Ylinen 2021; Patterson et al. 2022; Apel et al. 2023). This can help financial institutions reduce their exposure to financial and reputational risks, as well as contribute to sustainable and responsible business practices. Furthermore, the integration of ESG and AI in finance can also contribute to the development of more inclusive and equitable financial systems (e.g., Katterbauer and Moschetta 2022a, b). By using AI-powered tools to analyze demographic and socioeconomic data, financial institutions can identify and address disparities in access to financial services and opportunities. AI-powered credit scoring models can take into account factors beyond traditional credit history, such as education, employment, and social capital, to provide fairer and more inclusive credit assessments. In another example, the integration of ESG and AI in finance can also have broader societal implications, contributing to the achievement of sustainable development goals and addressing global challenges such as climate change, poverty, and inequality (e.g., Angelova et al. 2021; Chen 2021; Kharlanov et al. 2022). By employing AI to support investment in companies and projects that contribute to positive social and environmental outcomes, financial institutions can play a critical role in promoting sustainable and responsible business practices, as well as driving positive social and environmental change.

There has been increasing engagement on this convergent topic. In a special issue at Journal of Sustainable Finance and Investment at March 2022 that aimed to provide a platform "*to shine new light on [the] debates [on AI in ESG and sustainable finance]*", Abdalmuttaleb et al. (2022) shared that "*sustainable investments and sustainable business models can be achieved by acknowledging the importance of CSR reporting, ethical considerations of AI, assessing ESG risks, and the future of AI and FinTech*". Beyond this, the paper acknowledged Kumar et al. (2022) by broadening the scope of the convergent topic to include "*all activities and factors that would make finance sustainable and contribute to sustainability including [AI] systems, applications and models*".

To date, there is a dearth of systematic literature mapping papers that map this convergent topic. This study seeks to provide (i) an objective data-driven mapping of the

landscape of extant literature previously published; (ii) a cross-sectional gauge of how pivotal each research area were and their associated AI techniques; and (iii) an understanding of their evolution across time for trend evaluation purposes.

3 Methodology and data

Systematic literature mapping provides a comprehensive overview of a research domain, using a systematic protocol to identify trends, gaps, and research methods, ensuring reproducibility and minimizing bias. Unlike traditional literature reviews, which synthesize knowledge on a topic without a strict protocol, systematic literature mapping focuses on breadth over depth. In contrast, bibliometric analysis quantitatively evaluates publication patterns without delving into content depth.

The systematic literature mapping approach was conducted utilizing the methodology applied in, Kabudi et al. (2021), Lim et al. (2023), and Petersen et al. (2015). The mapping approach included the following three methodological stages, namely: (i) search and selection, (ii) classification and analysis, and (iii) validity evaluation.

EndNote X9, NVivo11 and Excel spreadsheets were utilized for the organization of information. Other tools and resources employed for information extraction, visualization of analyses, and AI techniques and tools are elaborated in the next sub-sections.

3.1 Search and selection

As a guideline employed to conduct the search and selection phase, the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* or the PRISMA approach recommends a protocol including details such as eligibility criteria, information source, search rules, data recording and data synthesis, as part of the PRISMA-P checklist (Moher et al. 2009). The PRISMA process is diagrammatically represented in Fig. 1.

Google Scholar is widely rated as the most comprehensive and multidisciplinary bibliometric crawler-based search system with the largest citation coverage (Martín-Martín et al. 2018), covering an estimated total of over 300 million records (Delgado López-Cózar et al. 2019). As the research topic was framed by a broad theme with vast scholarship, the study utilized Google Scholar at the first stage of PRISMA, or the *identification* stage, to identify the eligible papers to be included in the analyses. The search entry was as follows: *+finance+("ESG" OR green OR climate OR inclusive OR carbon OR sustainability OR "social impact" OR ecology)+("artificial intelligence" OR "machine learning" OR "supervised learning" OR "unsupervised learning" OR "reinforcement learning" OR "deep learning")*. Subject relevant keywords, such as *green* or *sustainability*, informed and refined from the literature, were added to the search entry to achieve a more extensive level of search results in the search records. Google Scholar indexes titles, abstracts, and the full text of papers. While search results prioritize matches in a paper's title and abstract, results from the full text of papers would be returned. Further, the search was limited to English language results, and the publication year from 2008 onwards. This research coverage period compassed 15 full years. The decision to focus on publications from 2008 onwards was driven by recency considerations. Given the rapid advancements in both AI and ESG domains, especially in the last decade and a half, it was deemed essential to concentrate on more recent literature to capture the most relevant and up-to-date trends, methodologies, and insights in the field. This stage identified a corpus of 18,000 papers.
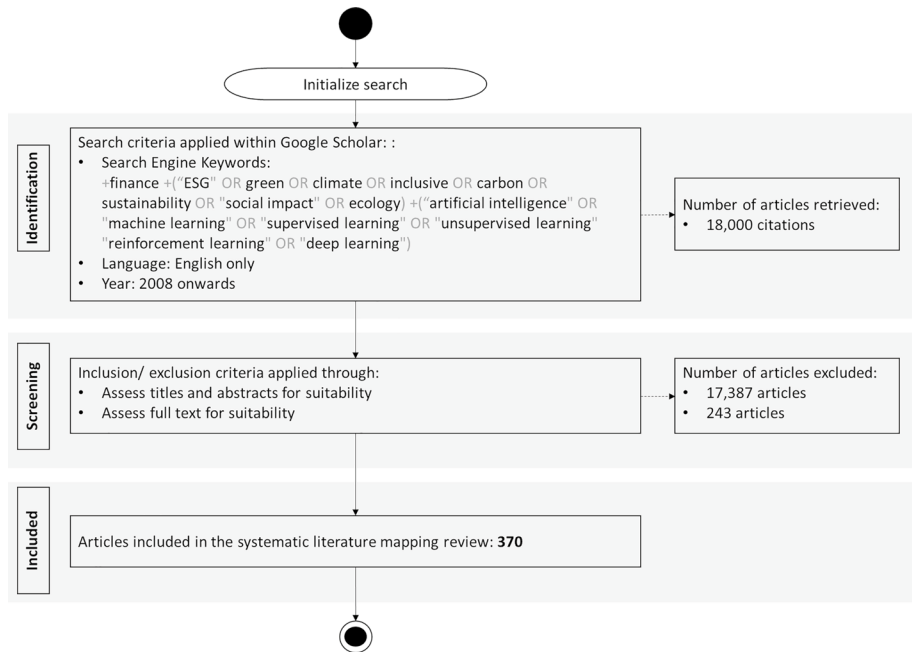
Fig. 1 PRISMA—the systematic mapping process

The next stage of PRISMA, the screening stage, involved a meticulous review process:

i. Title and abstract review: Initial scanning of titles and abstracts was conducted to exclude papers that were clearly unrelated to the research topic. This step removed a significant number of papers that, while matching the search criteria, were not directly relevant to the intersection of AI, ESG, and finance.

ii. Duplication check: Duplicated papers were identified and removed. Given the extensiveness of Google Scholar's database, there were instances where the same paper was indexed multiple times.

iii. Full text review: For papers that passed the initial screening, a full review of the text body was conducted to assess their suitability. Only papers that had fully accessible text and were directly relevant to the research topic were retained.

iv. Relevance and quality check: Papers that did not provide substantive insights or lacked rigorous methodology, even if they touched upon the research topic, were also excluded to ensure the quality of the final sample.

Through this rigorous process, 17,630 papers were omitted, leaving a total of 370 papers retained for the systematic literature mapping review. Data extracted from Google Scholar included: (i) author names, (ii) article title; (iii) publication title, (iv) year of publication, (v) publisher, and (vi) citation count.

3.2 Classification and analysis

First, the study undertook a thorough paper-by-paper review of the 370 papers for the purposes of tabulating the following information:

  i. AI application(s): This distinguishes the type(s) of AI technique and specific learning algorithm(s) applied (e.g., decision tree algorithm utilized for supervised learning etc.) in each paper.
 ii. Research areas: This details how each paper examines ESG within the field of finance (e.g., examining stock excess returns following ESG news events etc.).
iii. Type of paper: This includes original research, review article, book, case study, perspective, opinion and commentary paper, and regulatory study or guideline.

Next, research employed a corpus analysis platform known as *CorTexT* (Breucker et al. 2016) to parse the text data. Unsupervised pattern recognition text mining techniques of topic modelling and network mapping were performed to identify key latent thematic representations within the corpus, so as to understand the research archetypes within the landscape of *research areas*.

Topic modelling was performed utilizing the Python library *pyLDAvis* (Sievert and Shirley 2014). Building upon the Latent Dirichlet Allocation algorithm, topic modelling produced a topic representation of the *research areas* corpus' textual fields, which characterizes latent topics based on relevant *research areas* keywords. In essence, the text mining process considered each topic as a keyword probability distribution, and each document as a topic probability distribution. Based on the number of topics defined, topics were probabilistically assigned to documents to infer the topic model, and mapped using a mutidimensional scaling algorithm into a 2-dimensional plane for the purposes of visualization.

While topic modelling accorded an initial assessment of the possible latent topics based on the *research areas*, performance of network analysis further allowed a visualization of thematic representations of *research areas,* through the clustering of distinct *research areas* connected via similarity measures. This required the use of Louvain hierarchical community detection algorithm (Aynaud 2020). Louvain algorithm is efficient in large networks; it utilizes modularity optimization to compute the optimal linkage densities, accounting for between-cluster and within-cluster linkages.

A cross examination of the results of topic modelling, network analysis and the full papers would allow the inference of distinctive research archetypes. The discovered archetypes would then be further analyzed to examine the research impact, and the machine learning techniques employed for each distinct class of archetype. Finally, the study would put together a summary of findings to allow generalization and generate practical takeaways for each distinct archetypical domains for practitioners and researchers.

3.3 Validity evaluation

To evaluate if the methodology was robustly constructed in the application of systematic literature mapping, it was useful to consider the types of research validity. This included: (i) external and internal validity, (ii) interpretive validity, (iii) descriptive validity, and (iv) theoretical validity (Petersen and Gencel 2013). This could enhance research repeatability.

   i. External and internal validity: External validity describes the generalizability and extendibility of the results to other studies. Internal validity looks at whether the study design, implementation and analysis support the research claims and represent the truth in the population studied. It was of the view that since the methodology employed in the systematic literature mapping review was generally supported by a wide multidisciplinary range of similar literature, there should not exist major threats for generalizability of the study. However, it was acknowledged that external validity may be influenced by factors including the type of bibliometric database used (Martín-Martín et al. 2021), and future studies can help alleviate this concern.

  ii. Interpretive validity: This describes the validity of the conclusions drawn, based on the data extracted and coded. One area of concern may be researcher biasness. To reduce threats in interpretation, this was mitigated by ensuring that no papers written by authors were included in the 370 primary papers evaluated.

      Further, an independent external reviewer played a crucial role in ensuring the validity and accuracy of the classifications. In addition to auditing the methodology and data extraction process, the reviewer also examined the accuracy of paper classifications, both from the automated process and the subsequent manual verification. Any discrepancies identified were addressed, and the classification model was refined accordingly. This dual-layered approach ensured that the classifications were both consistent with the study's objectives and accurate in their representation of the papers' content.

 iii. Descriptive validity: This describes the presence of accurate and objective observations. This threat was mitigated through the objectification of the data extraction process, using a systematic and prolific bibliometric search system (in the form of Google Scholar), and use of data extraction software (in the forms of EndNote X9 and NVivo 11) and coding spreadsheet designed to support data recording and interventive correction to ensure accuracy.

 iv. Theoretical validity: This describes if the study was able to capture what was purported to be captured. The study sought to ensure that the patterns of the real world were depicted accurately by the thematic phenomena established by the paper. To lower the probability of excluding or underrepresenting critical research information, Google Scholar was employed as a comprehensive web-crawler based search engine to enhance the diversity of data sources. In terms of paper screening, the recency of literature, extensive in-depth reviews were applied in the titles, abstracts and full texts to validate if each paper included was relevant. To reduce potential biasness and for quality assessment, the methodology, data extraction process and analytical tools were audited by an independent external reviewer, who holds subject matter expertise. This step shields against biased interpretation and judgment in the screening of papers for conceptual consistency and thematic compatibility.

3.4 Limitations

Google Scholar is widely agreed to be vast source for bibliometric data retrievals, especially for the field of business, economics and management, where it outperforms bibliometric databases like Web of Science (WOS) and Scopus by large margins, owing to its automated and inclusive approach of indexing papers through the use of robotic web crawlers (Martín-Martín et al. 2019, 2021). It has the added advantage of coverage beyond journal articles and conference papers, by indexing, among others, monographs, institutional reports, and regulatory

guidelines, which extends the output formats for bibliometric search. In contrast, bibliometric databases such as Scopus and Web of Science have limited coverage of their journal articles, as they produce a curated set of scholarly documents, but may suffer from issues of biasness owing to their selective indexing criteria (Martín-Martín et al. 2019).

However, the approaches across the use of different bibliometric databases differ in the notion of rigor (i.e., reproducibility), against effort (i.e., programmatic or manual process) (Buyuklieva and Raimbault 2023). Relative to bibliometric databases like WOS and Scopus, Google Scholar's search filter criteria are limited in functionality (e.g., filtering by discipline, or peer review status etc.), and papers can vary significantly in terms of quality due to the lack of curation (Martín-Martín et al. 2021). This increases the onus on the researcher to perform manual screening and eligibility inclusion. Further, metadata such as abstract or references can be selected to be included in the data extraction step at WOS or Scopus for further analysis; for Google Scholar, these information are not included, and the researcher would have to perform manual web scrapping. This research seeks to provide a comprehensive coverage of the landscape, and Google Scholar is fit for purpose. However, for future research, to improve the quality of metadata obtained, curated bibliometric databases such as WOS and/or Scopus may be considered.

4 Findings

4.1 RQ1: What are the key research themes that outline the research scape for ESG and AI in finance?

To generate an optimal number of topic clusters with the highest topic coherence, the study performed topic modelling. The topic modelling results were cross examined with the topic clustering outputs of network analysis. The latter was undertaken for pattern recognition to collectively cluster similar topics using an unsupervised learning approach.

Both topic modelling and network analysis identified eight latent topics, and their results mirrored well with each other. The cluster members derived from network analysis in Fig. 2 corresponded well to the top keywords from the latent topics in Table 1. As an illustration, Fig. 3 shows the topic modelling output for the latent topic *ESG Disclosure, Measurement and Governance.*

Cross examination of topic modelling, network analysis and full paper reviews allowed the identification of eight research thematic archetypes. The archetypical domains were as follows, namely: (i) *Trading and Investment*, (ii) *ESG Disclosure, Measurement and Governance*, (iii) *Firm Governance*, (iv) *Financial Markets and Instruments*, (v) *Risk Management*, (vi) *Forecasting and Valuation*, (vii) *Data*, and (viii) *Responsible Use of AI.*

The eight research thematic archetypes are introduced hereforth. To improve the granularity of insights into the archetypical domains, the study further broke down the archetypes into sub-research themes, wherever possible. Selected recent literature were discussed in Tables 2, 3, 4, 5, 6, 7, 8, 9 to provide a thematic disposition of the state-of-the-art.

4.1.1 Trading and investment

This research archetype comprises papers involving the applications of AI in trading and investment activities within the ESG domain, associated with ESG news or factors, or expressing ESG considerations.
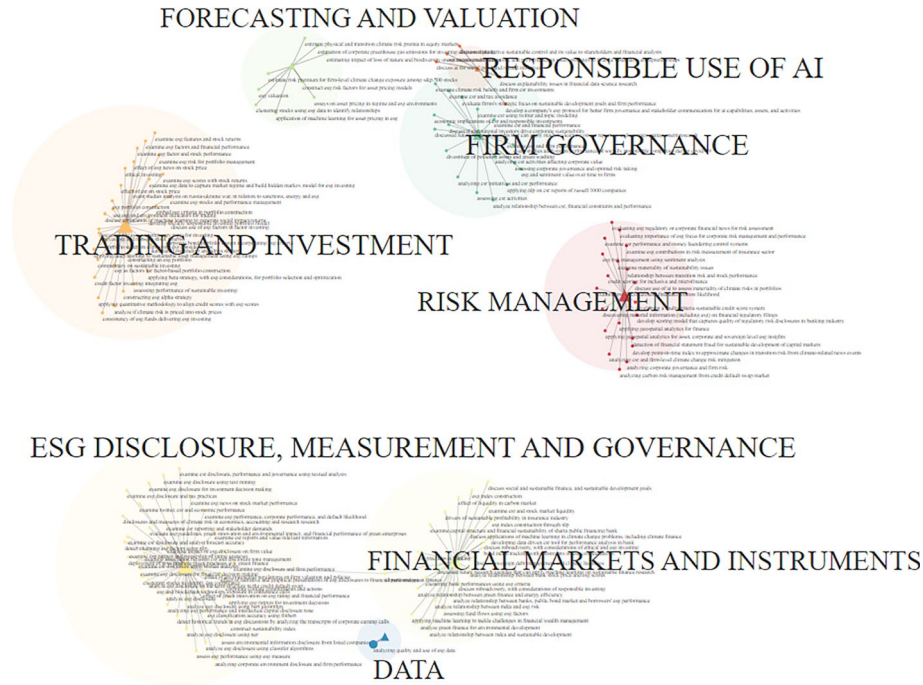
Fig. 2 Network analysis of ESG and AI in finance

Efficient and effective investment strategies and portfolio selection and optimization have been major areas of research in finance. In recent years, the application of AI techniques has revolutionized investment management. These techniques enable automation and intelligent investment, which involves predicting market trends, recommending trading signals, and minimizing risk through causal representations of limit order book markets (Cao 2020).

Incorporating ESG factors into investment strategies and portfolio selection has become increasingly important. One example of this is portfolio risk analysis, for instance, where AI techniques are employed to detect exceptional decoupling scenarios such as correlation changes, structural breaks or simultaneous asset shocks in portfolio assets to minimize risk (e.g., Taleb et al. 2020; Fabozzi and Karagozoglu; 2021; Serafeim and Yoon 2022; Zhang et al. 2022). AI techniques can also be used to analyze the impact of ESG factors on investment performance (e.g., Erhardt 2020; Ielasi et al. 2020; Ullah et al. 2021; Twinamatsiko and Kumar 2022; Yoo 2022). For instance, natural language processing (NLP) can be applied to analyze news and social media content to identify ESG-related trends and issues.

One of the critical areas of exploration is designing and implementing intelligent trading and investment decision-support platforms, online services, and mobile applications that consider ESG factors (e.g., Hakala 2019; Yang et al. 2020; He et al. 2021; Sokolov et al. 2021b; Katterbauer and Moschetta 2022a, b; Katterbauer et al. 2022). For example, machine learning-enabled recommenders and game theory can be used to analyze loan supply–demand equilibrium and risk-return balance in peer-to-peer lending

Table 1 Topic modelling—Latent topic and top keywords

| Topic No	Latent topic	Percentage of tokens (%)	Top keywords
1	ESG disclosure, measurement and governance	15.10	Performance; examine; financial; CSR; corporate; ESG; firm; predict; governance
2	Responsible use of AI	9.20	Responsible; explainable; trustworthy; auditable; policy; tool; governance; protocol; manage
3	Firm governance	14.70	ESG; firm; CSR; corporate; rating; capital; environment; stock; management
4	Financial markets and instruments	11.90	Index; bank; green; carbon; climate; ESG; financing; Islamic; technology
5	Data	9.90	Data; dataset; method; quality; generate; methodology; parameter; decision; issue
6	Forecasting and valuation	10.70	Predict; price; factor; score; rating; emission; reaction; stock; bond
7	Risk management	11.20	ESG; risk; score; rating; assessment; default; credit; news; transition
8	Trading and investment	17.30	Stock; ESG; market; price; impact; return; rate; bond; sovereign
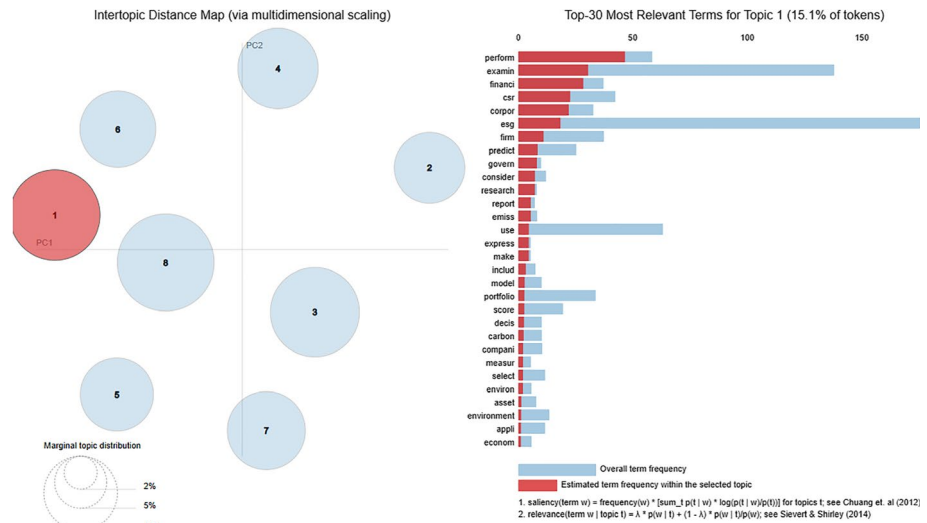
Fig. 3 Topic modelling of keyword corpuses

loans. Personalized stock recommendations can also be made by considering investor preferences, behaviors, past performance, and ESG factors.

This thematic area had the highest number of papers ($n = 91$), with average citation count of 17.3. The publication types were diversified, in the form of book ($n = 1$), case study ($n = 1$), review article ($n = 1$), perspectives, opinions and commentaries ($n = 3$), and original research ($n = 85$). Publication avenues include *Journal of Banking and Finance, Journal of Sustainable Finance and Investment, Journal of Portfolio Management, Journal of Impact and ESG Investing, Journal of Financial Data Science, Sustainability, Decision Support Systems, IEEE Symposium on Computational Intelligence for Financial Engineering and Economics,* and *ACM International Conference on AI in Finance*.

Papers from this thematic area can be further segregated into the following sub-research themes: (i) *trading and investing design and strategies*, (ii) *online and offline portfolio optimization*, (iii) *automated and smart investment*, and (iv) *market anomaly analysis* (Table 2).

4.1.2 ESG disclosure, measurement and governance

This research archetype relates to research associated with ESG disclosure, measurement and governance aspects that involves the application of AI, spanning across from firm to macro level considerations. Examples of related literature in the sub-research themes *ESG disclosure*, *measurement*, *governance* are shown in Table 3.

ESG disclosure refers to the information that companies provide to investors about their ESG performance. This information can include data on a company's environmental impact, social policies, and governance practices. Analyzing ESG disclosure data can identify trends and insights associated with equity research and investor sentiment analysis, among others (e.g., Goloshchapova et al. 2019; Clarkson et al. 2020; Raman et al. 2020). One example of how AI is being used to analyze ESG disclosure data is through textual analysis. Researchers have used machine learning algorithms to analyze corporate

Table 2 Sub-theme(s) within research thematic area of trading and investment

Research sub-theme(s)	Example(s) of related literature
Trading and investing design and strategies	• Melas (2021), Coqueret and Guida (2020), Haghshenas and Karim (2022), and Cherief et al. (2022) implemented ESG factors in factor investing, utilizing mainly multivariate regression. The latter two further utilized hidden Markov model, and a combination of gradient boosting and enhanced random forest respectively
	• Jacobsen et al. (2019), Antoncic (2020), Erhardt (2020), and Chen and Liu (2020) implemented multivariate regression, natural language processing, XGBoost and a basket of regularized regression, support vector regression, random forest and LSTM approaches respectively, to identify alpha signals in ESG investing
	• Guo et al. (2020) proposed a deep learning framework incorporating natural language processing, known as *esg2risk*, to predict stock volatility using ESG news
	• Brusseau (2021) proposed a model for ethical investing for AI-intensive companies
	• Quinn et al. (2021) examined the consistency of ESG funds delivering ESG investing using multivariate regression
	• Rannou et al. (2022) applied fuzzy c-means clustering and k-means clustering to examine greenness in the portfolios of funds holding the socially responsible investment (SRI) labels at stock level
	• Novak et al. (2018) investigated players and their interactions in the impacting investing market using support vector machine, naïve bayes and network analysis
	• Zhang (2021) examined impact ventures, fundraising and business performance using multivariate regression and dynamic Bayesian model
	• Begenau and Siriwardane (2022), Kieffer et al. (2021) and Kirppu (2019) examined private equity and ESG considerations; the former two used multivariate regression, while the latter utilized genetic algorithm
	• de la Barcena Grau (2021) discussed the application of machine learning to generate social impact returns
Online and offline portfolio optimization	• Hanine et al. (2021) explored fuzzy approach that incorporate ESG factors within multiple objective portfolio optimization
	• Meier and Danzinger (2022), and Dreżewski et al. (2018) applied evolutionary learning-based genetic algorithm, whereas Maree and Omlin (2022), Yang et al. (2020) and Vo et al. (2019) proposed reinforcement learning based approaches on portfolio selection expressing ESG considerations
	• Reyners (2021) employed tree-based regression with gradient boosting, and gaussian process regression to examine impact of ESG criteria in risk and returns of optimal portfolios
	• Gobet and Lage (2021) employed an optimal transport and multistage optimization criterion approach to align credit scores with ESG scores for credit portfolios
Automated and smart investment	• Katterbauer and Moschetta (2022a, b) and Katterbauer et al. (2022) looked at robo-advisory platforms for Islamic finance instruments
	• Hakala (2019) studied the use of AI in robo-advisors for private wealth advisory services

Table 2 (continued)

Research sub-theme(s)	Example(s) of related literature
Market anomaly analysis	Market anomaly analysis generally involves multivariate regression
	• Deng et al. (2022a) performed an event studies analysis on stock market's reaction to Russia-Ukraine war, particularly in relation to sanctions, energy and ESG
	• Caferra et al. (2022) examined the sustainable orientation of investors during Covid-19
	• Faccini et al. (2021), and Mousa et al. (2021) studied the impact of climate risk on stock prices
	Recent studies further incorporate natural language processing to identify signals from text data. These studies can be divided into two sub-types
	• One approach involves the processing and conversion of text data into market signals to identify event impacts, such as Bessec and Fouquau (2020) that examined the impact of green sentiment on stock returns
	• Another approach is the application of post-processed sentiment data into numerical input attributes that can be directly added into multivariate regressions to investigate event impacts, such as Naumer and Yurtoglu (2020) that examined tonality of news flow and the cross section of expected stock returns, taking ESG scores into account

Table 3 Sub-theme(s) within research thematic area of ESG disclosure, measurement and governance

Research sub-theme(s)	Example(s) of related literature
ESG disclosure	• Clarkson et al. (2020) performed textual analysis to analyze ESG disclosure using classifier algorithms including random forest and XGBoost
	• Goloshchapova et al. (2019) examined corporate social responsibility disclosure using natural language processing
	• Raman et al. (2020) detected historical trends of ESG discussions by analyzing the transcripts of corporate earning calls using pre-trained BERT, XLNet and RoBERTa
ESG measurement	• Bouyé and Menville (2020) examined sovereign ESG ratings using regularized regression and principal component regression
	• Huang et al. (2023) developed FinBERT, a language model adapted to the financial domain that can help improve ESG sentiment analysis and classification accuracy
	• Briere and Ramelli (2021) proposed a Green Sentiment Index that captures shifts in investors' appetite for environmental responsibility using multivariate regression
	• Chang and Lee (2019) proposed a Sustainable Development Progress Index based on the circular economy, using forest-based learning, clustering and multivariate regression
	• Reig-Mullor et al. (2022) proposed a neutrosophic AHP-TOPSIS based approach that applies fuzzy set, analytic hierarchy process, and multicriteria decision analysis to assess corporate ESG performance
ESG governance	• Chen et al. (2022a, b, c) evaluated ESG guidelines, green innovation and environmental impact, and financial performance of green enterprises using multivariate regression
	• Fan and Wu (2022) studied the effect of environmental regulations on firm valuation and policies using natural language processing and multivariate regression

Table 4 Sub-theme(s) within research thematic area of firm governance

Research sub-theme(s)	Example(s) of related literature
Smart operations, CSR and governance	• Seele (2017) studied predictive policing of corporate sustainability management
	• Hrazdil et al. (2021) examined corporate executive personalities and CSR performance based on S&P 500 firms using multicriteria decision analysis and multivariate regression
	• Chava et al. (2021) investigated if managers walk the talk on environmental and social issues, using pre-trained RoBERTa and multivariate regression
	• Moniz and Jong (2014) examined the impact of employee satisfaction on firm earnings using natural language processing
	• Ranta and Ylinen (2021) looked at workplace diversity as a predictor of firm performance using XGBoost and regularized regression
	• Kiriu and Nozaki (2020) evaluated firms' CSR activities using natural language processing
	• Chae and Park (2018) employed natural language processing to examine CSR using Twitter and topic modelling
	• Economidou et al. (2022) examined whether a firm's engagement in ESG practices is material to market participants, using k-nearest neighbor and multivariate regression
	• Sukthomya and Laosiritaworn (2018) employed neural network to examine relationship between CSR and stock price
	• Chen (2021) applied natural language processing on CSR reports of Russell 1000 companies to measure corporate alignment with the United Nations Sustainable Development Goals
	• Hernandez-Perdomo et al. (2019) assessed corporate governance and optimal risk-taking using association analysis and decision tree
	• Svanberg et al. (2022) predicted corporate governance performance ratings using a range of machine learning techniques, including linear and RBF support vector machine, and quadratic discriminant analysis
Intelligent e-commerce and supply chain management	• Jebamikyous et al. (2023) leveraged AI and blockchain in e-commerce applications
	• Coqueret and Tran (2022) evaluated how ESG shocks can affect the returns of clients and suppliers using multivariate regression
	• Soni et al. (2022) applied fuzzy set to propose a framework for decision making for sustainable supply chain finance
Corporate finance	• Chava (2014) examined environmental externalities and cost of capital using multivariate regression
	• Bussmann, Tanda and Yu (2022) reviewed the role of ESG in a firm's cost of capital using XGBoost
	• De Lucia et al. (2020) investigated if good ESG performances are linked to better financial performances using a range of supervised and deep learning techniques, including support vector machine, regularized regression and neural network
	• Alkaraan et al. (2022) examined the impact of ESG on financial performance using textual analysis and multivariate regression
Intelligent marketing	• Wirtz et al. (2023) examined corporate digital responsibility in service firms and their ecosystems
	• He et al. (2021) investigated cognitive user interface for portfolio optimization to enhance user experience

Table 5 Sub-theme(s) within research thematic area of *Financial Markets and Instruments*

Research sub-theme(s)	Example(s) of related literature
Market systems and simulation	• Rolnick et al. (2022) discussed the applications of machine learning in climate change problems, including climate finance
	• Klusak et al. (2021) examined effect of climate change on sovereign creditworthiness using random forest and multivariate regression
	• Sun (2022) examined the relationship between green finance and carbon emissions using neural network
	• Hemanand et al. (2022) analyzed green finance for environmental development using neural network and financial maximally filtered graph (FMFG) algorithm
	• Lin and Zhao (2022) examined impact of green finance on the ecologicalization of urban industrial structures using k-nearest neighbor, random forest and multivariate regression
	• Khalfaoui et al. (2022a, b) examined spillover effects and connectedness among green commodities, Bitcoins, and US stock markets using multivariate regression
	• Bariz (2022) examined if credit default swap markets incorporate ESG-related information in their assessment of a firm's risk, using natural language processing and multivariate regression
	• Deng et al. (2022b) examined the stock market for Russia-Ukraine war and climate policy expectations
	• Roy, Rao and Zhu (2020) examined relationship between CSR and stock market liquidity using multivariate regression
	• Entrop et al. (2022) examined if religiosity affects liquidity for U.S. listed companies using multivariate regression
	• Strignert and Malm (2021) examined volatility between green and non-green ETFs using multivariate regression
Smart banking and payment	• Ishizaka et al. (2021) applied hierarchical clustering to evaluate bank performances using ESG criteria
	• Citterio (2020) used a range of machine learning approaches on ESG indicators, including linear discriminant analysis and k-nearest neighbor, to predict bank failures
	• Kneppers (2022) developed a CSR tool using natural language processing for performance analysis in banks
	• Miranti and Oktaviana (2022) examined capital structure and financial sustainability of Sharia public financing bank using multivariate regression
	• Similarly, applying multivariate regression, Newton et al. (2022) analyzed the relationship between banks, public bond market and borrowers' ESG performance, and Demir and Danisman (2021) analyzed relationship between bank stock price and ESG scores

Table 5 (continued)

Research sub-theme(s)	Example(s) of related literature
Financial products and services	• Sokolov et al. (2022) applied pre-trained BERT for ESG index construction
	• Slimane (2021) utilized genetic algorithm for bond index tracking with constraints on ESG considerations
	• Lichtenberger et al. (2022) examined performance of green against non-green bonds using decision tree and multivariate regression
	• Kanzi Belghiti (2022) examined Islamic finance indices and their conventional counterparts using multivariate regression
	• Soni et al. (2022) used fuzzy set to propose a framework for decision making for sustainable supply chain finance
	• Pettinari (2021), Chen (2021) and Hong et al. (2022) investigated mergers and acquisition and ESG value, risk and sustainable development, respectively. The former two utilized multivariate regression, whereas the latter utilized support vector machine and Adaboost
	• Fedorova et al. (2022) used transfer learning (BERT), random forest and multivariate regression to examine the impact of media sentiment on climate change and environmental policies on IPO underpricing
	• Vo (2020) applied a range of deep learning and machine learning models, including LSTM and ensemble models, to tackle challenges in wealth management
Financial technology	• Hakala (2019) discussed roboadvisory, with considerations of ethical and ESG investing
	• Khan and Ahmad (2022) proposed integrating ESG and machine learning considerations in decentralized finance
	• Faust et al. (2022) examined effects of altruism on crowdfunding outcomes in initial coin offerings using natural language processing and multivariate regression
	• Gidron et al. (2021) identified tech impact startups (TIS) within startup databases using pre-trained BERT

ESG reports and identify trends and insights associated with credit assessment. Another approach is the use of NLP to examine corporate social responsibility (CSR) disclosures and identify the specific ESG issues that companies are addressing.

ESG measurement refers to the process of measuring the social and financial impact of ESG factors on companies and investments. AI is being used to develop ESG measurement tools such as indices (e.g., Green Sentiment Index) that help investors and analysts anticipate changes in a company's ESG performance and make decisions accordingly (e.g., Chang and Lee 2019; Briere and Ramelli 2021; Reig-Mullor et al. 2022; Huang et al. 2023).

ESG governance refers to the processes and structures that companies have in place to identify and assess potential ESG risks, as well as to monitor and ensure compliance with relevant regulations and policies. AI is being used to automate the tracking and analysis of ESG data, which can assist regulators in enforcing ESG regulations and encourage companies to improve their ESG governance practices (e.g., Chen et al. 2022a, b, c; Fan and Wu 2022).

This thematic area had the second highest number of papers ($n = 77$), with average citation count of 10.5. The publication types were diversified, in the form of book ($n = 1$), review article ($n = 4$), perspectives, opinions and commentaries ($n = 2$), regulatory study or guidelines ($n = 1$), and original research ($n = 69$). Publication avenues include *Journal of Business Ethics, Review of Accounting Studies, European Journal of Finance, Economic*

Research sub-theme(s)	Example(s) of related literature
Risk management	• Patterson et al. (2022) and Yang and Broby (2020) applied geospatial analytics for macro ESG insights using computer vision
	• Angelova et al. (2021) examined sovereign rating methodologies, ESG and climate change risk using multivariate regression
	• Hofinger (2021) developed a scoring model that captures quality of regulatory risk disclosures in banking industry using principal component analysis, natural language processing and multivariate regression
	• Apel et al. (2023) developed a transition risk point-in-time index to approximate changes in transition risk from climate-related news events, using pre-trained BERT and multivariate regression
	• Jan (2021) used LSTM to detect financial statement fraud for sustainable development of capital markets
	• Fianu (2021) examined ESG contributions in risk measurement of insurance sector using network analysis and hierarchical clustering
	• Nguyen et al. (2021) used a range of machine learning approaches, including tree-based ensemble, k-nearest neighbor, and regularized regression, to predict corporate carbon footprints for financial risk analysis
	• Khanra et al. (2022) examined the materiality levels of corporate sustainability issues using multivariate regression
	• Hisano et al. (2020) predicted firms in negative screening list for ESG criteria, using natural language processing and random forest
	• Duong et al. (2022) analyzed firm carbon risk management from credit default swap market using multivariate regression
	• Hamidi et al. (2021) examined corporate reputation risk in social media using natural language processing
	• Mehra, Louka, and Zhang (2022) proposed ESGBERT, a text mining approach based on pre-trained BERT and multivariate regression, to identify material ESG risk and growth opportunities for investing

Table 6 Sub-theme(s) within research thematic area of *risk management*

Table 6 (continued)

Research sub-theme(s)	Example(s) of related literature
Credit management	• Nguyen et al. (2023) examined the relationship between loan portfolios and transition risk using multivariate regression
	• Hasan et al. (2022) used regularized regression and XGBoost to examine corporate default risk and ESG factors
	• Roy and Shaw (2022) utilized a fuzzy BWM and fuzzy TOPSIS approach to develop a multi-criteria sustainable credit score system
	• Katterbauer and Moschetta (2022a, b) applied random forest on credit scoring for inclusive and microfinance

Research, Sustainability, Technological Forecasting and Social Change, Machine Learning and Knowledge Extraction, and *AAAI Workshop on Knowledge Discovery from Unstructured Data in Financial Services.*

4.1.3 Firm governance

This research archetype relates to research on the application of AI on firm-related ESG studies, specifically encompassing several sub-research themes: (i) *smart operations, CSR and regulations,* (ii) *intelligent e-commerce and supply chain management,* (iii) *corporate finance,* (iv) *intelligent marketing*. Examples of related literature are shown in Table 4.

Smart operations, CSR and regulations involve a thorough analysis, optimization, and evaluation of operational, financial, and service risks to enhance performance and mitigate low-performing areas, failures, and losses (e.g., Seele 2017; Hernandez-Perdomo et al. 2019; Chava et al. 2021; Svanberg et al. 2022). For instance, firms can adopt an ESG perspective to assess and mitigate environmental risks associated with business operations. This can include identifying and reducing energy waste, monitoring and reducing carbon emissions, and predicting and preventing equipment failure can help firms reduce their carbon footprint.

Intelligent e-commerce and supply chain management require the estimation, prediction, and optimization of various business aspects, including pricing, demand, supply, production, storage, logistics, delivery, marketing, risk, and fraud (e.g., Coqueret and Tran 2022; Soni et al. 2022; Jebamikyous et al. 2023). To adopt an ESG perspective, firms can optimize logistics and delivery processes and predict demand for sustainable products and services to reduce their carbon footprint.

Corporate finance involves the analysis, prediction, and optimization of various financial aspects of business, including corporate financial budget, accounting integrity, auditing issues, and payment accuracy. Firms must detect and mitigate financial fraud, irregularities, and unethical behavior by company executives. From an ESG perspective, analyzing the impact of environmental policies and regulations on financial performance is necessary. Evaluating the social impact of corporate financial decisions, such as layoffs and plant closures, can help companies improve their overall governance practices (e.g., Chava 2014;

Research sub-theme(s)	Example(s) of related literature
Table 7 Sub-theme(s) within research thematic area of *forecasting and valuation*	
Forecasting	• Wang et al. (2021) used a random forest-based ensemble for feature extraction and deep learning LSTM model for carbon price forecasting
	• Jabeur et al. (2021) used a range of tree-based ensemble, including LightGBM, CatBoost, XGBoost, random forest, and a deep learning neural network model, to predict oil prices using green energy resources, ESG indices, and stock markets
	• García et al. (2020) used to rough set approach with multivariate regression to predict ESG ratings using financial performance variables
	• D'Amato et al. (2022) predicted ESG scores for ESG investing using random forest
	• Marozzi and Lanza (2022) used LSTM and pre-trained BERT and BERT derivatives, such as RoBERTa and XLM-RoBERTa, to formulate real-time forward Twitter-based ESG score for stocks
	• Hossain (2020) used a range of supervised and deep learning methods, such as naïve bayes and multilayer perceptron, to predict corporate green Islamic bond ratings
	• Yu et al. (2018) applied natural language processing, support vector machine, and a dynamic time warping-based clustering approach, to predict stock price reaction to negative news, including ESG news
	• Chen et al. (2019) used tree-base ensemble, restricted Boltzmann machine and bi-directional LSTM to incorporate fine-grained events such as ESG news on stock movement prediction

Research sub-theme(s)	Example(s) of related literature
Table 7 (continued)	
Valuation	• Applying regularized multivariate regression, Semet et al. (2021) priced ESG and sovereign risk in credits and credit ratings, and Joshi and Chauhan (2021) valued stocks incorporating ESG factors
	• Obrizzo (2021) applied a web-scraping approach using natural language processing and multivariate regression to ESG valuation
	• Han et al. (2021) used gradient boosted trees and neural network to estimate corporate greenhouse gas emissions for investing decision making
	• Agarwala et al. (2022) used random forest to value the impact of loss of nature and biodiversity on sovereign credit ratings
	• Katterbauer et al. (2022) used XGBoost to price Islamic bonds
	• Yang and Jiménez-Martin (2022) used multivariate regression to construct ESG risk factors for asset pricing models
	• Agliardi and Agliardi (2021) studied the determinants of green bond prices using multivariate regression
	• Sautner et al. (2021) estimates risk premium for firm-level climate change exposure among S&P 500 stocks using natural language processing, on top of multivariate regression

Table 8 Sub-theme(s) within research thematic area of *ESG as an alternative data*

Research sub-theme(s)	Example(s) of related literature
ESG as an Alternative Data	These are generally qualitative papers, with the exception of papers that focus on introducing novel methodologies to generate ESG datasets
	• Kotsantonis and Serafeim (2019), and Lopez et al. (2020) discussed about the quality and issues regarding the use of ESG data
	• In et al. (2019a, b) shared the integration of ESG data in investment decision making
	• In terms of generating ESG dataset, Geissler et al. (2022) used generative adversarial network to generate multivariate data such as ESG scores for financial scenarios generation, and Sokolov et al. (2021b) used the pre-trained BERT model for natural language processing to generate ESG scores
	• Gupta et al. (2021) presented a methodology to create an ESG dataset, and framework to gauge the importance of ESG parameters for investment decisions, using multivariate regression and random forest

Table 9 Sub-theme(s) within research thematic area of *responsible use of AI*

Research sub-theme(s)	Example(s) of related literature
Responsible and explainable AI	These are generally framework and/or qualitative-type papers • Lacoste et al. (2019) proposed a tool that quantifies carbon emissions of machine learning models for corporate practitioners • Hoepner et al. (2021) discussed the importance of explainability issues in financial data science research • Fritz-Morgenthal et al. (2022) exposited on governance issues to support the establishment of responsible, trustworthy, explainable, auditable and manageable AI in production in the finance industry • Sætra (2022) developed a company's ESG protocol for better firm governance and stakeholder communication for AI capabilities, assets, and activities • Seele (2017) discussed predictive policing of corporate sustainability management, and its value to shareholders and financial analysts

Teoh et al. 2019; De Lucia et al. 2020; Turunen 2021; Bussmann et al. 2022; Yadav et al.; 2022).

In terms of intelligent marketing, AI can help firms analyze marketing performance, recommend and optimize marketing campaigns, and understand customer needs, sentiment, satisfaction, and concerns (e.g., Dash and Kajiji 2020; He et al. 2021; Akter et al. 2022; Wirtz et al. 2023). To adopt an ESG perspective, firms can analyze the social impact of marketing campaigns and recommend socially responsible marketing strategies that address issues like diversity and inclusion. Firms should also consider the environmental impact of marketing campaigns and recommend sustainable marketing strategies to reduce their carbon footprint.

This thematic area had the third highest number of papers ($n = 52$), with average citation count of 20.8. The publication types were in the form of review article ($n = 4$), and original research ($n = 48$). Publication avenues include *Management Science, Journal of Applied Corporate Finance, Journal of Enterprise Information Management, Technological Forecasting and Social Change, Journal of the Operational Research Society*, and *Sustainability.*

4.1.4 Financial markets and instruments

This research archetype relates to research on the application of AI on ESG issues pertinent to the financial markets, market participants, products, activities and technology solutions. In particular, papers from the cluster can be further segregated into: (i) *market systems and simulation,* (ii) *smart banking and payment,* (iii) *financial products and services*, and (iv) *financial technology* (Table 5).

Market systems and simulation (i) examines the interplay, associations, and effects among macro and microeconomic elements, and (ii) emulates and evaluates market mechanisms, models, hypotheses, policies, innovative products and services, trading rules, and regulations using multiagent systems. It involves developing models to understand the impact of various economic, social, cultural, and political factors on financial markets and their resilience. From an ESG perspective, this encompasses studying the consequences of environmental threats on economic expansion, investigating the role of societal and

cultural components on financial markets, and examining the outcomes of policy interventions on sustainable economic growth (e.g., Semet et al. 2021; Wang et al. 2021; Tufail et al. 2022; Yu et al. 2022; Zhang and Han 2022).

Smart banking and payment addresses the design and analysis of intelligent, secure, and risk-averse digital banking and payment methods, tools, behaviors, and services. The goal is to study and forecast banking and payment trends, growth, risk, fraud, security, and malfunctions. From an ESG perspective, this involves supporting eco-friendly banking practices, investing in sustainable initiatives, ensuring access to banking services for underserved populations, safeguarding customer data and privacy, and promoting financial literacy among customers (e.g., Oro et al. 2020; Nguyen et al. 2023).

Financial products and services studies a range of products and services, ranging from wealth management products to internet finance services. For instance, in the area of insurance, studies focus on estimating, predicting, optimizing, and recommending insurance products and services, along with their pricing and market positioning. It also involves personalized product customization, fraud detection, and risk assessment. From an ESG standpoint, this includes identifying environmental risks linked to insured assets and liabilities, evaluating the carbon footprint and environmental impact of insured assets and services, and developing sustainable insurance products and services (e.g., Cherrington et al. 2020; Dugo 2021; Duchin et al. 2022; Sætra 2022).

The realm of financial technology can include studies on blockchain systems and mechanisms. This involve analyzing the intricacies of blockchain systems to improve their design and functioning, evaluating and enhancing bitcoin and cryptographic contract models, and optimizing pricing and portfolio management. From an ESG standpoint, this includes ensuring that blockchain systems are energy-efficient to minimize the environmental impact of cryptocurrency mining, examining the ESG implications of blockchain on various industries, such as supply chain transparency, ethical sourcing, and carbon footprint reduction, and developing sustainable crypto models (e.g., Yu 2022; Jebamikyous et al. 2023).

This thematic area had the forth highest number of papers ($n = 50$), with average citation count of 10.8 The publication types were in the form of review article ($n = 7$), case study ($n = 1$), and original research ($n = 42$). Publication avenues include *Journal of Corporate Finance, Research in International Business and Finance, Review of Financial Economics, Economic Research, Omega, Technological Forecasting and Social Change, ACM Computing Surveys, Journal of Artificial Intelligence and Technology, Computational Intelligence and Neuroscience, Neural Computing and Applications*, and *Annals of Operations Research*.

4.1.5 Risk management

This research archetype comprises papers involving the application of AI on risk management, spanning from macro level risk to portfolio level risk. In particular, papers from the cluster can be further segregated into: (i) *risk management,* and (ii) *credit management* (Table 6).

Within the realm of risk management, AI techniques are employed to model, forecast, and control risk elements, implications, and intensity, as well as fraud, criminal activity, security incidents, and money laundering linked to a wide range of financial products, methods, markets, and participants. With respect to ESG, this involves

utilizing ESG data to identify and prevent fraud and crime, estimate and tackle the repercussions of ESG-related occurrences, and enhance risk management approaches by incorporating ESG factors (e.g., Roy and Shaw 2021; Yang et al. 2022).

Credit management entails the application of AI to assess, forecast, and fine-tune credit scores, ceilings, assessments, timelines, defaults, repayments, refinancing, risk management, and fraud prevention. In the context of ESG, this encompasses providing green financing for renewable energy initiatives, granting credit accessibility for disadvantaged communities, determining the carbon footprint of credit portfolios, endorsing eco-friendly business operations, and supporting equitable lending practices (e.g., Liermann et al. 2021; Gobet and Lage 2021; Brogi et al. 2022; Mansouri and Momtaz 2022).

This thematic area had the fifth highest number of papers ($n = 41$), with average citation of 25.1. The publication types were in the form of review article ($n = 1$), perspectives, opinions and commentaries ($n = 3$), and original research ($n = 37$). Publication avenues include *Risks, Risk Management, The Accounting Review, Sustainability* and *Journal of Big Data.*

4.1.6 Forecasting and valuation

This research archetype comprises papers involving the application of AI to forecast ESG-related asset pricing, ratings or scores, or value ESG-related instruments, carbon emissions or biodiversity. In particular, papers from the cluster can be further segregated into: (i) *Valuation*, and (ii) *Forecasting* (Table 7).

Valuation research area is centered on the use of AI for estimating and predicting values, prices, demand, and supply with an emphasis on ESG factors. For instance, optimization of pricing, movement, supply, and demand for various energy sources, including electricity, oil, solar, gas, wind, nuclear, and water power. This research area also involves determining the environmental impact of factors such as carbon emissions, water consumption, and waste management. Additionally, it ascertains the supply and demand for sustainable practices in areas like investments (e.g., Cherrington et al. 2020; Dugo 2021; Duchin et al. 2022; Sætra 2022).

Forecasting focuses on developing models to predict market movements, trends, volatility, anomalies, and events from an ESG perspective. This includes anticipating the consequences of environmental and social events, such as natural disasters and resource depletion, on financial markets. Furthermore, it entails forecasting the influence of CSR practices on financial performance and projecting the future effects of governance policies on market volatility. Predicting pricing, movement, supply, and demand within the energy market is also an integral part of this research area (e.g., Anas et al. 2020; Jabeur et al. 2021; Larsson and Ling 2021; Gao et al. 2022; Guliyev and Mustafayev 2022).

This thematic area had the sixth highest number of papers ($n = 38$), with the second smallest average citation of 4.7. All publications belonged to the original research category. Publication avenues include *Decisions in Economics and Finance, Computational Management Science, Journal of Sustainable Finance and Investment, Sustainability, Science of the Total Environment*, and *Journal of Environment Management.*

4.1.7 Data

This research archetype comprises papers discussing issues related to the utilization of ESG data or methodologies proposed to create new ESG datasets. Examples of related literature are shown in Table 8.

This approach aims to identify and extract ESG-related information from vast amounts of unstructured data, including news articles, social media posts, company reports, and satellite images. Such data can be used to quantify various environmental factors, such as deforestation, air pollution, and water usage. From an ESG perspective, among other techniques, this research area includes leveraging textual data from corporate sustainability reports to extract ESG-related information. By using natural language processing techniques, researchers can create ESG scores for companies, which can help evaluate their ESG performance (e.g., Lopez et al. 2020; Gupta et al. 2021; Sokolov et al. 2021b; Geissler et al. 2022).

This thematic area had the second smallest number of papers ($n = 14$), with average citation of 14.7. All publications belonged to the original research category. Publication avenues include *Journal of Applied Corporate Finance, Journal of Impact and ESG Investing, Global Economic Review, Sustainability*, and *Big Data and Society.*

4.1.8 Responsible use of AI

This research archetype comprises papers discussing issues related to the responsible and explainable use of AI in finance, including but not limited to more efficient management of carbon emissions when developing AI models, and the introduction of firm or industry level ESG policing and governance to manage AI assets, capabilities and activities. Examples of related literature are shown in Table 9.

By adopting techniques like explainable AI, financial institutions can develop more transparent and interpretable models. This allows for a better understanding of the decision-making process, ensuring that it is responsible and ethical. From an ESG standpoint, key considerations include preventing machine learning algorithms from exacerbating or amplifying biases against any social or demographic group and guaranteeing the transparency and interpretability of models and their decisions (e.g., Lacoste et al. 2019; Hoepner et al. 2021; Fritz-Morgenthal et al. 2022).

This thematic area was the smallest in terms of number of papers ($n = 7$) published, with however, the highest average citation of 46.3. The publication types were in the form of review article ($n = 1$), perspectives, opinions and commentaries ($n = 3$), and original research ($n = 3$). Publication avenues include *European Journal of Finance, Frontiers in Artificial Intelligence,* and *Nature Machine Intelligence.*

Through the identification of distinct thematic research focal areas and sub-themes that underlie existing research efforts, as evidenced by extant literature, this review provides a thematic classification and disposition of the state-of-the-art.

4.2 RQ2: How has research intensity and interest in various archetypical domains evolved over time?

To understand the magnitude of key research efforts, broken down by the archetypical domains, we next studied the overall research intensity. Table 10 provides an indication

of the overall research intensity for each thematic research cluster, in terms of total paper count, total citation count and citation impact. A citation-based research metric, the Citation Impact, measures research impact by normalizing the citation count in terms of the number of publication, to obtain the average number of times each publication is cited (McMaster University 2022).

Research covered 370 publications generating a total of 5749 citations. This translated to a mean citation count per publication of 15.5. On an overall basis, it was observed that *Trading and Investment* generated the highest research attention in terms of the total number of papers published, and in turn the highest total citation count, translating to an above average citation count per publication. *ESG Disclosure, Measurement and Governance* followed in second place, but its overall citation count was relatively low, resulting in the second lowest citation count per publication.

Interestingly, it was *Responsible Use of AI* that brought about the highest traction in terms of citation impact of 46.3, followed by *Risk Management* and *Firm Governance*. In contrast, *Forecasting and Valuation* generated a meagre 4.7 in terms of citation count per publication; a one order-of-magnitude difference with *Responsible Use of AI*. Alongside *Forecasting and Valuation*, the aforementioned *ESG Disclosure, Measurement and Governance*, and *Financial Markets and Instruments* round up the bottom three positions.

The next natural question to evaluate was how the archetypical domains evolved across time. Figure 4 shows the absolute publication numbers, broken down by the archetypical domains, between 2008 and 2022. It was observed that 2018 appeared to be the inflexion point, beyond which research efforts grew significantly.

In terms of the evolution of the absolute citation count as shown in Fig. 5, *Trading and Investment* had historically generated the highest interest across the years. Citations within the *Risk Management*, *Firm Governance* and *ESG Disclosure, Measurement and Governance* domains grew considerably in the later years. The other domains generated relatively smaller absolute citation count numbers.

To measure the citation impact contribution of each research domain across the years, the study proportioned the citation impact values such that the relative contributions of each archetypical domain to the total contributions of all domains across time could be observed (Fig. 6).

In Fig. 6, it was noted that while *Trading and Investment* was a crowded space in terms of total publication numbers and citation counts, the relative research impact per publication was reduced over time. In contrast, while research within the *Risk Management* and *Responsible Use of AI* domains started later, their relative citation impacts were higher, and these impacts were picked up within a relatively short space of time.

Other further points to note in terms of relative research interest were as follows: (i) as a relative proportion to the collective papers in the search space, citation impact for the *Trading and Investment* and *Firm Governance* domains appeared to exhibit downward trends, and (ii) while citation impacts for the domains of *Data, ESG Disclosure, Measurement and Governance, Financial Markets and Instruments* and *Forecasting and Valuation* appeared to exhibit small tractions, these were offset by their continued growth trends and relatively late entries into the research space. They could yet make impressive strides going forward.

The insights above allow researchers to recognize where and how research intensity and interest, and their evolution occurred in recent years, so as to better assess and allocate their present research efforts going forward.

Table 10 Publication and citation numbers by research cluster

Thematic research area	Total paper count	Total citation count	Citation impact
Trading and investment	91	1578	17.3
ESG disclosure, measurement and governance	77	809	10.5
Firm governance	52	1082	20.8
Financial markets and instruments	50	542	10.8
Risk management	41	1030	25.1
Forecasting and valuation	38	178	4.7
Data	14	206	14.7
Responsible use of AI	7	324	46.3
Overall	370	5749	15.5

4.3 RQ3: which AI techniques have been employed in studies across the archetypical domains, and how have their usages changed over time?

It was interesting to see that different research archetypes exhibited different dominant AI techniques, as observed in Fig. 7.

i.   Trading and Investment: The AI techniques used by the papers in this domain were highly diversified, ranging from the application of relatively simple tree-based algorithms such as decision trees (e.g. Lanza et al. 2020) and ensemble models such as tree-based regression (e.g. Reyners 2021), to portfolio optimization algorithms such as Michaud optimization (e.g. De Spiegeleer et al. 2021; He et al. 2021), and deep reinforcement learning algorithms such as Q-learning (e.g. Yang et al. 2020; Maree and Omlin 2022).

ii. ESG Disclosure, Measurement and Governance: ESG information obtained through sources such as web scrapped reporting disclosure might be text-based. Text mining algorithms represented a significant proportion of papers in this domain. Text mining algorithms, most commonly applying Bidirectional Encoder Representations from Transformers (BERT), or other BERT variants such as RoBERTa, LinkBERT, FinBERT, ClimateBERT or SBERT, were applied to extract insights (e.g., Bingler et al. 2022; Ghosh and Naskar 2022; Koloski et al. 2022; Huang et al. 2023).

iii. Firm Governance: The majority of papers in *Firm Governance* utilized multivariate regression to examine the impact of ESG at the company level (e.g., Heath et al 2021; Alkaraan et al. 2022).

iv. Financial Markets and Instruments: Research practices in this domain applied multivariate regression and/or unsupervised analysis to examine relationships between ESG and macro market issues, market microstructure, market participants, financial products and activities, and technology influence (e.g., Ishizaka et al. 2021; Klusak et al. 2021; Bai et al. 2022). Evolutionary learning, deep learning and text mining have been applied to create new ESG products, such as ESG index construction (e.g., Chang et al. 2021; Slimane 2021; Sokolov et al. 2021a).
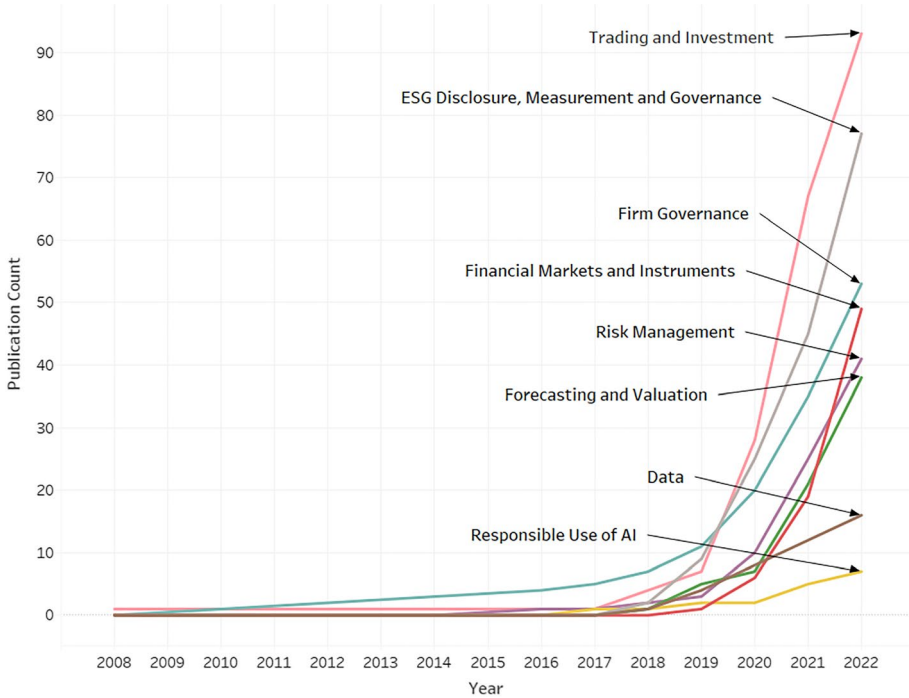
Fig. 4 Total publication count by research thematic areas between 2008 and 2022

v. Risk Management: The domain of *Risk Management* employed multivariate regression to analyze risk factors and contributions (e.g., Brogi, Lagasio and Porretta, 2018; Michalski and Low 2021), text mining and deep learning to detect changes in risk level or predict negative screening ESG lists (e.g., Hisano et al. 2020; Jan 2021), and unsupervised learning and computer vision to recognize risk patterns (e.g., Patterson et al. 2020, 2022; Yang and Broby 2020).

vi. Forecasting and Valuation: This domain primarily employed supervised learning approaches, which might be augmented by ensembling through different regularization (e.g., lasso) and boosting (e.g., XGBoost, LightBoost) techniques (e.g., Semet et al. 2021; Guliyev and Mustafayev 2022). Deep learning methods were increasingly being utilized to improve forecasting results (e.g., Jabeur et al. 2021; Wang et al. 2021), and finely grained news events could be integrated through text mining to achieve real-time prediction (e.g., Yu et al. 2018; Chen et al. 2019; Zhang 2022).

vii. Data: The domain of *Data* might involve simple supervised learning and natural language processing (e.g., Gupta et al. 2021; Sokolov et al. 2021b), to the use of generative AI (e.g., Geissler et al. 2022) for the creation of ESG scores and rating datasets. Only 36% of the papers reviewed employed AI techniques. The majority of the papers were concerned about providing qualitative assessments to the quality and use of ESG data.

viii. Responsible Use of AI: This domain was relatively scarce in terms of the employment of AI techniques, with only 29% of the papers reviewed employing some form
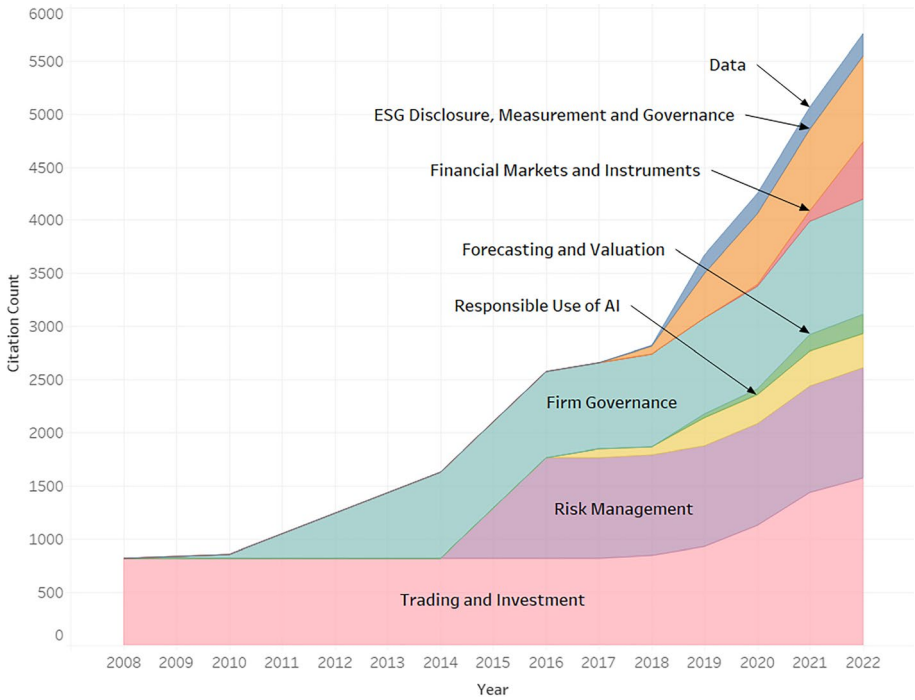
Fig. 5 Total citation count by research thematic areas between 2008 and 2022

of AI techniques. For instance, neural network had been employed as a tool to quantify carbon emissions of machine learning systems (Lacoste et al 2019), and assess token offerings to finance socially good sustainable entrepreneurship (Mansouri and Momtaz 2022). Other useful AI techniques include algorithmic fairness and bias mitigation techniques, and feature importance analysis, model interpretation, and local explanation methods for explainable AI. The majority of the papers reviewed discussed qualitatively on AI ethics issues and social good initiatives.

When viewed across time, it was observed that the use of AI techniques, in terms of the number of unique techniques employed, was growing at an exponential rate (Table 11). 2018 appeared to be the inflexion point. In 2018, there were a count of seven unique AI techniques applied by the papers in this emerging field. By 2022, this number grew by more than 18 times, to 129.

The bump graph analysis in Fig. 8 provided a visualization of the evolution. While only the more dominant techniques were represented in the graph, it could be clearly observed that a myriad of AI techniques were adopted and applied in recent years across different papers to uncover hidden ESG driven insights. Multivariate regression (and its various regularized or ensemble forms) continued to dominate, especially for papers looking to evaluate relationships between ESG and non-ESG attributes. This was followed by natural language processing techniques, which were useful to inspect semi-structured or unstructured alphanumeric ESG-related datasets.
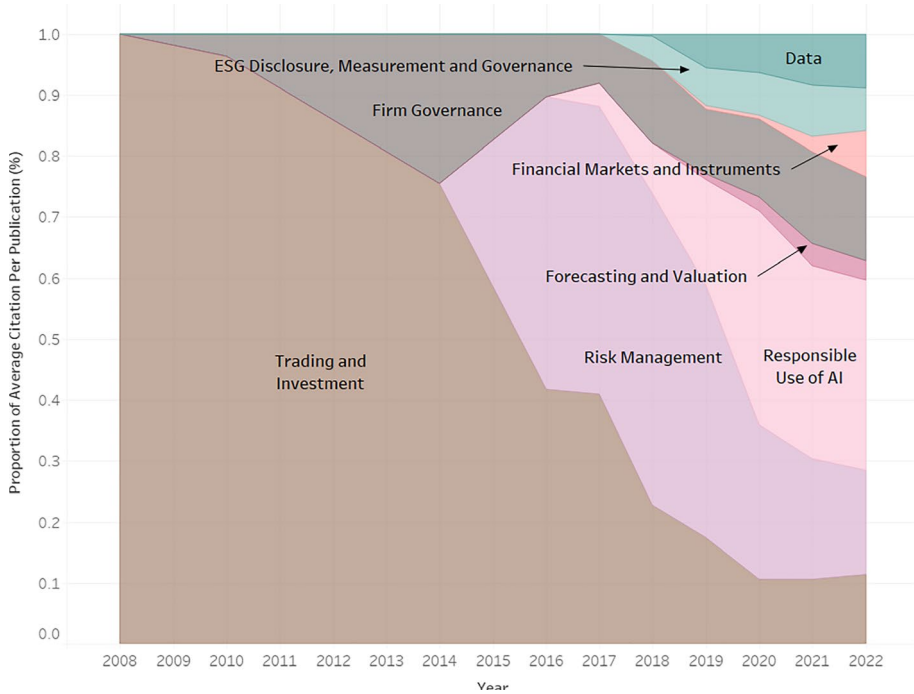
Fig. 6 Average citation count per publication by research thematic areas between 2008 and 2022

The analyses above provide researchers insights into how each research archetypical domain can differ in terms of the application of AI techniques. A time-series review of the techniques also revealed that while the application of unique techniques was experiencing exponential growth, multivariate regression continued to command the largest influence, and natural language processing models were increasingly dominant. This review provides an insight into the use and evolution of different AI techniques within the research scape.

5 Discussion

This section summarizes the key findings presented above, to provide explicit takeaways for practitioner insights. Figure 9, which provides a summary of takeaways, shows a visualization of the total citation count across time, and the relative contribution of citation impact in the research space, against all archetypes across time.

The archetype of *Trading and Investment* was the most popular and crowded research space; however, on average, the marginal research impact of each publication relative to other archetypical domains had been falling over the years. Given that journals place high attention to impact factors and have strong incentives to publish in popular fields, working on this archetype domain allows a safe route to publishing, although the contribution to popular literature may turn out to be minor (Edmans 2022). Incorporating ESG factors into
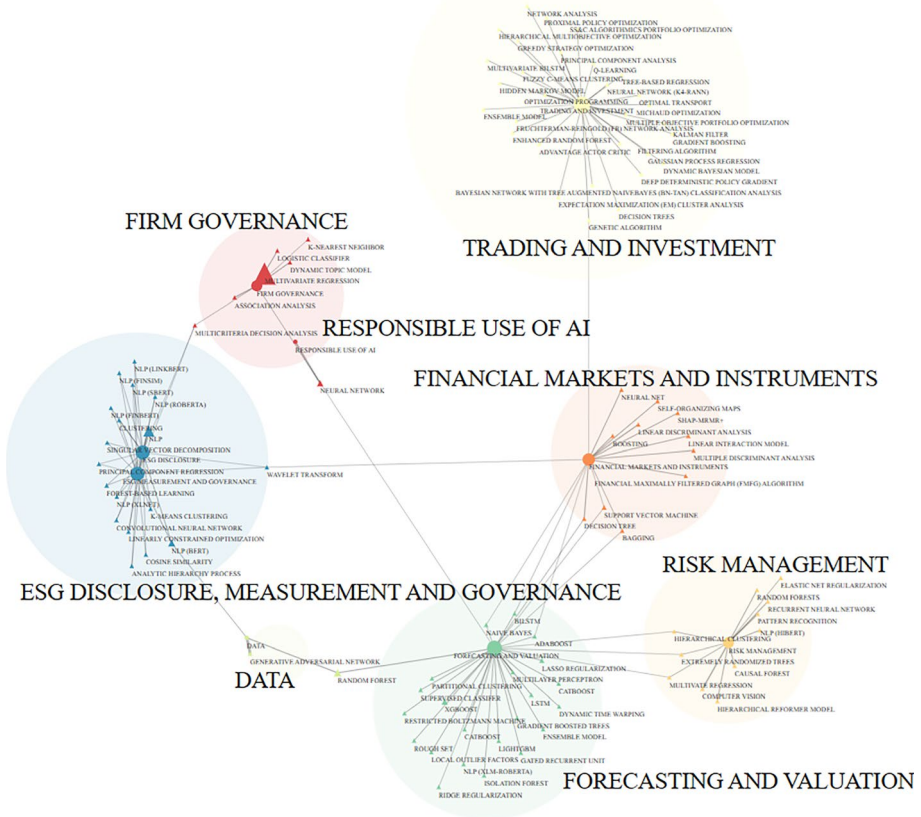
Fig. 7 Network analysis on research archetypical domains and AI techniques

Table 11 Number of unique dominant AI techniques utilized across time

Year	Count of unique type of learning algorithms
2016	2
2017	1
2018	7
2019	18
2020	57
2021	106
2022	129
Total	324

investment strategies and portfolio selection is becoming increasingly important. Diversified AI techniques, ranging from multivariate regression to reinforcement learning, have been used to minimize portfolio risk, analyze the impact of ESG factors on investment performance, and improve portfolio selection, optimization, and management. By designing intelligent trading and investment decision-support platforms that consider ESG factors, financial professionals can make more informed decisions that align with the values of their clients.

Papers within the archetype of *ESG Disclosure, Measurement and Governance* were later entrants into this research space, largely appearing since 2018. While the overall citation count was the second highest, the relatively late entry into the space affected the average citation impact of these papers (second lowest among all archetypes). From a time-series perspective, research in this archetypical domain was experiencing fair growth. Practitioners can leverage AI tools to analyze ESG disclosure data, develop ESG measurement tools, and improve ESG governance practices. Text mining
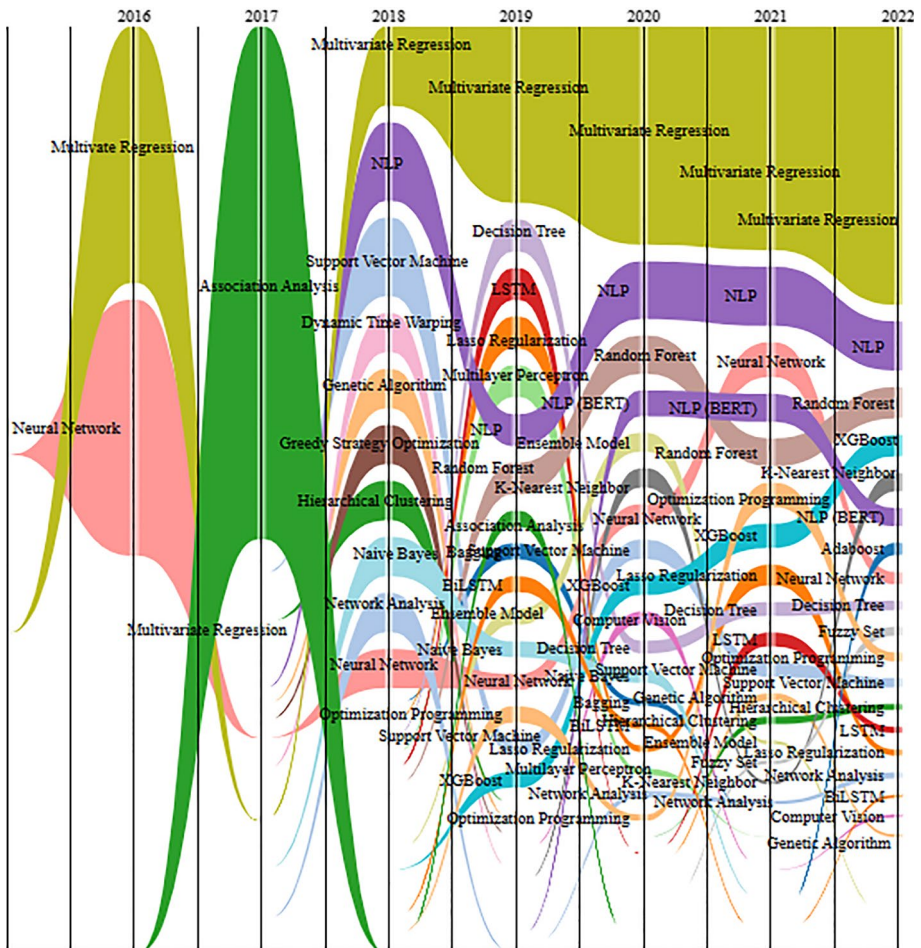

Fig. 8 Bump graph analysis of dominant AI techniques across time

algorithms, particularly those using BERT or its variants, are commonly used to extract insights from ESG-related text data.

The archetype of *Firm Governance* was also a relatively crowded research space. It generated the third highest absolute number of publications, second highest citation count and third highest citation impact. These said, on average, the marginal research impact of each publication relative to other archetypical domains had also been falling over the years, similar to *Trading and Investment*. To achieve sustainable and responsible governance practices, firms must prioritize ESG considerations throughout all aspects of their operations, including smart operations, supply chain management, corporate finance, and marketing. Analyzing and mitigating environmental risks associated with business operations, improving supply chain sustainability, and optimizing logistics and delivery processes can help reduce a company's carbon footprint. Additionally, detecting and mitigating financial fraud, irregularities, and unethical behavior and evaluating the social impact of corporate financial decisions can help firms maintain their financial integrity and social responsibility. Finally, recommending socially responsible marketing strategies that address issues like diversity and inclusion, environmental impact, and governance principles can improve customer engagement and satisfaction. Most papers in this archetype utilize multivariate regression.

Papers within the archetype of *Financial Markets and Instruments* were also late entrants into this research space, largely appearing since 2020. While this affected its citation impact (third lowest among all archetypes), its publication count and citation count were ranked at fourth and fifth respectively, a demonstration of strong recent interest. Researchers and practitioners in the financial sector can benefit from understanding the intricacies of market systems and simulation, smart banking and payment methods, the various financial products and services available, and the evolving landscape of financial technology. By considering the ESG perspective, they can contribute to a more sustainable, socially responsible, and ethically sound financial environment (e.g., energy-efficient and environmentally friendly blockchain systems, which also promote transparency, ethical sourcing, and carbon footprint reduction). Studies applied multivariate regression and/or unsupervised learning to investigate the effects and interplay between ESG and macro market concerns, market microstructure, market players,
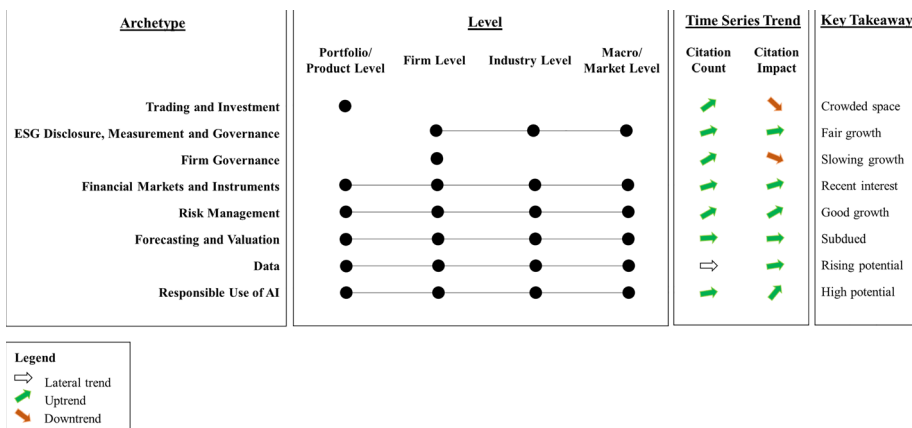
Archetype	Portfolio/ Product Level	Firm Level	Industry Level	Macro/ Market Level	Citation Count	Citation Impact	Key Takeaway
Trading and Investment	●		●	●	uptrend	downtrend	Crowded space
ESG Disclosure, Measurement and Governance		●	●	●	uptrend	uptrend	Fair growth
Firm Governance		●	●	●	uptrend	downtrend	Slowing growth
Financial Markets and Instruments	●		●	●	uptrend	uptrend	Recent interest
Risk Management	●		●	●	uptrend	uptrend	Good growth
Forecasting and Valuation	●	●	●	●	uptrend	uptrend	Subdued
Data	●	●	●	●	lateral	uptrend	Rising potential
Responsible Use of AI	●	●	●	●	uptrend	uptrend	High potential

Legend
⇨ Lateral trend
↗ Uptrend
↘ Downtrend

Fig. 9 Summary of takeaways

financial products and operations, and the impact of technology. Techniques such as evolutionary learning, deep learning, and text mining have been utilized to develop novel ESG offerings, including the creation of ESG indices.

Papers within the archetype of *Risk Management* were less than half the absolute number of publications in *Trading and Investment*. However, its citation impact was 45% higher (ranked second among all archetypes) On average, the marginal research impact of each publication relative to other archetypical domains grew respectably since 2014. Financial sector researchers and practitioners are encouraged to explore the advantages of AI in improving risk and credit management techniques. By integrating ESG principles, they can not only refine conventional risk and credit management procedures but also address issues related to sustainability, social responsibility, and ethical considerations. This methodology can lead to enhanced fraud and crime prevention, fine-tuned risk management strategies, encouragement of sustainable funding, and advocacy for fair lending practices. Multivariate regression was used to examine risk elements and their influence, while text mining and deep learning were employed for identifying shifts in risk levels or forecasting negative ESG screening lists. Additionally, unsupervised learning and computer vision were applied to discern risk patterns.

The archetype of *Forecasting and Valuation* exhibited subdued growth since 2018. Although it is fifth in terms of absolute publication numbers, it generated by far the lowest citation impact—a paltry 4.7, against an average of 15.5 across all archetypes. This said, its muted performance may be offset by its late entry into the research space, and it may yet exhibit research traction in the coming years. The *Forecasting and Valuation* research archetype offers valuable insights for researchers and practitioners in understanding the role of ESG factors in financial markets in resource and asset valuation, anticipating market trends, and understanding the supply and demand dynamics of assets and markets, through the application of AI. Under this archetype, supervised learning methods are predominantly used, which can be enhanced by combining various regularization techniques (such as ridge and lasso) and boosting methods (like CatBoost and XGBoost). The use of deep learning approaches is on the rise to refine forecasting outcomes, and detailed news events can be incorporated using text mining for real-time prediction capabilities.

The archetype of *Data* exhibited rising potential. On average, the marginal research impact of each publication relative to other archetypical domains had grown since 2018. Although its absolute publication number was ranked seventh among all archetypes, its citation impact was ranked fifth—10 more than the archetype of *Forecasting and Valuation*, at 14.7. By considering ESG as an alternative data source, this research area demonstrates the potential of harnessing unstructured data to evaluate various environmental factors and assess companies' ESG performance. Ultimately, this research contributes to the development of more accurate and comprehensive ESG metrics that can inform sustainable and responsible decision-making in the financial sector. AI techniques may range from basic supervised learning and natural language processing to employing generative AI for generating ESG scores and rating datasets. Most of these studies primarily focused on delivering qualitative evaluations regarding the quality and application of ESG data.

The archetype of *Responsible Use of AI* exhibited high potential, and more research can be done in this area. Although the absolute publication count was the lowest, its average citation impact was more than three times above mean (ranked first among all archetypes). Research under this archetype highlights the importance of ethical and explainable AI applications in finance. By focusing on transparency, interpretability, and the avoidance of biases, this research area contributes to the development of more responsible AI solutions. Ultimately, this fosters a more equitable and sustainable financial sector, aligning with ESG

principles and goals. Most of the papers analyzed primarily focused on qualitative discussions regarding AI ethical concerns and initiatives for social good. Other AI approaches involve algorithmic fairness and bias reduction techniques, as well as feature importance analysis, model interpretation, and local explanation methods for explainable AI.

Adapted and modified from Cao (2020), Table 12 provides a high-level overview of this research space, segregated into the eight archetypical domains.

6 Conclusion

The integration of ESG and AI in finance represents a promising direction for research and practice, offering new opportunities for sustainable and ethical investment practices. The latest research in this field has shown the potential of using machine learning algorithms to analyze ESG data and inform investment decisions, as well as the development of AI-powered platforms that can help investors integrate ESG considerations into their investment processes.

In conclusion, this study provides a comprehensive and systematic analysis of the research landscape concerning ESG, AI, and finance. Eight archetypical research domains were identified: *Trading and Investment, ESG Disclosure, Measurement and Governance, Firm Governance, Financial Markets and Instruments, Risk Management, Forecasting and Valuation, Data,* and *Responsible Use of AI.* The study offered valuable insights into the evolution of research intensity, interest, and AI techniques within each domain, contributing to a more nuanced understanding of this dynamic and rapidly growing field.

Future research directions can focus on the following areas:

i.   Investigating the potential of emerging AI techniques, such as graph neural networks, federated learning and generative models, for enhancing ESG-related financial applications and addressing concerns in attractive research potential areas, such as *Responsible Use of AI.* The exploration of these emerging AI techniques could enhance how financial institutions process and interpret ESG data, leading to more accurate predictions, better risk management, and more informed decision-making processes.

ii.   Exploring the interrelationships and synergies between the identified research archetypes, to develop more holistic and integrated approaches in addressing ESG, AI, and finance challenges. By understanding these interrelationships, the financial sector can potentially unlock new avenues of innovation, creating integrated solutions that address multiple challenges simultaneously. This holistic approach might lead to the development of novel financial products and strategies that are both profitable and sustainable.

iii. Assessing the impact of regulatory frameworks, industry standards, and stakeholder expectations on the adoption and integration of ESG and AI in the financial sector, to guide future policy development and best practices. This should also consider the regulatory and ethical challenges posed by generative AI, especially in terms of data authenticity and the potential for misuse in ESG-related financial simulations. By doing so, the financial sector can ensure that AI-driven ESG initiatives are both compliant and effective. This could pave the way for a more transparent, accountable,

Table 12 Summary of research space of ESG and AI in finance

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
Trading and investment	Trading and investing design and strategies; Online and offline portfolio optimization; Automated and smart investment; Market anomaly analysis	*Trading and investing design and strategies:* Discover and optimize strategies, signals and movements for trading and investment, etc	Identify trading strategies to promote environmentally friendly or socially responsible investments; analyzing the risks associated with investments in certain industries or sectors; developing risk management strategies that consider ESG factors, etc	Quantitative analysis, data mining, machine learning, behavior analysis, risk analytics, and optimization methods, etc	Yoo (2022); Ullah et al. (2021); Twinamatsiko and Kumar (2022); Ielasi et al. (2020); Erhardt (2020)
		Online and offline portfolio optimization: Selecting, optimizing and managing online or offline diversified forms and products of portfolios with market prediction and risk management, etc	Integration of ESG data into online portfolio management tools to enable investors to monitor the ESG performance of their investments; development of online ESG investment platforms that allow investors to easily invest in diversified ESG portfolios, etc	Market representation, prediction, learn to rank, game theories, reinforcement learning, recommender systems, behavior analysis, deep models, portfolio optimization, optimization methods, etc	Zhang and Chen (2021); Vo et al. (2019); Shea et al. (2021); Meier and Danzinger (2022); Jiang (2020); He et al. (2021)
		Automated and smart investment: Developing and optimizing intelligent investment models, algorithms, platforms and services with market forecasting and risk-averse management, etc	Development of ESG-focused robo-advisors that provide personalized investment recommendations to individual investors based on their ESG preferences, etc	Market representation, forecasting, portfolio optimization, learn to rank, reinforcement learning, recommender systems, behavior analysis, deep models, game theories, optimization methods, etc	Yang et al. (2020); Sokolov et al. (2021b); Katterbauer et al. (2022); Katterbauer and Moschetta (2022a, b); He et al. (2021); Hakala (2019)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
		Market anomaly analysis: Recognize and predict abnormal movements, trends, behaviors, events inside/outside markets and of participants, etc	Detecting and predicting abnormal market behavior that may be related to environmental or social events; identifying trends in governance practices that may affect market behavior; analyzing the impact of ESG factors on market volatility and risk, etc	Outlier detection, novelty/exception/change detection, behavior analytics, pattern mining, event modeling, probabilistic modeling, clustering, and classification, etc	Zhang et al. (2022); Taleb et al. (2020); Serafeim and Yoon (2022); Fabozzi and Karagozoglu (2021)
ESG disclosure, measurement and governance	ESG disclosure ESG measurement ESG governance	*ESG Disclosure:* Analyze ESG disclosure data and identify trends and insights associated with credit assessment, equity research, investor sentiment analysis, etc	Assess the tone of ESG disclosures and investor sentiment towards companies in ESG reports and categorize them based on their positive or negative sentiment, etc	Event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, etc	Clarkson et. al (2020); Goloshchapova et al. (2019); Raman et al. (2020)
		ESG Measurement: Measure the social impact, and financial impact of climate change of companies and investments, etc	Develop predictive models on ESG measurement tools such as indices to help investors and analysts anticipate changes in a company's ESG performance and make decisions accordingly, etc	Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, etc	Huang et al. (2023); Reig-Mullor et al. (2022); Briere and Ramelli (2021); Chang and Lee (2019)
		ESG Governance: Identify and assess potential ESG risks, as well as to monitor and ensure compliance with relevant regulations and policies, etc	Monitor and enforce ESG compliance by automating the tracking and analysis of ESG data, to assist regulators in enforcing ESG regulations and encourage companies to improve their ESG governance practices, etc	Probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, outlier detection, novelty/exception/change detection, behavior analytics, pattern mining, event modeling, etc	Chen et al. (2022a, b, c); Fan and Wu (2022)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
Firm governance	Smart operations, CSR and regulations Intelligent e-commerce and supply chain management Corporate finance Intelligent marketing	*Smart operations, CSR and regulations:* Evaluating and optimizing operation, CSR and governance performance; discovering factors, problems, failures, low-performing areas, risk and loss of operations and governance; analyzing operational, financial, CSR, regulatory, personnel and service risk; etc	Analyzing and mitigating environmental risks associated with business operations; evaluating operational sustainability; identifying and reducing energy waste; predicting and preventing equipment failure; monitoring and reducing carbon emissions, etc	Process analysis, risk analytics, behavior analytics, event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, etc	Seele (2017); Chava et al. (2021); Svanberg et al. (2022); Hernandez-Perdomo et al. (2019)
		Intelligent e-commerce and supply chain management: Estimating, predicting and optimizing pricing, demand, supply, production, storage, logistics, delivery, marketing, risk, fraud, security, etc	Reducing carbon footprint by optimizing logistics and delivery processes; predicting demand for sustainable products and services, etc	Profiling, predictive modeling, network analysis, web analysis, social media analysis, text analysis, distributed learning, behavior analytics, user modeling, interaction modeling, trajectory modeling, recommender systems, risk analytics, etc	Jebamikyous et al. (2023); Soni et al. (2022); Coqueret and Tran (2022)
		Corporate finance: Analyzing, predicting and optimizing corporate financial budget, balance, accounting integrity, auditing issues, and payment accuracy; detecting and mitigating financial fraud, overpayment, irregular behaviors and activities, and risk; etc	Analyzing the impact of environmental policies and regulations on financial performance; evaluating the social impact of corporate financial decisions, such as layoffs and plant closures; detecting and mitigating financial fraud, irregularities, and unethical behavior by company executives, etc	Financial time series analysis, numerical optimization, anomaly detection, probabilistic learning, relation learning, risk analytics, representation learning, and supervised and unsupervised learning, etc	Yadav et al. (2022); Turunen (2021); Teoh et al. (2019); Tanthanongsakkun et al. (2023)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
		Intelligent marketing: Analyzing marketing performance, product/company competitiveness, campaign effect, competitor advantage and strategies, market share change, recommending and optimizing marketing campaign strategies, actions, and target; understanding and predicting customer needs, sentiment, satisfaction, concerns, complaints, circumstance change, new demand, potential churning, mitigation strategies, etc	Analyzing the social impact of marketing campaigns and recommending socially responsible marketing strategies that address issues like diversity and inclusion; environmental impact of marketing campaigns and recommending sustainable marketing strategies to reduce the carbon footprint; governance impact of marketing campaigns and recommending ethical marketing strategies that adhere to principles like transparency and honesty; analyzing customer sentiment and satisfaction to improve social responsibility and customer engagement; understanding customer demand for environmentally-friendly products and services to promote sustainability initiatives, etc	Numerical modeling, econometrics, forecasting, prediction, event analysis, behavior analysis, interaction analysis, game theories, reinforcement learning, recommender systems, optimization methods, profiling, prediction, interaction modeling, behavior analytics, change analysis, social media analysis, text analysis, and recommender systems, etc	Akter et al. (2022); Wirtz et al. (2023); He et al. (2021); Dash and Kajiji (2020)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
Financial markets and instruments	Market systems and simulation Smart banking and payment Financial products and services Financial technology	*Market systems and simulation—Impact and interaction analysis:* Coupling and analyzing the interactions, relations and influence between macro and microeconomic variables; modeling relations, interactions and influence between financial markets, regions, countries, companies and financial indicators; modeling relations and influence of economic, social, cultural and political aspects on financial markets; modeling financial crisis, influence and contagion; etc *Market systems and simulation—Artificial financial markets and agent-based modeling:* Simulating and testing market mechanisms, models, hypotheses, policies, new products and services, trading rules, regulations and their effect in multiagent systems, etc	Analyzing the effects of environmental risks on economic growth; modeling the influence of social and cultural aspects on financial markets; modeling the effects of social and political unrest on financial markets; analyzing the impact of environmental regulations on industries, etc Simulating the impact of environmental regulations on economic growth; simulating the impact of policy interventions on sustainable economic growth; exploring the impact of social policies on income inequality; modeling the effects of governance structures on financial stability, etc	Mathematical modeling, statistical modeling, multi-source/modal/view analysis, coupling learning, hybrid methods, event analysis, behavior analysis, interaction learning, multivariate analysis, dependence modeling, relation learning, interaction learning, sequence modeling, quantitative analysis, game theories, theories of complex systems, simulation, machine learning, network theories, graph theories, etc Computer simulation, agent-based modeling, multiagent systems, game theories, theories of complex systems, human machine interaction, optimization methods, reinforcement learning, behavior modeling, visualization, etc	Patterson et al. (2022); Yang and Broby (2020); Zheng et al. (2022); Hofinger (2021); Jan (2021); Fianu (2021); Katterbauer and Moschetta (2022a, b); Tufail et al. (2022); Semet et al. (2021); Wang et al. (2021); Yu et al. (2022); Zhang and Han (2022); Xu et al. (2022); Silgjerd (2021) Geissler et al. (2022); Sukthomya and Laosiritaworn (2018); Sokolov et al. (2022); Khalfaoui et al. (2022a, b)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
		Smart banking and payment: Supporting smart, secure and risk-averse online/mobile and other banking and payment methods, tools, behaviors and services; analyzing and predicting banking and payment demand, trend, growth, risk, fraud, security, mal-functions, etc	Green banking practices and investments in sustainable projects; ensuring access to banking services for underserved communities, protecting customer data and privacy; educating customers on financial literacy, promoting inclusion, and protecting customers from fraudulent activities, etc	Various methods of data mining, machine learning, deep learning, distributed learning, recommender systems, behavior informatics, risk analytics, security informatics, etc	Oro et al. (2020); Nguyen et al. (2023)
		Financial products and services—Insurance: Estimating, predicting, optimizing and recommending insurance products and services and their pricing and market positioning; personalized product customization and recommendation; detecting fraud and risk; etc	Identifying environmental risks associated with insured assets and liabilities; estimating carbon footprint and environmental impact of insured assets and services; creating sustainable insurance products and services, etc	Profiling, classification, statistical modeling, mathematical modeling, outlier detection, behavior analysis, sequence modeling, interaction learning, and document analysis, social media analysis, risk analytics, recommender systems, deep learning, etc	Sætra (2022); Dugo (2021); Duchin et al. (2022); Cherrington et al. (2020)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
		Financial products and services—Wealth management: Discovering wealthy people and demand; recommending personalized products, services and new requirements; customizing risk management, training and social trading services; etc	Providing personalized services to clients with social impact investment preferences; providing investment options aligned with ethical values of clients, etc	Customer profiling, behavior analysis, sentiment analysis, prediction, active learning, intent learning, capability and propensity modeling, personalized recommendation, knowledge engineering, etc	Vo (2020)
		Financial products and services—Internet finance: Automating, predicting, securing and optimizing Internet-based financing, investment, wealth management, trust, credit, insurance, payment, etc	Internet-based financing for microfinance and social lending for underprivileged communities; Internet-based financing for impact investing in renewable energy projects; ensuring transparency and accountability in crowdfunding platforms, etc	Online/web/network analysis, online user modeling, interaction modeling, behavior analytics, text analysis, prediction, distributed learning, recommender systems, outlier detection, risk analytics, etc	Chueca Vergara and Ferruz Agudo (2021)
		Financial technology—Blockchain systems and mechanisms: Modeling blockchain system complexities to optimize blockchain mechanisms and design; evaluating and optimizing bitcoin and cryptographic contracts and models; optimizing pricing and portfolio; etc	Ensuring that blockchain systems are energy-efficient, reducing the environmental impact of cryptocurrency mining; ESG impact of blockchain on industries, such as supply chain transparency, ethical sourcing, and carbon footprint reduction; developing sustainable crypto models, etc	Theories of complex systems, game theories, representation learning, agent-based modeling, reinforcement learning, machine learning, deep learning, distributed learning, online learning, behavior analytics, prediction, semantic web, optimization methods, etc	Yu (2022); Jebamikyous et al. (2023)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
		Financial technology—Blockchain security: Enabling secure, privacy-preserving, risk-averse and anti-attack blockchain systems and smart contracts; detecting and mitigating malicious attacks and criminal activities; assuring active governance and regulation; etc	Ensuring active governance and regulation to promote ethical and socially responsible behavior in the blockchain ecosystem; designing and implementing secure, privacy-preserving, and anti-attack blockchain systems and smart contracts, etc	Process analysis, event analysis, behavior analytics, outlier detection, change detection, distributed learning, risk analytics, security data analytics, fraud detection, and benchmarking, etc	Choithani et al. (2023)
Risk management	Risk management Credit management	*Risk management:* Modeling, predicting and managing risk factors, effect and its severity, fraud, crime, security-related events and money laundering associated with diversified financial products, mechanisms, markets and participants, etc	Using ESG data for fraud and crime detection; predicting and managing impact of ESG-related events; optimizing risk management strategies using ESG criteria, etc	Risk analytics, probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, deep neural models and reinforcement learning, etc	Yang et al. (2022); Roy and Shaw (2021)
		Credit management: Estimating, predicting and optimizing credit rating, limit, valuation, scheduling, default, refund, repayment, refinance, risk and fraud management, etc	Providing sustainable financing for renewable energy projects; providing access to credit for underprivileged communities; measuring the carbon footprint of credit portfolios; incentivizing environmentally friendly business practices; promoting fair lending practices, etc	Profiling, forecasting, prediction, sequential and recurrent modeling, game theory, reinforcement learning, behavior analytics, risk analytics, optimization, etc	Sokolov et al. (2021a); Liermann et al. (2021); Gobet and Lage (2021); Brogi et al. (2022); Mansouri and Momtaz (2022)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
Forecasting and valuation	Valuation	*Valuation*: Estimating valuation, pricing, demand and supply; etc	Valuing the impact on the environment, such as carbon emissions, water usage, and waste management, estimating the demand of sustainability in real estate investment trusts; optimizing the pricing, movement, supply, demand of electricity, oil, solar, gas, wind, nuclear and water power etc	Multivariate time series, machine learning, statistical learning, data mining, optimization methods, knowledge discovery, evolutionary computing, text analysis, social media analysis, behavior analytics, recommender systems, etc	Sætra (2022); Dugo (2021); Duchin et al. (2022); Cherrington et al. (2020)
	Forecasting	*Forecasting*: Modeling and predicting market movement, trend, volatility dynamics, exceptions, events, etc	Predicting the impact of environmental and social events such as natural disasters and resource depletion on financial markets; forecasting the impact of corporate social responsibility practices on financial performance; modeling future influence of governance policies on market volatility; predicting the pricing, movement, supply, demand of energy, etc	Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, etc	Larsson and Ling (2021); Anas et al. (2020); Ashley et al. (2021); Jabeur et al. (2021); Gao et al. (2022); Guliyev and Mustafayev (2022)

Table 12 (continued)

Archetype	Research sub-theme(s)	Typical financial problems	Typical ESG areas	Typical AI techniques	Example(s) of related literature
Data	ESG as an alternative data	*ESG as an Alternative Data:* Identify and extract ESG-related information from large volumes of unstructured data, such as news articles, social media posts, company reports, and satellite imageries to identify and quantify various environmental factors, such as deforestation, air pollution, and water usage, etc	Accessing textual data from corporate sustainability reports to extract ESG-related information and create ESG scores for companies, using natural language processing techniques, etc	Text analysis, pattern mining, classification, generative adversarial network, prediction, evolutionary computing	Lopez et al. (2020); Geissler et al. (2022); Gupta et al. (2021); Sokolov et al. (2021b)
Responsible use of AI	Responsible and explainable AI	*Responsible and Explainable AI:* By using techniques such as explainable AI, financial institutions can create more transparent and interpretable models, enabling them to better understand how decisions are being made and ensure they are responsible, etc	Ensuring machine learning algorithms do not perpetuate or amplify biases against any social or demographic group; ensure transparency and interpretability of models and their decisions, etc	Feature importance analysis, model interpretation, local explanation methods, algorithmic fairness, bias mitigation, differential privacy, secure multi-party computation, forecasting, prediction, machine learning, and deep models	Lacoste et al. (2019); Hoepner et al. (2021); Fritz-Morgenthal et al. (2022)

and ethical financial industry, where stakeholders can trust AI-driven processes and decisions.

iv. Search parameter in the PRISMA process for the domain area is limited to 'finance'. It will be interesting to extend this search to include closely related search terms such as 'audit and assurance' and 'accounting information systems'. This could enrich the research, for instance, in the areas of firm governance and risk management. Broadening the scope to encompass these related domains could reveal new opportunities and challenges, catalyzing a deeper understanding of the research landscape.

v. A bibliometric analysis incorporating bibliographic coupling, citation analysis, co-word analysis, and co-authorship analysis (Khanra et al. 2022) may extend and add value to this study. While systematic literature mapping provides a structured overview of existing literature, bibliometric techniques may help reveal the interconnectedness of publications, the influence and impact of specific works, the evolution of key terms and concepts, and collaborations among researchers. This multi-faceted approach provides a richer, more nuanced understanding of the research domain, highlighting influential nodes, emerging trends, and the collaborative nature of the field.

By delving further into these research directions, scholars and practitioners can advance the understanding of ESG and AI's role in shaping a more sustainable, responsible, and equitable financial sector, and drive meaningful innovation and progress in the years to come.

Author contributions TL is the sole author of the article.

Data availability Data is available upon reasonable request.

Declarations

Competing interests There are no financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

Ethical approval It is not necessary to obtain ethics approval.

Research involving in human participants As this study does not involve human participants.

References

Abdalmuttaleb MA, Al-Sartawi M, Hussainey K, Razzaque A (2022) The role of artificial intelligence in sustainable finance. J Sustain Fin Invest. https://doi.org/10.1080/20430795.2022.2057405

Agarwala M, Burke M, Klusak P, Kraemer M, Volz U (2022) Nature loss and sovereign credit ratings. Report, Finance for Biodiversity Initiative. https://www.bennettinstitute.cam.ac.uk/wp-content/uploads/2022/06/NatureLossSovereignCreditRatings.pdf. Accessed 25 Mar 2023

Akter S, Dwivedi YK, Sajib S, Biswas K, Bandara RJ, Michael K (2022) Algorithmic bias in machine learning-based marketing models. J Bus Res 144:201–216. https://doi.org/10.1016/j.jbusres.2022.01.083

Ali S, Liu B, Su JJ (2022) Does corporate governance have a differential effect on downside and upside risk? J Bus Financ Acc 49(9–10):1642–1695

Alkaraan F, Albitar K, Hussainey K, Venkatesh VG (2022) Corporate transformation toward Industry 4.0 and financial performance: the influence of environmental, social, and governance (ESG). Technol Forecast Soc Change 175:121423. https://doi.org/10.1016/j.techfore.2021.121423

Allman E (2022) Pricing climate change risk in corporate bonds. J Asset Manag 23:596–618. https://doi.org/10.1057/s41260-022-00294-w

Amin MH, Mohamed EK, Elragal A (2021) CSR disclosure on Twitter: evidence from the UK. Int J Account Inf Syst 40:100500. https://doi.org/10.1016/j.accinf.2021.100500

Anas M, Mujtaba G, Nayyar S, Ashfaq S (2020) Time-frequency based dynamics of decoupling or integration between Islamic and conventional equity markets. J Risk Fin Manag 13(7):156. https://doi.org/10.3390/jrfm13070156

Angelova D, Bosello F, Bigano A, Giove S (2021) Sovereign rating methodologies, ESG and climate change risk: an overview. SSRN Electron J. https://doi.org/10.2139/ssrn.3841948

Anquetin T, Coqueret G, Tavin B, Welgryn L (2022) Scopes of carbon emissions and their impact on green portfolios. Econ Model 115:105951. https://doi.org/10.1016/j.econmod.2022.105951

Antoncic M (2020) Uncovering hidden signals for sustainable investing using big data: artificial intelligence, machine learning and natural language processing. J Risk Manag Fin Inst 13(2):106–113

Antoncic M, Bekaert G, Rothenberg RV, Noguer M (2020) Sustainable investment—exploring the linkage between alpha, ESG, and SDGs. SSRN Electron J. https://doi.org/10.2139/ssrn.3623459

Apel M, Betzer A, Scherer B (2023) Real-time transition risk. Financ Res Lett 53:103600. https://doi.org/10.1016/j.frl.2022.103600

Armbrust F (2022) Deep sustainable finance: an end-to-end text analysis of the financial and environmental narratives in corporate disclosures. Thesis. University of Stuttgart. https://elib.uni-stuttgart.de/handle/11682/12287. Accessed 25 Mar 2023

Ashley J, Papenbrock J, Schwendner P (2021) Accelerated data science, AI and GeoAI for sustainable finance in central banking and supervision. IFC Bulletins chapters. In: Bank for International Settlements (ed) Statistics for sustainable finance, vol. 56, Bank for International Settlements. https://ideas.repec.org/h/bis/bisifc/56-23.html. Accessed 25 Mar 2023

Assael J, Carlier L, Challet D (2022) ESG features explain one bit of idiosyncratic price returns. Preprint at https://arxiv.org/abs/2201.04393

Aynaud T (2020) Python-louvain. Louvain algorithm for community detection. https://github.com/taynaud/python-louvain. Assessed 15 Mar 2023

Badreldin A, Nietert B (2022) Cost of capital for ESG and Non-ESG stocks: regression-versus theory-based approaches. SSRN Electron J. https://doi.org/10.2139/ssrn.4131385

Bae KH, El Ghoul S, Gong ZJ, Guedhami O (2021) Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. J Corp Finan 67:101876. https://doi.org/10.1016/j.jcorpfin.2020.101876

Bai J, Chen Z, Yan X, Zhang Y (2022) Research on the impact of green finance on carbon emissions: evidence from China. Econ Res Ekonomska Istraživanja 35(1):6965–6984

Bajo Traver M, Rodríguez Alfonso E (2022) Integrating the carbon footprint into the construction of corporate bond portfolios. Banco de España Documentos de Trabajo. https://repositorio.bde.es/handle/123456789/22642. Accessed 25 Mar 2023

Banham R (2019) Getting serious about ESG risks. Risk Manage 66(5):28–31

Bariz H (2022) From shareholder to stakeholder capitalism: value creation by board composition, ownership structure and information disclosure. Thesis. Technical University of Darmstadt. https://tuprints.ulb.tu-darmstadt.de/20088/. Accessed 25 Mar 2023

Bartram SM, Lohre H, Pope PF, Ranganathan A (2021) Navigating the factor zoo around the world: an institutional investor perspective. J Bus Econ 91(5):655–703

Begenau J, Siriwardane E (2022) How do private equity fees vary across public pensions? National Bureau of Economic Research Working Paper, 29887. https://doi.org/10.3386/w29887

Benjamin SJ, Biswas PK, Marathamuthu M, Arunachalam M (2022) Social media sentiments and firm value. Appl Econ 54(26):2983–2997

Berchicci L, King A (2022) Corporate sustainability: a model uncertainty analysis of materiality. J Fin Report 7(2):43–74. https://doi.org/10.2308/JFR-2021-022

Beretta V, Demartini C, Trucco S (2019) Does environmental, social and governance performance influence intellectual capital disclosure tone in integrated reporting? J Intellect Cap 20(1):100–124

Beretta V, Demartini MC, Lico L, Trucco S (2021) A tone analysis of the non-financial disclosure in the automotive industry. Sustainability 13(4):2132. https://doi.org/10.3390/su13042132

Berg F, Koelbel JF, Pavlova A, Rigobon R (2022) ESG confusion and stock returns: tackling the problem of noise. National Bureau of Economic Research Working Paper, 30562. Doi: https://doi.org/10.3386/w30562

Bessec M, Fouquau J (2020) Green sentiment in financial markets: a global warning. In: Proceedings of Paris December 2020 Finance Meeting EUROFIDAI-ESSEC. Université Paris-Dauphine Research Paper, p 3710489. https://doi.org/10.2139/ssrn.3710489

Bessec M, Fouquau J (2021) A green wave in media, a change of tack in stock markets. SSRN Electron J. https://doi.org/10.2139/ssrn.3924837

de Bettignies JE, Liu HF, Robinson DT (2020) Corporate social responsibility and imperfect regulatory oversight: theory and evidence from greenhouse gas emissions disclosures. National Bureau of Economic Research Working Paper, p 28159. https://doi.org/10.3386/w28159

Bilicka KA, Casi-Eberhard E, Seregni C, Stage B (2022) Tax strategy disclosure: a greenwashing mandate? TRR 266 Accounting for Transparency Working Paper Series, p 40. https://doi.org/10.2139/ssrn.3672420.

Bingler JA, Kraus M, Leippold M, Webersinke N (2022) Cheap talk in corporate climate commitments: the role of active institutional ownership, signaling, materiality, and sentiment. Swiss Fin Inst Res Paper. https://doi.org/10.2139/ssrn.4000708

Bingler JA (2022) Expect the worst, hope for the best: the valuation of climate risks and opportunities in sovereign bonds. CER-ETH Working Paper, 22/371. https://doi.org/10.2139/ssrn.4076323

Bławeat B, Dietl M, Wiśniewski T (2020) ESG-rated stock performance under Covid-19: an empirical study of Warsaw Stock Exchange-listed companies. In: Proceeds of the Central European Scientific Conference on Green Finance and Sustainable Development, October 2020. pp 17–28

Boitan IA, Marchewka-Bartkowiak K (2023) Sovereign debt management in the face of climate liabilities: perspective of European Union member states. Econ Res Ekonomska Istraživanja 36(1):1120–1145

Borms S, Boudt K, Holle FV, Willems J (2021) Semi-supervised text mining for monitoring the news about the ESG performance of companies. Data Sci Econ Fin Methodol Appl 2021:217–239

Bouyé E, Menville D (2020) The convergence of sovereign environmental social, and governance ratings. SSRN Electron J. https://doi.org/10.2139/ssrn.3568547

Braga J, Lichtenberger A, Semmler W (2021) Sustainable finance with green bonds for a low carbon economy. Euroframe Conference 2021. https://www.euroframe.org/files/user_upload/euroframe/docs/2021/Conference/Session%20A1/EUROF21_Braga_etal.pdf. Accessed 25 Mar 2023

Breucker P, Cointet J, Hannud Abdo A, Orsal G, de Quatrebarbes C, Duong T, Martinez C, Ospina Delgado JP, Medina Zuluaga LD, Gómez Peña DF, Sánchez Castaño TA, Marques da Costa J, Laglil H, Villard L, Barbier M (2016) CorTexT Manager (version v2). https://docs.cortext.net. Accessed 24 Mar 2023

Briere M, Ramelli S (2021) Green sentiment, stock returns, and corporate behavior. SSRN Electron J. https://doi.org/10.2139/ssrn.3850923

Brogi M, Lagasio V, Porretta P (2022) Be good to be wise: environmental, social, and governance awareness as a potential credit risk mitigation factor. J Int Financ Manag Acc 33(3):522–547

Brown DA (2019) Zero-sum games & zero-sum frames: employee cognitive consequences of financial firm performance. Thesis. Harvard University. https://www.proquest.com/openview/8d6764390344af5a1ff5aad153d1b0a1/1?pq-origsite=gscholar&cbl=44156. Accessed 25 Mar 2023

Brusseau J (2021) AI human impact: toward a model for ethical investing in AI-intensive companies. J Sustain Fin Invest. https://doi.org/10.1080/20430795.2021.1874212

Bua G, Kapp D, Ramella F, Rognone L (2022) Transition versus physical climate risk pricing in European financial markets: a text-based approach. SSRN Electron J. https://doi.org/10.2139/ssrn.4154034

Budsaratragoon P, Jitmaneeroj B (2021) Fund ratings of socially responsible investing (SRI) funds: a precautionary note. Sustainability 13(14):7548. https://doi.org/10.3390/su13147548

Burnaev E, Mironov E, Shpilman A, Mironenko M, Katalevsky D (2023) Practical AI cases for solving ESG challenges. Sustainability 15(17):12731

Bussmann N, Tanda A, Yu EPY (2022) Can ESG shape cost of capital? A bibliometric review and empirical analysis through ML. SSRN Electron J. https://doi.org/10.2139/ssrn.4173890

Buyuklieva B, Raimbault J (2023) Estimating bibliometric links using google scholar: a semi-systematic literature mapping of migration and housing. Preprint at https://arxiv.org/abs/2302.10791

Caferra R, Falcone PM, Morone A, Morone P (2022) Is COVID-19 anticipating the future? Evidence from investors' sustainable orientation. Eurasian Bus Rev 12(1):177–196

Caglio A, Melloni G, Perego P (2020) Informational content and assurance of textual disclosures: evidence on integrated reporting. Eur Acc Rev 29(1):55–83

Cai R, Lv T, Deng X (2021) Evaluation of environmental information disclosure of listed companies in China's heavy pollution industries: a text mining-based methodology. Sustainability 13(10):5415. https://doi.org/10.3390/su13105415

Cao L (2020) AI in finance: a review. SSRN Electron J. https://doi.org/10.2139/ssrn.3647625

Cao J, Goyal A, Zhan X, Zhang WE (2022) Unlocking ESG premium from options. Swiss Finance Institute Research Paper, pp 21–39. https://doi.org/10.2139/ssrn.3878123.

Ceccarelli M, Glossner S, Homanen M, Schmidt D (2021) Which institutional investors drive corporate sustainability? SSRN Electron J. https://doi.org/10.2139/ssrn.3988058

Chae B, Park E (2018) Corporate social responsibility (CSR): a survey of topics and trends using twitter data and topic modeling. Sustainability 10(7):2231. https://doi.org/10.3390/su10072231

Chan Y, Hogan K, Schwaiger K, Ang A (2020) ESG in factors. J Impact ESG Invest 1(1):26–45

Chang YL, Lee YY (2019) Applied machine learning: a creation of sustainable development progress index based on circular economy. In: 2019 international conference on computational science and computational intelligence (CSCI). IEEE, pp 1263–1268. https://doi.org/10.1109/CSCI49370.2019.00237

Chang R, Chu L, Jun TU, Zhang B, Zhou G (2021) ESG and the market return. Research Collection Lee Kong Chian School of Business. https://ink.library.smu.edu.sg/lkcsb_research/6899. Accessed 25 Mar 2023

Charoenwong B, Kwan A (2021) Alternative data, big data, and applications to finance. In: Choi PMS, Huang SH (eds) Fintech with artificial intelligence, big data, and blockchain. Blockchain technologies. Springer, Singapore, https://doi.org/10.1007/978-981-33-6137-9_2

Chasiotis I, Gounopoulos D, Konstantios D, Patsika V (2020) ESG reputational risk corporate payouts and firm value. SSRN Electron J. https://doi.org/10.2139/ssrn.4180523

Chava S (2014) Environmental externalities and cost of capital. Manage Sci 60(9):2223–2247

Chava S, Du W, Malakar B (2021) Do managers walk the talk on environmental and social issues? Georgia Tech Scheller College of Business Research Paper, p 3900814. https://doi.org/10.2139/ssrn.3900814.

Cheema-Fox A, LaPerla BR, Wang H, Serafeim G (2021) Corporate resilience and response to COVID-19. J Appl Corp Financ 33(2):24–40

Chen L, Wang Y, Jin S (2022a) How green credit guidelines policy affect the green innovation in China? Environ Eng Manag J 21(3):469–481

Chen M, Mussalli G, Amel-Zadeh A, Weinberg MO (2022b) NLP for SDGs: measuring corporate alignment with the sustainable development goals. J Impact ESG Invest 2(3):61–81. https://doi.org/10.3905/jesg.2021.1.035

Chen M, von Behren R, Mussalli G (2022c) Practical applications of the unreasonable attractiveness of more ESG data. Pract Appl. https://doi.org/10.3905/pa.2022.pa500

Chen Q, Liu XY (2020) Quantifying ESG alpha using scholar big data: an automated machine learning approach. In: Proceedings of the first ACM international conference on AI in finance, pp. 1–8. https://doi.org/10.1145/3383455.3422529

Chen D, Zou Y, Harimoto K, Ren X, Sun X (2019) Incorporating fine-grained events in stock movement prediction. Preprint at https://arxiv.org/abs/1910.05078

Chen RL (2021) Bang for your (Green) buck: the effects of ESG risk on US M&A performance. Thesis. Duke University. https://sites.duke.edu/djepapers/files/2021/09/RichardChen-dje.pdf. Accessed 25 Mar 2023

Cherief A, Ben Slimane M, Dumas JM, Fredj H (2022) Credit factor investing with machine learning techniques. SSRN Electron J. https://doi.org/10.2139/ssrn.4155247

Cherkasova V, Nenuzhenko I (2022) Investment in ESG projects and corporate performance of multinational companies. J Econ Integr 37(1):54–92

Cherrington M, Lu Z, Xu Q, Airehrour D, Madanian S, Dyrkacz A (2020) Deep learning decision support for sustainable asset management. In: Ball A, Gelman L, Rao B (eds) Advances in asset management and condition monitoring: smart innovation systems and technologies. Springer, Cham

Choi HY, Park J (2022) Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technol Forecast Soc Chang 182:121802. https://doi.org/10.1016/j.techfore.2022.121802

Choithani T, Chowdhury A, Patel S, Patel P, Patel D, Shah M (2023) A comprehensive study of artificial intelligence and cybersecurity on bitcoin, crypto currency and banking system. Ann Data Sci. https://doi.org/10.1007/s40745-022-00433-5

Chueca Vergara C, Ferruz Agudo L (2021) Fintech and sustainability: do they affect each other? Sustainability 13(13):7012. https://doi.org/10.3390/su13137012

Citterio A (2020) Bank failures: review and comparison of prediction models. SSRN Electron J. https://doi.org/10.2139/ssrn.3719997

Citterio A, King T (2023) The role of ESG in predicting bank financial distress: cross country evidence. Financ Res Lett 51:103411. https://doi.org/10.1016/j.frl.2022.103411

Clark C, Lalit H (2020) ESG improvers: an alpha enhancing factor. Rockefeller Asset Management. https://rcm.rockco.com/wp-content/uploads/2020/09/ESG-Improvers-Whitepaper-1.pdf. Accessed 25 Mar 2023

Clarkson PM, Ponn J, Richardson GD, Rudzicz F, Tsang A, Wang J (2020) A textual analysis of US corporate social responsibility reports. Abacus 56(1):3–34

Cojoianu T, Hoepner AG, Ifrim G, Lin Y (2020) Greenwatch-shing: using AI to detect greenwashing. SSRN Electron J 2020:10

Cook DO, Luo S (2022) Does perception of social issues affect portfolio choices? Evidence from the #MeToo movement. Financ Manage 51(2):613–634

Coqueret G, Guida T (2020) Machine learning for factor investing: R version. CRC Press, Boca Raton

Coqueret G, Tran VL (2022) ESG news spillovers to (and from) the supply chain. SSRN Electron J. https://doi.org/10.2139/ssrn.4002705

Coqueret G, Stiernegrip S, Morgenstern C, Kelly J, Frey-Skött J, Österberg B (2021) Boosting ESG-based optimization with asset pricing characteristics. SSRN Electron J. https://doi.org/10.2139/ssrn.3877242

Cowls J, Tsamados A, Taddeo M, Floridi L (2021) A definition, benchmark and database of AI for social good initiatives. Nat Mach Intell 3(2):111–115

D'Amato V, D'Ecclesia R, Levantesi S (2021) Fundamental ratios as predictors of ESG scores: a machine learning approach. Decisions Econ Finan 44:1087–1110

D'Amato V, D'Ecclesia R, Levantesi S (2022) ESG score prediction through random forest algorithm. CMS 19(2):347–373

Dash GH, Kajiji N (2020) Multiobjective behavioral portfolio selection with efficient esg factors and learning network estimation of asset returns. Paper presented at 2nd Frontiers of Factor Investing Conference, Lancaster University, UK. http://wp.lancs.ac.uk/fofi2020/files/2020/04/FoFI-2020-123-Gordon-Dash-Jr.pdf. Accessed 25 Mar 2023

Dash GH, Kajiji N (2021) Behavioral portfolio management with layered ESG goals and AI estimation of asset returns. SSRN Electron J. https://doi.org/10.2139/ssrn.3953440

De Franco C, Geissler C, Margot V, Monnier B (2020) ESG investments: filtering versus machine learning approaches. Preprint at https://arxiv.org/abs/2002.07477

de la Barcena Grau AM (2021) Social impact returns: filling the finance gap with data value. Risk Manag. https://doi.org/10.5772/intechopen.97407

De Lucia C, Pazienza P, Bartlett M (2020) Does good ESG lead to better financial performances by firms? Machine learning and logistic regression models of public enterprises in Europe. Sustainability 12(13):5317. https://doi.org/10.3390/su12135317

De Spiegeleer J, Höcht S, Jakubowski D, Reyners S, Schoutens W (2021) ESG: a new dimension in portfolio allocation. J Sustain Fin Inv. https://doi.org/10.1080/20430795.2021.1923336

de Vincentiis P (2022) Do international investors care about ESG news? Qual Res Fin Market. https://doi.org/10.1108/QRFM-11-2021-0184

Debrah C, Darko A, Chan APC (2022) A bibliometric-qualitative literature review of green finance gap and future research directions. Climate Dev. https://doi.org/10.1080/17565529.2022.2095331

Delgado López-Cózar E, Orduna-Malea E, Martín-Martín A (2019) Google scholar as a data source for research assessment. In: Glaenzel W, Moed H, Schmoch U, Thelwall M (eds) Springer handbook of science and technology indicators. Springer, Berlin

Demers E, Wang VX, Wu K (2022) Corporate human capital disclosures: early evidence from the SEC's disclosure MANDATE. SSRN Electron J. https://doi.org/10.1016/j.ribaf.2021.101508

Demir E, Danisman GO (2021) Banking sector reactions to COVID-19: the role of bank-specific factors and government policy responses. Res Int Bus Financ 58:101508

Deng M, Leippold M, Wagner AF, Wang Q (2022a) Stock prices and the Russia-Ukraine war: sanctions, energy and ESG. CEPR Discussion Paper, DP17207. https://ssrn.com/abstract=4121382. Accessed 25 Mar 2023

Deng M, Leippold M, Wagner AF, Wang Q (2022b) The Russia-Ukraine war and climate policy expectations: evidence from the stock market. Swiss Finance Institute Research Paper, pp 22–29. https://doi.org/10.2139/ssrn.4080181

Dong Y, Liang C, Wanyin Z (2023) Board diversity and firm performance: impact of ESG activities in China. Econ Res Ekonomska Istraživanja 36(1):1592–1609

Douhan O, Nirbrant A (2020) Corporate social responsibility and the equity markets: a quantitative analysis. Thesis. University of Gothenburg. https://gupea.ub.gu.se/handle/2077/66966. Accessed 25 Mar 2023

Dreżewski R, Dziuban G, Pająk K (2018) The bio-inspired optimization of trading strategies and its impact on the efficient market hypothesis and sustainable development strategies. Sustainability 10(5):1460. https://doi.org/10.3390/su10051460

Du S, Yu K (2021) Do corporate social responsibility reports convey value relevant information? Evidence from report readability and tone. J Bus Ethics 172:253–274

Duchin R, Gao J, Xu Q (2022) Sustainability or greenwashing: evidence from the asset market for industrial pollution. SSRN Electron J. https://doi.org/10.2139/ssrn.4095885

Dugo, I. (2021). Finance embraces sustainability: An empirical analysis of the financial performances of ETFs investing in sustainable real estate and green building. Thesis. Università Ca' Foscari Venezia. http://dspace.unive.it/handle/10579/20153. Accessed 25 Mar 2023

Duong HN, Kalev PS, Kalimipalli M, Trivedi S (2022) Do firms benefit from carbon risk management? Evidence from the credit default swaps market. SSRN Electron J. https://doi.org/10.2139/ssrn.4095816

Dupire M, Filbien JY, M'Zali B (2022) Non-governmental organization (NGO) tweets: do shareholders care? Bus Soc 61(2):419–456

Dzielinski M, Eugster F, Sjöström E, Wagner AF (2022) Climate talk in corporate earnings calls. Misum Working Paper Series 2022–06. https://swopec.hhs.se/hamisu/papers/hamisu2022_006.1.pdf. Accessed 25 Mar 2023

Economidou C, Gounopoulos D, Konstantios D, Tsiritakis E (2022) Is sustainability rating material to the market? Fin Manag 52(1):127–179. https://doi.org/10.1111/fima.12406

Edmans A (2022) The purpose of a finance professor. Fin Manag 51(1):3–26

Ehrhardt A, Nguyen MT (2022) Automated ESG report analysis by joint entity and relation extraction. In: Machine learning and principles and practice of knowledge discovery in databases: international workshops of ECML PKDD 2021, virtual event, September 13–17, 2021, proceedings, part II. Springer International Publishing, pp 325–340

Eng LL, Fikru M, Vichitsarawong T (2022) Comparing the informativeness of sustainability disclosures versus ESG disclosure ratings. Sustain Acc Manag Policy J 13(2):494–518

Entrop O, Rohleder M, Seruset M (2022) Local religiosity and stock liquidity. SSRN Electron J. https://doi.org/10.2139/ssrn.4020466

Erhardt D (2020) The search for ESG alpha by means of machine learning—a methodological approach. SSRN Electron J. https://doi.org/10.2139/ssrn.3514573

European Banking Authority (EBA) (2021) On management and supervision of esg risks for credit institutions and investment firms. EBA Report, EBA/REP/2021/18. https://www.eba.europa.eu/sites/default/documents/fifiles/document_library/Publications/Reports/2021/1015656/EBA%20Report%20on%20ESG%20risks%20management%20and%20supervision.pdf. Accessed 25 Mar 2023

European Commission (2021) Overview of sustainable finance. European Commission. https://finance.ec.europa.eu/sustainable-finance/overview-sustainable-finance_en. Accessed 25 Mar 2023

Fabozzi F, Karagozoglu AK (2021) Novel risks and sources of volatility: identification and measurement challenges for portfolio management. J Portfol Manag 47(9):109

Faccini R, Matin R, Skiadopoulos GS (2021) Dissecting climate risks: are they reflected in stock prices? SSRN Electron J. https://doi.org/10.2139/ssrn.3795964

Fan G, Wu X (2022) Going green: the effect of environmental regulations on firms. SSRN Electron J. https://doi.org/10.2139/ssrn.4098403

Fauser DV, Gruener A (2020) Corporate social irresponsibility and credit risk prediction: a machine learning approach. Credit Capital Markets 53(4):513–554

Faust L, Kolbe M, Mansouri S, Momtaz PP (2022) The crowdfunding of altruism. J Risk Fin Manag 15(3):138. https://doi.org/10.3390/jrfm15030138

Fedorova E, Druchok S, Drogovoz P (2022) Impact of news sentiment and topics on IPO underpricing: US evidence. Int J Acc Inf Manag 30(1):73–94

Fekete TG, Hagen E (2021) Do investors reward gender diversity? An event study of the MSCI world women's leadership index. Thesis. NHH Norwegian School of Economics. https://openaccess.nhh.no/nhh-xmlui/handle/11250/2982846. Accessed 25 Mar 2023

Ferriani F (2022) Issuing bonds during the Covid-19 pandemic: is there an ESG premium? SSRN Electron J. https://doi.org/10.2139/ssrn.4091794

Fianu ES (2021) Understanding environmental, social and governance (ESG) contributions in the downside systematic and systemic risk measurement of the insurance sector. SSRN Electron J. https://doi.org/10.2139/ssrn.4042802

Fijałkowska J, Hadro D (2022) Risk information in non-financial disclosure. Risks 10(1):11. https://doi.org/10.3390/risks10010011

Filippou I, Taylor MP (2021) Pricing ethics in the foreign exchange market: environmental, social and governance ratings and currency premia. J Econ Behav Organ 191:66–77

Fischer I, Beswick C, Newell S (2021) Rho AI—leveraging artificial intelligence to address climate change: financing, implementation and ethics. J Info Technol Teach Cases 11(2):110–116

Fritz-Morgenthal S, Hein B, Papenbrock J (2022) Financial risk management and explainable, trustworthy, responsible AI. Front Artif Intell. https://doi.org/10.3389/frai.2022.779799

Fu W, Irfan M (2022) Does green financing develop a cleaner environment for environmental sustainability: empirical insights from ASEAN economies. Front Psychol 13:904768. https://doi.org/10.3389/fpsyg.2022.904768

Gailhofer P, Herold A, Schemmel JP, Scherf CS, de Stebelski CU, Köhler AR, Braungardt S (2021) The role of artificial intelligence in the European Green Deal. In: Study for the special committee on artificial intelligence in a digital age (AIDA), policy department for economic, scientific and quality of life policies. European Parliament, Luxembourg. https://www.europarl.europa.eu/RegData/etudes/STUD/2021/662906/IPOL_STU(2021)662906_EN.pdf. Accessed 25 Mar 2023

Galema R, Plantinga A, Scholtens B (2008) The stocks at stake: return and risk in socially responsible investment. J Bank Fin 32(12):2646–2654

Gao X, Wang J, Yang L (2022) An explainable machine learning framework for forecasting crude oil price during the COVID-19 pandemic. Axioms 11(8):374. https://doi.org/10.3390/axioms11080374

García F, González-Bueno J, Guijarro F, Oliver J (2020) Forecasting the environmental, social, and governance rating of firms by using corporate financial performance variables: a rough set approach. Sustainability 12(8):3324. https://doi.org/10.3390/su12083324

Geissler C, Morizet N, Rizzato M, Wallart J (2022) Generative adversarial networks applied to synthetic financial scenarios generation. Preprint at https://arxiv.org/abs/2209.03935

Ghoddusi H, Creamer GG, Rafizadeh N (2019) Machine learning in energy economics and finance: a review. Energy Economics 81:709–727. https://doi.org/10.1016/j.eneco.2019.05.006

Ghosh S, Naskar SK (2022) Ranking environment, social and governance related concepts and assessing sustainability aspect of financial texts. In: Proceedings of the fourth workshop on financial technology and natural language processing (FinNLP@ IJCAI-ECAI 2022), Vienna, Austria. pp 87–92

Gidron B, Israel-Cohen Y, Bar K, Silberstein D, Lustig M, Kandel D (2021) Impact tech startups: a conceptual framework, machine-learning-based methodology and future research directions. Sustainability 13(18):10048. https://doi.org/10.3390/su131810048

Gimeno R, González CI (2022) The role of a green factor in stock prices: when Fama & French go green. SSRN Electron J. https://doi.org/10.2139/ssrn.4064848

Gionchetti E (2022) Twitter, social corporate responsibility and economic performance: how multinational companies exploit social media. Thesis. Università Ca' Foscari Venezia. http://hdl.handle.net/10579/20842. Accessed 25 Mar 2023

Gobet E, Lage C (2021) Optimal ecological transition path of a credit portfolio distribution, based on Multidate Monge-Kantorovich formulation. https://hal.science/hal-03423114/

Goel T, Jain P, Verma I, Dey L, Paliwal S (2020) Mining company sustainability reports to aid financial decision-making. In: Proceedings of AAAI workshop on know. disc. from unstructured data in finance services. https://www.researchgate.net/profile/Ishan-Verma/publication/343305380_Mining_company_sustainability_reports_to_aid_financial_decision-making/links/5f226de4a6fdcccc43994601/Mining-company-sustainability-reports-to-aid-financial-decision-making.pdf. Accessed 25 Mar 2023

Goldberg LR, Mouti S (2019) Sustainable investing and the cross-section of maximum drawdown. Preprint at https://arxiv.org/abs/1905.05237

Goloshchapova I, Poon SH, Pritchard M, Reed P (2019) Corporate social responsibility reports: topic analysis and big data approach. Eur J Fin 25(17):1637–1654

Gopal S, Pitts J, Inampudi K, Xu Y, Cook G (2021) The evolving landscape of big data analytics and ESG materiality mapping. J Impact ESG Invest 2(2):77–100. https://doi.org/10.3905/jesg.2021.1.034

Grealish A, Kolm PN (2021) Robo-advisory: from investing principles and algorithms to future developments. SSRN Electron J. https://doi.org/10.2139/ssrn.3776826

Gulenko M, Kohlhase S, Kosi U (2022) CSR reporting under the non-financial reporting directive: evidence from non-publicly listed firms. SSRN Electron J. https://doi.org/10.2139/ssrn.4040946

Guliyev H, Mustafayev E (2022) Predicting the changes in the WTI crude oil price dynamics using machine learning models. Resour Policy 77:102664. https://doi.org/10.1016/j.resourpol.2022.102664

Guney Y, Hernandez-Perdomo E, Rocco CM (2020) Does relative strength in corporate governance improve corporate performance? Empirical evidence using MCDA approach. J Op Res Soc 71(10):1593–1618

Guo T, Jamet N, Betrix V, Piquet LA, Hauptmann E (2020) Esg2risk: a deep learning framework from ESG news to stock volatility prediction. Preprint at https://arxiv.org/abs/2005.02527

Guo T, Jamet N, Betrix V, Piquet LA, Hauptmann E, Investments RA (2022) A deep learning framework for climate responsible investment. RAM Active Investments. https://www.ram-ai.com/en/research/deep-learning-framework-climate-responsible-investment-academic-paper-2020-10-14. Accessed 25 Mar 2023

Gupta A, Sharma U, Gupta SK (2021) The role of ESG in sustainable development: an analysis through the lens of machine learning. In: 2021 IEEE international humanitarian technology conference (IHTC). IEEE, pp 1–5

Gutierrez M (2020) Text mining for global reporting initiative (GRI) standards: study of Nordic listed companies. Thesis. Arcada University of Applied Sciences. https://www.theseus.fi/handle/10024/342439. Accessed 25 Mar 2023

Habermann F (2020) Over-investment in the environmental, social, and governance pillar: is there a cost of being too sustainable? In: Proceedings of 11th international conference on modern research in management, economics and accounting. Pp 20–44. https://doi.org/10.33422/11th.meaconf.2020.12.80

Haghshenas A, Karim M (2022) Factor investing and ESG integration in regime-switching models—an empirical study on ESG factor integration using infinite hidden Markov models. Thesis. University of Gothenburg. https://gupea.ub.gu.se/handle/2077/72403. Accessed 25 Mar 2023

Hakala K (2019) Robo-advisors as a form of artificial intelligence in private customers' investment advisory services. Thesis. Aalto University. https://aaltodoc.aalto.fi/handle/123456789/39329. Accessed 25 Mar 2023

Hamidi SR, Ismail MA, Shuhidan SM (2021) Corporate reputation risk in social media. In: 2021 international conference on computer science and engineering (IC2SE). IEEE, pp 1–8

Hamza S, Jarboui A (2022) CSR or social impression management? Tone management in CSR reports. J Fin Rep Acc 20(3/4):599–617

Han Y, Gopal A, Ouyang L, Key A (2021) Estimation of corporate greenhouse gas emissions via machine learning. Preprint at https://arxiv.org/abs/2109.04318

Hanine Y, Lamrani Alaoui Y, Tkiouat M, Lahrichi Y (2021) Socially responsible portfolio selection: an interactive intuitionistic fuzzy approach. Mathematics 9(23):3023. https://doi.org/10.3390/math9233023

Hansen KB, Borch C (2022) Alternative data and sentiment analysis: prospecting non-standard data in machine learning-driven finance. Big Data Soc 9(1):20539517211070700. https://doi.org/10.1177/20539517211070701

Hao J, Rezaee Z (2021) Determinants and consequences of sustainability narrative and graphical disclosures. SSRN Electron J. https://doi.org/10.2139/ssrn.3927388

Hasan I, Lynch DK, Siddique AR (2022) Usefulness of hard information and soft information: case of default risk and ESG factors. SSRN Electron J. https://doi.org/10.2139/ssrn.4015878

Hassan MK, Rabbani MR, Brodmann J, Bashar A, Grewal H (2022) Bibliometric and scientometric analysis on CSR practices in the banking sector. Rev Fin Econ. https://doi.org/10.1002/rfe.1171

Hassanein A, Mostafa MM, Benameur KB, Al-Khasawneh JA (2021) How do big markets react to investors' sentiments on firm tweets? J Sustain Fin Invest. https://doi.org/10.1080/20430795.2021.1949198

Hayes RM, Jiang F, Pan Y, Tang H (2021) COVID racial disparities in financial complaints and the role of corporate social attitudes. SSRN Electron J. https://doi.org/10.2139/ssrn.3952885

He Y, Romanko O, Sienkiewicz A, Seidman R, Kwon R (2021) Cognitive user interface for portfolio optimization. J Risk Fin Manag 14(4):180. https://doi.org/10.3390/jrfm14040180

Heath D, Macciocchi D, Michaely R, Ringgenberg MC (2021) Does socially responsible investing change firm behavior? In: European corporate governance institute–finance working paper, 762/2021. https://doi.org/10.2139/ssrn.3837706

Hemanand D, Mishra N, Premalatha G, Mavaluru D, Vajpayee A, Kushwaha S, Sahile K (2022) Applications of intelligent model to analyze the green finance for environmental development in the context of artificial intelligence. Comput Intell Neurosci. https://doi.org/10.1155/2022/2977824

Henriques ACL (2022) The performance of ETFs aligned with sustainable development goals and ESG ETFs. Thesis. University of Minho. https://hdl.handle.net/1822/79127. Accessed 25 Mar 2023

Hernandez-Perdomo E, Guney Y, Rocco CM (2019) A reliability model for assessing corporate governance using machine learning techniques. Reliab Eng Syst Saf 185:220–231

Heurtebize T, Soupé F, Carvalho RLD (2022) Corporate carbon footprint: a machine learning predictive model for unreported data. SSRN Electron J. https://doi.org/10.2139/ssrn.4038436

Hidayati, R., Kanamori, K., Feng, L., & Ohwada, H. (2016). Combining feature selection with decision tree criteria and neural network for corporate value classification. In: Knowledge management and acquisition for intelligent systems: 14th Pacific Rim knowledge acquisition workshop, PKAW 2016, Phuket, Thailand, August 22–23, 2016, proceedings. Springer International Publishing, pp 31–42

Hildinger M (2022) Can climate sentiment predict stock returns? An investigation of the UK stock market. Thesis. Hanken School of Economics. https://helda.helsinki.fi/dhanken/bitstream/handle/10227/480545/Hildinger_Maija.pdf?sequence=1. Accessed 25 Mar 2023

Hisano R, Sornette D, Mizuno T (2020) Prediction of ESG compliance using a heterogeneous information network. J Big Data 7:1–19

Hoepner AG, McMillan D, Vivian A, Wese Simen C (2021) Significance, relevance and explainability in the machine learning age: an econometrics and financial data science perspective. Eur J Fin 27(1–2):1–7

Hoepner AG, Korca B, Schiemann F (2023) Sustainability disclosure channels and firm risk: evidence from initiated and continued social disclosure between SEC-filings, sustainability reports, and financial reports. SSRN Electron J. https://doi.org/10.2139/ssrn.4020453

Hofinger J (2021) Regulatory risk disclosure in the banking industry: a scoring model approach. Thesis. Sheffield Hallam University. https://www.proquest.com/openview/4505382bdcbc4ee4c50a5c08b6acd7e2/1?pq-origsite=gscholar&cbl=2026366&diss=y. Accessed 25 Mar 2023

Hong X, Lin X, Fang L, Gao Y, Li R (2022) Application of machine learning models for predictions on cross-border merger and acquisition decisions with ESG characteristics from an ecosystem and sustainable development perspective. Sustainability 14(5):2838. https://doi.org/10.3390/su14052838

Hossain AT, Masum AA (2022) Does corporate social responsibility help mitigate firm-level climate change risk? Financ Res Lett 47:102791. https://doi.org/10.1016/j.frl.2022.102791

Hossain GS (2020) Predicting corporate green sukuk rating. Thesis. Hamad Bin Khalifa University. https://www.proquest.com/openview/6f63f2da402b916f4ccd2e16c0dfc317/1?pq-origsite=gscholar&cbl=2026366&diss=y. Accessed 25 Mar 2023

Hrazdil K, Mahmoudian F, Nazari JA (2021) Executive personality and sustainability: Do extraverted chief executive officers improve corporate social responsibility? Corp Soc Responsib Environ Manag 28(6):1564–1578

Hsiao CY, Huang SM, Kang YY, Li YX (2022) The impact of ESG performance on business performance before and after the COVID-19-taking the Chinese listed companies as a sample. Asian J Econ Bus Acc 22(5):56–68

Hsiao C, Chen H (2021) Application of corporate social responsibility—taking Chinese listed companies in the COVID-19 as an example. https://doi.org/10.20944/preprints202109.0259.v1

Hu X, Zhong A, Cao Y (2022) Greenium in the Chinese corporate bond market. Emerg Mark Rev 53:100946. https://doi.org/10.1016/j.ememar.2022.100946

Huang Q, Lin M (2022) Do climate risk beliefs shape corporate social responsibility? Glob Financ J 53:100739. https://doi.org/10.1016/j.gfj.2022.100739

Huang C, Mirza SS (2023) Green business practices and corporate financialization: role of female directors in Chinese small and medium enterprises (SMEs). J Corp Acc Fin 34(1):137–151

Huang AH, Wang H, Yang Y (2023) FinBERT: a large language model for extracting information from financial text. Contemp Acc Res. https://doi.org/10.1111/1911-3846.12832

Hughes A, Urban MA, Wójcik D (2021) Alternative ESG ratings: how technological innovation is reshaping sustainable investment. Sustainability 13(6):3551. https://doi.org/10.3390/su13063551

Husse T, Pippo F (2021) Responsible minus irresponsible—a determinant of equity risk premia? J Sustain Fin Invest. https://doi.org/10.1080/20430795.2021.1961557

Ielasi F, Ceccherini P, Zito P (2020) Integrating ESG analysis into smart beta strategies. Sustainability 12(22):9351. https://doi.org/10.3390/su1222935

In SY, Rook D, Monk A (2019a) Integrating alternative data (also known as ESG data) in investment decision making. Glob Econ Rev 48(3):237–260

In SY, Rook D, Monk A, Rajagopal R (2019b) Alternative ESG data for investment decision making. SSRN Electron J. https://doi.org/10.2139/ssrn.3380835

Ishizaka A, Lokman B, Tasiou M (2021) A stochastic multi-criteria divisive hierarchical clustering algorithm. Omega 103:102370. https://doi.org/10.1016/j.omega.2020.102370

Jabeur SB, Khalfaoui R, Arfi WB (2021) The effect of green energy, global environmental indexes, and stock markets in predicting oil price crashes: evidence from explainable machine learning. J Environ Manage 298:113511. https://doi.org/10.1016/j.jenvman.2021.113511

Jacobsen B, Lee W, Ma C (2019) The alpha, beta, and sigma of ESG: better beta, additional alpha? J Port Manag 45(6):6–15

Jan C-L (2021) Detection of financial statement fraud using deep learning for sustainable development of capital markets under information asymmetry. Sustainability 13(17):9879. https://doi.org/10.3390/su13179879

Jaunin C, Terracciano T (2022) Investors are listening: how green funds are reshaping firms' incentives. Swiss Finance Institute Research Paper Series, 22–19. https://ideas.repec.org/p/chf/rpseri/rp2219.html. Accessed 25 Mar 2023

Jebamikyous H, Li M, Suhas Y, Kashef R (2023) Leveraging machine learning and blockchain in E-commerce and beyond: benefits, models, and application. Discov Artif Intell. https://doi.org/10.1007/s44163-022-00046-0

Jha V (2019) Implementing alternative data in an investment process. In: Guida T (ed) Big data and machine learning in quantitative investment. Wiley, Hoboken. https://doi.org/10.1002/9781119522225.ch4

Jiang L (2020) Corporate social responsibility performance and money laundering control systems: evidence from Australian financial institutions. Thesis. Curtin University of Technology. http://hdl.handle.net/20.500.11937/81968. Accessed 25 Mar 2023

Jona J, Soderstrom N (2022) Evolution of climate-related disclosure guidance and application of climate risk measurement in research. In: Adams C (ed) Handbook of accounting and sustainability. Edward Elgar Publishing, Northampton, pp 397–420

Joshi H, Chauhan R (2021) Determinants of price multiples for technology firms in developed and emerging markets: variable selection using shrinkage algorithm. Vision. https://doi.org/10.1177/09722629211023011

Kabudi T, Pappas I, Olsen DH (2021) AI-enabled adaptive learning systems: a systematic mapping of the literature. Comput Educ: Artif Intell 2:100017

Kang SA, Cho SM (2020) Management overconfidence and CSR activities in Korea with a big data approach. Sustainability 12(11):4406. https://doi.org/10.3390/su12114406

Kanzi Belghiti MH (2022) Historical price data analysis of Islamic finance indices and their conventional counterparts in the 2006–2021 period. Thesis. Princeton University. https://dataspace.princeton.edu/handle/88435/dsp01nv935602w. Accessed 25 Mar 2023

Karelberg M (2018) The future of responsible investments in the context of algorithm-based decisions. Thesis. Lahti University of Applied Sciences. https://www.theseus.fi/bitstream/handle/10024/146763/Karelberg_Marjut.pdf?sequence=1. Accessed 25 Mar 2023

Katterbauer K, Moschetta P (2022a) A robo-advisory framework for Islamic and environmental, social and governance (ESG) compliance—a benchmark study on the S&P 500 stock index. J Muamalat Islamic Fin Res. https://doi.org/10.33102/jmifr.v19i1.408

Katterbauer K, Moschetta P (2022b) A deep learning approach to risk management modeling for Islamic microfinance. Eur J Islamic Fin 9(2):35–43

Katterbauer K, Syed H, Cleenewerck L, Genc SY (2022) Robo-Sukuk pricing for Chinese equities. Borsa Istanbul Rev 22(5):854–860

Kempf F (2022) Essays in empirical asset pricing with machine learning. Thesis. King's College London. [Online]. Retrieved: https://kclpure.kcl.ac.uk/portal/files/177882797/2022_Kempf_Felix_1655313_ethesis.pdf. Accessed 25 Mar 2023

Kennett H, Diaz-Rainey I, Biswas PK, Kuruppuarachchi D (2021) Climate transition risk in New Zealand equities. J Sustain Fin Invest. https://doi.org/10.1080/20430795.2021.1904774

Khalfaoui R, Jabeur SB, Dogan B (2022a) The spillover effects and connectedness among green commodities, Bitcoins, and US stock markets: evidence from the quantile VAR network. J Environ Manage 306:114493. https://doi.org/10.1016/j.jenvman.2022.114493

Khalfaoui R, Stef N, Wissal BA, Sami BJ (2022b) Dynamic spillover effects and connectedness among climate change, technological innovation, and uncertainty: evidence from a quantile VAR network and wavelet coherence. Technol Forecast Soc Chang 181:121743. https://doi.org/10.1016/j.techfore.2022.121743

Khan N, Ahmad T (2022) DCarbonX decentralised application: carbon market case study. Preprint at https://arxiv.org/abs/2203.09508

Khandpur RP, Nanda AA, Daviz M, Li C, Nurmanbetov D, Gaur S, Talukder A (2021) Adverse media mining for KYC and ESG compliance. Preprint at https://arxiv.org/abs/2110.11542

Khanra S, Kaur P, Joseph RP, Malik A, Dhir A (2022) A resource-based view of green innovation as a strategic firm resource: present status and future directions. Bus Strateg Environ 31(4):1395–1413

Kharlanov AS, Bazhdanova YV, Kemkhashvili TA, Sapozhnikova NG (2022) The case experience of integrating the SDGs into corporate strategies for financial risk management based on social

responsibility (with the example of Russian TNCs). Risks 10(1):12. https://doi.org/10.3390/risks10010012

Kheradmand E, Serre D, Morales M, Robert CB (2021) A NLP-based analysis of alignment of organizations' climate-related risk disclosures with material risks and metrics. Presented in NeurIPS 2021 Workshop on Tackling Climate Change with Machine Learning. https://www.climatechange.ai/papers/neurips2021/69. Accessed 25 Mar 2023

Kieffer E, Pinel F, Meyer T, Gloukoviezoff G, Lucius H, Bouvry P (2021) Evolutionary learning of private equity recommitment strategies. In: 2021 IEEE symposium series on computational intelligence (SSCI). IEEE, pp 1–8

Kiriu T, Nozaki M (2020) A text mining model to evaluate firms' ESG activities: an application for Japanese firms. Asia-Pacific Finan Markets 27(4):621–632

Kirppu A (2019) Impact investing in private equity. Thesis. Aalto University. https://aaltodoc.aalto.fi/handle/123456789/398470. Accessed 25 Mar 2023

Klusak P, Agarwala M, Burke M, Kraemer M, Mohaddes K (2021) Rising temperatures, falling ratings: the effect of climate change on sovereign creditworthiness. Energy Policy Research Group Working Paper, 2110. https://www.jstor.org/stable/resrep32424. Accessed 27 Mar 2023

Kneppers MM (2022) Developing a data driven CSR tool for impactful performance analysis at a Dutch bank: leading towards the exclusion of investments incontroversial activities of (potential) clients. Thesis. NOVA University Lisbon. http://hdl.handle.net/10362/140853. Accessed 25 Mar 2023

Kölbel JF, Leippold M, Rillaerts J, Wang Q (2020) Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. Swiss Finance Institute Research Paper, 21–19. https://doi.org/10.2139/ssrn.3616324

Koloski B, Montariol S, Purver M, Pollak S (2022) Knowledge informed sustainability detection from short financial texts. In: Proceedings of the fourth workshop on financial technology and natural language processing (FinNLP). pp 228–234

Kotsantonis S, Serafeim G (2019) Four things no one will tell you about ESG data. J Appl Corp Financ 31(2):50–58

Krappel T, Bogun A, Borth D (2021) Heterogeneous ensemble for ESG ratings prediction. Preprint at https://arxiv.org/abs/2109.10085

Kumar V, Srivastava A (2022) Trends in the thematic landscape of corporate social responsibility research: a structural topic modeling approach. J Bus Res 150:26–37

Kumar S, Sharma D, Rao S, Lim WM, Mangla SK (2022) Past, present, and future of sustainable finance: insights from big data analytics through machine learning of scholarly research. Ann Oper Res. https://doi.org/10.1007/s10479-021-04410-8

Kvam E, Molnár P, Wankel I, Ødegaard BA (2022) Do sustainable company stock prices increase with ESG scrutiny? Evidence using social media. SSRN Electron J. https://doi.org/10.2139/ssrn.4057988

Lacoste A, Luccioni A, Schmidt V, Dandres T (2019) Quantifying the carbon emissions of machine learning. Preprint at https://arxiv.org/abs/1910.09700

Lai C, Chen DN, Tsuo Y, Liu JH (2022) Predicting firm performance using ESG scores, annual reports, and patents. In: PACIS 2022 proceedings, 129. https://aisel.aisnet.org/pacis2022/129. Accessed 25 Mar 2023

Lanza A, Bernardini E, Faiella I (2020) Mind the gap! Machine learning, ESG metrics and sustainable investment. SSRN Electron J. https://doi.org/10.2139/ssrn.3659584

Larsson K, Ling F (2021) Time series forecasting of the SP global clean energy index using a multivariate LSTM. Thesis. KTH Royal Institute of Technology. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1594049&dswid=-295. Accessed 25 Mar 2023

LaViers L, Sandvik J, Xu D (2022) CEO pay ratio voluntary disclosures and stakeholder reactions. Rev Acc Stud. https://doi.org/10.1007/s11142-022-09720-1

Le Guenedal T, Roncalli T (2022) Portfolio construction with climate risk measures. SSRN Electron J. https://doi.org/10.2139/ssrn.3999971

Lee JH (2021) Understanding the motives behind corporate charitable donations: a machine learning approach. Georgia State University, Georgia

Lee J-H, Lee S-Y (2022) Effect of the absence of unethical controlling shareholders on firm value and the moderating role of corporate governance: evidence from South Korea. Sustainability 14(6):3607. https://doi.org/10.3390/su14063607

Lee K-J, Lu S-L (2021) The impact of COVID-19 on the stock price of socially responsible enterprises: an empirical study in Taiwan stock market. Int J Environ Res Public Health 18(4):1398. https://doi.org/10.3390/ijerph18041398

Lee O, Joo H, Choi H, Cheon M (2022) Proposing an integrated approach to analyzing ESG data via machine learning and deep learning algorithms. Sustainability 14(14):8745. https://doi.org/10.3390/su14148745

Li Z, Jia J, Chapple LJ (2022) Textual characteristics of corporate sustainability disclosure and corporate sustainability performance: evidence from Australia. Meditari Acc Res. https://doi.org/10.1108/MEDAR-03-2021-1250

Li Z (2020) Corporate sustainability in Australia: performance, disclosure and governance. Thesis. Queensland University of Technology. https://scholar.archive.org/work/imdqzovayvcbfc6mjjkidwa6xm/access/wayback/https://eprints.qut.edu.au/202715/1/Zhongtian_Li_Thesis.pdf. Accessed 25 Mar 2023

Lichtenberger A, Braga JP, Semmler W (2022) Green bonds for the transition to a low-carbon economy. Econometrics 10(1):11. https://doi.org/10.3390/econometrics10010011

Liermann V, Li S, Waizner J (2021) Distributed calculation credit portfolio models. In: Liermann V, Stegmann C (eds) The Digital Journey of Banking and Insurance. Springer, New York, pp 119–134. https://doi.org/10.1007/978-3-030-78829-2_7

Lim T, Gottipati S, Cheong M (2023) Artificial intelligence in today's education landscape: understanding and managing ethical issues for educational assessment. Preprint (Version 1) at Research Square. https://doi.org/10.21203/rs.3.rs-2696273/v1

Lin K, Zhao H (2022) The impact of green finance on the ecologicalization of urban industrial structure—based on GMM of dynamic panel system. J Artif Intell Technol 2(3):123–129

Lin L, Chang HL, Shahzad I, Waseem N (2022) A nexus between the rule of law, green innovation, growth and sustainable environment in top Asian countries: fresh insights from heterogeneous panel estimation. Econ Res Ekonomska Istraživanja 35(1):5434–5445

Lipuš R, Smith D (2019) Taming big data. In: Guida T (ed) Big data and machine learning in quantitative investment. Wiley, Hoboken. https://doi.org/10.1002/9781119522225.ch2

Liu N, Liu C, Guo Q, Da B, Guan L, Chen H (2019) Corporate social responsibility and financial performance: a quantile regression approach. Sustainability 11(13):3717. https://doi.org/10.3390/su11133717

Lopez C, Contreras O, Bendix J (2020) Disagreement among ESG rating agencies: Shall we be worried? Preprint, Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/id/eprint/103027. Accessed 25 Mar 2023

Lu S, Hayashi T (2021) A text-mining analysis on non-financial reporting practices and the quality of disclosure. Thesis. Keio University. https://koara.lib.keio.ac.jp/xoonips/modules/xoonips/download.php/KO40003001-00002021-3888.pdf?file_id=165267. Accessed 25 Mar 2023

Luccioni A, Baylor E, Duchene N (2020) Analyzing sustainability reports using natural language processing. Preprint at https://arxiv.org/abs/2011.08073

Ma Z (2019) Three essays on asset pricing in regime and ESG environments. Thesis. Dalhousie University. https://dalspace.library.dal.ca/handle/10222/76839. Accessed 25 Mar 2023

Macpherson M, Gasperini A, Bosco M (2021) Implications for artificial intelligence and ESG data. SSRN Electron J. https://doi.org/10.2139/ssrn.3863599

Manescu C (2010) Economic implications of corporate social responsibility and responsible investments. Thesis. University of Gothenburg. https://gupea.ub.gu.se/bitstream/handle/2077/23828/gupea_2077_23828_2.pdf?sequence=2. Accessed 25 Mar 2023

Mansouri S, Momtaz PP (2022) Financing sustainable entrepreneurship: ESG measurement, valuation, and performance. J Bus Ventur 37(6):106258. https://doi.org/10.1016/j.jbusvent.2022.106258

Maree C, Omlin CW (2022) Balancing profit, risk, and sustainability for portfolio management. In: 2022 IEEE symposium on computational intelligence for financial engineering and economics (CIFEr). Helsinki, Finland, pp 1–8. https://doi.org/10.1109/CIFEr52523.2022.9776048

Margot V, Geissler C, de Franco C, Monnier B, Advestis F, Ossiam F (2021) ESG investments: filtering versus machine learning approaches. Appl Econ Fin 8(2):1–16. https://doi.org/10.11114/aef.v8i2.5097

Marozzi A, Lanza F (2022) Modelling ESG with Twitter data. White Paper, ESGStack. https://esg-stack.ghost.io/content/files/2022/01/White-Paper--Modelling-ESG-with-Twitter-Data-.pdf. Accessed 25 Mar 2023

Martín-Martín A, Orduna-Malea E, Thelwall M, López-Cózar ED (2018) Google scholar, web of science, and Scopus: a systematic comparison of citations in 252 subject categories. J Info 12(4):1160–1177. https://doi.org/10.31235/osf.io/42nkm

Martín-Martín A, Thelwall M, Orduna-Malea E, Delgado López-Cózar E (2021) Google Scholar, Microsoft Academic, Scopus, Dimensions, Web of Science, and OpenCitations' COCI: a multidisciplinary comparison of coverage via citations. Scientometrics 126:871–906. https://doi.org/10.1007/s11192-020-03690-4

Martín-Martín A, Orduna-Malea E, Thelwall M, Delgado-López-Cózar E (2019) Google Scholar, Web of Science, and Scopus: Which is best for me? Impact of Social Sciences Blog. London School of Economics (LSE) Research Online. https://eprints.lse.ac.uk/103443/1/impactofsocialsciences_2019_12_03_google_scholar_web_of_science_and.pdf. Accessed 25 Mar 2023

Matson A, Brantestig N (2022) CSR, stakeholders and financial performance: investigating the impact of CSR on financial performance in the European Technology industry. Thesis. Uppsala University. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1681684&dswid=-2243. Accessed 25 Mar 2023

Mazzarano M, Guastella G, Pareglio S, Xepapadeas A (2021) Carbon boards and transition risk: explicit and implicit exposure implications for total stock returns and dividend payouts. Fondazione Eni Enrico Mattei (FEEM) Working Paper, 029.2021. https://www.jstor.org/stable/resrep37452. Accessed 25 Mar 2023

McAvoy M (2021) Essays on machine learning in asset pricing. Thesis. Brandeis University. https://www.proquest.com/openview/81ce901abb7e3ed814c9f8c317f257d8/1?pq-origsite=gscholar&cbl=18750&diss=y. Accessed 25 Mar 2023

McBride R, Dastan A, Mehrabinia P (2022) How AI affects the future relationship between corporate governance and financial markets: a note on impact capitalism. Manag Financ 48(8):1240–1249. https://doi.org/10.1108/MF-12-2021-0586

McMaster University (2022) Citation-based metrics. Health Sciences Library, McMaster University. https://hslmcmaster.libguides.com/impact/types/citation-based. Accessed 25 Mar 2023

Mehra S, Louka R, Zhang Y (2022) ESGBERT: language model to help with classification tasks related to companies environmental, social, and governance practices. Preprint at https://arxiv.org/abs/2203.16788

Meier R, Danzinger R (2022) Personalized portfolio optimization using genetic (AI) algorithms. In: Soldatos J, Kyriazis D (eds) Big data and artificial intelligence in digital finance. Springer, Cham. https://doi.org/10.1007/978-3-030-94590-9_11

Melas D (2021) The future of factor investing. J Port Manag 48(2):15–25

Mercier F, Narsimhan M (2022) Discovering material information using hierarchical reformer model on financial regulatory filings. Preprint at https://arxiv.org/abs/2204.05979

Mezzera S (2022) An overview on the Italian sustainability reporting: the social pillar. Thesis. Polytechnic University of Milan. https://www.politesi.polimi.it/handle/10589/189661?mode=complete. Accessed 25 Mar 2023

Michalski L, Low RKY (2021) Corporate credit rating feature importance: does ESG matter? SSRN Electron J. https://doi.org/10.2139/ssrn.3788037

Miranti T, Oktaviana UK (2022) Effect of capital structure on financial sustainability of sharia public financing bank (BPRS). Ad-Deenar Jurnal Ekonomi Dan Bisnis Islam 6(01):137–152

Mitsuzuka K, Ling F, Ohwada H (2017) Analysis of CSR activities affecting corporate value using machine learning. In: Proceedings of the 9th international conference on machine learning and computing. pp 11–14

Moher D, Liberati A, Tetzlaff J, Altman DG (2009) Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med 6(7):e1000097. https://doi.org/10.1371/journal.pmed.1000097

Moniz A, de Jong F (2014) Sentiment analysis and the impact of employee satisfaction on firm earnings. In: Advances in information retrieval: 36th European conference on information retrieval research, ECIR 2014, Amsterdam, The Netherlands, April 13–16, 2014. Proceedings 36. Springer International Publishing, pp 519–527

Monk A, Prins M, Rook D (2020) Data defense in sustainable investing. Sustainable investing. Routledge, pp 263–284

Moreno AI, Caminero T (2022) Application of text mining to the analysis of climate-related disclosures. Int Rev Financ Anal 83:102307. https://doi.org/10.1016/j.irfa.2022.102307

Mousa M, Saleem A, Sági J (2021) Are ESG shares a safe haven during COVID-19? Evidence from the Arab Region. Sustainability 14(1):208. https://doi.org/10.3390/su14010208

Murakami S, Muraoka S (2021) Exploring the potential of internet news for supply risk assessment of metals. Sustainability 14(1):409. https://doi.org/10.3390/su14010409

Muslu V, Mutlu S, Radhakrishnan S, Tsang A (2019) Corporate social responsibility report narratives and analyst forecast accuracy. J Bus Ethics 154:1119–1142

Naeem N, Cankaya S, Bildik R (2022) Does ESG performance affect the financial performance of environmentally sensitive industries? A comparison between emerging and developed markets. Borsa Istanbul Rev 22(2):S128–S140. https://doi.org/10.1016/j.bir.2022.11.014

Nakagawa K, Sashida S, Kitajima R, Sakai H (2020) What do good integrated reports tell us? An empirical study of Japanese companies using text-mining. In: 2020 9th international congress on advanced applied informatics (IIAI-AAI). IEEE, pp 516–521

Naouar A (2021) ESG performance and ESG rating: a critical review of the screening methodologies and the way forward. In: Ftiti Z, Ameur HB, Louhichi W (eds) Financial and economic systems: transformations and new challenges. World Scientific Publishing Co Pte Ltd, Singapore, pp 327–359

Napier E (2019) Technology enabled social responsibility projects and an empirical test of CSR's impact on firm performance. Georgia State University, Georgia. https://doi.org/10.57709/14263139

Naumer HJ, Yurtoglu BB (2020) Good news, bad news, no news: the media and the cross section of stock returns. SSRN Electron J. https://doi.org/10.2139/ssrn.3541037

Newton D, Ongena S, Xie R, Zhao B (2022) Banks vs. markets: are banks more effective in facilitating sustainability? BOFIT Discussion Paper, 5/2022. https://ssrn.com/abstract=4095642. Accessed 25 Mar 2023

Nguyen Q, Diaz-Rainey I, Kuruppuarachchi D (2021) Predicting corporate carbon footprints for climate finance risk analyses: a machine learning approach. Energy Econ 95:105129. https://doi.org/10.1016/j.eneco.2021.105129

Nguyen Q, Diaz-Rainey I, Kuruppuarachchi D, McCarten M, Tan EK (2023) Climate transition risk in US loan portfolios: are all banks the same? Int Rev Financ Anal 85:102401. https://doi.org/10.1016/j.irfa.2022.102401

Ning X, Yim D, Khuntia J (2021) Online sustainability reporting and firm performance: lessons learned from text mining. Sustainability 13(3):1069. https://doi.org/10.3390/su13031069

Nourbakhsh A, Bang G (2019) A framework for anomaly detection using language modeling, and its applications to finance. Preprint at https://arxiv.org/abs/1908.09156

Novak PK, Amicis LD, Mozetič I (2018) Impact investing market on Twitter: influential users and communities. Appl Netw Sci. https://doi.org/10.1007/s41109-018-0097-9

Nugent T, Stelea N, Leidner JL (2021) Detecting environmental, social and governance (ESG) topics using domain-specific language models and data augmentation. In: Flexible query answering systems: 14th international conference, FQAS 2021, Bratislava, Slovakia, September 19–24, 2021, Proceedings 14. Springer International Publishing, pp 157–169, https://doi.org/10.1007/978-3-030-86967-0_12.

Obrizzo S (2021) ESG valuation: a web scraping approach. Thesis. Università Ca' Foscari Venezia. http://dspace.unive.it/handle/10579/19299. Accessed 25 Mar 2023

Okuyama A, Shuichi T, Chiaki M, Shunsuke M (2021) Can tax payments complement high environmental, social, and governance reputational risk? Preprint, Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/110464/. Accessed 25 Mar 2023

Oro E, Ruffolo M, Pupo F (2020) A cognitive automation approach for a smart lending and early warning application. In: Proceedings of the EDBT/ICDT 2020 joint conference, 2578. http://ceur-ws.org/Vol-2578/DARLIAP6.pdf. Accessed 25 Mar 2023

Østrup-Møller CB, Dyngbo F, Brøgger A (2021) Impact of ESG ratings on stock performance & resiliency. Thesis. Copenhagen Business School. https://research.cbs.dk/files/68329908/1186098_20210516_Master_s_Thesis_CBM_FDY_VFinal.pdf. Accessed 25 Mar 2023

Oware KM, Botchway DK (2022) Exchange and moral capital of CSR disclosure and financial distress likelihood of family management firms: evidence from India. Manag Res Rev 46(4):625–646. https://doi.org/10.1108/MRR-09-2021-0694

Pang X (2019) Corporate social responsibility engagement and disclosure behaviors in China: a stakeholder perspective. Thesis. Imperial College. https://theses.lib.polyu.edu.hk/handle/200/10000. Accessed 25 Mar 2023

Park J, Choi W, Jung SU (2022) Exploring trends in environmental, social, and governance themes and their sentimental value over time. Front Psychol 13:890435. https://doi.org/10.3389/fpsyg.2022.890435

Pástor Ľ, Stambaugh RF, Taylor LA (2022) Dissecting green returns. J Financ Econ 146(2):403–424

Pastore L (2020) The usefulness of sharing social impact data: early findings from an international benchmarking on SROI assessments. J Entrep Org Divers 9(2):45–61. https://doi.org/10.5947/jeod.2020.008

Patterson DJ, Ariel Y, Burks B, Gratcheva EM, Hosking JS, Klein N, Protopopova L, Ruiz EET, Schmitt S, Shackelton B, Wang D, Wuebbles DJ (2020) Spatial finance: challenges and opportunities in a changing world. World Bank, Washington

Patterson DH, Schmitt S, Izquierdo P, Tibaldeschi P, Bellfield H, Wang D, O'Reilly Gurhy B, d'Aspremont A, Tello P, Bonfils-Bierer C, Brumby S, Barabino J, Volkmer N, Zheng J, Tayleur C, D'Agnese FA, Armstrong D'Agnese J (2022) Geospatial ESG: the emerging application of

geospatial data for gaining "environmental" insights on the asset, corporate and sovereign level. World Bank, Washington

Petersen K, Vakkalanka S, Kuzniarz L (2015) Guidelines for conducting systematic mapping studies in software engineering: an update. Inf Softw Technol 64:1–18

Petersen K, Gencel C (2013) Worldviews, research methods, and their relationship to validity in empirical software engineering research. In: 2013 joint conference of the 23rd international workshop on software measurement and the 8th international conference on software process and product measurement. IEEE, pp 81–89

Pettinari N (2021) Sustainable M&A: the value of ESG. Do bidders prefer to acquire or create sustainability? Thesis. LUISS Guido Carli. http://tesi.luiss.it/29866/. Accessed 25 Mar 2023

Plog M, El Zein SA (2022) Sustainable news and their impact on company's market capitalization does sustainable news about a company have a positive relationship with its stock price? https://doi.org/10.21203/rs.3.rs-1216445/v1

Proietti F (2021) The relationship between market performance and ESG signals. A comprehensive analysis. Thesis. Hong Kong Polytechnic University. https://spiral.imperial.ac.uk/bitstream/10044/1/94804/2/Proietti-F-2021-CEP-MSc-Thesis.pdf. Accessed 25 Mar 2023

Quang PT, Thao DP (2022) Analyzing the green financing and energy efficiency relationship in ASEAN. J Risk Fin 23(4):385–402. https://doi.org/10.1108/JRF-02-2022-0046

Quinn C, Fisch J, Robertson AZ (2021) Do ESG mutual funds deliver on their promises? Mich Law Rev 120(3):393–450

Raghupathi V, Ren J, Raghupathi W (2020) Identifying corporate sustainability issues by analyzing shareholder resolutions: a machine-learning text analytics approach. Sustainability 12(11):4753. https://doi.org/10.3390/su12114753

Raman N, Bang G, Nourbakhsh A (2020) Mapping ESG trends by distant supervision of neural language models. Mach Learn Knowl Extr 2(4):453–468

Ramanan RR (2018) Introduction to sustainability analytics. CRC Press

Rannou Y, Boutabba MA, Mercadier M (2022) How green are SRI labeled funds? Insights from a machine learning based clustering approach. SSRN Electron J. https://doi.org/10.2139/ssrn.4037373

Ranta M, Ylinen M (2021) Board composition and workplace diversity: a machine learning approach. SSRN Electron J. https://doi.org/10.2139/ssrn.3812296

Raudys S, Raudys A, Pabarskaite Z, Liubaviciute A (2022) Immunology-based sustainable portfolio management. Sustainability 14(5):2531. https://doi.org/10.3390/su14052531

Reig-Mullor J, Garcia-Bernabeu A, Pla-Santamaria D, Vercher-Ferrandiz M (2022) Evaluating ESG corporate performance using a new neutrosophic AHP-TOPSIS based approach. Technol Econ Dev Econ 28(5):1242–1266

Reyners S (2021) Data applications in quantitative finance. Thesis. KU Leuven. https://kuleuven.limo.libis.be/discovery/fulldisplay?docid=lirias3473738&context=SearchWebhook&vid=32KUL_KUL:Lirias&search_scope=lirias_profile&adaptor=SearchWebhook&tab=LIRIAS&query=any,contains,LIRIAS3473738&offset=0. Accessed 25 Mar 2023

Rizvi SKA, Naqvi B, Mirza N (2022) Is green investment different from grey? Return and volatility spillovers between green and grey energy ETFs. Ann Oper Res 313:495–524. https://doi.org/10.1007/s10479-021-04367-8

Rizzello A, Kabli A (2020) Social finance and sustainable development goals: a literature synthesis, current approaches and research agenda. ACRN J Fin Risk Perspect 9:120–136. https://doi.org/10.35944/jofrp.2020.9.1.010

Rolnick D, Donti PL, Kaack LH, Kochanski K, Lacoste A, Sankaran K, Bengio Y (2022) Tackling climate change with machine learning. ACM Comput Surv (CSUR) 55(2):1–96

Rook D, In SY, Monk A (2021) The resilience manifesto: integrating ESG and risk management, in investment portfolios and organizations. SSRN Electron J. https://doi.org/10.2139/ssrn.3942909

Roy PK, Shaw K (2021) Developing a multi-criteria sustainable credit score system using fuzzy BWM and fuzzy TOPSIS. Environ Dev Sustain 24:5368–5399. https://doi.org/10.1007/s10668-021-01662-z

Roy PP, Rao S, Zhu M (2022) Mandatory CSR expenditure and stock market liquidity. J Corp Finan 72:102158. https://doi.org/10.1016/j.jcorpfin.2022.102158

Sætra HS (2022) The AI ESG protocol: evaluating and disclosing the environment, social, and governance implications of artificial intelligence capabilities, assets, and activities. Sustain Dev. https://doi.org/10.1002/sd.2438

Sahin Ö, Bax K, Paterlini S, Czado C (2021) ESGM: ESG scores and the missing pillar. SSRN Electron J. https://doi.org/10.2139/ssrn.3890696

Sautner Z, Van Lent L, Vilkov G, Zhang R (2021) Pricing climate change exposure. SSRN Electron J. https://doi.org/10.2139/ssrn.3792366

Schena R, Russo A, Pinkse J (2022) Employee domain and non-financial performance: the moderating effect of digital reputation. Meditari Acc Res 30(4):893–913

Schmidt A (2019) Sustainable news—a sentiment analysis of the effect of ESG information on stock prices. SSRN Electron J. https://doi.org/10.2139/ssrn.3809657

Seele P (2017) Predictive sustainability control: a review assessing the potential to transfer big data driven 'predictive policing' to corporate sustainability management. J Clean Prod 153:673–686

Selmi R, Hammoudeh S, Errami Y, Wohar ME (2021) Is COVID-19 related anxiety an accelerator for responsible and sustainable investing? A sentiment analysis. Appl Econ 53(13):1528–1539

Semet R, Roncalli T, Stagnol L (2021) ESG and sovereign risk: what is priced in by the bond market and credit rating agencies? SSRN Electron J. https://doi.org/10.2139/ssrn.3940945

Serafeim G, Yoon A (2022) Stock price reactions to ESG news: the role of ESG ratings and disagreement. Rev Acc Stud. https://doi.org/10.1007/s11142-022-09675-3

Sharma U, Gupta A, Gupta SK (2022) The pertinence of incorporating ESG ratings to make investment decisions: a quantitative analysis using machine learning. J Sustain Fin Invest. https://doi.org/10.1080/20430795.2021.2013151

Shea Y, Steiner M, Radatz E (2021) Sustainable investing meets natural language processing—a systematic framework for building customized theme portfolios. SSRN Electron J 2021:1–13

Shields R, Ajour El Zein S, Vila Brunet N (2021) An analysis on the NASDAQ's potential for sustainable investment practices during the financial shock from COVID-19. Sustainability 13(7):3748. https://doi.org/10.3390/su13073748

Shobande OA, Ogbeifun L (2022) Sustainable blueprint: do stock investors increase emissions? J Risk Fin Manag 15(2):70. https://doi.org/10.3390/jrfm15020070

Sievert C, Shirley KE (2014) LDAvis: a method for visualizing and interpreting topics. In: Proceedings of the workshop on interactive language learning, visualization, and interfaces. Baltimore, Maryland, pp 63–70

Silgjerd O (2021) ESG: all bark and no bite? Exploring the utility of environmental, social and governance variables in empirical asset pricing via machine learning. Thesis. NHH Norwegian School of Economics. https://openaccess.nhh.no/nhh-xmlui/handle/11250/2774583. Accessed 25 Mar 2023

Slimane MB (2021) Bond index tracking with genetic algorithms. Amundi Working Paper. https://research-center.amundi.com/article/bond-index-tracking-genetic-algorithms. Accessed 25 Mar 2023

Sofian FNRM, Mohd-Sabrun I, Muhamad R (2022) Past, present, and future of corporate social responsibility and earnings management research. Australas Acc Bus Fin J 16(2):116–144

Sokolov A, Caverly K, Mostovoy J, Fahoum T, Seco L (2021a) Weak supervision and Black-Litterman for automated ESG portfolio construction. J Fin Data Sci 3(3):129–138

Sokolov A, Mostovoy J, Ding J, Seco L (2021b) Building machine learning systems for automated ESG scoring. J Impact ESG Invest 1(3):39–50. https://doi.org/10.3905/jesg.2021.1.010

Sokolov A, Mostovoy J, Losing E, Ceccarelli M, Zhang QE, Zhang Y, Laurion K, Jackson B, Seco L (2022) Assessing the impact of sustainability on fund flows: an excess information approach and US-based case study. J Impact ESG Invest. https://doi.org/10.3905/jesg.2022.1.057

Soni G, Kumar S, Mahto RV, Mangla SK, Mittal ML, Lim WM (2022) A decision-making framework for industry 4.0 technology implementation: the case of FinTech and sustainable supply chain finance for SMEs. Technol Forecast Soc Change 180:121686. https://doi.org/10.1016/j.techfore.2022.121686

Stanley M (2023) How AI can bolster sustainable investing. Institute for sustainable investing, Morgan Stanley. https://www.morganstanley.com/ideas/ai-sustainable-investing-use-potential. Accessed 17 Oct 2023

Strignert A, Malm E (2021) ESG investing through ETFs—an effective way to circumvent volatility? Thesis. Lund University. https://lup.lub.lu.se/student-papers/record/9036881/file/9036887.pdf. Accessed 25 Mar 2023

Su CW, Chen Y, Hu J, Chang T, Umar M (2023) Can the green bond market enter a new era under the fluctuation of oil price? Econ Res Ekonomska Istraživanja 36(1):536–561

Sukthomya D, Laosiritaworn W (2018) Modeling of the relationship between corporate social responsibility and stock price with artificial neural network. In: 2018 7th international conference on industrial technology and management (ICITM). IEEE, pp 213–217

Sun C (2022) The correlation between green finance and carbon emissions based on improved neural network. Neural Comput Appl 34(15):12399–12413

Svanberg J, Ardeshiri T, Samsten I, Öhman P, Neidermeyer PE, Rana T, Semenova N, Danielson M (2022) Corporate governance performance ratings with machine learning. Intell Syst Acc Fin Manag 29(1):50–68. https://doi.org/10.1002/isaf.1505

Taleb W, Le Guenedal T, Lepetit F, Mortier V, Sekine T, Stagnol L (2020) Corporate ESG news and the stock market. SSRN Electron J. https://doi.org/10.2139/ssrn.3723799

Tang DY, Yan J, Yao CY (2022) The determinants of ESG ratings: rater ownership matters. SSRN Electron J. https://doi.org/10.2139/ssrn.3889395

Tanthanongsakkun S, Treepongkaruna S, Jiraporn P (2023) Carbon emissions, corporate governance, and staggered boards. Bus Strateg Environ 32(1):769–780

Tattersall KR (2020) The impact of environmental performance on corporate profitability: evidence from South African publicly listed metal & mining companies. Thesis. Independent Institute of Education. http://iiespace.iie.ac.za/handle/11622/426. Accessed 25 Mar 2023

Teoh TT, Heng QK, Chia JJ, Shie JM, Liaw SW, Yang M, Nguwi Y Y (2019) Machine learning-based corporate social responsibility prediction. In 2019 IEEE international conference on cybernetics and intelligent systems (CIS) and IEEE conference on robotics, automation and mechatronics (RAM). IEEE, pp 501–505

The Global Compact (2004) Who cares wins: connecting the financial markets to a changing world? United Nations Report. [Online]. https://www.unglobalcompact.org/docs/issues_doc/Financial_markets/who_cares_who_wins.pdf. Accessed 25 Mar 2023

Tufail M, Song L, Umut A, Ismailova N, Kuldasheva Z (2022) Does financial inclusion promote a green economic system? Evaluating the role of energy efficiency. Econ Res Ekonomska Istraživanja 35(1):6780–6800

Turunen J (2021) Exploring the corporate financial and social performance relationship with net impact method. Thesis. Tampere University. https://trepo.tuni.fi/handle/10024/134449. Accessed 25 Mar 2023

Twinamatsiko E, Kumar D (2022) Incorporating ESG in decision making for responsible and sustainable investments using machine learning. In 2022 international conference on electronics and renewable systems (ICEARS). IEEE, pp 1328–1334

Ullah AKM, Sultana S, Faisal F, Rahi M, Islam M, Alam M, Alam M, Rabiul G (2021) A brief review of responsible AI and socially responsible investment in financial and stock trading. TechRxiv. https://doi.org/10.36227/techrxiv.15093762.v1

Vinogradnaitė A (2020) Impact of corporate social responsibility on tax avoidance. Thesis. Kaunas University of Technology. https://trepo.tuni.fi/handle/10024/134449. Accessed 25 Mar 2023

Vo NNY (2020) Machine learning algorithms for wealth data analytics. University of Technology, Sydney

Vo NN, He X, Liu S, Xu G (2019) Deep learning for decision making and the optimization of socially responsible investments and portfolio. Decis Support Syst 124:113097. https://doi.org/10.1016/j.dss.2019.113097

Vojinović Ž, Milutinović S, Sertić D, Leković B (2022) Determinants of sustainable profitability of the Serbian insurance industry: panel data investigation. Sustainability 14(9):5190. https://doi.org/10.3390/su14095190

Wang J, Sun X, Cheng Q, Cui Q (2021) An innovative random forest-based nonlinear ensemble paradigm of improved feature extraction and deep learning for carbon price forecasting. Sci Total Environ 762:143099. https://doi.org/10.1016/j.scitotenv.2020.143099

Wirtz J, Kunz WH, Hartley N, Tarbit J (2023) Corporate digital responsibility in service firms and their ecosystems. J Serv Res 26(2):173–190. https://doi.org/10.1177/10946705221130467

Wu N, Xiao W, Liu W, Zhang Z (2022) Corporate climate risk and stock market reaction to performance briefings in China. Environ Sci Pollut Res 29(35):53801–53820

Xu B, Li S, Afzal A, Mirza N, Zhang M (2022) The impact of financial development on environmental sustainability: a European perspective. Resour Policy 78:102814. https://doi.org/10.1016/j.resourpol.2022.102814

Yadav H, Kar AK, Kashiramka S (2022) How does entrepreneurial orientation and SDG orientation of CEOs evolve before and during a pandemic. J Enterp Inf Manag 35(1):160–178

Yan L, Wang H, Athari SA, Atif F (2022) Driving green bond market through energy prices, gold prices and green energy stocks: evidence from a non-linear approach. Econ Res Ekonomska Istraživanja 35(1):6479–6499

Yan J, Meng B (2021) Stock market reactions to firms' first publication of sustainability reports: evidence from multiple industries in Nordic countries, the United States, and China. Thesis. Lund University. https://lup.lub.lu.se/student-papers/record/9050782/file/9050786.pdf. Accessed 25 Mar 2023

Yang R, Jiménez-Martin JA (2022) Method, ESG score or data? What matters most in capturing ESG risk factors. SSRN Electron J. https://doi.org/10.2139/ssrn.4069454

Yang R, Caporin M, Jiménez-Martin JA (2022) ESG risk exposure: a tale of two tails. SSRN Electron J. https://doi.org/10.2139/ssrn.4082332

Yang Z, Broby D (2020) Sustainable finance: AI applications in satellite imagery and data. Discussion paper, University of Strathclyde. https://strathprints.strath.ac.uk/id/eprint/73828. Accessed 25 Mar 2023

Yang H, Liu XY, Zhong S, Walid A (2020) Deep reinforcement learning for automated stock trading: an ensemble strategy. In: Proceedings of the first ACM international conference on AI in finance. pp 1–8, https://doi.org/10.1145/3383455.3422540

Yoo P (2022) ESG investing: a tale of two preferences. SSRN Electron J. https://doi.org/10.2139/ssrn.4069015

Yu ZH (2022) Disruptive innovation on ESG: evidence from blockchain exposure in conference calls. SSRN Electron J. https://doi.org/10.2139/ssrn.4160037

Yu X, Xin X, Chen L, Kim HS (2018) Predicting market reactions to bad news. SSRN Electron J. https://doi.org/10.2139/ssrn.3144041

Yu G, Liu Y, Cheng W, Lee CT (2022) Data analysis of ESG stocks in the Chinese stock market based on machine learning. In: 2022 2nd international conference on consumer electronics and computer engineering (ICCECE). IEEE, pp 486–493. https://doi.org/10.1109/ICCECE54139.2022.9712837

Zhang Y (2021) Impact investing and venture capital industry: experimental evidence. SSRN Electron J. https://doi.org/10.2139/ssrn.3959117

Zhang R (2022) New funding and pricing mechanism in alternative and sustainable finance: the role of non-financial factors. University of Regensburg, Regensburg

Zhang J, Chen X (2021) Socially responsible investment portfolio construction with a double-screening mechanism considering machine learning prediction. Discret Dyn Nat Soc. https://doi.org/10.1155/2021/7390887

Zhang J, Han W (2022) Carbon emission trading and equity markets in China: how liquidity is impacting carbon returns? Econ Res Ekonomska Istraživanja 35(1):6466–6478

Zhang Z, Su Z, Wang K, Zhang Y (2022) Corporate environmental information disclosure and stock price crash risk: evidence from Chinese listed heavily polluting companies. Energy Econ 112:106116. https://doi.org/10.1016/j.eneco.2022.106116

Zhao D, Zhou YM (2020) A real options perspective on corporate social responsibility: evidence using causal forest. SSRN Electron J. https://doi.org/10.2139/ssrn.4084084

Zheng J, Khurram MU, Chen L (2022) Can green innovation affect ESG ratings and financial performance? Evidence from Chinese GEM listed companies. Sustainability 14(14):8677. https://doi.org/10.3390/su141486

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