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 centers around three research questions: key research themes for ESG and AI in finance, research intensity and interest evolution, and the use and progression of AI techniques within these themes. 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.

1.0 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. 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 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*" (Lim, Gottipati and Cheong, 2023; Petersen, Vakkalanka and Kuzniarz, 2015). 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 were the key research themes that outline the research scape for ESG and AI in finance?

Through the use of topic modelling and network analysis, this question looked to identify distinct research archetypical domains that underlie existing research efforts. Within each thematic research focal areas, wherever feasible, the study also looked to determine research sub-themes that were well scoped and evidenced by extant literature. This review provides a thematic classification and disposition of the state-of-the-art.

RQ2: How were the research intensity and research interest across various research archetypical domains, and how did they evolve across time?

This question looked to identify the research intensity and research interest, in terms of publication and citation numbers within each research archetypical domain, and investigate how these elements have evolved across recent years. This review provides an insight into the magnitude and evolution of key research efforts and their research significance within the research scape.

RQ3: How were the use and evolution of different AI techniques employed across the research archetypical domains, and how did they evolve over time?

This question looked to identify distinctive patterns of the use of AI techniques within each research archetypical domain, and how these AI techniques employed have evolved across time. This review provides an insight into the type and evolution of key AI techniques utilized within the research scape.

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, through systematic meta-analysis of extant literature, (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.

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.

2.0 Background and Literature Review

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. 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. Research on AI in finance started around the 2004 to 2006 period (Cao, 2020). 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.

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 2,460 in the five years between 2004 to 2008, to 18,000 in the years between 2018 to 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. 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., Apel, Betzer and Scherer, 2021; Ranta and Ylinen, 2021; Patterson et al., 2022; Yang and Broby, 2020). This can help financial institutions to 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, 2022). 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 et al., 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.

3.0 Methodology and Data

The systematic literature mapping approach was conducted utilizing the methodology applied in, Kabudi, Papas and Olsen (2021), Lim, Gottipati and Cheong (2023), and Petersen, Vakkalanka and Kuzniarz (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. In addition, the search was limited to English language results, and the publication year of 2008 onwards. This research coverage period compassed 15 full years. This stage identified a corpus of 18,000 papers.

The next stage of PRISMA, or the *screening* stage, required scanning of titles, abstracts and full papers to exclude unrelated, inappropriate or duplicated papers. At this stage, papers that did not have relevant titles and abstracts or were duplicates were directly removed. Otherwise, a full review of the text body would be conducted to assess for suitability. Only papers that had fully accessible text were included. This step omitted 17,630 papers. In total, 370 papers were 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:

- *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.
- *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.*).
- *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 muti-dimensional 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.

- *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.
- *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.
- *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.
- *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 and data extraction process 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; Martín-Martín et al., 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.

4.0 Findings

4.1 RQ1: What were 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.*

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

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 Table 2 to Table 9 to provide a thematic disposition of the state-of-the-art.

- *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.

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 et al., 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., Zhang et al., 2022; Taleb et al., 2020; Serafeim and Yoon, 2022; Fabozzi and Karagozoglu; 2021). AI techniques can also be used to analyze the impact of ESG factors on investment performance (e.g., Yoo, 2022; Ullah et al., 2021; Twinamatsiko and Kumar, 2022; Ielasi, Ceccherini and Zito, 2020; Erhardt, 2020). 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., Yang et al., 2020; Sokolov et al., 2021b; Katterbauer et al., 2022; Katterbauer and Moschetta, 2022; He et al., 2021; Hakala, 2019). 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 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).

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, Lee and Ma (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, Fisch and Robertson (2021) examined the consistency of ESG funds delivering ESG investing using multivariate regression. • Rannou, Boutabba and Mercadier (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, Amicis and Mozetič (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, Dziuban and Pająk (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 (2022) 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.
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, Matin, and Skiadopoulos (2021), and Mousa, Saleem and Sági (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.

- *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., Clarkson et. Al, 2020; Goloshchapova et al., 2019; Raman, Bang and Nourbakhsh, 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 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., Huang, Wang and Yang, 2021; Reig-Mullor et al., 2022; Briere and Ramelli, 2020; Chang and Lee, 2020) .

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, Wang and Jin, 2022; 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, Sustainability, Technological Forecasting and Social Change, Machine Learning and Knowledge Extraction*, and *AAAI Workshop on Knowledge Discovery from Unstructured Data in Financial Services.*

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, Bang and Nourbakhsh (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, Wang and Yang (2021) developed FinBERT, a language model adapted to the financial domain that can help improve ESG sentiment analysis and classification accuracy. • Briere and Ramelli (2020) proposed a Green Sentiment Index that captures shifts in investors' appetite for environmental responsibility using multivariate regression. • Chang and Lee (2020) 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, Wang and Jin (2022) 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.

- *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; Chava, Du, and Malakar, 2021; Svanberg et al., 2022; Hernandez-Perdomo, Elvis; Guney, Yilmaz; Rocco, 2019). 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., Jebamikyous et al.,2023; Soni et al., 2022; Coqueret and Tran, 2022). 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; Bussmann, Tanda and Yu; 2022; De Lucia, Pazienza and Bartlett, 2020; Yadav, Kar and Kashiramka; 2022; Turunen, 2021; Teoh et al., 2019).

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., Akter et al., 2022; Wirtz et al., 2023; He et al., 2021; Dash and Kajiji, 2020). 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*.

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, Mahmoudian, and Nazari (2021) examined corporate executive personalities and CSR performance based on S&P 500 firms using multicriteria decision analysis and multivariate regression. • Chava, Du, and Malakar (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 et al. (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, Elvis; Guney, Yilmaz; Rocco (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, Pazienza and Bartlett (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.

- *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., Tufail et al., 2022; Semet, Roncalli and Stagnol, 2021; Wang et al., 2021; 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, Ruffolo and Pupo, 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., Sætra, 2022; Dugo, 2021; Duchin, Gao and Xu, 2022; Cherrington et al., 2020).

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.*

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, Jabeur and Dogan (2022) 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, Rohleder, and Seruset (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, Lokman and Tasiou (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.
Financial products and services	• Sokolov et al. (2020) applied pre-trained BERT for ESG index construction. • Slimane (2021) utilized genetic algorithm for bond index tracking with constraints on ESG considerations. • Lichtenberger, Braga and Semmler (2022) examined performance of green against non-green bonds using decision tree and multivariate regression. • Kanzi and Moula (2021) 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. (2021) 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, Druchok and Drogovoz (2021) 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 (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.

- *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., Yang, Caporin and Jiménez-Martin, 2022; Roy and Shaw, 2021).

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, Li and Waizner, 2021; Gobet and Lage, 2021; Brogi, Lagasio and Porretta, 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.*

Table 6

Sub-theme(s) within research thematic area of *Risk Management*

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, Betzer and Scherer (2021) 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, Diaz-Rainey and Kuruppuarachchi (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. • Khan, Serafeim and Yoon (2016) examined the materiality levels of corporate sustainability issues using multivariate regression. • Hisano, Sornette, and Mizuno (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.
Credit management	• Nguyen et al. (2020) examined the relationship between loan portfolios and transition risk using multivariate regression. • Hasan, Lynch and Siddique (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 (2022) applied random forest on credit scoring for inclusive and microfinance.

- *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., Sætra 2022; Dugo, 2021; Duchin, Gao and Xu, 2022; Cherrington et al., 2020).

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., Larsson and Ling, 2021; Anas et al., 2020; Jabeur, Khalfaoui and Arfi, 2021; Gao, Wang and Yang, 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.*

Table 7

Sub-theme(s) within research thematic area of *Forecasting and Valuation*

Research sub-theme(s)	**Example(s) of Related Literature**
Forecasting	• Wang et al. (2021) used a random forest-based ensemble for feature extraction and deep learning LSTM model for carbon price forecasting. • Jabeur, Khalfaoui and Arfi (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, D'Ecclesia, and Levantesi (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.
Valuation	• Applying regularized multivariate regression, Semet, Roncalli and Stagnol (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.

- *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, Contreras and Bendix, 2020; Geissler et al., 2022; Gupta, Sharma and Gupta, 2021; Sokolov et al., 2021b).

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.*

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, Contreras and Bendix (2020) discussed about the quality and issues regarding the use of ESG data. • In, Rook and Monk (2019) 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, Sharma and Gupta (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.

- *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, Hein and Papenbrock, 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.*

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, Hein and Papenbrock (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.

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 were the research intensity and research interest across various research archetypical domains, and how did they evolve across 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).

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**

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 to 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.

4.3 RQ3: How were the use and evolution of different AI techniques employed across the research archetypical domains, and how did they evolve over time?

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

- *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, Bernardini and Faiella, 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. Maree and Omlin, 2022; Yang et al., 2020).
- *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., Ghosh and Naskar, 2022; Bingler et al., 2022; Koloski et al., 2022; Huang, Wang, and Yang, 2023).

- *Firm Governance*: The majority of papers in *Firm Governance* utilized multivariate regression to examine the impact of ESG at the company level (e.g., Alkaraan et al., 2022; Heath et al, 2021).
- *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., Klusak et al., 2021; Bai et al., 2022; Ishizaka, Lokman and Tasiou, 2021). Evolutionary learning, deep learning and text mining have been applied to create new ESG products, such as ESG index construction (e.g., Slimane, 2021; Chang et al., 2021; Sokolov et al., 2021a).
- *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., Jan, 2021; Hisano, Sornette and Mizuno, 2020), and unsupervised learning and computer vision to recognize risk patterns (e.g., Patterson et al., 2020; Yang and Broby, 2020; Patterson et al., 2022).
- *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., Guliyev and Mustafayev, 2022; Semet, Roncalli and Stagnol, 2021). Deep learning methods were increasingly being utilized to improve forecasting results (e.g., Wang et al., 2021; Jabeur, Khalfaouiand and Arfi 2021), and finely grained news events could be integrated through text mining to achieve real-time prediction (e.g., Chen et al., 2019; Yu et al., 2018; Zhang, 2022).
- *Data*: The domain of *Data* might involve simple supervised learning and natural language processing (e.g., Gupta, Sharma and Gupta, 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.
- *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 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, 2021). 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.

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**

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.

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.

5.0 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 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 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, 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 et al. (2020), Table 12 provides a high-level overview of this research space, segregated into the eight archetypical domains.

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. - *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. - *Automated and smart investment*: Developing and optimizing intelligent investment models, algorithms, platforms and services with market forecasting and risk-averse management, etc. - *Market anomaly analysis*: Recognize and predict abnormal movements, trends, behaviors, events inside/outside markets and of participants, 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. - 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. - Development of ESG-focused robo-advisors that provide personalized investment recommendations to individual investors based on their ESG preferences, 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.	- Quantitative analysis, data mining, machine learning, behavior analysis, risk analytics, and optimization methods, etc. - Market representation, prediction, learn to rank, game theories, reinforcement learning, recommender systems, behavior analysis, deep models, portfolio optimization, optimization methods, etc. - Market representation, forecasting, portfolio optimization, learn to rank, reinforcement learning, recommender systems, behavior analysis, deep models, game theories, optimization methods, etc. - Outlier detection, novelty/exception/change detection, behavior analytics, pattern mining, event modeling, probabilistic modeling, clustering, and classification, etc.	- Yoo (2022); Ullah et al. (2021); Twinamatsiko and Kumar (2022); Ielasi, Ceccherini and Zito (2020); Erhardt (2020) - Zhang and Chen (2021); Vo et al. (2019); Shea, Steiner and Radatz (2021); Meier and Danzinger (2022); Jiang (2020); He et al. (2021) - Yang et al. (2020); Sokolov et al. (2021b); Katterbauer et al. (2022); Katterbauer and Moschetta (2022); He et al. (2021); Hakala (2019) - 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. - *ESG Measurement*: Measure the social impact, and financial impact of climate change of companies and investments, etc. - *ESG Governance*: Identify and assess potential ESG risks, as well as to monitor and ensure compliance with relevant regulations and policies, 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. - 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. - 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.	- Event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, etc. - Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, 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.	- Clarkson et. al (2020); Goloshchapova et al. (2019); Raman, Bang and Nourbakhsh (2020) - Huang, Wang and Yang (2021); Reig-Mullor et al. (2022); Briere and Ramelli (2020); Chang and Lee (2020) - Chen, Wang and Jin (2022); Fan and Wu (2022)

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. - *Intelligent e-commerce and supply chain management*: Estimating, predicting and optimizing pricing, demand, supply, production, storage, logistics, delivery, marketing, risk, fraud, security, etc. - *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. - *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 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. - Reducing carbon footprint by optimizing logistics and delivery processes; predicting demand for sustainable products and services, 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. - 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.	- Process analysis, risk analytics, behavior analytics, event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, 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. - Financial time series analysis, numerical optimization, anomaly detection, probabilistic learning, relation learning, risk analytics, representation learning, and supervised and unsupervised learning, 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.	- Seele (2017); Chava, Du, and Malakar (2021); Svanberg et al. (2022); Hernandez-Perdomo, Elvis; Guney, Yilmaz; Rocco (2019) - Jebamikyous et al. (2023); Soni et al. (2022); Coqueret and Tran (2022) - Yadav, Kar and Kashiramka (2022); Turunen (2021); Teoh et al. (2019); Tanthanongsakkun, Treepongkaruna and Jiraporn (2023) - Akter et al. (2022); Wirtz et al. (2023); He et al. (2021); Dash and Kajiji (2020)
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*	- 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. - 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	- 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,	- Patterson et al. (2022); Yang and Broby (2020); Zheng, Khurram, and Chen (2022); Hofinger (2021); Jan (2021); Fianu (2021); Katterbauer and Moschetta (2022); Tufail et al. (2022); Semet, Roncalli and Stagnol (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);

Archetype	Research sub-theme(s)	Typical Financial Problems	Typical ESG Areas	Typical AI Techniques	Example(s) of Related Literature
		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. - *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. - *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. - *Financial products and services - Wealth management*: Discovering wealthy people and demand; recommending personalized products, services and customer care; detecting circumstance change and new requirements; customizing risk management, training and social trading services; etc. - *Financial products and services - Internet finance*: Automating, predicting, securing and optimizing Internet-based financing, investment, wealth management, trust, credit, insurance, payment, etc. - *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. - *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	literacy, promoting inclusion, and protecting customers from fraudulent activities, 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. - Providing personalized services to clients with social impact investment preferences, providing investment options aligned with ethical values of clients, 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. - 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. - 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.	optimization methods, reinforcement learning, behavior modeling, visualization, etc. - Various methods of data mining, machine learning, deep learning, distributed learning, recommender systems, behavior informatics, risk analytics, security informatics, 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. - Customer profiling, behavior analysis, sentiment analysis, prediction, active learning, intent learning, capability and propensity modeling, personalized recommendation, knowledge engineering, etc. - Online/web/network analysis, online user modeling, interaction modeling, behavior analytics, text analysis, prediction, distributed learning, recommender systems, outlier detection, risk analytics, 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. - Process analysis, event analysis, behavior analytics, outlier detection, change detection, distributed learning, risk analytics, security data analytics, fraud detection, and benchmarking, etc.	Khalfaoui et al. (2022) - Oro, Ruffolo and Pupo (2020); Nguyen et al. (2023) - Sætra (2022); Dugo (2021); Duchin, Gao and Xu (2022); Cherrington et al. (2020) - Vo (2020) - Chueca Vergara and Ferruz Agudo (2021) - Yu (2022); Jebamikyous et al. (2023) - Choithani et al. (2023)

Archetype	Research sub-theme(s)	Typical Financial Problems	Typical ESG Areas	Typical AI Techniques	Example(s) of Related Literature
		governance and regulation; etc.			
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. - *Credit management*: Estimating, predicting and optimizing credit rating, limit, valuation, scheduling, default, refund, repayment, refinance, risk and fraud management, 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. - 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.	- Risk analytics, probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, deep neural models and reinforcement learning, etc. - Profiling, forecasting, prediction, sequential and recurrent modeling, game theory, reinforcement learning, behavior analytics, risk analytics, optimization, etc.	- Yang, Caporin and Jiménez-Martin (2022); Roy and Shaw (2021) - Sokolov et al. (2021a); Liermann, Li and Waizner (2021); Gobet and Lage (2021); Brogi, Lagasio and Porretta (2022); Mansouri and Momtaz (2022)
Forecasting and Valuation	- Valuation - Forecasting	- *Valuation*: Estimating valuation, pricing, demand and supply; etc. - *Forecasting*: Modeling and predicting market movement, trend, volatility dynamics, exceptions, events, 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. - 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.	- 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. - Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, etc.	- Sætra (2022); Dugo (2021); Duchin, Gao and Xu (2022); Cherrington et al. (2020) - Larsson and Ling (2021); Anas et al. (2020); Ashley, Papenbrock and Schwendner (2021); Jabeur, Khalfaoui and Arfi (2021); Gao, Wang and Yang (2022); Guliyev and Mustafayev (2022)
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 adverserial network, prediction, evolutionary computing	- Lopez, Contreras and Bendix (2020); Geissler et al. (2022); Gupta, Sharma and Gupta (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, Hein and Papenbrock (2022)

6.0 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:

- Investigating the potential of emerging AI techniques, such as graph neural networks and federated learning, for enhancing ESG-related financial applications and addressing concerns in attractive research potential areas, such as *Responsible Use of AI.*
- Exploring the interrelationships and synergies between the identified research archetypes, to develop more holistic and integrated approaches in addressing ESG, AI, and finance challenges.
- 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.

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.

Declarations

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

It is not necessary to obtain ethics approval, as this study does not involve human participants.

Data is available upon reasonable request.

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Figures

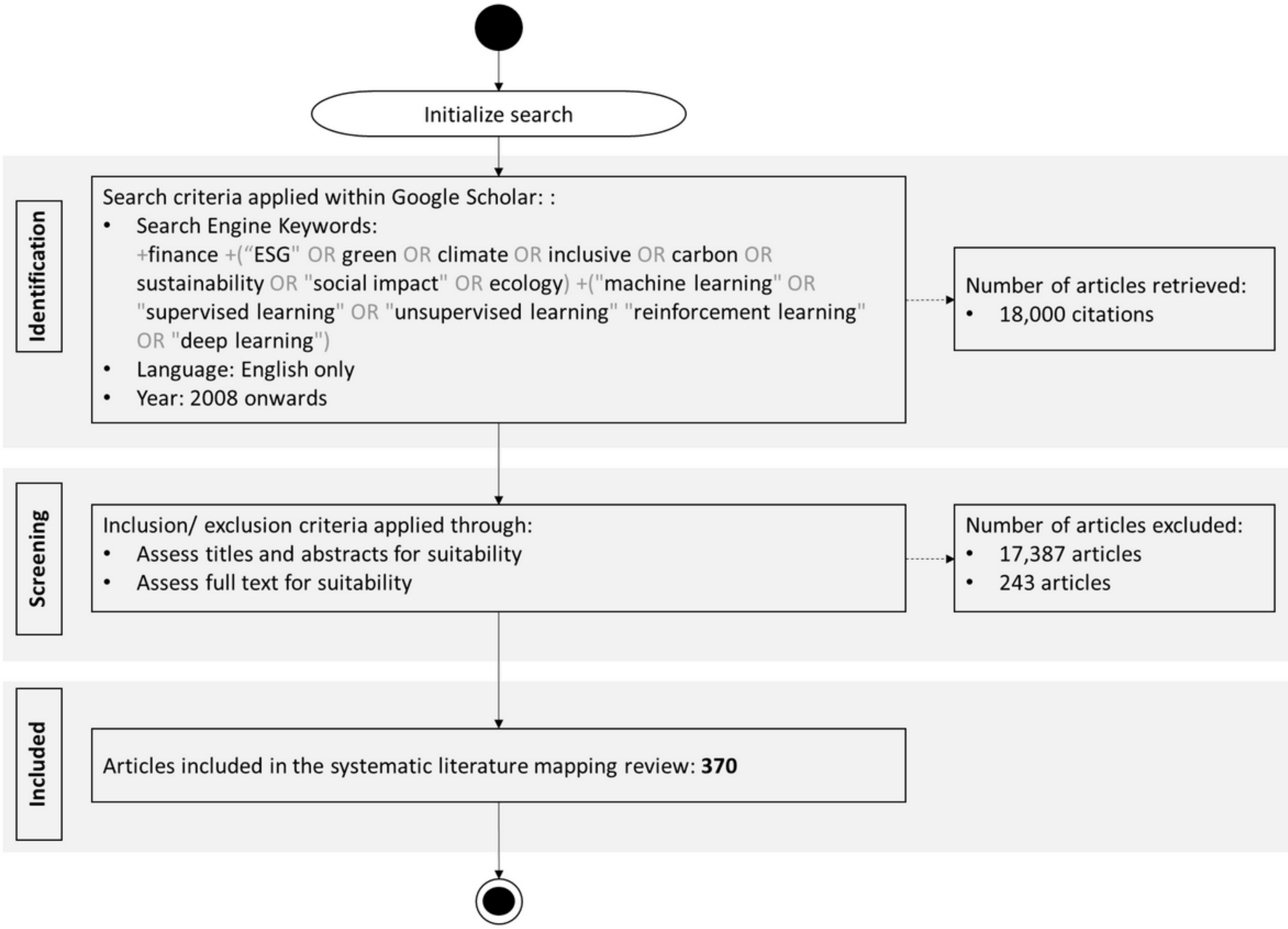

Figure 1

PRISMA - The systematic mapping process

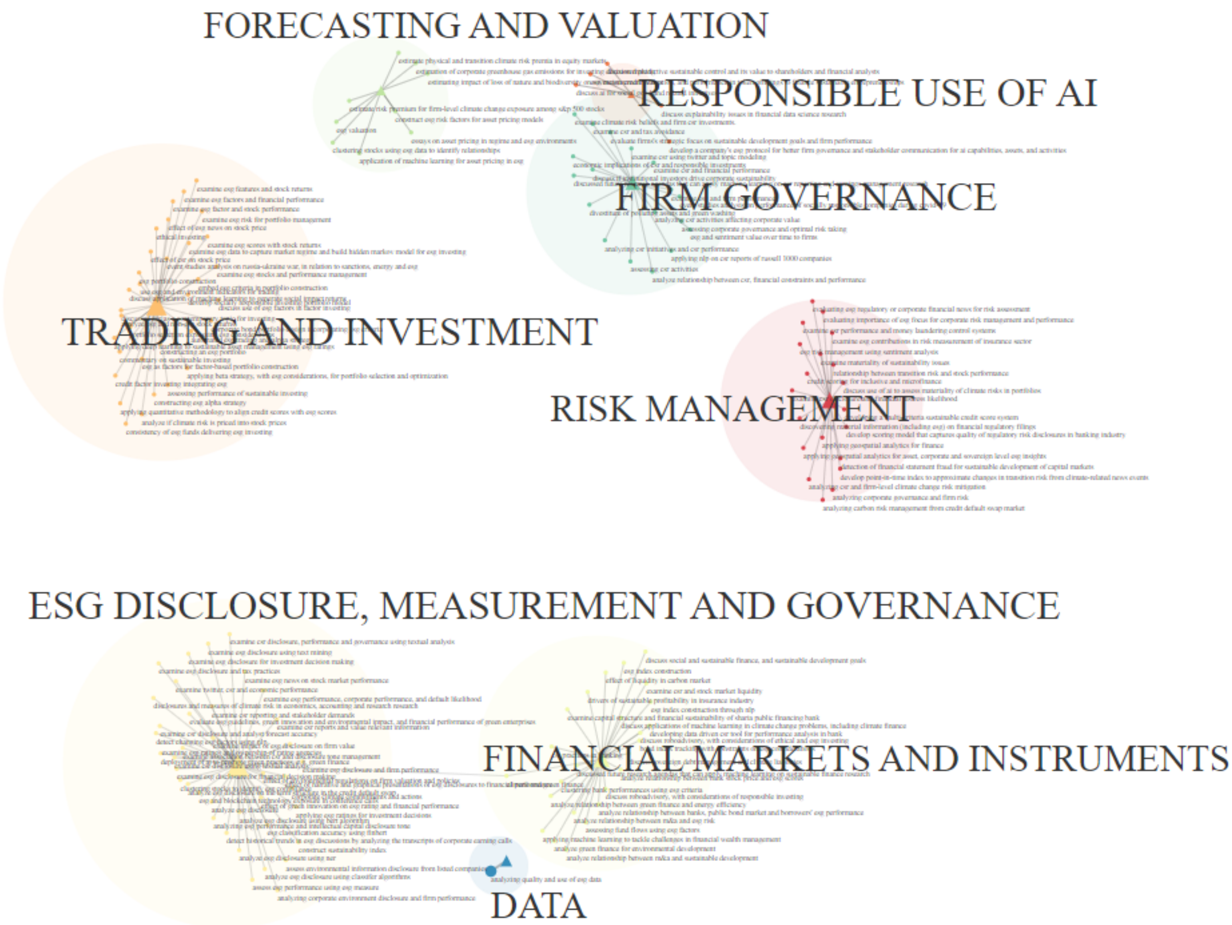

Figure 2

Network analysis of ESG and AI in Finance

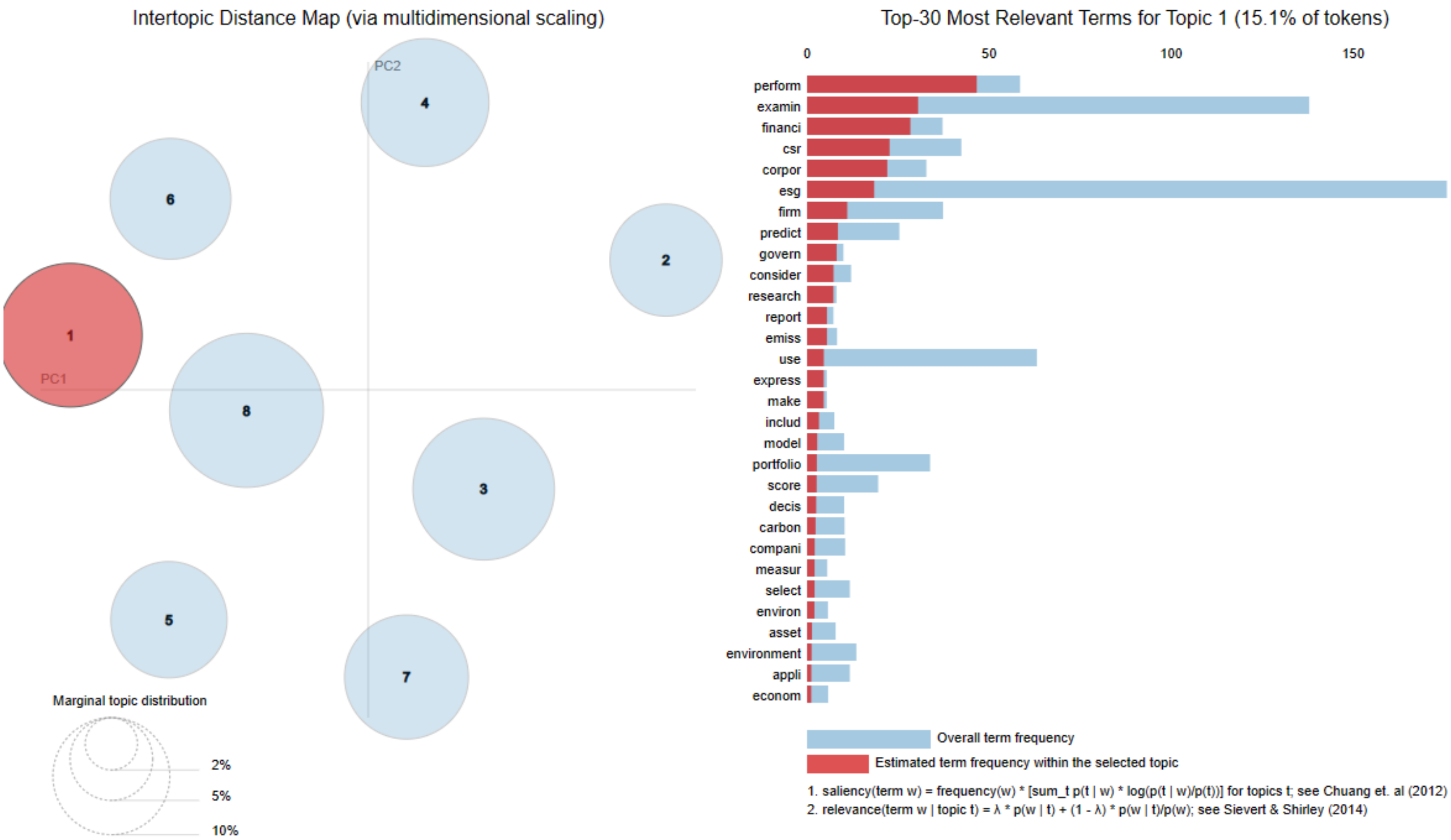

Figure 3

Topic modelling of keyword corpuses

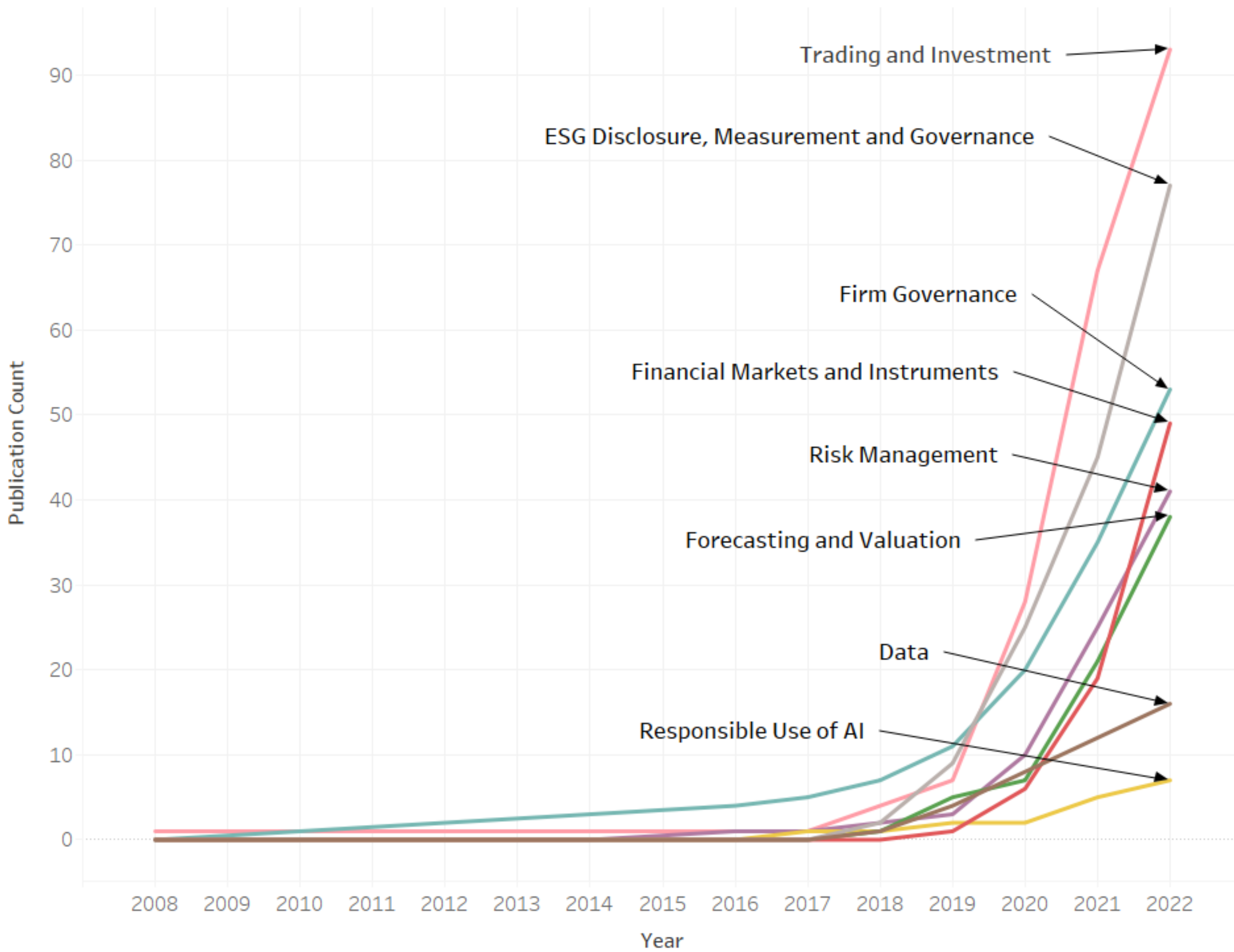

Figure 4

Total publication count by research thematic areas between 2008 and 2022

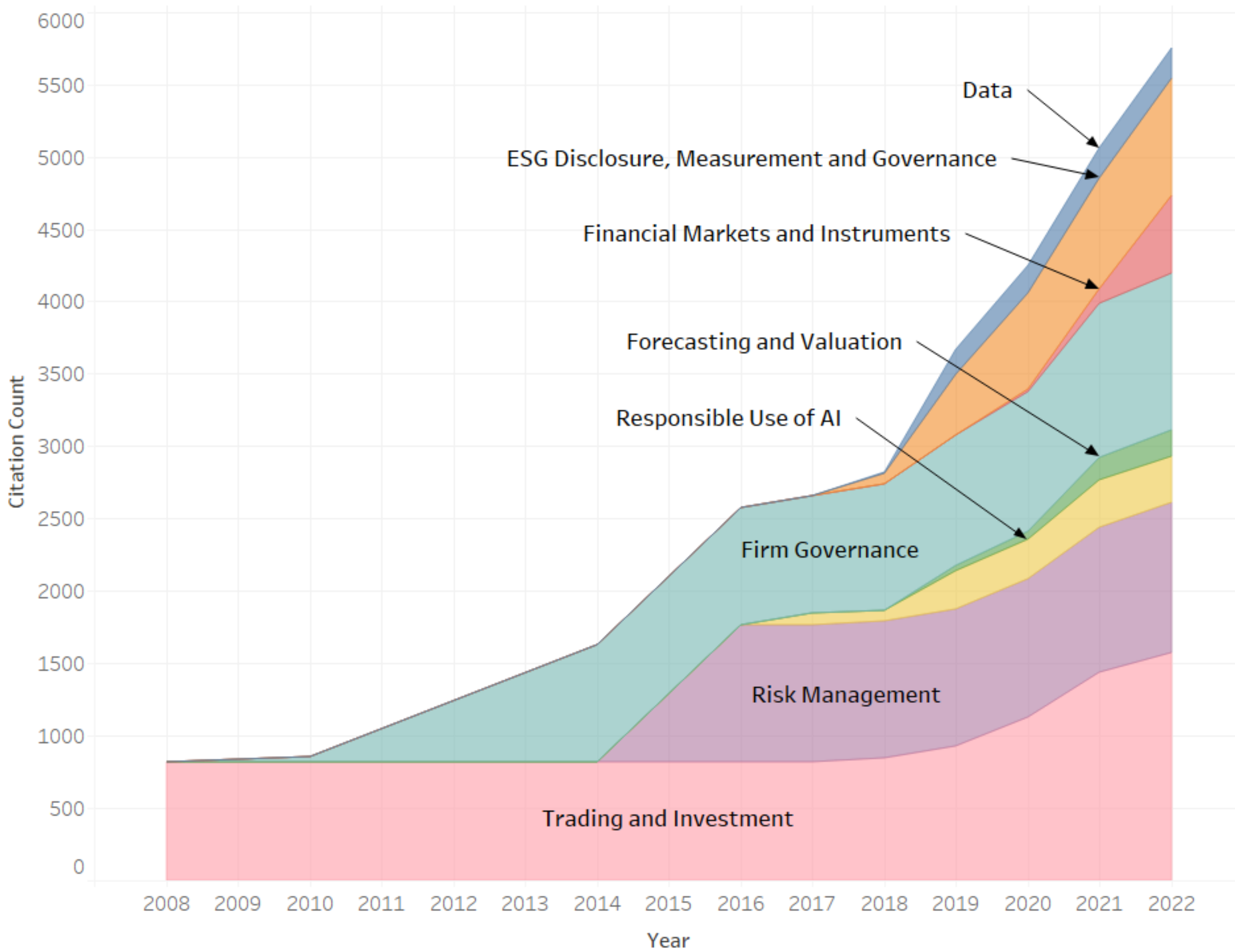

Figure 5

Total citation count by research thematic areas between 2008 and 2022

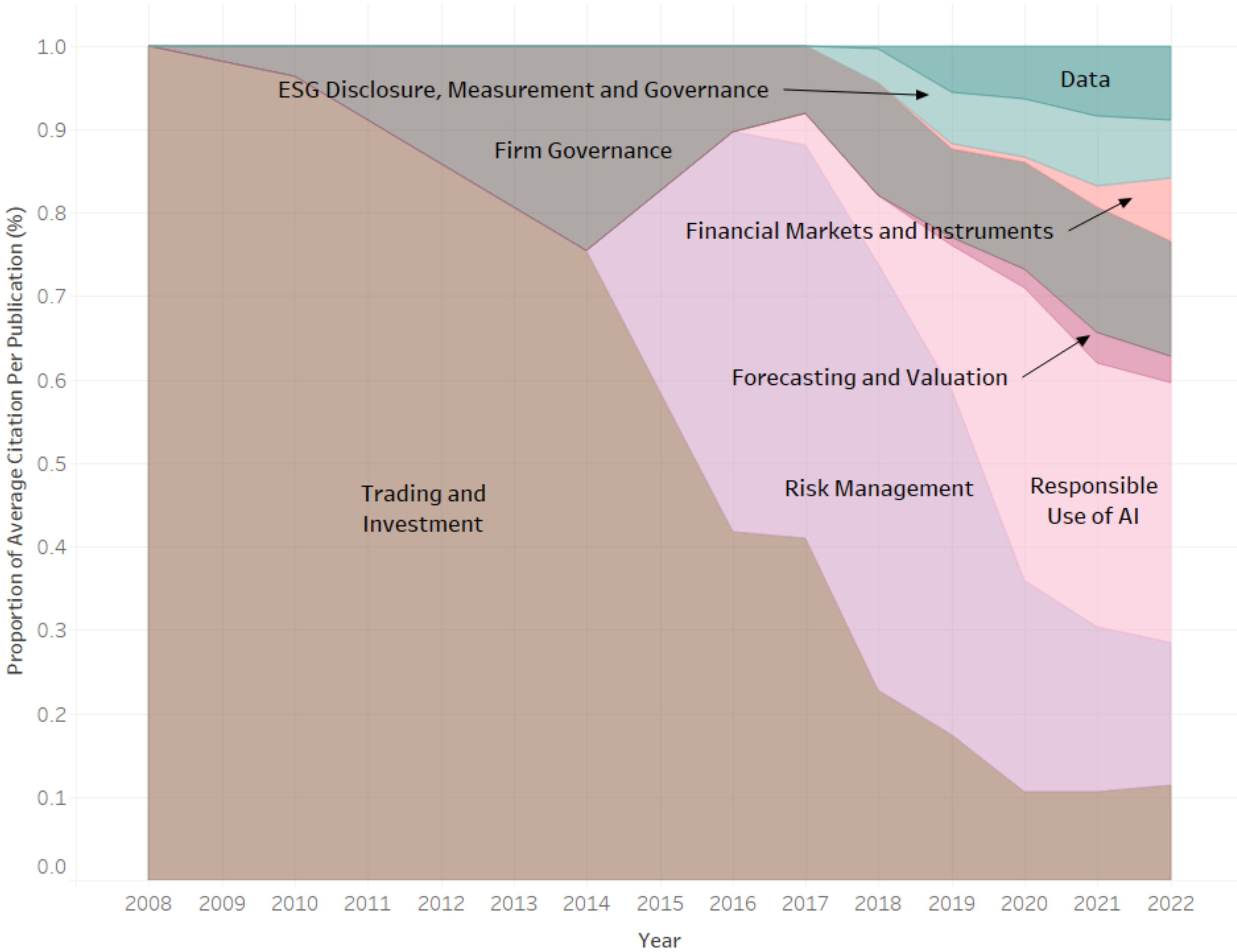

Figure 6

Average citation count per publication by research thematic areas between 2008 and 2022

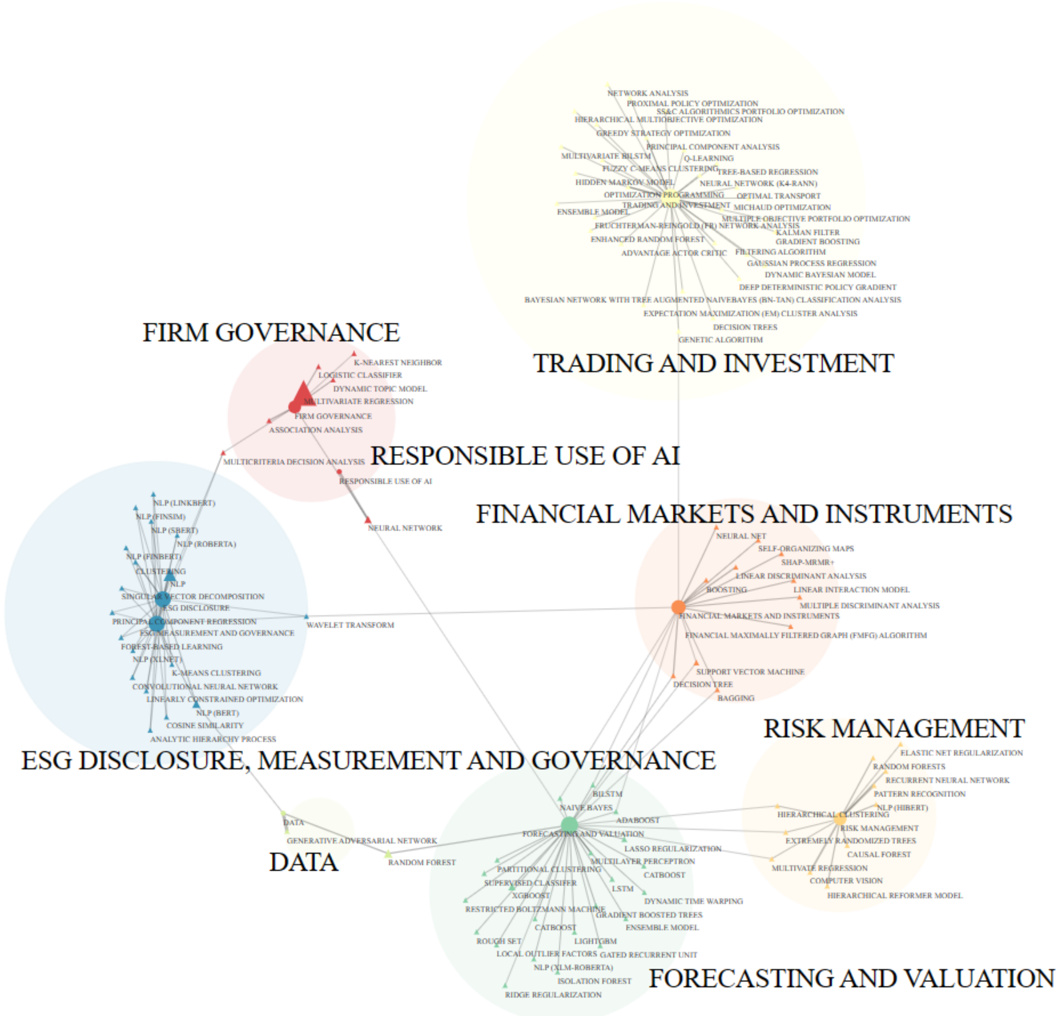

Figure 7

Network analysis on research archetypical domains and AI techniques

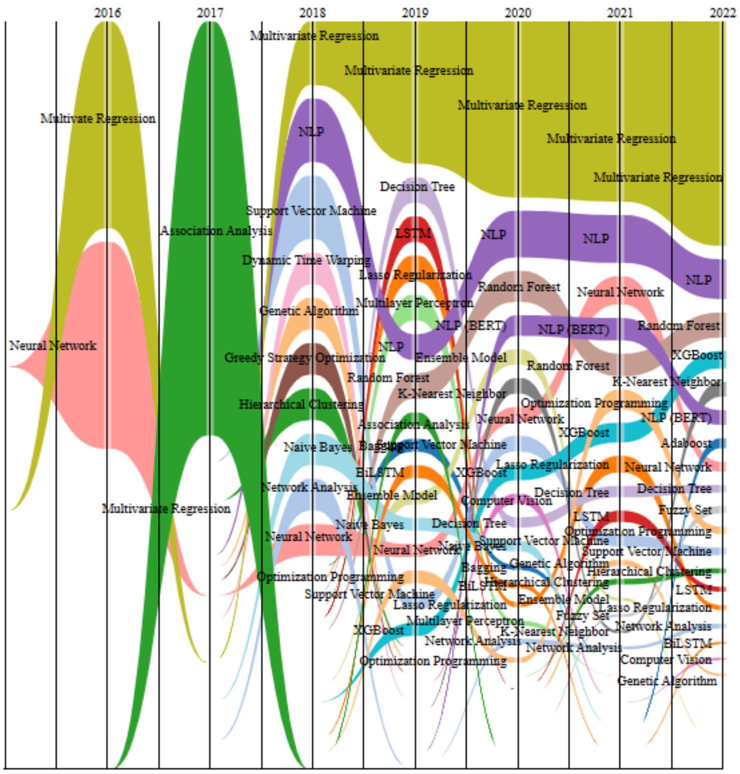

Figure 8

Bump graph analysis of dominant AI techniques across time

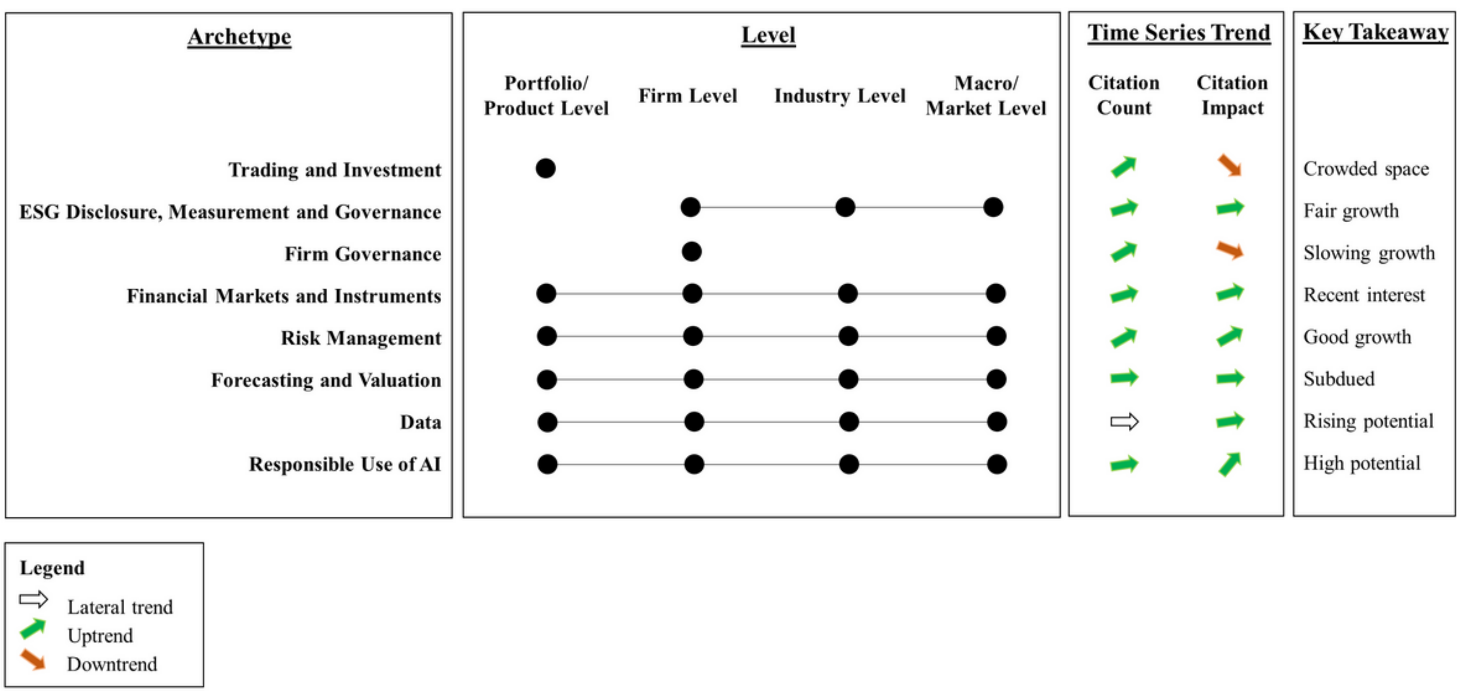

Figure 9

Summary of takeaways