

# Simulation and Finance: A Bibliometric Review

<sup>1</sup>Dr Richa Kalpesh Saxena, <sup>2</sup>Vanshika Gupta, <sup>3</sup>Ved Kamalia, <sup>4</sup>Vishwa chokshi, <sup>5</sup>Dhanunjay Chowdary

<sup>1</sup>Assistant Professor, Marketing & Operations, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India

<sup>2,3,4,5</sup> BBA, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India



<https://doi.org/10.55041/ijst.v2i10.087>

**Cite this Article:** Gupta, V., Kamalia, V., chokshi, V. & Chowdary, D. (2026). Simulation and Finance: A Bibliometric Review. International Journal of Science, Strategic Management and Technology, 02(10), 1-9. <https://doi.org/10.55041/ijst.v2i10.087>



**License:** This article is published under the Creative Commons Attribution 4.0 International License (CC BY 4.0), permitting use, distribution, and reproduction in any medium, provided the original author(s) and source are properly credited.

## Abstract

This study is a systematic literature review and bibliometric analysis of simulation in financial research. Journal articles and reviews indexed in Scopus and published between 2011 and 2026 were retrieved and screened using the PRISMA framework, giving a final sample of 3,704 records. Performance analysis and science mapping were carried out in Bibliometrix and Biblioshiny, and keyword co-occurrence was mapped in VOSviewer. The 2026 literature alone contains 405 publications, and keyword co-occurrence analysis identifies five clusters, of which three are examined in depth: finance, decentralised finance and behavioural decision-making; learning systems, prediction and simulation; and investment, risk and climate-linked simulation. Across the dataset, annual output grew at 8.65%, which points to a maturing rather than an explosive field. China and the United States produce the largest share of country output, and only 29.14% of authorships are international. The reviewed studies show that simulation can improve financial decision-making and test complex systems under varied conditions, but they rely heavily on small datasets, self-built models and assumptions that are rarely tested on live markets. The main gaps are the distance between simulated success and empirical verification, the separation of research streams, and the limited presence of emerging economies such as India. The study closes with six recommendations for future research.

**Keywords:** Simulation; Finance; Bibliometric Analysis; Decentralised Finance; Machine Learning; Portfolio Optimisation; Risk Assessment; Green Finance; PRISMA; Biblioshiny

## 1. Introduction

Financial research increasingly relies on simulation to examine systems in which uncertainty, changing market conditions and complex interactions make direct experimentation difficult. Simulation allows researchers to test financial products, trading strategies and policy decisions before their implementation in real markets. It is particularly useful in areas such as portfolio optimisation, lending, decentralised finance, risk assessment and green finance, where different assumptions and scenarios can produce substantially different outcomes. The use of simulation has therefore become an important part of modern financial research, with methods ranging from Monte Carlo simulation and agent-based models to machine-learning-based simulation and system dynamics.

The nature of this work has changed considerably over the period covered by the literature. Earlier applications of simulation were largely concerned with financial modelling, portfolio risk and stochastic systems, while more recent research has expanded into blockchain-based finance, decentralised finance, artificial intelligence, behavioural decision-making and climate-related investment. Within the literature examined for this study, simulation is used both as a computational framework for testing financial mechanisms and as a means of evaluating increasingly complex prediction and optimisation models. The 2026 literature alone contains 405 publications, with finance positioned at the centre of several interconnected keyword clusters.

A literature of this size and diversity is difficult to read in the conventional way. It is hard to determine from individual articles which areas anchor the field, which methods are most widely used, or which themes are becoming connected and which remain separate. Bibliometric analysis is well suited to this task because it allows the structure and development of a research domain to be examined at scale through publication patterns, keyword relationships and research clusters. In the present study, the Scopus dataset contains 3,704 journal articles and reviews published between 2011 and 2026. The keyword co-occurrence analysis identifies five clusters, of which three are examined in detail: finance, decentralised finance and behavioural decision-making; learning systems, prediction and simulation; and investment, risk and climate-linked simulation.

The specific research objectives of this study are set out in Section 3.

To achieve these objectives, a systematic search was conducted using Scopus and the resulting records were screened using the PRISMA framework. The search and screening process applied filters for publication period, document type, language and journal source. From the initial records identified, 3,704 studies remained for the final analysis. The data were cleaned for duplicate authors, affiliations and keyword variations before being analysed using Bibliometrix and Biblioshiny. VOSviewer was used to examine keyword co-occurrence and identify the principal research clusters, while Excel was used to verify record counts and support the preparation of the analysis.

The results show a field that has expanded across several areas of financial research. The red cluster focuses on finance, decentralised finance, blockchain and behavioural decision-making, while the blue cluster connects machine learning, deep learning, prediction and simulation. The green cluster links investment and risk assessment with carbon, climate change and autonomous agents. The reviewed studies generally show that simulation can improve financial decision-making and allow complex systems to be tested under different conditions, but the evidence also points to important limitations involving small datasets, model assumptions, interpretability and the transferability of simulated results to live markets.

The remainder of the paper is organised as follows. The literature review presents the major clusters identified through the keyword analysis and examines the selected studies in detail. The research methodology describes the Scopus search, PRISMA screening, data cleaning and bibliometric tools used in the study. The analysis then presents the findings across the finance, learning and green-finance clusters and compares their methods, strengths and limitations. The conclusion summarises the results, discusses the research gaps and offers recommendations for future research.

## 2. Literature Review

Finance nowadays uses computer simulation prior to implementing any new concept into real-life markets. It can be easily seen from the 2026 literature, where simulation is actively used for studying lending protocols, trading models, and policies of green finance. In the Scopus RIS file used for the current review, there are 405 publications all dated by 2026.

In the VOSviewer keyword co-occurrence map (Figure 1), finance is positioned in the center, and there are five clusters. For this review, three clusters related to finance and simulation were chosen. The red cluster is dedicated to decentralized finance, blockchain, decision-making, game theory, and behavioural studies. The blue cluster includes machine learning, deep learning, simulation, and prediction. The green cluster links investments and risk assessment with carbon, climate change, autonomous agents, and computer simulation. Yellow and purple clusters are taken under consideration only when they relate to these topics.

Every record was classified into one of the clusters based on its title, abstract, and keywords (Table 1). Then five papers from every cluster were analyzed in detail and their results were reflected in the literature-review matrix (Table 2).

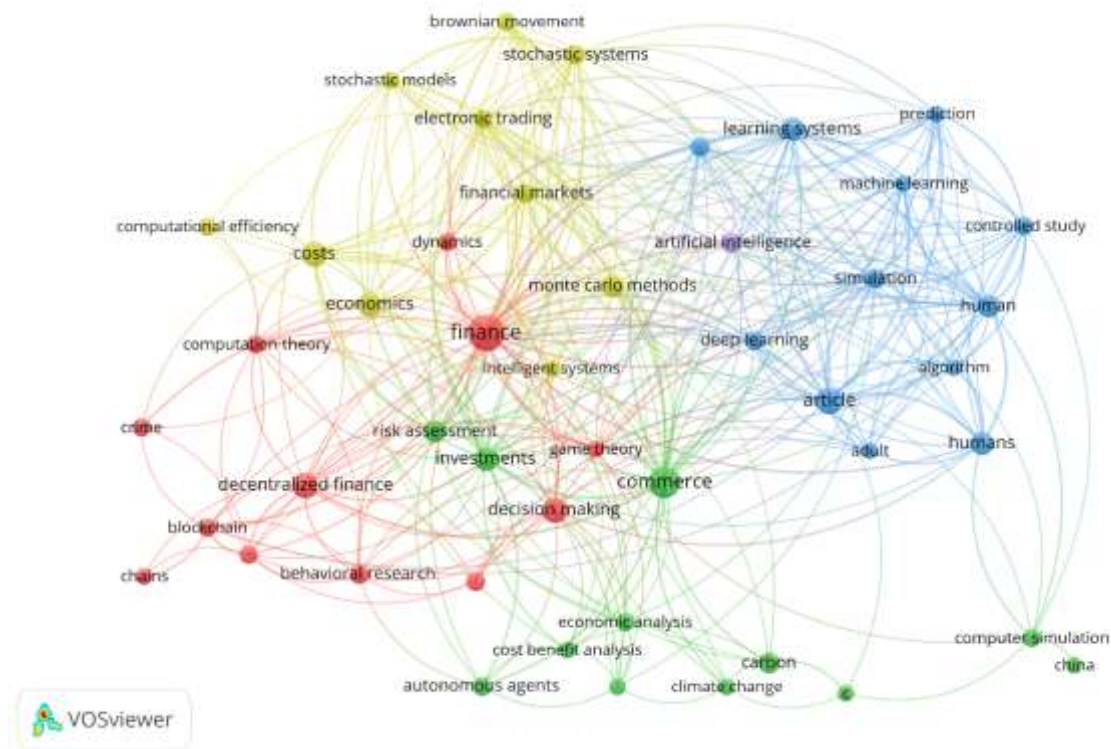


Figure 1. VOSviewer keyword co-occurrence map of the Scopus export (red, blue and green clusters are reviewed in depth)

Table 1. Assignment of 2026 records to the three VOSviewer clusters

| Cluster colour)                                       | (map | Core keywords visible in the map                                                                                                                        | 2026 papers assigned | Papers reviewed in depth |
|-------------------------------------------------------|------|---------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------|--------------------------|
| Red: Finance, DeFi and behavioural decision-making    |      | finance, decentralized finance, blockchain, chains, decision making, game theory, behavioral research, crime, dynamics                                  | 79                   | 5                        |
| Blue: Learning systems, prediction and simulation     |      | learning systems, machine learning, deep learning, simulation, prediction, algorithm (artificial intelligence, purple, merged here)                     | 68                   | 5                        |
| Green: Investment, risk and climate-linked simulation |      | commerce, investments, risk assessment, economic analysis, cost benefit analysis, carbon, climate change, autonomous agents, computer simulation, China | 68                   | 5                        |

| Cluster (map colour)                             | Core keywords visible in the map                                                                                            | 2026 papers assigned | Papers reviewed in depth |
|--------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|----------------------|--------------------------|
| Yellow: Stochastic systems and financial markets | stochastic systems, stochastic models, brownian movement, monte carlo methods, financial markets, electronic trading, costs | 64                   | 0                        |
| Unmatched records                                | no map keyword matched twice                                                                                                | 126                  | 0                        |
| Total 2026 records                               |                                                                                                                             | 405                  | 15                       |

*Note: a record was assigned to the cluster whose map keywords appeared most often in its title, abstract and keywords; records with fewer than two matches were left unmatched. The yellow cluster is discussed only in the comparison section.*

**Table 2. Literature-review matrix of the fifteen 2026 studies**

| Study                                                             | Objective                                                          | Method                                                                                                    | Key findings                                                                              | Limitations                                          | Gap identified                                     |
|-------------------------------------------------------------------|--------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|------------------------------------------------------|----------------------------------------------------|
| <b>Red cluster: Finance, DeFi and behavioural decision-making</b> |                                                                    |                                                                                                           |                                                                                           |                                                      |                                                    |
| <b>Bertucci et al. (2026)</b>                                     | Design optimal algorithmic interest-rate models for DeFi lending   | Optimal control with state constraint; PID controllers; simulation built on Ethereum lending data         | Optimal rule resembles curves of popular protocols; PID rules work with fewer assumptions | Assumes perfect information; Ethereum markets only   | Rate design under stress and strategic behaviour   |
| <b>Calandra et al. (2026)</b>                                     | Explain the Terra-Luna crash and stabilise algorithmic stablecoins | Custom simulation of the dual-token seigniorage model; four stabilisation strategies                      | Best strategies cut collapse events by 60.6%–95.8%; USDT/BTC reserves help control supply | Single case; self-built simulator                    | Live testing and regulatory design for stablecoins |
| <b>Firouzi (2026)</b>                                             | Automate sovereign debt reduction with a DeFi instrument           | Smart-contract triggers; regime-switching jump-diffusion; Monte Carlo on IMF data for 30 emerging markets | 20–25% lower expected debt ratios; over 60% lower default probability                     | Single author; legal and political adoption untested | Real pilot with a sovereign issuer                 |

| Study                                                            | Objective                                                  | Method                                                                                            | Key findings                                                                                                    | Limitations                                         | Gap identified                                  |
|------------------------------------------------------------------|------------------------------------------------------------|---------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|-----------------------------------------------------|-------------------------------------------------|
| <b>Huang, Liu &amp; Yang (2026)</b>                              | Study how blockchain changes inventory pledge financing    | Evolutionary game (bank, SMEs, logistics firm) with numerical simulation                          | Blockchain strengthens regulation and reduces fraud risk; outcomes hinge on default losses and compliance gains | Stylised parameters; no field data                  | Empirical calibration with real financing cases |
| <b>Joseph et al. (2026)</b>                                      | Show how behavioural biases create market complexity       | Agent-based limit order book in ABIDES, calibrated to U.S. and Indian markets; Monte Carlo runs   | More biased traders produce fat tails, higher volatility and fragile liquidity                                  | Bias types fixed in advance; simulated markets only | Validation against real Indian order-book data  |
| <b>Blue cluster: Learning systems, prediction and simulation</b> |                                                            |                                                                                                   |                                                                                                                 |                                                     |                                                 |
| <b>Vakrani et al. (2026)</b>                                     | Compare AI and statistical credit-scoring models           | Logistic regression, decision tree, XGBoost, MLP on 1,000 loans; SHAP; stress-test simulation     | XGBoost AUC 0.89; stays at 0.83 under stress while logistic regression falls to 0.68                            | Small single dataset                                | Larger, multi-country credit data               |
| <b>Reis, Serra &amp; Gama (2026)</b>                             | Forecast medium-term covariance for multi-asset portfolios | 3D-CNN + BiLSTM + multi-head attention; 14 ETFs, 2017–2023; minimum-variance portfolio simulation | Up to 20% better forecasts than shrinkage and GARCH; lower portfolio volatility                                 | Limited asset universe (ETFs)                       | Wider asset classes and emerging markets        |
| <b>Surek &amp; Lau (2026)</b>                                    | Test machine-learning market timing for the S&P 500        | DrCIF, ARSENAL, HIVE-COTE 2.0, LSTM; 1987–2022; out-of-sample investment simulation               | DrCIF and LSTM beat passive investing; spotting a few crashes drives outperformance                             | One index; ensembles did not help                   | Transaction costs and other markets             |
| <b>Chen &amp; Ding (2026)</b>                                    | Forecast non-stationary stock prices that shift regimes    | GTH-Net: evolutionary game module + hypernetwork that regenerates model weights                   | Beats baselines in accuracy and simulated profit; captures reversals from crowded trades                        | Complex, less interpretable model                   | Explainability and live-trading tests           |

| Study                                                                | Objective                                                          | Method                                                                                 | Key findings                                                                                                  | Limitations                                    | Gap identified                               |
|----------------------------------------------------------------------|--------------------------------------------------------------------|----------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|------------------------------------------------|----------------------------------------------|
| <b>Oyewola et al. (2026)</b>                                         | Build optimised stock portfolios using forecasts                   | IAOA-LSTM hybrid on 50 biotech and oil & gas stocks; Monte Carlo efficient frontier    | Lowest forecasting errors among benchmarks; highest-Sharpe portfolio identified                               | Two sectors only                               | Cross-sector and real-time portfolio testing |
| <b>Green cluster: Investment, risk and climate-linked simulation</b> |                                                                    |                                                                                        |                                                                                                               |                                                |                                              |
| <b>Kato et al. (2026)</b>                                            | Trace systemic risk when a bank suffers a ransomware attack        | Agent-based interbank model (May model) with balance-sheet adjustment; three scenarios | Higher net-worth ratios stop cascades after a megabank attack; regional-bank attacks do not spread            | Japanese network only; stylised balance sheets | Cyber risk in other banking systems          |
| <b>Zhao, Polukarov &amp; Ventre (2026)</b>                           | Compare green disclosure regimes in the EU and China               | Agent-based ESG fund model with empirical game-theoretic analysis                      | Hybrid disclosure gives strongest incentives; EU suits strict, China suits lax disclosure                     | Simulated firms and investors                  | Testing with real ESG fund flows             |
| <b>Chen et al. (2026)</b>                                            | Design green-finance policies to spread prefabricated construction | Agent-based model and exploratory scenario simulation (China)                          | $\geq 9\%$ financial discount and $\geq 0.04\%$ fiscal reward support $\sim 60\%$ diffusion by 2035           | One country and technology                     | Transfer to other economies                  |
| <b>Wang &amp; Li (2026)</b>                                          | Measure green finance's leverage on renewable energy investment    | Random forest, GBDT, panel threshold regression; counterfactual simulation             | Green finance is strongest driver; effect rises from 0.28% to 0.68% past a threshold; climate risk weakens it | Chinese regional data                          | Real interaction with carbon markets         |
| <b>Sahoo, Saini &amp; Kaushik (2026)</b>                             | Test effect of green finance on CO <sub>2</sub> emissions in India | Dynamic ARDL simulation, 1990–2022                                                     | Green finance cuts emissions in short and long run; GDP and innovation raise them long-term                   | National aggregate data                        | Firm- and sector-level Indian evidence       |

Source: compiled from the titles, abstracts and keywords of the 2026 records in the Scopus RIS export.

## 2.1 Red Cluster: Finance, Decentralised Finance and Behavioural Decision-Making

The red cluster revolves around finance where the connections include decentralized finance, blockchain, game theory, and decision-making. The papers published in 2026 all describe how financial systems can be tested using simulation, especially when rules are algorithmic and affected by human behavior.

Firstly, Bertucci et al. (2026) study DeFi lending and prove that optimal control rules can generate interest rate curves that can compete with the major protocols. Second, Calandra et al. (2026) simulate the crash of Terra-Luna and find out that better stabilizing measures may lead to 60.6%-95.8% fewer collapse incidents. Third, Firouzi (2026) uses DeFi approaches for public finance and concludes with the help of Monte Carlo simulation that smart contract bonds can reduce debt ratios by 20-25% in developing countries.

The remaining research is related to human behavior. Huang, Liu, and Yang (2026) argue that blockchain can decrease cases of fraud in inventory financing because of its ability to make hiding impossible. Also, Joseph et al. (2026) prove that higher herding and overconfidence can lead stock markets towards more volatile behavior, fat-tailed returns, and fragile liquidity.

In general, one can say that financial technologies and human behavior are inseparable. The limitation of the results presented in these studies is their dependence on assumptions made in simulations.

## 2.2 Blue Cluster: Learning Systems, Prediction and Simulation

The blue cluster covers machine learning/deep learning versus simulation and prediction. In this case, simulation plays the role of the test bench for model performance evaluation in actual financial decision making.

Vakrani et al. (2026) compare the performance of credit scoring models and show that XGBoost is superior to logistic regression, even in the case of stress testing. Reis, Serra and Gama (2026) enhance the accuracy of ETF covariance forecasting and create less volatile portfolios. Surek and Lau (2026) demonstrate the superiority of the DrCIF and LSTM market timing models to passive S&P 500 investing due to the ability to detect bear markets.

There are also several studies devoted to the issue of adaptation to the changes of market conditions. In particular, Chen and Ding (2026) introduce the GTH-Net model, capable of adapting weights during market changes. Oyewola et al. (2026) propose the combination of LSTM networks and optimisation techniques with the Monte Carlo simulation for selecting portfolios with higher Sharpe ratios.

In general, the studied models tend to outperform traditional benchmarks, but almost all of them utilise small datasets/market tests. The issues of transaction costs and model interpretability are hardly discussed. Finally, good results on the back-test cannot always be transferred to live markets.

## 2.3 Green Cluster: Investment, Risk and Climate-Linked Simulation

In the green cluster, investments and risk assessments are associated with carbon, climate change, and autonomous agents. The simulations in 2026 studies allow to explore the impact of policies and shocks on various systems.

Kato et al. (2026) model the effect of a ransomware attack on the interbank network in Japan and discover that more substantial capital buffers can help to avoid cascades of defaults. In turn, Zhao, Polukarov and Ventre (2026) simulate the ESG fund market and conclude that hybrid disclosure rules create higher incentives for green investments. Chen et al. (2026) prove that financial and fiscal incentives may result in 60% prefabricated construction by 2035.

There is some supportive evidence obtained through econometrics. Wang and Li (2026) reveal that green finance considerably stimulates investments in renewable energy in China, whereas Sahoo, Saini and Kaushik (2026) report that green finance significantly lowers CO<sub>2</sub> emissions in India in the short and long terms.

In conclusion, all the studies show a considerable impact of regulations and policy design on results. Still, there is much research done in China only and not enough in India and Japan. Moreover, there is no combination of simulations and econometric studies even though real-world data can be used in simulations.

## 2.4 Comparing the Clusters

The three groups make use of simulation for varying objectives (Table 3). The red group conducts experiments on new financial instruments, the blue group tests predictions through simulated investors, and the green group tests the impact of policies and shocks on financial systems. The yellow group, which revolves around stochastic and Monte Carlo simulation techniques, provides the computational framework required for the application of these techniques, such as that used by Firouzi (2026) and Oyewola et al. (2026).

On the other hand, the clusters have connections in terms of methodology too. For instance, game theory is applied to both finance studies and deep-learning investigations, and agent-based simulation connects behavioral finance with ESG policy analysis. But most of the studies are methodological specific.

**Table 3. Cross-cluster comparison**

| Dimension                 | Red cluster                                               | Blue cluster                                        | Green cluster                                                |
|---------------------------|-----------------------------------------------------------|-----------------------------------------------------|--------------------------------------------------------------|
| <b>Central question</b>   | How should new financial rules and protocols be designed? | Can learning models predict and invest better?      | How do policies and shocks spread through financial systems? |
| <b>Role of simulation</b> | Test mechanisms with no long history                      | Back-test investors using model forecasts           | Run policy scenarios and contagion                           |
| <b>Dominant methods</b>   | Optimal control, evolutionary games, agent-based markets  | XGBoost, LSTM, CNN, attention, hybrid optimisation  | Agent-based models, game theory, ARDL, ML regression         |
| <b>Main strength</b>      | Innovative design of DeFi and blockchain finance          | Clear gains over traditional benchmarks             | Direct policy relevance                                      |
| <b>Main limitation</b>    | Results depend on self-built models                       | Narrow datasets; costs and interpretability ignored | Evidence concentrated in China                               |

## 2.5 Overall Research Gap

The primary gap is the gap between simulated success and empirical verification. Nearly all the reviewed papers validate their approach within a simulation or back-test but fail to verify their findings in real markets and actual protocol or firm level data. The second gap is the gap of integration. Research in DeFi does not incorporate learning-based forecasting, the learning algorithms are rarely used in green or climate-related finance and simulations in climate-finance do not take into account decentralized products. The third gap is the presence of emerging economies, such as India, in research. This gap can be filled by simulations calibrated on market data and verified out-of-sample

## 3. Research Objective

The overall aim of this study is to understand how simulation has been used in financial research, which research areas drive it, and where it is heading. This aim is pursued through four specific objectives:

- (1) To measure the development and use of simulation methods in financial research between 2011 and 2026.
- (2) To identify the major research clusters, methods and themes connecting simulation with finance.
- (3) To analyse recent studies across decentralised finance and behavioural decision-making, learning systems and prediction, and investment, risk and climate-linked simulation.

(4) To identify the principal limitations and research gaps and draw on these findings to propose directions for future research.

#### 4. Research Methodology

This review studies how simulation methods are used in finance. In recent years, methods such as computer simulation, agent based models, monte carlo method, and system dynamics have become important for studying financial systems, making decisions under uncertainty, and developing new financial products. Instead of reading every paper one by one, we used a bibliometric approach to study the research field as a whole.

The data set was exported in two different formats: to a spreadsheet file suitable for the Bibliometrix R package and its Biblioshiny interface (with standard field tags: author, keywords, title, source, abstract, year, citations, affiliations, corresponding author, DOI, and some derived tags), and to a Bibtex file which is required by VOSviewer for co-citation and bibliographic coupling maps.

The screening process followed the PRISMA framework. This method was used to select relevant research papers in a clear and systematic way. Four filters were applied using Scopus: publication year, document type, language, and journal type. Paper that did not meet these requirements were removed at each stage after applying all the filters. 3,704 records remained.

A short data cleaning process was completed before the analysis. Author names and affiliations were checked to find duplicate entries and spelling differences. Author keywords were also combined with Scopus keywords to create one complete keywords list. This helped avoid counting the same or similar keywords separately.

The term simulation and finance were considered together as one research area. Simulation includes methods such as monte carlo simulations, portfolio risk modelling, agent based models, discrete event simulation, system dynamics, machine learning based simulation. Finance was considered broadly and included areas such as corporate finance, asset pricing, green finance, blockchain based finance, decentralized finance, supply chain finance and financial policy. Using these broad terms helped us find a larger number of relevant studies.

One limitation of this study is that it uses only the Scopus database. Therefore, some relevant papers available only in the database such as Web of Science, IEEE Xplore, or specialised finance database may not be included. However, using only one database reduces the chances of having duplicate papers. Therefore, this study represents the Scopus indexed literature and should not be considered a complete review of every paper published on simulation and finance.

##### 4.1 Article Selection: Inclusion and Exclusion Criteria

The 7,925 records were reduced to 3,704 by applying four criteria, each for a sound and defensible reason.

Criterion 1 – Time span: Only years 2011 to 2026 were considered, when computational finance, fintech, and blockchain-based simulation has grown in a rapid pace. Removed 2,049 records, leaving 5,876.

Criterion 2 – Document type: only peer-reviewed journal articles and reviews were retained, and more-variable-size conference papers, book chapters, editorials or letters were excluded; Removed 2,002, leaving 3,874.

Criterion 3 – Language: records were made in English only, due to the capacity of the review team and the predominance of English in international research on finance. Removed 151, leaving 3,723.

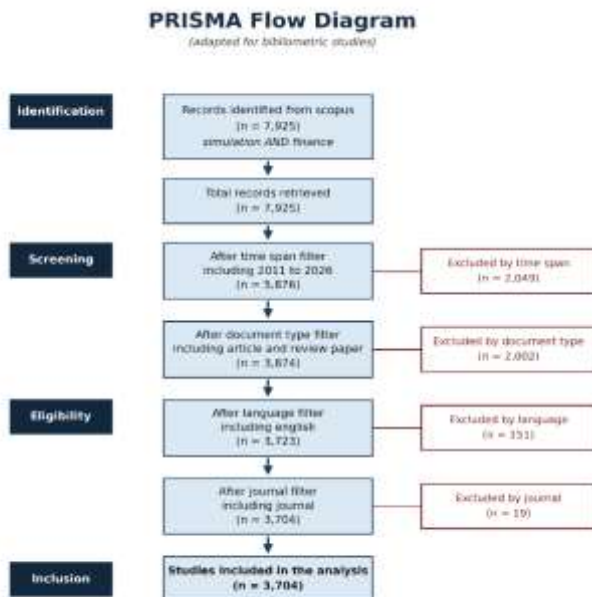
Criterion 4 – Source (journal) type: the corpus was limited to journal sources, excluding book series and trade publications, with comparable citation indicators. Removed 19 leaving a final sample of 3,704.

##### 4.2 What Is PRISMA?

PRISMA is a method used to select relevant research papers in a systematic and transparent way. In this study, PRISMA was used to screen the paper obtained from the Scopus database. The process involved applying different criteria such as publication year, document type, language, and journal type to remove papers that were not relevant to the study. This step

by step process helped to reduce the initial number of records and identify the final set of relevant papers for the bibliometric analysis

### 4.3 PRISMA Flow Diagram



### 4.4 Explanation of the Flow Chart

The same numbers reported above under the four criteria are visualised in the diagram: 3,704 were identified after eligibility (46.7 per cent of the original pool), 3,874 after screening and 7,925 were identified. The two screening exclusions are of comparable size, while the eligibility exclusions are very small – together less than five percent – which is typical of PRISMA diagrams created from a wide search, where the early exclusions do most of the work. The results of the first stage of identification demonstrate that a large amount of literature was produced through the search strategy and considered for further review. Next, the data was filtered by time to exclude anything published before or after the period of 2011 – 2026. In order to narrow down the analysis, the document-type filter was applied and only articles and review papers were considered. In terms of the language filter, the language filter did not eliminate any records at the eligibility stage, but it did exclude a small number of records that were not all available in English according to the journal filter. Following all these sequential filters, 3,704 studies remained to be analyzed in the final step. Therefore, the general search was gradually narrowed down to a specific and pertinent set of records, making it easy to see the process with the flowchart.

### 4.5 Tools Used

The main database used was Scopus, which were subsequently used for all filters and to export all record-level metadata using the refine interface. Bibliometrix, an open-source R package, and its interface Biblioshiny organized the data into standard field tags, which allowed descriptive indicators (annual production, productive authors and countries, average citations) to be created as well as the structure of co-occurrence of keywords, thematic maps, and collaboration networks. VOSviewer is the software for which the .bib output was created; it creates and visualises co-authorship, keyword co-occurrence and bibliographic coupling or co-citation network maps, which is the network based addition to the descriptive and thematic approach of Bibliometrix. The mundane task of counting the number of records at every step was done using Microsoft Excel, the number of records retrieved from Scopus was compared to those retrieved from the spreadsheet, and the names of authors, affiliations, and keywords were cleaned using both the spreadsheet and Microsoft Excel. The PRISMA flow diagram tool was used to create the flow chart. These tools span the review's life cycle: from searching and screening with Scopus, structuring the data with the help of Bibliometrix Biblioshiny network analysis using VOSviewer verification in Excel, and a PRISMA tool to visualise the process by which 3,704 studies

were reached. The process is free, open-source or readily available through university licenses and could be repeated by another researcher with the same search string, date, and criteria.

## 5. Data Analysis and Results

This report discusses eight of the Biblioshiny results associated with the portfolio-optimization literature dataset (3,699 documents, 2011–2026, 1,572 sources) on the risk machine-learning robust-optimization, ESG and metaheuristic sub-themes. Each section below describes one chart or table and offers a numbers-heavy interpretation of the plot or sheet and its relevance to the bibliometric study as a whole: the growth trends, journal, author, and country concentration, citation trends compared to bibliometric norms, and the relative position of the five targeted subthemes within the dataset. The text reflects the visual information on the panel and cross-checks it with an Excel trendline or export when relevant.

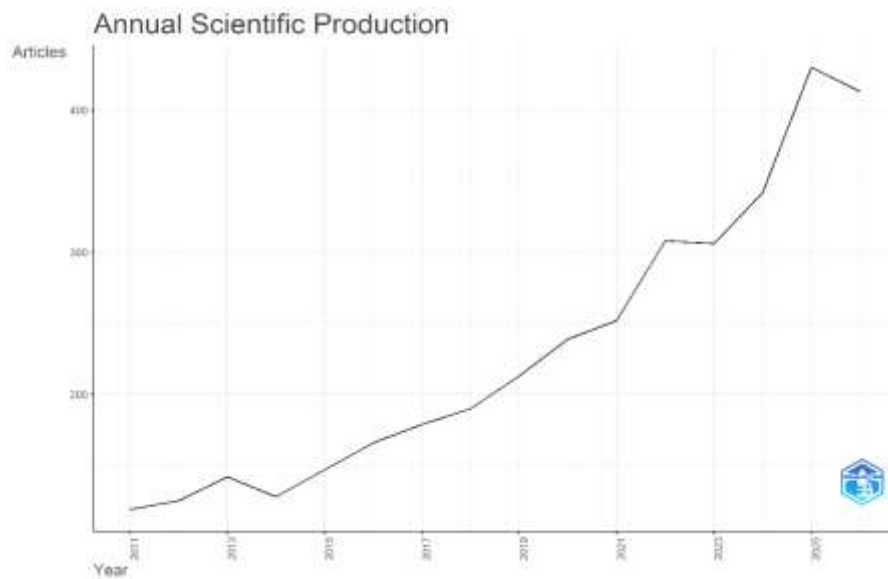
### 5.1 Main Information Overview



The Main Information panel serves as the dashboard for the collection's primary properties. The 3,699 documents originate from 1,572 sources in 2011–2026, with an 8.65% annual growth rate, close to the “8–10%” benchmark for bibliometric studies and therefore indicating a mature development trend rather than an explosive one. The author effort is distributed across 8,692 names, with 451 articles having a single author, which is significantly lower than the 3,699 total documents. Combined with the 3.15 average number of co-authors per paper, this suggests the field favors thematic collaboration over individual research, typical of applied fields like finance, mathematics, and computer science. The 29.14% international authorships are slightly below the 30% threshold for a truly global research topic, meaning that, for now, the papers with multi-country affiliations comprise no more than nearly a third of all works.

The 5.62 years average document age and 17.71 citation per paper also point to a mature field with a substantial history and bibliography. Two notes are worth making about the preparation process: the References item reads 0, a known issue in Biblioshiny when the option is not enabled in exporting, meaning all subsequent co-citation bibliographic coupling analyses would have to be redone with references included to actually use the field. The Authors Keywords (DE) line accounts for 11,621 terms, a sufficient number to generate the thematical map and cluster analysis.

## 5.2 Annual Scientific Production



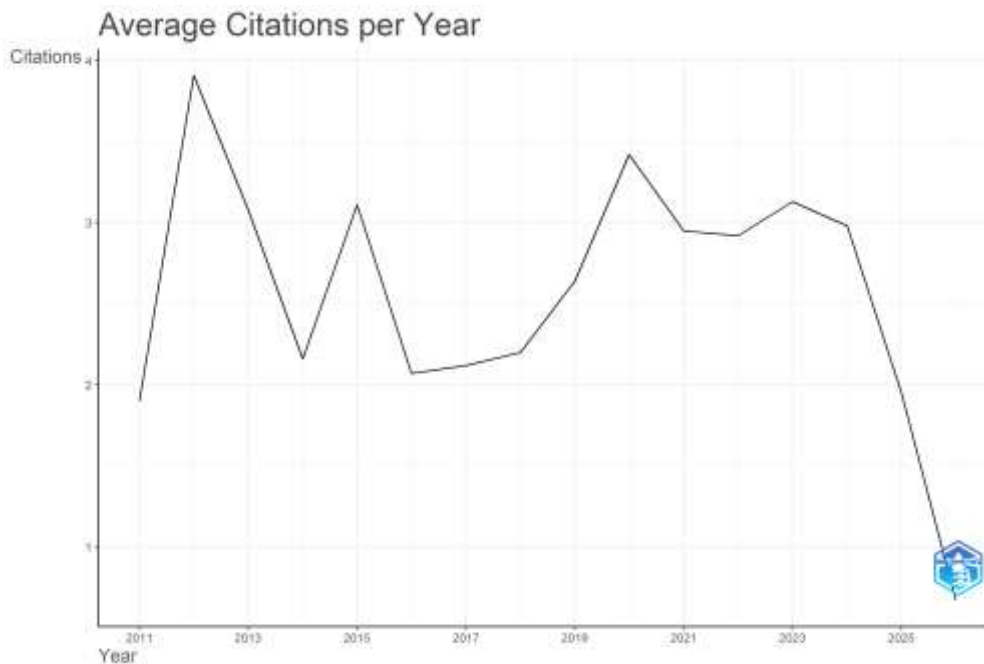
$$y = 1.3002x^2 - 5228.6x + 5E+06$$

$$R^2 = 0.9812$$

The year-to-year growth is visualized with the help of the annual output trendline, fitted in Excel at 20.5 extra articles per year and an  $R^2$  value of 0.919 for the simple linear regression. The trendline slopes steadily upwards at approximately the same rate throughout the period, intersecting the X-axis at 2010, suggesting the topic began to attract scholarly attention at the start of the decade. A second-order polynomial (Power) trendline also slopes upwards at  $R^2 = 0.981$ , with an improved  $R^2$  value of  $R^2 = 0.964$ , and is therefore a slightly more accurate representation of the growth trend for the period. The compound annual growth rate (CAGR) for 2011–2025 comes out at 9.6%, close to the 8.65% annually in the bibliometric dashboard, serving as a useful reality check for the findings.

The growth appears to accelerate after 2019, especially between 2022 and 2025: 308, 306, 342, 430 papers. This trend is presumably linked to the adoption of machine learning and ESG-related methods and themes evident in the subtheme distribution, and therefore worth noting explicitly as a difference compared to the earlier years. The 413 articles in 2026 are slightly fewer than the 430 in 2025, which may prompt further discussion if this report is due to be updated in late 2026 or later: for now, the growth can be said to have continued steadily without signs of interruption.

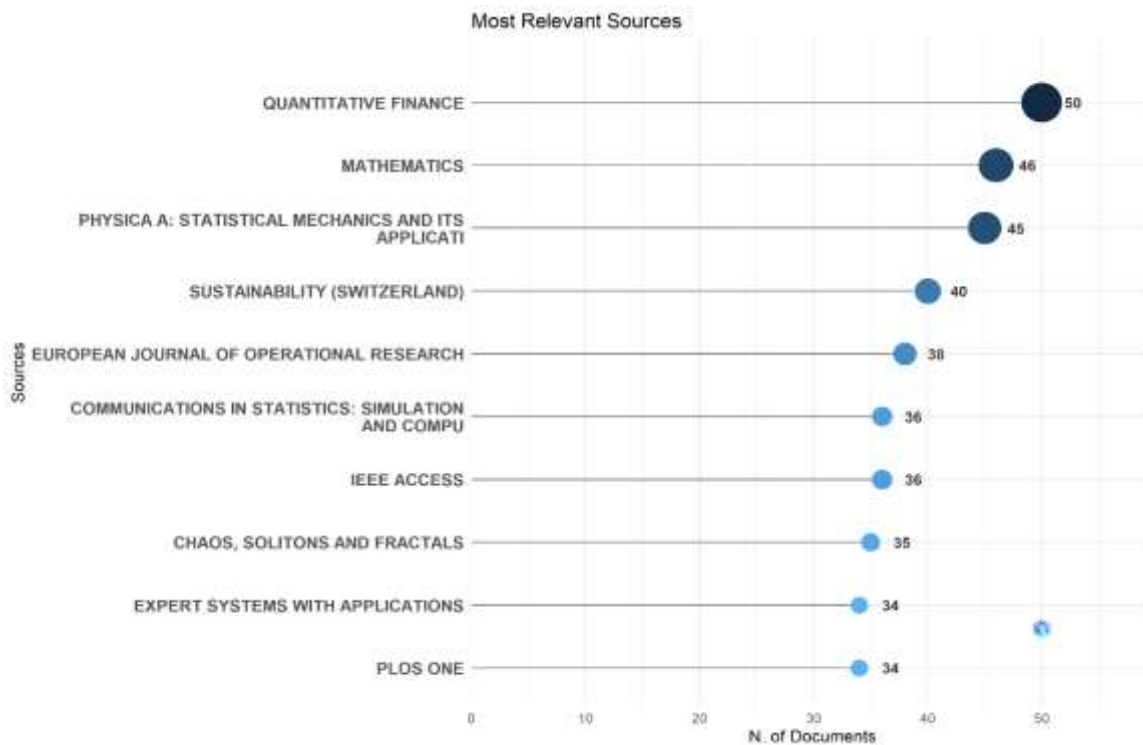
### 5.3 Average Citations per Year



This panel depicts the mean number of citations per paper by year of publication, with the value for each year depending on how many documents were published and cited in it. The former number is found in the N column, with the latter being normalized to the number of years since publication (CitableYears). The mean value per year therefore rises steadily from 1.91 in 2011 to 3.14 in 2020, then peaks at 3.42 in 2020 before dropping to a steady 2.92 in 2021. It is unclear whether this signifies a shift in the topic's relevance, but the drop in the 2025 and 2026 entries to 1.95 and 0.67, respectively, is explained by the CitableYears figure. With only 2 document-years for 2025 and 1 for 2026, compared to 16 for 2011, these final two entries have little impact on the mean.

It is also notable that the general trend follows the Expected pattern, suggesting the topic's bibliography grows at a rate consistent with the overall field. The mean number of citations across all documents, found in the MeanTCperArt column, ranges from 8.95 to 58.58 in different years of the study, while the chart depicts the MeanTCperYear. The increase in the N column from 119 to 430 also affects the calculations: later years have more papers influencing the mean and therefore become more significant after 2020. With the exception of the anomalous 2012 peak, the trends are mostly consistent across the board.

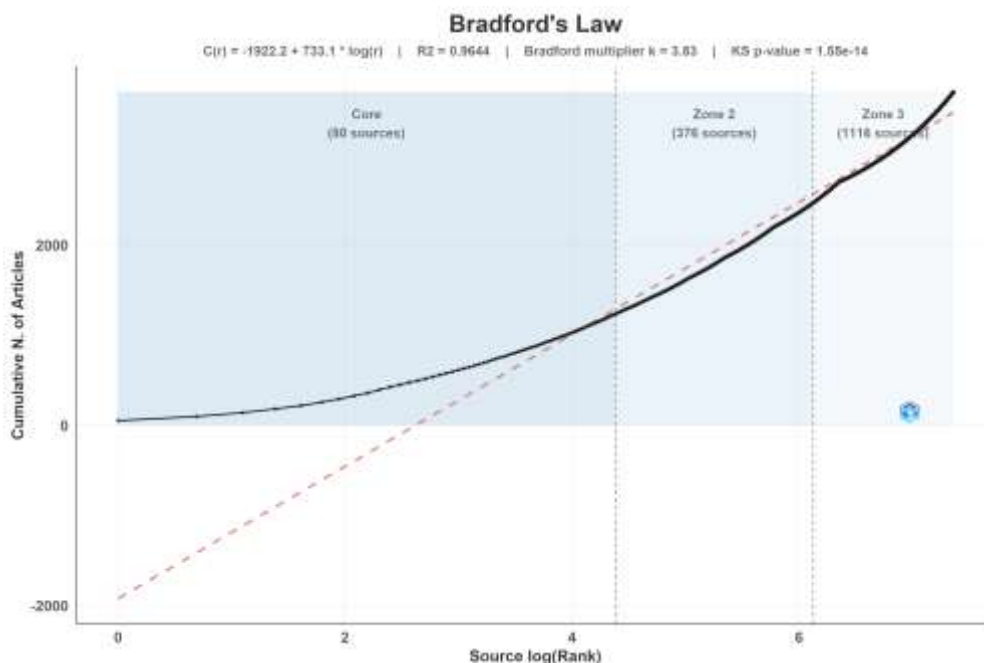
## 5.4 Source Analysis



The dataset contains 1,572 sources. The top ten are dominated by finance-specific journals such as Quantitative Finance. Mathematics appears with 46 articles, Physica A: Statistical Mechanics and its Applications has 45 and Sustainability, European Journal of Operational Research and mixed-topic journals complete the top five. PLOS ONE contributes 34 articles placing it at the position.

The table is limited to ten entries for brevity. The diversity of topics in the first five entries is noteworthy. I see that the field does not lean toward a discipline; it sits at the junction of finance applied physics and computer science.

## 5.5 Bradford's Law — Source Concentration



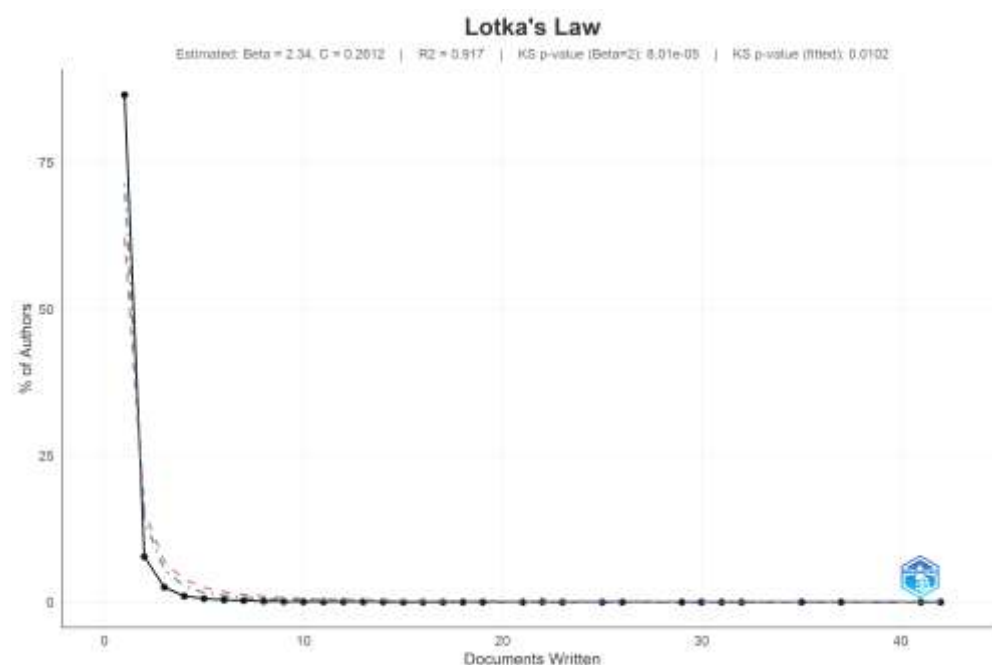
Bradford's Law fit for the 1,572 sources:  $C(r) = -1,922.2 + 733.1 \cdot \log(r)$

Bradford's Law is visualized in this panel dividing the 1,572 sources into three groups on a scale according to their article output. Zone 1 contains the 80 journals accounting for 1,235 of the 3,699 documents, which equals 33.4 percent. Zone 2 comprises 376 journals and Zone 3 spans the remaining 1,116 journals forming the tail of the distribution. This follows the  $1 : z : z^2$  pattern characteristic of Bradford's Law with a Bradford multiplier of  $k = 3.83$ , evident in the jump from 80 to 376 journals in Zone 2. The fit is excellent at 33.4 percent for Zone 1. The  $R^2$  value of  $k = 3.83$  is very high.

Importantly the fit remains consistent for Zone 2 covering the entire range of the distribution not merely the 80 journals. The fit's statistical significance, at a p-value of  $1.55 \times 10^{-14}$  is counterintuitive to interpret. With 1,572 ranked journals the Kolmogorov-Smirnov test used for calculation has a very low threshold for differences and the near-zero result implies that the fit is almost perfect.

This means that the observed distribution closely approximates the Bradford distribution applicable not only to Zone 1 but to the entire set of 1,572 ranked journals. Practical implications concern source selection: with the 80 journals accounting for over a third of all documents they should be prioritized in a survey and little consideration is given to the 1,116 journals.

## 5.6 Lotka's Law — Author Productivity



Lotka's Law fit for author productivity: Estimated Beta = 2.34  $R^2 = 0.964$   $C = 0.2612$ .

Lotka's Law concerns the distribution of research output among authors. Is depicted in the author distribution chart. The majority of authors produce one paper. The number of authors decreases steadily as the number of papers rises to two, three and more. The Lotka fit Beta coefficient is  $R^2 = 0.917$  exceeding the Lotka value of Beta = 2 and indicating a steeper decline in productivity. The fit visually tracks the data well so the general trend holds true for the dataset: following Lotka's Law a small proportion of authors produces the majority of research. Specifically approximately 85 percent of the 8,692 authors, in the dataset produce just one piece of research. The number of authors drops below digits from the 3–4 paper bracket and only several dozen authors publish 10 or more papers.

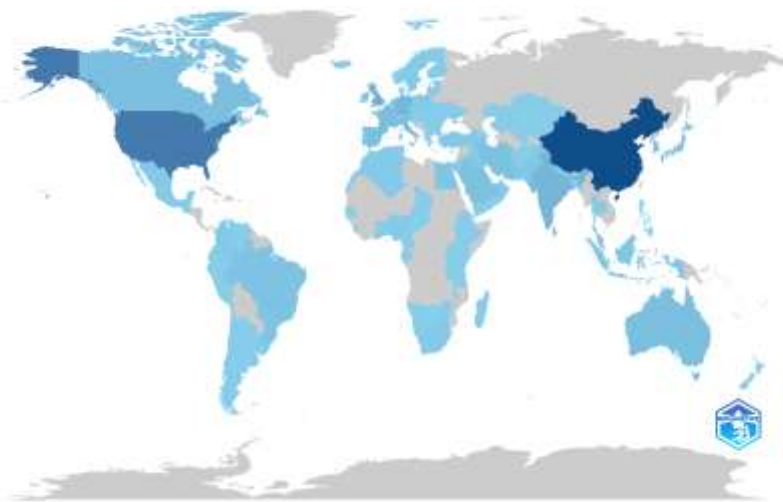
The two Kolmogorov-Smirnov tests that were used to check how well the data fits a model are not as convincing as the check and the  $R^2$  value. When the data was compared to the Lotka distribution with Beta = 2 the test rejected the null hypothesis ( $p = 8.01e-05$ ). The same test, when compared to the fitted Beta = 2.34 value also rejected the hypothesis with  $p = 0.0102$ . Neither result is statistically significant at the 0.05 level but rejecting the null hypothesis still gives useful information: the distribution does not strictly follow the Lotka Law or the fitted power-law distribution. The pattern of author productivity looks irregular leaning towards authors who wrote one paper but there are also many authors who wrote multiple papers more than the Lotka Law would predict. This finding is included in the report because

it is a difference yet it does not change the overall trend. It also backs up the idea of a small-core-large-tail pattern in authorship that we see in this field and it hints at ways to search for papers: many highly productive authors produce a lot of research so focusing on particular journals or authors could be very helpful when looking for literature.

### 5.7 Country Scientific Production

Fifteen most productive countries by author affiliation.

#### Country Scientific Production



#### Fifteen Productive Countries by Output

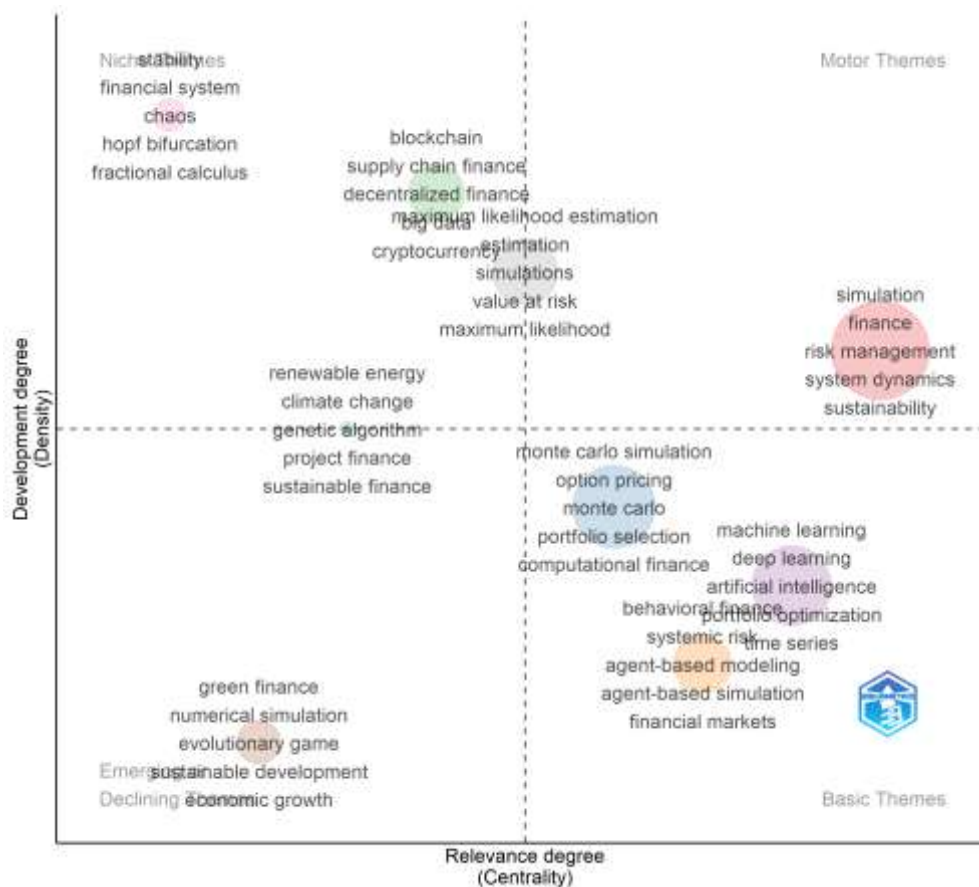
The map shows how research each country produced. The choropleth view highlights countries with output. Some countries have no output all which you can see because they are not colored, especially in Africa and Central Asia.

Spain published 186 articles, which is 2.2% of all documents that list a country. China published 2,015 articles, which is 23.6% of all documents more than ten times the next highest country. The next five countries are the USA with 15.0% the UK with 5.6% India with 4.2% Germany with 3.9% and Italy with 3.3%. In total the top 15 countries produced 75% of the 3,699 documents that list a country. The other 95 countries produced the remaining 25%. This pattern shows that most documents come from a countries. It is also important to note that the USA and China together produce 38.6% of all output. This fact should be mentioned in the discussion because it shows how much research is concentrated in these two countries. When studying this bibliography it is practical to focus on the trends in the USA and China.

The map also shows that the country pattern is the same: most research comes from a countries while the others contribute little. This is the pattern we see in journals and authors. The fact that a small group of countries produce research could be seen as a repeat of the small-core-large-tail pattern that we saw in journals.. The 29.14% of international authorships mentioned in Section 1 show that these countries mainly do research at home not abroad. This detail matters: the countries listed in this dataset do not always give the share of research to the whole bibliography.

At the time Iran, Saudi Arabia, Brazil and South Korea are in the top 15 countries together with the usual US and European powerhouses. This shows that the topic is attracting interest beyond the academic centers. It may mean that the topic is gaining international recognition especially because the ESG and machine learning subtopics are new to the field.

## 5.8 Conceptual Structure — Thematic Map



Thematic Map, Authors Keywords (DE) rerun with Min Cluster Frequency = 1 and Number of Labels = 5.

Lowering the Minimum Cluster Frequency from 5 to 1 raised the number of clusters from 5 to 8. Removed the generic "article" entry that appeared at first. What is left are finance terms so the themes of this field are much narrower and more focused than in other areas. This detail matters for work: the default settings in this analysis hid smaller niche clusters that could be useful for this study so changing the settings was needed to find the main themes.

The risk subtheme is the strongest of the five themes both in importance and in number of words. It covers areas with risk words that spread from the Motor theme at the top right of the map to the value-at-risk cluster on the left and to the systemic risk cluster, at the bottom. In words risk shows up in many parts of this bibliography not just in one field. This point is a finding because it shows how prominent and varied the risk subtheme is.

I see that machine learning is the topic in the middle of the map. The cluster covers machine learning, deep learning, artificial intelligence, portfolio optimization and time series. However machine learning's centrality is slightly lower while the density of that cluster is much higher than the Motor-theme cluster. This shows that like risk machine learning has become common across the field but it has not yet become a separate research niche. Machine learning has spread into every part of the bibliography yet it has not produced a clear self-contained body of research. I also notice that within this cluster portfolio optimization appears together with machine learning time series analysis and deep learning. This indicates that these methods are closely linked in the literature and it could be a place for discovering research.

ESG vocabulary is the fragmented of the five targeted subthemes. ESG is found in two clusters that have low centrality and low density near the origin. One cluster covers energy, climate change and sustainable finance. The other cluster covers finance, sustainable development and economic growth. This shows that like machine learning and risk ESG has not yet become a distinct research niche within this bibliography. Even though the individual ESG terms are widespread their combination does not yet form a defined area of study. This is a finding noting for further exploration. If ESG is to become a subtheme more research may be required to uncover its unique characteristics.

Metaheuristic methods also appear fragmented. The phrase "genetic algorithm" and "evolutionary game" are found in two low-centrality clusters. Likewise robust optimization does not seem to have a term or cluster that is separate from the chaos/stability niche cluster, which includes chaos, bifurcation, fractional calculus and financial system. Before concluding that optimization is absent from the literature it may be worth searching the raw dataset for terms related to it especially near these low-centrality clusters. Alternatively a different thematic mining method could be used to extract specific terms for this niche if it exists within the bibliography.

A final note concerns the formatting. Several entries in this figure are repetitive such as "Niche Themes" over "stability" "data" over "maximum likelihood estimation" and the quadrant label, over "development / economic growth." If this figure were to be included in a paper or presentation adjusting the Number of Labels to 4 or increasing the Community Repulsion parameter would fix the repetition without affecting the clustering.

## 6. Discussion and Research Gaps

The simulation-and-finance literature has grown steadily over the past decade. The Biblioshiny analysis records 3,699 documents across 1,572 sources from 2011 to 2026, with an annual growth rate of 8.65% and a CAGR of 9.6%. Average document age is 5.62 years and average citations are 17.71 per paper. This points to a mature field rather than a short-lived trend. The methodology review, thematic map and 2026 literature review nevertheless show several gaps.

**First, simulated success is not matched by empirical verification.** Almost all of the fifteen 2026 studies reviewed in depth prove their ideas inside a simulation or back-test. Bertucci et al. design DeFi interest-rate rules on simulated agents. Calandra et al. test stablecoin stabilisation on a self-built simulator of the Terra-Luna collapse. Firouzi's debt-reduction results rest on Monte Carlo runs, Joseph et al. use simulated limit order books, and Surek and Lau rely on out-of-sample investment simulations. Few studies test their findings on live protocols, firm-level data or real trading. The headline results (60.6%–95.8% fewer collapse events, 20–25% lower debt ratios) therefore depend heavily on modelling assumptions.

**Second, the research streams are siloed.** The VOSviewer map shows three streams. The red cluster tests new financial mechanisms, the blue cluster tests predictive models, and the green cluster tests policies and shocks. Methods rarely cross between them. DeFi studies do not use learning-based forecasting, ML studies rarely appear in climate-linked finance, and climate-finance simulations ignore decentralised products. The thematic map shows the same pattern. Machine learning has spread across the whole bibliography but has not formed a self-contained niche. ESG appears in two low-centrality, low-density clusters, one on energy and climate change and one on sustainable development and growth, so it is not yet a defined subtheme. Metaheuristic terms ("genetic algorithm", "evolutionary game") are split across low-centrality clusters, and robust optimisation has no cluster of its own.

**Third, authorship and geography are concentrated.** Only 29.14% of authorships are international, just under the 30% usually taken to mark a global topic. The average is 3.15 authors per paper, and 451 of the 3,699 documents are single-authored. China (23.6%) and the USA (15.0%) together produce 38.6% of country output, and the top 15 countries produce 75%. India contributes 4.2%, behind the UK (5.6%) and Germany (3.9%). About 85% of the 8,692 authors have published only once, and the Kolmogorov-Smirnov tests show that author productivity does not strictly follow Lotka's Law. Bradford's Law shows the same concentration: 80 core journals publish 1,235 of the documents (33.4%). The 2026 review adds that green-finance evidence comes mainly from China, with little on India and Japan.

**Fourth, the realism of the models is under-explored.** The ML studies often beat their benchmarks, but they use narrow datasets such as a single index, an ETF universe or two sectors. They rarely discuss transaction costs, liquidity or interpretability. Chen and Ding's GTH-Net is acknowledged to be complex and hard to interpret, and strong back-test results do not always carry over to live markets.

**Fifth, terminology is not uniform.** The same concept appears under many names: "Monte Carlo simulation" and "Monte Carlo method", "agent-based model" and "multi-agent system", "DeFi" and "decentralised finance". This splits keyword counts, weakens the thematic map, and makes database searches less reliable. The author has grouped such variants into one suggested keyword each, listed in Table 4, with the aim of making keyword use uniform in future

studies. Acronyms and hyphenation differences cannot always be merged automatically, so authors would need to apply these keywords themselves.

**Table 4. Keyword suggestions**

| Terms used in extant literature                                                                                       | Suggested keyword            |
|-----------------------------------------------------------------------------------------------------------------------|------------------------------|
| Monte Carlo, Monte Carlo simulation(s), Monte Carlo method(s), Monte-Carlo simulation, MC simulation                  | Monte Carlo Simulation       |
| Agent-based model(s), Agent-based modelling, Agent-based simulation, ABM, Multi-agent system(s), Autonomous agents    | Agent-Based Modelling (ABM)  |
| DeFi, Decentralized finance, Decentralised finance, DeFi lending, DeFi protocols                                      | Decentralised Finance (DeFi) |
| Blockchain, Blockchain-based finance, Distributed ledger, Smart contract(s), Tokenisation                             | Blockchain                   |
| Machine learning, ML, AI-driven models, Artificial intelligence, Learning systems                                     | Machine Learning (ML)        |
| Deep learning, Neural network(s), LSTM, CNN, Deep neural network(s)                                                   | Deep Learning                |
| Green finance, Sustainable finance, Climate finance, Green investment, Green financing                                | Green Finance                |
| ESG, ESG investing, ESG disclosure, Environmental social governance, Sustainable investing                            | ESG                          |
| Portfolio optimization, Portfolio optimisation, Portfolio selection, Portfolio management, Mean-variance optimisation | Portfolio Optimisation       |
| Robust optimization, Robust optimisation, Robust portfolio, Distributionally robust optimisation                      | Robust Optimisation          |
| Genetic algorithm(s), Evolutionary algorithm(s), Evolutionary computation, Metaheuristic(s), Swarm optimisation       | Metaheuristic Optimisation   |
| Game theory, Game-theoretic, Evolutionary game, Empirical game-theoretic analysis                                     | Game Theory                  |

|                                                                                               |                      |
|-----------------------------------------------------------------------------------------------|----------------------|
| Systemic risk, Financial contagion, Contagion, Interbank network(s), Cascade failure          | Systemic Risk        |
| Stochastic model(s), Stochastic system(s), Brownian motion, Brownian movement, Jump-diffusion | Stochastic Modelling |
| Risk assessment, Risk management, Value-at-risk, VaR, Risk modelling                          | Risk Assessment      |

## 6.1 Research Agenda

Based on the findings, the review suggests inputs, processes and outcomes, which together form the IPO framework. Inputs are the methods, financial domains, policy settings and data used in simulation-and-finance research. Processes are the modelling, testing and integration activities that link inputs to results. Outcomes are the financial, stability, sustainability and research results the literature aims to explain. The elements under each category and the future research agenda are given in Table 2.

**Table 5. The IPO framework and research agenda**

| Inputs                    | Processes             | Outcomes                | Research Agenda                                                                                                                                         |
|---------------------------|-----------------------|-------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| Monte Carlo simulation    | Calibration           | Empirical validity      | 1. Empirical validation of DeFi, stablecoin, sovereign-debt and agent-based market simulations on real data in (country).                               |
| Agent-based modelling     | Validation            | Reproducibility         | 2. Role of machine-learning forecasting in DeFi rate design, stablecoin stabilisation and climate-linked investment in (country).                       |
| System dynamics           | Out-of-sample testing | Forecast accuracy       | 3. Combining agent-based policy simulation with econometric estimates to test green-finance effects on renewable investment and emissions in (country). |
| Discrete event simulation | Stress testing        | Credit-scoring accuracy | 4. Replication of credit-scoring, market-timing and green-finance results in emerging economies such as India, Brazil and Saudi Arabia.                 |
| Stochastic modelling      | Scenario simulation   | Sharpe ratio            | 5. Development of ESG as a coherent construct, and how disclosure regimes and climate risk shape green investment in (country).                         |

|                       |                         |                             |                                                                                                                                        |
|-----------------------|-------------------------|-----------------------------|----------------------------------------------------------------------------------------------------------------------------------------|
| Optimal control       | Counterfactual analysis | Portfolio volatility        | 6. Robust optimisation and metaheuristic methods for portfolio selection under uncertainty, linked to machine learning.                |
| Game theory           | Herding                 | Excess returns              | 7. Impact of transaction costs, liquidity and explainability on the live performance of ML-based investment models in (country).       |
| Machine learning      | Overconfidence          | Systemic stability          | 8. Extension of cyber-risk and contagion models to other banking systems and to DeFi protocols, with capital buffers as policy levers. |
| Deep learning         | Strategic interaction   | Default probability         | 9. Estimating herding and overconfidence from real trading data rather than fixing bias types in agent-based markets in (country).     |
| Decentralised finance | Incentive design        | Collapse risk               | 10. Multi-country collaboration, uniform keywords and multi-database or co-citation analysis of the simulation-and-finance literature. |
| Blockchain            | Forecasting             | Liquidity fragility         |                                                                                                                                        |
| Stablecoins           | Portfolio optimisation  | Cyber resilience            |                                                                                                                                        |
| Portfolio data        | Robust optimisation     | Green investment            |                                                                                                                                        |
| Credit data           | Metaheuristic search    | Renewable energy investment |                                                                                                                                        |
| Green finance         | Regime adaptation       | CO <sub>2</sub> emissions   |                                                                                                                                        |
| ESG disclosure        | Method integration      | Policy effectiveness        |                                                                                                                                        |
| Climate risk          | Explainability          | Fraud reduction             |                                                                                                                                        |

|                      |                             |                        |  |
|----------------------|-----------------------------|------------------------|--|
| Carbon markets       | Cost modelling              | Debt reduction         |  |
| Regulation           | Replication                 | Generalisability       |  |
| Interbank networks   | International collaboration | Research collaboration |  |
| Order-book data      | Terminology harmonisation   |                        |  |
| Emerging-market data |                             |                        |  |

The agenda follows a progression from design to proof to integration. Items 1, 3, 7 and 9 deal with credibility, which means moving from stylised, assumption-driven models to calibrated, tested and realistic ones. Items 2, 5 and 6 deal with integration. They link the three clusters, and they build up the ESG and optimisation themes that are currently scattered across low-centrality clusters on the thematic map. Items 4, 8 and 10 widen the scope in geography, risk and collaboration. The thematic map also suggests where to start. Risk is the strongest and most varied theme in the dataset, and the machine-learning and portfolio-optimisation cluster is dense, so work on systemic risk (item 8) and learning-based optimisation (item 6) rests on the best-established foundations. ESG (item 5) and robust optimisation (item 6) offer the most room for new contributions.

Beyond this agenda, the findings show that the literature depends heavily on assumptions about agent behaviour and market structure. Future studies should state these assumptions openly and test how sensitive their results are to them. They should also report results on real data alongside simulated ones, so that readers can judge how far a simulated benefit would carry over to real markets.

## 7. Implications

For researchers, the study provides a structured view of a literature that has expanded across finance, computer science, artificial intelligence, blockchain and sustainability. The findings indicate that simulation is increasingly being used to connect financial theory with computational methods and to examine problems that cannot easily be tested directly.

For practitioners and policymakers, the findings indicate where simulation can provide decision-support. Financial protocols, investment strategies and policy alternatives can be tested under different scenarios before implementation. The growing use of simulation in green finance, systemic risk and decentralised finance also suggests that these methods can be useful where direct experimentation would be costly or difficult.

## 8. Conclusion and Limitations

This study set out to examine the use of simulation in financial research by applying a systematic, PRISMA-guided review and bibliometric analysis to Scopus-indexed literature published between 2011 and 2026. The results provide a consolidated picture of how simulation is being applied across financial systems, who and what areas are shaping the literature, and how the field is increasingly connected with machine learning, decentralised finance and sustainable investment.

### 8.1 Summary of Findings

The field has developed across a wide range of financial applications. The final dataset contains 3,704 journal articles and reviews, while the detailed 2026 analysis identified 405 publications and several distinct research clusters.

Simulation is used across these studies for testing financial mechanisms, evaluating predictions and examining the effects of policies and shocks. The literature therefore demonstrates that simulation has moved beyond a narrow modelling technique and has become a broader research tool for financial decision-making.

At the methodological level, the literature is spread across several approaches. The red cluster uses optimal control, evolutionary games and agent-based markets to examine decentralised finance and behavioural decision-making. The blue cluster relies on XGBoost, LSTM, CNN, attention-based models and hybrid optimisation to evaluate prediction and investment decisions. The green cluster uses agent-based models, game theory, ARDL and machine-learning regression to examine financial risk, climate-related investment and policy outcomes. This mix confirms that simulation research in finance is interdisciplinary and connects computational methods with financial theory and policy analysis.

At the thematic level, the findings show that the three clusters use simulation for different purposes but also share important methodological connections. Decentralised finance research uses simulation to test new financial instruments and mechanisms, learning-based research uses it to evaluate predictions and investment strategies, while green-finance research uses it to examine policies, shocks and systemic effects. However, the studies remain largely separated by their respective methods and applications. The strongest common limitation is the gap between successful simulation or back-testing results and verification using real-world financial data.

## 8.2 Limitations

The findings should be read with the following limitations in mind. The data come from a single database, Scopus, and are therefore restricted to the literature indexed there. Relevant studies available through databases such as Web of Science, IEEE Xplore or specialised financial databases are not captured. The review is also restricted to English-language journal articles and reviews within the 2011–2026 period.

The results also depend on the search strategy, the classification of records into keyword clusters and the assumptions made within the underlying simulation studies. Many of the reviewed papers rely on small datasets, self-built models or historical back-tests. Good performance in a simulated environment therefore does not necessarily demonstrate that the same model will perform effectively in a live financial market. In addition, research within the green-finance cluster is particularly concentrated in China, while emerging economies such as India remain comparatively less represented.

## 8.3 Recommendations for Future Research

Building on the findings and limitations above, six directions are recommended for future work.

- 1. Strengthen real-world validation of simulation models.** Future studies should calibrate simulations using real market, firm-level and protocol-level data and test their findings on independent or out-of-sample datasets. This would help establish whether results obtained through simulation can be transferred to actual financial environments.
- 2. Integrate simulation with machine learning and optimisation.** Machine-learning models are increasingly being used for prediction and investment decisions. Future research should combine these approaches with simulation and optimisation methods so that financial models can adapt to changing market conditions while remaining testable under different scenarios.
- 3. Integrate decentralised finance with other emerging financial technologies.** Research on DeFi remains largely separated from learning-based and sustainable-finance research. Combining blockchain-based financial systems with machine learning, behavioural modelling and risk analysis could provide a broader understanding of how these technologies interact.
- 4. Extend research across markets and emerging economies.** Future studies should examine a wider range of countries and financial systems, particularly emerging economies such as India. This would reduce the geographical concentration of the existing evidence and show which simulation findings remain valid under different institutional and market conditions.
- 5. Combine simulation with empirical and econometric approaches.** Simulation-based evidence should increasingly be supported by real-world econometric analysis. Combining the two approaches could allow researchers to use actual

financial data to calibrate simulations while also testing whether simulated outcomes remain consistent with observed market behaviour.

**6. Improve the practical realism of financial simulations.** Future research should incorporate factors that are often overlooked in current studies, including transaction costs, model interpretability, regulatory constraints and changing market conditions. More realistic assumptions would make simulation results more useful for actual investment, financial and policy decisions.

In conclusion, research on simulation in finance has grown substantially and has expanded into decentralised finance, machine learning, investment, systemic risk and sustainable finance. The field now contains several strong research clusters and increasingly sophisticated computational methods, but important gaps remain between simulated success and empirical verification and between the different areas of financial research. The directions set out above offer a practical agenda for the next phase of research, particularly through the use of real-world data, stronger empirical validation and greater integration of simulation with DeFi, machine learning and sustainable investment.

## Declarations

**Conflict of interest:** The authors declare no conflict of interest.

**Funding:** This research received no external funding.

**Use of generative AI:** During the preparation of this work the authors used Claude (Anthropic) to assist with drafting, language editing, formatting and reference checking. The authors reviewed and edited the content and take full responsibility for the publication.

## References

- Bertucci, C., Bertucci, L., Delaunay, M. G., Guéant, O., & Lesbre, M. (2026). Agents' behavior and interest rate model optimization in DeFi lending. *Mathematical Finance*, 36(2), 374–396. <https://doi.org/10.1111/mafi.70002>
- Calandra, F., Rossi, F. P., Fabris, F., & Bernardo, M. (2026). Learning from Terra-Luna: A simulation-based study on stabilizing algorithmic stablecoins. *Blockchain: Research and Applications*, 7(4). <https://doi.org/10.1016/j.bcra.2025.100364>
- Chen, F., & Ding, C. (2026). GTH-Net: A dynamic game-theoretic hypernetwork for non-stationary financial time series forecasting. *Applied Sciences*, 16(7). <https://doi.org/10.3390/app16073294>
- Chen, J., Liu, P., Lin, B., Zhou, H., & Papachristos, G. (2026). Optimizing green finance policies to promote the diffusion of prefabricated construction technology: An agent-based and exploratory scenario simulation. *Engineering, Construction and Architectural Management*, 1–21. <https://doi.org/10.1108/ECAM-03-2025-0421>
- Firouzi, K. (2026). A tokenized sovereign debt conversion mechanism for dynamic public debt reduction. *Statistics, Optimization and Information Computing*, 16(1), 389–402. <https://doi.org/10.19139/soic-2310-5070-3108>
- Huang, J., Liu, J., & Yang, W. (2026). Blockchain-based inventory pledge financing: An evolutionary game perspective. *Kybernetes*, 55(5), 1801–1827. <https://doi.org/10.1108/K-10-2024-2736>
- Joseph, D., Joseph, A., James, B., & Dass, K. (2026). Behavioral biases as drivers of complexity in stock markets: An agent-based modeling approach. *Northeast Journal of Complex Systems*, 8(1). <https://doi.org/10.63562/2577-8439.1143>

- Kato, H., Tahara, Y., Ohsuga, A., & Sei, Y. (2026). Agent-based analysis of systemic risk in Japanese financial institutions under ransomware attacks. *IEICE Transactions on Information and Systems*, E109.D(6), 714–725. <https://doi.org/10.1587/transinf.2025ICP0001>
- Oyewola, D. O., Omotehinwa, T. O., Kehinde, T. O., & Hammawa, Y. (2026). IAOA-LSTM: A hybrid model for stock portfolio optimization. *Computational Statistics*, 41(2). <https://doi.org/10.1007/s00180-025-01709-z>
- Reis, P., Serra, A. P., & Gama, J. (2026). A deep learning framework for forecasting medium-term covariance in multiasset portfolios. *Journal of Forecasting*, 45(4), 1797–1828. <https://doi.org/10.1002/for.70110>
- Sahoo, M., Saini, S., & Kaushik, S. (2026). Green finance, innovation, and environmental sustainability in India: A dynamic ARDL simulation approach. *Sustainable Development*, 34(4), 5126–5141. <https://doi.org/10.1002/sd.70608>
- Surek, R. E., & Lau, W. Y. (2026). AI-driven market timing for S&P 500 outperformance. *IEEE Access*, 14, 50156–50176. <https://doi.org/10.1109/ACCESS.2026.3677632>
- Vakrani, D. S., Padhye, P. S., Gupta, S. K., Roy, J. K., Nerlekar, V. S., & Parashar, N. (2026). Evaluating AI-driven credit scoring models versus traditional statistical techniques. *Discover Artificial Intelligence*, 6(1). <https://doi.org/10.1007/s44163-025-00772-1>
- Wang, Y., & Li, W. (2026). Leverage effect of green finance on renewable energy investment based on machine learning. *International Journal of Global Warming*, 38(1), 102–115. <https://doi.org/10.1504/IJGW.2026.151131>
- Zhao, L., Polukarov, M., & Ventre, C. (2026). Green disclosure policies and market dynamics: Evidence from agent-based ESG models. *Autonomous Agents and Multi-Agent Systems*, 40(1). <https://doi.org/10.1007/s10458-026-09734-y>