(IJAER) 2022, Vol. No. 24, Issue No. V, November **e-ISSN: 2231-5152, p-ISSN: 2454-1796**

FINTECH RISK MANAGEMENT: CHALLENGES FOR ARTIFICIAL INTELLIGENCE IN FINANCE

Sreedhar Yalamati

Solutions Architect, Celer Systems Inc. Technology Services, sreedharyalamati@gmail.com, CA, USA, 0009-0009-4504-1467

ABSTRACT

Artificial Intelligence in finance largely encompasses the utilization of Artificial Intelligence based techniques within economic enterprises. This field has attracted interest for many years, as evidenced by the general application of traditional AI techniques—like decision trees and linear regression—and modern techniques—like deep learning and reinforcement learning—across progressively larger spheres of the economy, society, and finance. Rather than just listing specific issues, features, and prospects in finance that have profited from these specific AI techniques—especially those arising from the fields of new-generation AI and data science (AIDS)—this review attempts to offer an extensive and detailed road map of the challenging obstacles, methods, and prospects encountered in AI research in finance over the last few decades.

The review begins by describing the circumstances and difficulties specific to financial data and processes. After that, it provides a thorough classification and concise overview of the development of AI research in finance over the previous few decades. This comprehensive classification and synopsis ought to engender trust in the data provided. It then organises and clarifies the processes of learning and data-driven analytics in financial operations. There is a comparison, analysis, and discussion of traditional versus contemporary AI methods designed for the banking industry.

Finally, the review takes a forward-thinking approach by delving into the open issues and opportunities that are balanced to shape the trajectory of future AI-empowered finance and the intersection of finance-driven AI research. This exploration of future opportunities should inspire you to think ahead and consider the potential of AI in finance.

INTRODUCTION

The intersection of artificial intelligence (AI) and finance has captivated researchers for decades. Conventional financial markets, trading, banking, insurance, risk assessment, regulation, and marketing are just a few examples of the traditional fields of AI-driven finance and economics that have given rise to newer forms of financial technology, or FinTech. This evolution has enabled innovative digital currencies, lending platforms, payment systems, asset management solutions, risk analysis tools, and accounting innovations. In this context, "finance" encompasses a broad spectrum, including capital markets, banking services, insurance, investments, risk management, compliance, auditing, and various aspects of financial infrastructure, operations, and ethics. Moreover, the fusion of economics and finance (EcoFin) is increasingly intertwined with the broader AI landscape.

Data science and new-generation AI advances are the main factors behind EcoFin's recent metamorphosis and paradigm shift of Artificial Intelligence and Data Science (AIDS). These developments are transforming and combining media, communication, financial services, technology, and social systems. Logic, statistical modelling, optimisation, expert systems, and other conventional methods are all included in AIDS, along with more contemporary methods like deep learning, machine learning, and quantum computing. These techniques drive surges of revolutionary innovations towards proactive, personalised, intelligent, interconnected, secure, and trustworthy financial goods and services. They also redefine the goals and services of the new era of EcoFin and FinTech.

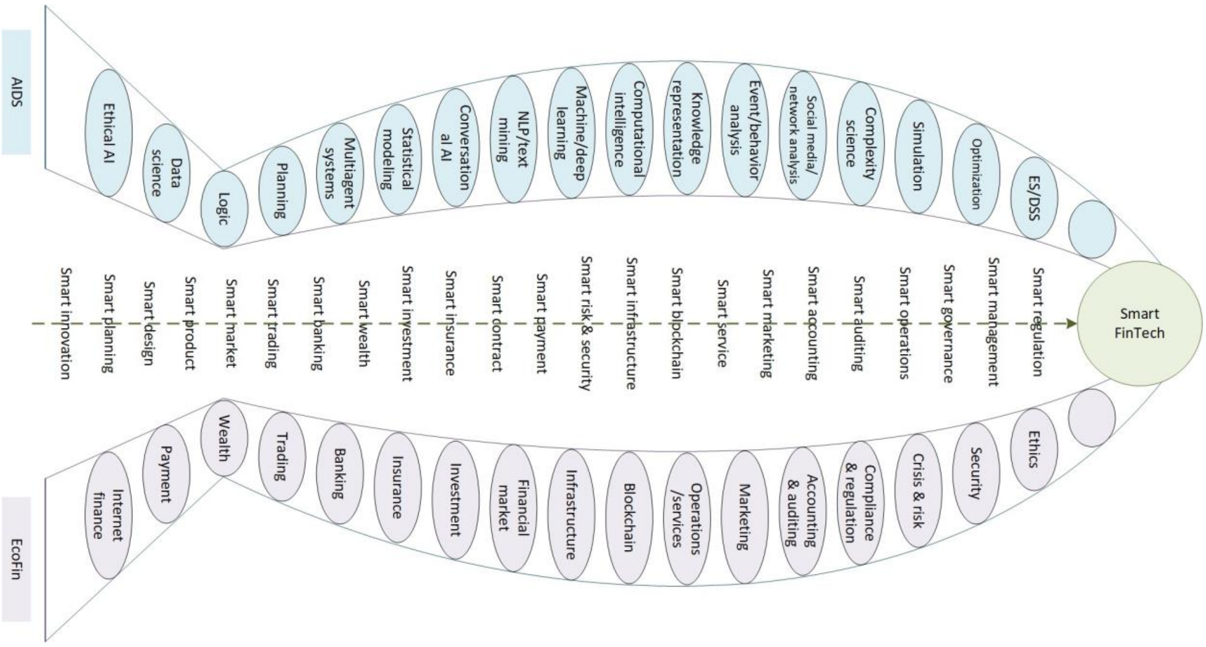

Fig. 1. Intelligent Financial Technology: Combining HIV Methods with EcoFin business

Figure 1 illustrates the symbiotic association of major AIDS techniques and EcoFin businesses and their synergy. The emergence of "smart FinTech" embodies various synthetic areas, including intelligent core business functions, operational enhancements, and future-oriented innovations. Respective AIDS techniques are tailored to imbue these areas with intelligence and automation, giving rise to a spectrum of FinTech domains such as BankingTech, LendTech, WealthTech, and RegTech.

Various review articles examining AI in finance are included in existing research. These papers concentrate on business challenges (fraud detection or market forecasting) or specific techniques/methods (such as machine learning and time series analysis). Still, thorough analyses covering the whole spectrum of methods, enterprises, and their interrelationships must be accessible. Although earlier studies provided insights from the perspective of financial applications, this research adopts a technical approach to present a structured analysis of essential business and data difficulties in finance related to AIDS approaches. It seeks to provide a thorough and detailed overview of the technological ecology of artificial intelligence in finance, making it an invaluable tool for practitioners and scholars.

AI RESEARCH IN FINANCE OVERVIEW

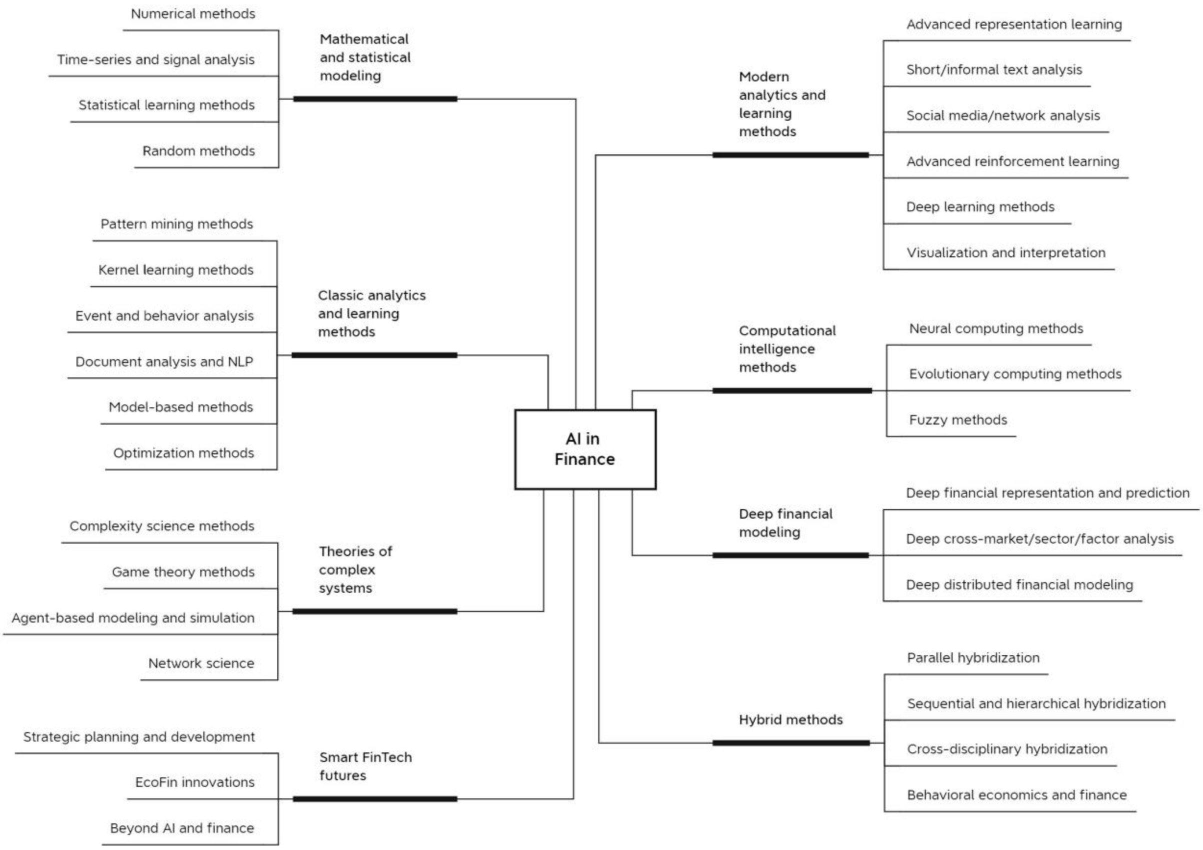

Fig. 2. Data science and AI's Technical Family in Finance.

The range of AIDS methods created to support EcoFin companies and handle their data is vast and constantly changing. These methods cover many business requirements and difficulties, as outlined in [13]. Here, we group the main AIDS strategies for astute FinTech into the following categories and offer succinct descriptions of their pertinent contributions. The general categorization of AIDS in finance is shown in Figure 2:

(a) Mathematical and statistical modelling: This includes statistical learning, random methods, time-series analysis, signal analysis, and numerical techniques.

(b) Complex system methods: This category of techniques, known for their intricate nature, includes game theory, complexity science, network science, and agent-based modelling (ABM), all offering sophisticated solutions to financial complexities.

(c) Conventional analysis and learning techniques: This includes social network analysis, document analysis, natural language processing (NLP), event and behaviour analysis, pattern mining, and kernel learning techniques.

(d) Computational intelligence techniques encompass fuzzy set, evolutionary, and neural computing techniques.

(e) Advanced representation learning, optimisation strategies, deep learning systems, reinforcement learning systems, and visualisation and interpretation approaches are all examples of modern analytics and learning methodologies.

(f) Hybrid methods: This versatile group combines multi-method and ensemble approaches, offering the benefits of both, such as increased accuracy and robustness, making them a valuable tool in analytics and learning.

Table 1 Highlights the use of various Two approaches in EcoFin.

AIDS areas	**AIDS areas**	**AIDS areas**
Mathematical and statistical modeling	Numerical methods	Valuation, pricing, portfolio simulation and optimization, capital budgeting, hedging
	Time-series and signal analysis	Price prediction, market movement, IPO prediction, equity-derivative correlation analysis
	Statistical learning methods	Price estimation, value-at-risk (VaR) forecasting, financial variable dependency modelling, portfolio performance Estimate
	Random methods	Abnormal behaviour analysis, market event analysis, influence transition analysis, associated account analysis
Complex system methods	Complexity science methods	Market simulation, mechanism design, globalization analysis, crisis contagion, market information flow
	Game theory methods	Policy simulation, regional conflict, mechanism testing, and cryptocurrency mechanism testing
	Agent-based modelling	Testing economic hypotheses, simulating policies, supply/chain relations, portfolio optimization

Modeling based on Mathematics and Statistics

Mathematical and statistical modelling is the cornerstone for understanding, formulating, and analyzing EcoFin systems, including their mechanisms, problems, and solutions [1]. Here, we delve into four pertinent techniques widely employed to quantify and analyze EcoFin systems:

(1) Numerical methods: Utilized for building quantitative representations and conducting analyses of EcoFin systems and problems. Applications include Value at Risk (VaR) estimation, option valuation, portfolio optimization, and capital budgeting. Typical methods encompass linear and nonlinear equations, least squares methods, optimization techniques, and Monte Carlo simulation.

(2) Time-series and signal analysis: Employed to characterize, analyze, and forecast temporal movements of financial variables. This involves treating EcoFin indicators as time series and signals to discern patterns, trends, and changes. Techniques encompass state space modelling, spectral analysis, Kalman filter, and nonlinear time-series analysis [6].

(3) Statistical learning methods: Using probabilistic theories to estimate uncertainty, risk, and dependencies within EcoFin systems. Examples include option pricing, portfolio performance forecasting, and modelling sequential trading behaviours. Methods range from random walk models to Bayesian networks and Monte Carlo methods [11, 16].

(4) Random methods: Focus on characterizing EcoFin problems regarding randomness and uncertainty. This involves modelling abnormal market behaviours and global events. Techniques include random sampling, stochastic theory, and random forest models.

Complex Systems Theories

The theory of complex systems finds extensive application in understanding, simulating, and analyzing the mechanisms and complexities of EcoFin systems [12]. Here, we introduce four methods within this framework:

(5) Complexity science methods: Model EcoFin systems as complex entities to comprehend their intricate mechanisms, global economy, and evolution. Techniques include theories of complexities, chaos theory, and agent-based modelling.

(6) Game theory methods: Design mathematical models to analyze interactions, cooperation, and conflict within complex EcoFin systems. This encompasses strategic-form, evolutionary, and Bayesian games.

(7) Agent-based modelling and simulation: Utilized to simulate the dynamics and interactions between entities within EcoFin systems. This approach employs multiagent systems to model complex behaviours and mechanisms [15].

(8) Network science: This field characterizes and analyzes connections and interactions between participants and entities in EcoFin systems using network models. Techniques include graph networks and influence diffusion theories.

Classic Analytics and Learning Methods

Classic analytics and learning methods contribute significantly to enhancing the intelligence of EcoFin systems by analyzing data and identifying patterns. Six essential methods within this category include:

(1) Pattern mining methods: Identify and analyze patterns and behaviours within EcoFin systems, such as arbitrage trading and high-frequency trading strategies [18].

(2) Kernel learning methods: Represent and analyze numerical relations and similarities between EcoFin indicators using kernel functions.

(3) Event and behaviour analysis: This technique characterizes occurrences and behaviours within EcoFin systems, aiding in detecting abnormal events and behaviours [16, 17].

(4) Document analysis and NLP methods: Extract and analyze information from EcoFin documents and news using natural language processing techniques.

(5) Model-based methods: Represent and analyze EcoFin phenomena using hypotheses and models, encompassing numerical computation models and machine learning techniques [8, 11].

(6) Optimization methods: Model and optimize EcoFin systems and problems, ranging from portfolio optimization to algorithmic trading strategies [4].

Computational Intelligence Techniques

Computational intelligence techniques, designed to mirror the operational dynamics of EcoFin systems, are not just theoretical concepts. They are practical tools that can be used to solve real-world problems in the field of finance and economics. These methods, inspired by natural, biological, and evolutionary systems and fuzzy logic, find applications in investment analysis, economic forecasting, portfolio assessment, inflation projection, and more.

Neural computing techniques capture the interrelationships, structures, sequential patterns, transitions, and impacts among EcoFin variables through neural networks, notably DNN, in contemporary contexts. They are utilized for various purposes, such as modelling dependencies between stock prices, market indices, foreign currency, derivative market movements, and macroeconomic factors like petrol and gold prices. Additionally, they aid in detecting irregular market behaviours, anomalies, or fraudulent activities across corporate finance, accounting, insurance, and banking sectors. Neural computing also plays a crucial role in predicting corporate bankruptcy, devising pricing and hedging strategies, algorithmic trading strategies, and analyzing financial reports, announcements, and events. Various neural network architectures are employed, including classic ANN, RNN, wavelet neural networks, genetic neural networks, fuzzy neural networks, and advanced DNN variants like attention networks and Bayesian neural networks.

Evolutionary computing techniques, inspired by biological and evolutionary models, are not just about understanding EcoFin systems. They are about improving their performance. These methods, focused on characterizing, simulating, analyzing, and optimizing EcoFin systems' workings, evolution, interactions, variances, performance, and risks, have the potential to significantly enhance financial outcomes. Applications include the following: estimating and optimising security prices, market indices, exchange rates, and inflation rates; finding trading rules for algorithmic trading; identifying operational problems; assisting with credit scoring and profiling; and multi-objective optimisation in EcoFin. They also find use in simulating and optimising the development and evolution of newly released financial products in markets.

Fuzzy systems and fuzzy sets logic theories are used in fuzzy approaches to define the structures, linkages, and distributions within EcoFin systems. Market momentum, pricing, capital costs, risk, financial solvency, financial structures, the connections between costs and profits between capital costs and economic structures, and multi-objective evolution are all modelled using these methodologies. In addition to hybrid approaches incorporating other models such as fuzzy neural networks, evolutionary fuzzy logic models, fuzzy convolutional networks, and fuzzy rough neural networks, they include fundamental fuzzy approaches based on fuzzy set theories, fuzzy logic, and fuzzy systems.

Modern Learning Methods and Analytics

In recent years, various modern analytics and learning techniques, encompassing new-generation developments of classic approaches, have emerged as focal points for addressing EcoFin challenges. These methodologies span representation learning, short and informal text analysis, social media/network analysis, reinforcement learning, and deep learning. Interested readers are encouraged to explore references [13] and numerous specific surveys and technical papers for comprehensive discussions on the state-of-the-art research topics and advancements in AIDS pertinent to EcoFin.

Representation learning methods in EcoFin aim to understand and model the underlying processes, interactions, structures, and characteristics of financial systems, products, and issues. For instance, they involve creating probabilistic, mathematical, or neural representations of assets, participants, and their interactions in derivative markets. These methods encompass various approaches, including visual models like candlestick charts, probabilistic models such as latent Dirichlet allocation, and graph-based models like Bayesian networks. Additionally, they extend to analyzing sentiment from social media communications about securities. Typical methods include visual, probabilistic, graph-based, and neural techniques [9].

Short text analysis in EcoFin focuses on extracting, analyzing, and categorizing information from social media, SMS, and instant messages related to financial institutions, products, services, and trends. This data complements traditional market data and provides insights into price trends, market sentiment, and customer feedback. Methods range from explicit text understanding techniques like segmentation and classification to implicit analysis methods such as word embedding and contextual analysis using neural models like LSTM and Transformer.

Social media and network analysis delve into characterizing, detecting, and predicting interactions, sentiments, and abnormal behaviours within EcoFin systems. By treating financial systems as social networks, these methods utilize data from social media and messaging platforms to understand the interplay between social communications and market behaviours. Techniques include social media analysis, sentiment analysis, and network science methods, often employing neural language models like BERT and graph neural networks [3, 5].

Reinforcement learning approaches model EcoFin systems as reinforcement processes, optimizing actions, policies, and rewards. Examples include portfolio management, price forecasting, and order routing optimization. Methods range from classic reinforcement learning techniques like Q-learning to deep reinforcement learning methods such as deep Q-networks and recurrent reinforcement learning.

Deep learning methods and intense neural networks provide representations of financial variables and relationships within EcoFin systems. These methods are applied for stock representation, trend prediction, risk assessment, and anomaly detection. Models include CNNs, RNNs, attention networks, and graph neural networks, facilitating tasks like sentiment analysis and financial crisis prediction [20].

Hybrid approaches integrate multiple AI techniques to address complex EcoFin problems, combining methods like expert systems, neural networks, and game theory. These hybrids can be parallel, sequential, hierarchical, or cross-disciplinary, leveraging the strengths of each approach to tackle diverse EcoFin challenges [10, 7].

Analysis of EcoFin time series data serves various purposes and employs diverse methodologies:

1. Learning representations of financial time series, like stock prices, through deep autoregressive models, LSTM, or CNNs. These representations can be trained using labelled historical data to predict future movements.

2. Forecasting tick-by-tick and high-frequency prices by modelling historical price data with RNNs and predicting future prices using regression or recurrent neural networks.

3. Modeling stock price or market index movements using sequential processes such as RNNs, Hawkes, or dynamic Markov processes [16].

4. Predicting stock market indices based on the efficient market hypothesis, time series analysis, artificial neural networks (ANN), or deep neural networks (DNNs).

5. Exploring inter-financial variable couplings and influences by considering variables' couplings, dynamics, and variance, utilizing techniques such as reinforcement learning to enhance portfolio objectives [19].

6. Utilizing quantum-based entropy time series for modelling financial multivariate time series (MTS), calculating the similarity between time series using dynamic time warping, and modelling co-evolving momentum and trends between them.

7. Modeling dependencies between MTS using coupled hidden Markov models, probabilistic models, or DNNs, and conducting time series forecasting via transfer learning across multiple data sources or modalities [16].

8. Analyzing couplings and decouplings between time series and changes and inconsistencies for representing stocks and cryptocurrencies [2, 20]. Additionally, foreign exchange rates can

be modelled through time series and sequence analysis, ANN, or DNNs, and relationships between multi-foreign currency rates can be analyzed as MTS.

Classic EcoFin time series analysis techniques encompass regression, autocorrelation analysis, linear programming, trend forecasting methods, and signal processing techniques like spectral and wavelet analysis, Hawkes processes, and Markov processes. Recent advancements include multiple sequence analysis, nonoccurring sequence analysis, and neural sequence modeling such as RNNs [11, 14].

In the realm of Economic-Financial (EcoFin) text analysis, both long and short texts serve as crucial sources of information. Long texts encompass EcoFin news, announcements, financial reports, and other formal documents, while short texts comprise communication data from call centres, chatbots, social media, and SMS. These texts, whether online or offline, collectively form what we refer to as "economic-financial text."

Analyzing EcoFin text provides insights into various aspects such as fraud detection, event prediction, sentiment analysis, and topic classification concerning financial entities like companies, instruments, products, or services. This analysis serves diverse purposes in financial engineering, economic computing, quantitative analysis, and decision support.

Examples of tasks benefiting from EcoFin text analysis include:

1. Extracting nuanced information, opinions, sentiments, and expert insights about companies, financial instruments, products, or sectors.

2. Extracting knowledge and profiles from mixed-format EcoFin text, which may include text descriptions alongside tables and statistics.

3. Analyzing and predicting asset price or index trends based on textual information and its influence.

4. Assessing the impact of EcoFin text on asset prices, market popularity, and profitability and predicting asset performance accordingly.

5. Evaluating the influence of EcoFin text on a company's branding, reputation, competitiveness, and performance.

6. Classifying and summarizing EcoFin text sentiments and their impact on market movements.

7. Creating embeddings and representations of assets, companies, or financial products based on related textual context and market performance.

8. Identifying risk-sensitive factors, events, entities, and sentiments in the financial text to quantify risk ratings for assets, companies, or products.

9. Analyzing customer communications from call centres, chatbots, and social media to understand market concerns, product feedback, and demand.

10. Extracting quality, performance, and demand-related insights from human conversations and providing tailored recommendations.

11. Categorizing opinions, complaints, sentiments, emotions, and expert insights from social media, news, and discussion groups.

These tasks leverage advanced text analysis, sentiment analysis, discourse analysis, and argumentation summarization techniques to extract meaningful insights from EcoFin text data.

Analysing financial text involves a range of practical methods that span text mining and natural language processing (NLP). These include document clustering, classification, summarization, categorization, concept extraction, and entity relation modelling. We employ statistical models like Bayesian networks, decision trees, and case-based reasoning, along with NLP techniques such as part-of-speech tagging, syntactic parsing, and linguistic analysis. Moreover, topic modelling and sentiment analysis methods, like latent Dirichlet allocation models, are pivotal in our practical approach.

Word embedding models like Word2Vec, Glove, and BERT, along with recurrent neural networks (RNNs) such as LSTM, are not just theoretical concepts, but powerful tools in sequence modeling. These models have the potential to predict the next word in a financial news article, based on the context of the previous words, thereby revolutionizing the field. The advent of newer neural language models, notably Transformer and its variations, have further enhanced this domain, sparking excitement in the field. Attention networks further enhance neural word embedding and language models, making them even more effective in financial text analysis.

When it comes to applying these methods to long versus short financial texts, we see clear distinctions in the content hierarchy. Long texts involve layers spanning words, sentences, paragraphs, and documents. Brief texts, on the other hand, are primarily composed of words and phrases. Furthermore, input length and context variations arise, encompassing pre- and post-sentences and paragraphs. Learning tasks vary as well, depending on whether the focus is on individual words, subsequent sentences, or categorization of the input. This versatility reassures us of the adaptability of these methods to different text lengths.

AI RESEARCH IN FINANCE LIMITATION

AI and Finance Research Distinctions

Despite the extensive research on AI in finance, notable gaps exist stemming from the differing perspectives and objectives of the AI and finance communities. These disparities lead to variations in practices and create voids in research.

There's a burgeoning interest in integrating AI into financial practices within the economics and finance communities, particularly within FinTech. Numerous academic, industrial, and governmental forums and events have been convened to explore AI's applications in finance, including smart payments, blockchain, and Internet finance. Traditionally, these fields have relied on mathematical and statistical models, but now they're incorporating complex system methods, data analytics, machine learning, and computational intelligence into their frameworks. However, several vital disparities persist:

1. Preference for Simplicity: AI techniques in finance tend to be simplistic, prioritizing practical applications over deep understanding.

2. Supplementary Role of AI: AI is often a supplementary tool rather than a primary driver of innovation in finance.

3. Limited Innovations: There are few significant innovations originating from economics/finance-driven AI research.

4. Superficial Understanding: Some applications demonstrate a superficial grasp of AI concepts and methods.

5. Small Data Usage: Financial applications of AI frequently utilize small datasets.

6. EcoFin-centric Evaluation: Evaluation of results focuses on their relevance to economic and financial objectives rather than comprehensive AI evaluation.

Conversely, AI research in finance tends to focus on:

1. Novel Methods and Applications: Emphasizing innovation in AI techniques and their application within finance.

2. Domain Application: AI research in finance often needs deep domain expertise, leading to less domain-friendly interpretations.

3. Limited Contribution to Economic Theories: Little emphasis is placed on how AI advancements contribute to improving economic theories.

4. Data-Driven Abstraction: Problems are often abstracted to fit models or data-driven discovery without strong ties to economic theories.

5. Large Data Utilization: AI research in finance frequently involves large datasets.

6. AI-centric Evaluation: Results are evaluated primarily based on comprehensive AI evaluation measures, with less consideration of financial impact.

This disparity highlights the need for:

1. Interdisciplinary Understanding: Deeper collaboration and understanding between AI and finance communities to foster brilliant FinTech synthesis.

2. Cross-disciplinary Theories: Developing cross-disciplinary theories and tools to enhance innovative finance, economy, and society.

3. Problem-Oriented AI Theories: Creation of economic/financial problems-oriented AI theories and tools tailored to address the complexities of economic and financial challenges.

Table 2. Comparison of Interdisciplinary Practice in AI and Finance.

Comparison	AI communities	Finance communities
Challenges	Issues and challenges related to AI research that are related to or inspired by financial complications and concerns with applications in finance	Financial difficulties and obstacles with the use of AI techniques or AI inspiration
Rationale	Respecting AI culture and ideas while developing AI applications and theories	advancing financial theories and interpretation while adhering to financial culture and philosophies
Data	Large-scale financial and/or economic data that is particularly complex	Compact, easily interpreted financial and economic statistics
Method	AI developments with sophisticated conception and application	Advancements in financial theories or enhanced comprehension of the issue
Evaluation	AI benchmarks, assessment techniques, and metrics	Financial benchmarks, assessment techniques, and metrics
Result	Reaching noteworthy results in terms of statistics and technology, or bringing forth advancements in financial applications	Improved outcomes or additional insights for the financial justification

Table 2 further delineates the disparities between the AI and finance communities regarding problem-solving approaches, data utilization, methodological preferences, evaluation criteria, and result interpretation.

AI-ENABLED INNOVATIONS IN ECONOMIC AND FINANCIAL SECTORS

The emergence of next-generation AI technologies, including machine learning and deep learning, has catalyzed a transformative shift from traditional economic and financial paradigms, which relied heavily on social science theories and methods, towards a new era characterized by deep data analysis and data-driven decision-making. This transition encompasses a wide array of innovation opportunities, from enhancing and redefinition established economic and financial systems, theories, products, and services to creating entirely new systems and solutions that address the complexities of modern economies, financial landscapes, societies, and environments.

In the context of multi-faceted, multi-instrumental, and multi-source economic and financial data, real-world analytical and learning approaches in smart FinTech are evolving beyond traditional whole-object and cohort analyses based on Independent and Identically Distributed (IID) assumptions. Instead, they are adapting to address the intricate complexities inherent in contemporary economic and financial data. This necessitates combining bottom-up (individualistic) and top-down (holistic) approaches, leading to systematic thinking and modelling methodologies. This approach seeks to balance individually tailored yet contextually generalizable results, stationary and non-stationary scenarios, aspect-specific privacy considerations, and systemic openness.

Table 3. The Benefits and Drawbacks of Statistical and Mathematical Methods in Financial Applications.

Techniques	Methods	Pros in finance	Cons in finance
Numerical methods	Equations both linear and nonlinear, finite difference techniques, dependence modelling, Monte-Carlo simulation, etc.	Forecasting, model-driven, testing hypotheses, mathematical modelling of key financial processes, mechanisms, and dynamics, analysis and interpretation of approximations or findings, etc.	The population size, high-dimensional/order, low-quality (e.g., missing, incomplete, inconsistent) data, nonstationary, heterogeneous, dynamic, uncertain, and huge data, complex processes, mechanisms, and dynamics, etc.
Time-series and signal analysis	Time-series analysis, spectrum analysis, long-memory time-series analysis, state space modelling, nonstationary analysis, etc. .	modelling multidimensional relations and movements; trends, movements, changes, and forecasting; temporal processes, relations, dynamics, and consequences, etc.	Non-temporal, complex, and heterogeneous relations, processes, and dynamics; mixed components, data, relations, and processes; stylistic effects and poor data quality, such as noise; sample dynamics and structure and nonstationarity; overfitting; density of the population, etc.
Statistical learning methods	Copula methods, nonparametric methods, factor models, stochastic volatility models,	Testing hypotheses and using models; sampling; latent variables, relations, and models; probabilistic	Including mixed observable data, poor-quality data, scalability issues with big data sets, modelling other and mixed relations, processes, and dynamics, as well as result actionability.

	random walk models, etc.	interpretability; dependencies, uncertainties, and randomness, etc.	
Random methods	Stochastic theory, fuzzy set theory, random forest, random walk models, random sampling, quantum mechanics, etc.	modelling random relations, dynamics, processes; randomness, fuzziness, uncertainty; impartiality and fairness in representation; etc.	Too few or too many people, complicated (e.g., imbalanced, unequal) data, dynamic data, complex mixed data, bias and error, etc.

Several examples illustrate how these demands and challenges are being addressed:

1. Modeling, analyzing, and predicting economic and financial phenomena while accounting for real-world data characteristics such as scale, dynamics, non-stationarity, uncertainty, and other data quality issues.

2. Consider real-world market circumstances When modelling and predicting economic and financial outcomes, including class imbalance, unlabeled cases, evolving market behaviours, and contextual factors.

3. Addressing limitations in modelling complex economic and financial data, including overfitting, weak generalization, and adaptive learning capabilities.

4. Evaluating the performance of conventional models and techniques in handling the complexities of modern economic and financial systems.

5. Enhancing multi-agent reinforcement learning techniques for portfolio management by addressing local minima, multi-objective optimization, and asset couplings.

6. Review the roles, performance, and interpretability of AI-enabled financial engineering techniques to ensure their accuracy, transparency, and ethical compliance.

Furthermore, AI technologies such as deep learning and data science are poised to revolutionize various aspects of intelligent economy and finance. This includes:

1. Developing universal representations of economic and financial systems, products, and services.

2. Modeling compound economic and financial targets while considering contextual factors and distributed learning.

3. Automating investment processes by developing trading, financing, and advising systems.

4. Constructing more discriminative features from economic and financial data for improved analytics and decision-making.

5. Building automated trading systems integrating fundamental and technical analyses with machine learning methods.

In summary, AI-enabled innovations are reshaping economic and financial landscapes, ushering in a new era of data-driven decision-making and transformative solutions to complex challenges.

Table 4. Complex system theories: benefits and drawbacks for financial applications.

Techniques	Methods	Pros in finance	Cons in finance
Complexity science	Complex adaptive systems, random fractal theory, chaos theory, and systems theory, among others.	incorporating social science; modelling system complexity; modelling intricate financial processes, methods, and features; trial and error; etc.	Limited and incomplete comprehension; combining quantitative and qualitative factor modelling; assessment and optimisation, etc.
Game theory	games with a zero-sum, differential, combinatorial, evolutionary, Bayesian, etc. structure.	Testing hypotheses, designing with rules, analysing scenarios, trail and test, including reinforcement learning, etc.	intricate relationships and design; including ideas, procedures, and regulations related to finance; intricate financial qualities, etc.
Agent-based modelling	Reactive models, multiagent systems, swarm intelligence, reinforcement learning, belief-desire-intention models, etc.	Self-organizing mechanisms, simulation, rule-based models and controlled experiments, mechanism testing, etc.	Complex financial scenarios, dynamics, formal and quantitative models, runtime behaviours and decision-making, etc.
Network science	Contagion theory, power law, small worlds, graph approaches,	modelling social influence, visualisation, networking	Multi-aspects, sources, and modalities; heterogeneous and high-dimensional financial systems and mechanisms; intricate relationships, interactions, and processes, etc.

	linkage analysis, etc.	modalities, interactions, and processes, etc.	

Table 5. Classic Analytics and Learning Methods and their Pros and Cons in Financial Applications.

Techniques	**Methods**	**Pros in finance**	**Cons in finance**
Pattern mining methods	Sequence analysis, integrated pattern mining, high-utility pattern mining, tree pattern, network pattern, knot pattern, interactive pattern, and frequent itemset mining are a few examples.	Extracting and identifying interpretable rules, actionable structures, modes, and relations, etc. .	Rare occurrences and actions; elevated false positives; omission of significant financial events and activities; relationships and exchanges, etc.
Kernel learning methods	spectral kernel, Fisher kernel, nonlinear kernel, vector space kernel, tree kernel, support vector machine, multi-kernel techniques, etc.	Kernel techniques for modelling complicated problems; scalable; metric attributes, etc. .	Selecting the right kernel, calibrating it, training it, making it interpretable and actionable, etc.
Event and behaviour analysis	Analysis of nonoccurring behaviour, Markov chain process, high-impact and high-utility behaviour, and sequence analysis, etc.	Financial event, process, interaction, activity, and simulation modelling; sequential modelling; influence of behaviour on events; visualisation; actionable; etc.	Inadequate theories and methods for event/behavior modelling; intricate processes, interactions, and behaviours; mixed and dynamic processes; uncertainty and change; predicted consequences, etc.
Document analysis and NLP	Language models, Bayesian model,	Subjective and objective aspects,	intricate syntactic and semantic relationships and structures; informality of expression;

	latent Dirichlet allocation, Transformer, BERT, statistical language model, etc.	sentiment, opinion, unstructured data, lengthy and short texts, linguistic and semantic representation and analysis, etc.	embedding of financial knowledge; interactions and heterogeneities across multiple languages; scalability; etc.
Model-based methods	Deep neural networks, Bayesian networks, expectation-maximization models, clustering, classification, and probabilistic graphical models, among others.	Testing of hypotheses; modelling design-based processes, dynamics, and behaviours; modelling tools and paradigm dependence; broad applicability, etc.	Runtime and dynamic modelling; problems with handcrafting; model selection; under- and over-fitting; financial explainability and semantics; etc.
Social media analysis	Topic modelling, linkage analysis, influence analysis, sentiment analysis, emotional analysis, and interaction learning, among other techniques.	modelling social interactions, influence, and financial events, feelings, and attitudes, etc.	Financial procedures, processes, and systems; misinformation; bias; mixed financial data and information; etc.

CONCLUSIONS

The integration of AI into finance has remained a prominent research trajectory for several decades, witnessing a surge in cross-disciplinary collaborations and convergence among AI, data science, machine learning, finance, and economics. This trend has been propelled further in recent years by the rapid advancements in next-generation AI and data science technologies, facilitating their widespread application across diverse financial domains. This review offers a comprehensive and nuanced examination of the strengths and limitations of traditional and contemporary AI techniques within finance. Notably, we delve into the efficacy of data-driven methodologies in financial contexts. Moreover, our review stimulates discourse surrounding the unresolved challenges and prospects inherent in adopting next-generation AI in finance and the potential synergies they entail. By consolidating insights from related reviews, we transcend the narrow focus on specific AI methods or financial issues, providing a holistic perspective. Additionally, this review complements our previous systematic analysis of the broad spectrum of financial applications enriched by classical and modern AI research.

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