AI in Finance: A Review

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The recent booming of AI in FinTech further highlights the decades of significant developments and potentials of AI for making smart economy, finance and society. AI-empowered finance and economy has been a sexy and increasingly critical area in AI, data science, economics, finance, and other relevant research disciplines and business domains. This long history of AI in finance has been further enhanced by the new-generation AI, data science and machine learning, which are fundamentally and seamlessly transforming the vision, missions, objectives, paradigms, theories, approaches, tools and social aspects of economics and finance and driving smart FinTech. AI is empowering more personalized and advanced and better, safer and newer mainstream and alternative economic-financial mechanisms, products, models, services, systems, and applications. This review summarizes the lasting research on AI in finance and focuses on creating a comprehensive, multidimensional and economic-financial problems-driven research landscape of the roles and research directions of both classic and modern AI in finance.

CCS Concepts: • **Artificial Intelligence** → **General**; • **Data** → General.

Additional Key Words and Phrases: Artificial intelligence, AI, data science, data analytics, advanced analytics, machine learning, FinTech, finance, economics, AI in FinTech, AI in finance

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1 INTRODUCTION

In the recent decades, economics and finance (EcoFin for short)[*] have become increasingly interactive and interconnected with the advancements in broad artificial intelligence and data science (AIDS)[†] [2, 18, 19, 51, 63, 72, 79, 182]. This carries forward the long-term increasing trend of interdisciplinary synergy between AI, finance and economics [16, 26, 42, 75, 90, 157], which has been substantially strengthened recently due to the new-generation AIDS advancement and emergent applications for FinTech [8, 20, 27, 102, 118, 134, 141].

The above observation is evidenced by the monthly search trend in Google[‡] in terms of key AIDS terms: AI-Finance, AI-Economics, AI-FinTech, NN-EcoFin, ML-EcoFin, DM-EcoFin, DS-EcoFin, and DA-EcoFin, as shown in Fig. 1. Here, AI-Finance merges the monthly search numbers for keywords

[*]This article complements the paper 'AI in Finance: Challenges, Techniques and Opportunities' [21] available at https://ssrn.com/abstract=3647625 and 'Data science and AI in FinTech: An overview' [25] at https://ssrn.com/abstract=3890556 from the same author.

[*]In this paper, we broadly refer both *economy and finance* and *economics and finance* to the abbreviation EcoFin for brevity and broad reference convenience, since both economic and financial areas and both economic and financial disciplines are often interrelated particularly in the present highly interactive disciplines. Many discussed aspects in this paper and in the literature involve both.

[†]We interchangeably use AI and AIDS in this paper as DS also involves other broad disciplines and plays increasing important roles in AI, finance and FinTech (or Fintech, i.e., financial technology in full).

[‡]The Google Trend API only supports the search back to 2004.

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'artificial intelligence in finance', 'artificial intelligence for finance', 'AI in finance', and 'AI for finance'. Similar keywords are set for collecting the search data for AI-Economics and AI-FinTech. The values for the other keywords refer to their monthly search data corresponding to the prefix term plus for/in economics/finance, e.g., NN-EcoFin corresponds to the keywords 'neural network in/for economics' and 'neural network in/for finance'. ML refers to machine learning, DM refers to data mining, DS refers to data science, and DA refers to data analytics and data analysis.

This Google trend also discloses the following information. (1) 'AI in finance' and 'data analysis in finance' have been consistently popular search terms. In 2004 and 2005, terms 'neural network in finance' and 'data mining in finance' hit intensive search interest in some months. Keywords 'data science in finance' started to attract strong interest in late 2004 and early 2005, while 'machine learning in finance' became recognized since middle 2006. (2) In contrast, except for 'data analysis in economics' which has attracted consistent and substantial search interest, there were very rare Google searches of the above AIDS keywords combined with economics, e.g., 'AI in economics', 'machine learning in economics' and 'neural network in economics' before some 2013. However, this situation has been replaced by increasing search interest on most of the above AIDS keywords since 2013. (3) Interestingly, between middle 2006 and about middle 2016, there was overall much less interest shown in Google search of all listed keywords, while terms such as 'AI in finance', 'data analysis in finance', 'machine learning in finance' and 'data science in finance' attracted reasonable and stable interest. (4) While 'data analytics in finance' emerged in Oct. 2006 and then has built increasingly stronger interest since Jul. 2008, the term 'AI in FinTech' only coined its incredible attraction since Feb 2016. (5) In the recent five years, AI, data science, machine learning, data analytics and FinTech combined with finance and economics have seen increasingly stronger interest (4-5 times of that before 2015) in Google.

The above Google trend analysis shows a snapshot of the emergent yet critical roles of the new-generation AIDS techniques, in particular, new-generation artificial intelligence, data science, machine learning and deep learning[§] in finance and economics. An important fact is that FinTech [8, 9, 20, 44, 102] has emerged at the epicentre of synergizing, innovating and transforming financial services, economy, technology, media and communication by applying new-generation AIDS techniques. In a broad sense, the symbiosis of AIDS and EcoFin, on one hand, drives AIDS technologies to cultivate new-generation EcoFin and FinTech demand and challenges [9, 16, 33, 42, 49, 70, 75, 107]. On the other hand, the new EcoFin and FinTech developments further promote the novel AIDS research, innovation, and applications [2, 102].

The new-generation AIDS forms the keystone enabler of the new era of EcoFin and FinTech, which is data and intelligence-driven and smart. The recent AIDS advances are reshaping and redefining the scope, concepts, objectives, content and tasks of smart EcoFin and FinTech [20]. AIDS essentially and comprehensively transform the ways and effect that modern economic and financial (economic-financial)[¶] businesses operate, transact, interact and collaborate with their participants (incl. economic-financial consumers, markets and regulators) and environments. As we have seen in the recent decades, AIDS have strengthened the efficiency, cost-effectiveness, customer experience, risk mitigation, regulation and security of existing economic-financial systems and services. More importantly, AIDS are nurturing new economic-financial mechanisms, innovations, models, products, services, and creating many tangible and intangible assets and opportunities.

[§]Here, AIDS techniques broadly refer to areas including statistical learning, mathematical programming, knowledge representation, intelligent systems, decision-support systems, machine learning, pattern recognition, data science, data analytics, knowledge discovery, computer vision, signal processing, image processing, natural language processing (NLP), biometrics, computational intelligence, information retrieval, recommender systems, and optimization.

[¶]To avoid differentiating economic and financial aspects explicitly, we refer both or either side to as *economic-financial* in this paper for brevity and generality.

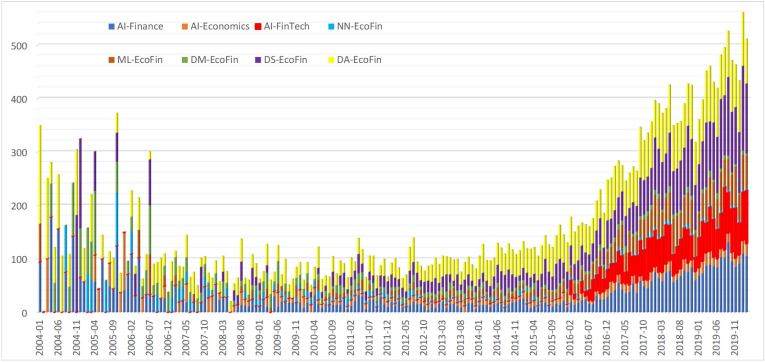

Fig. 1. The Google search trend of AIDS-related areas in/for finance and economics between Jan. 2004 and Feb. 2020.

Consequently, AIDS invent and bring unprecedented and more intelligent, efficient, personalized, user-friendly, explainable, secure, risk-averse, anti-fragility and proactive economic-financial systems, products and services to everybody at everywhere and any time. In one word, we are in the era of 'smart EcoFin' and 'smart FinTech' from both business and disciplinary perspectives.

Below, a comprehensive review of the synergy between AIDS and EcoFin is given, which highlights some key developments of AI in economics and finance in the recent half century with a focus on the recent decade of advancements and applications of AI in finance. Due to space limitation, our motivation is not on introducing and commenting on individual and specific techniques presented in each of the thousands of papers identifiable in the literature. Instead, we aim to synthesize the AIDS with EcoFin problems and categorize them into a comprehensive, problem-oriented, multidimensional, multiview and hierarchical landscape of the interdisciplinary, cross-domain and evolutionary developments of AIDS in EcoFin. This aim is embodied by summarizing, categorizing and highlighting the major findings about the core aspects of AIDS-empowered smart EcoFin and FinTech: (1) the roles of AIDS in EcoFin; and (2) the major research directions in terms of both classic and modern AIDS research for smart EcoFin and FinTech. This article complements the others in [21, 25] which further discuss (1) the challenges of economic-financial businesses, data and FinTech, (2) the techniques for addressing the challenges, (3) the landscape of smart FinTech, and (4) open opportunities of AIDS for smart futures of EcoFin and FinTech.

2 THE ROLES OF AI IN FINANCE

AI could play unique, irreplaceable and significant roles in addressing the various areas and challenges for smart EcoFin and FinTech (see more discussion in [21]) [9, 20, 75, 102, 141]. Fig. 2 presents a four-dimensional, systematic and interactive landscape of the synthesis between AI and finance that drives smart FinTech and EcoFin [9, 20, 102, 118]. The landscape connects the main EcoFin businesses (bottom) to the EcoFin data and repositories (left), the broad-based AIDS techniques (right), and the EcoFin business objectives (top).

On one hand, **high-level AI roles and contributions** can be made to address many major and high-end EcoFin aspects and objectives [9, 20, 70, 157]. We highlight the following: (1) economic-financial simulations, (2) economic-financial modeling, (3) economic-financial representations, (4) economic-financial computing, (5) economic-financial analysis and forecasting, (6) economic-financial learning and prediction, (7) economic-financial anomaly detection, (8) economic-financial event analysis, (9) economic-financial behavior insight, (10) economic-financial planning, (11) economic-financial optimization, (12) economic-financial recommendation and intervention, (13)

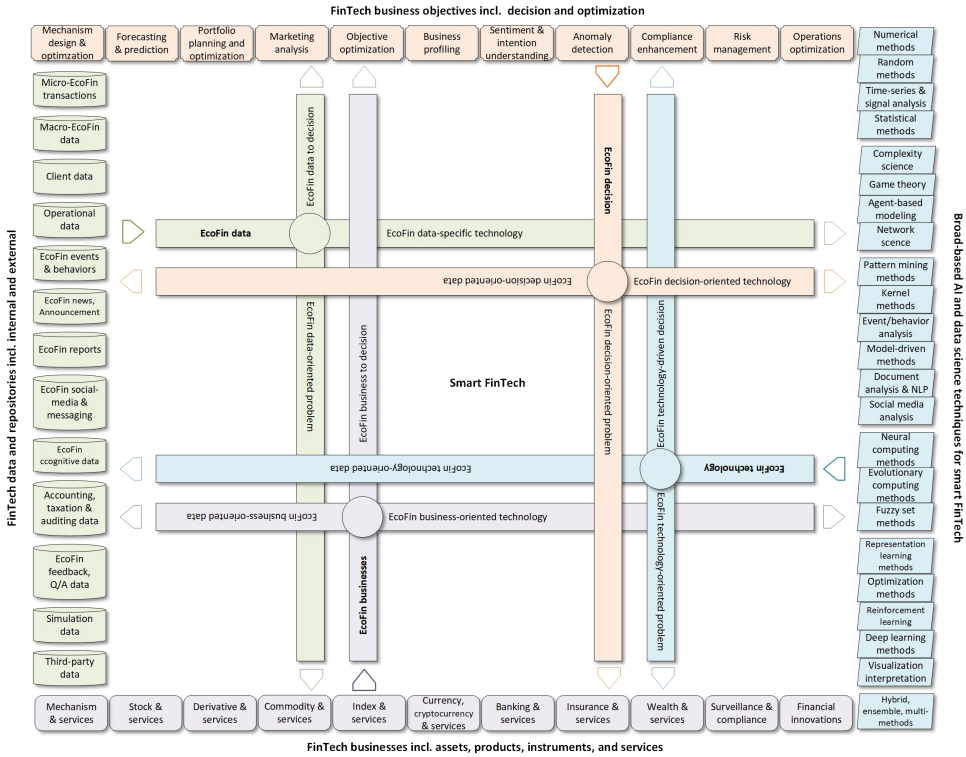

Fig. 2. A four-dimensional landscape of the synthesis between AIDS and EcoFin toward fostering smart FinTech. Shapes in different colors represent distinct dimensions in the synthetic landscape. Each dimension initiates its interactions and communications with the three other dimensions through its same-colored, directed connectors and channels. Each channel carries business, problem, data (incl. information and knowledge), intelligence, and technology, etc. from one end to another. The four dimensions interact with each other to address specific economic-financial business problems of underlying businesses by particular AIDS techniques on the corresponding data.

economic-financial intelligent systems, (14) economic-financial intelligent services, (15) economic-financial visualization, (16) economic-financial security assurance, (17) economic-financial compliance and risk management, (18) economic-financial ethics assurance, and (19) economic-financial innovations. We will further explain different research tasks, topics and directions of these aspects in the following sections.

On the other hand, many **low-level AI roles and contributions** have been made to address enormous specific business problems, data challenges, and strategic objectives in smart EcoFin and FinTech, e.g., [5, 9, 12, 23, 28, 35, 50, 85, 89, 96, 104, 116, 125, 138–140, 143]. Examples include but are not limited to (1) analyzing and modeling complex coupling relationships, dependencies, interactions, relations, linkage, connections and networking in EcoFin; (2) analyzing and modeling local, regional and global economic-financial activities, behaviors, events and their evolution and dynamics; (3) analyzing, modeling, monitoring, managing and intervening the present and future consequences, effect, impact and risk of economic-financial mechanisms, models, products, services, and behaviors; (4) simulating, analyzing, modeling and optimizing economic-financial policies, rules, strategies and operations for regulation, compliance, risk, innovation, and development; (5) jointly modelling natural, online, social, economic, cultural and political factors, their relations and

influence on economic-financial products, services, and systems; (6) analyzing and modeling the influence of economic-financial mechanisms, policies, strategies, services, products, innovation and development on society, economy, culture, and futures; (7) analyzing and modeling multisource, multimodal, multi-channel, multi-platform and cross-domain economic-financial data, information and knowledge; (8) analyzing and modeling high-dimensional, sequential and evolving economic-financial data, behaviors, and events; (9) analyzing and modeling economic-financial expert's knowledge, intent, experience, and speciality; (10) analyzing, modeling, monitoring, managing and intervening economic-financial failures, accidents, disasters and crises and their influence, influence propagation, and effect; (11) constructing and evaluating economic-financial benchmarks, measurement, and evaluation metrics and tools; (12) constructing and evaluating benchmarkable economic-financial data, knowledge graph, repositories, practice, and case studies; (13) designing, evaluating and optimizing faster, cheaper, smarter and more accessible and personalized new economic-financial mechanisms, models, products, and services; (14) conducting real-time intelligent economic-financial analysis and processing of cloud, online, mobile, IoT and wifi-based economic-financial services, products and systems; (15) developing autonomous, intelligent and human-machine-cooperative regulation technologies (RegTech) for digital authentication, identification and re-identification, and intelligent regulation, risk and compliance management; (16) developing actionable, active, real-time, tailored and automated regulation of new, digital and mobile economic-financial services, products, and systems; (17) incorporating intelligences and innovations into transforming credit loans, SME financing, individual financing, P2P lending, crowdfunding, robo-advising, digital payment, dynamic credit rating, and asset pricing; (18) analyzing, predicting and intervening novel, emerging and exceptional cybersecurity, fraud and risk in banking, insurance, and finance; (19) conducting descriptive, non-IID, shallow, deep and reinforced analysis, representation and learning of economic-financial businesses, networks, systems, problems, and outcomes; (20) conducting cross-market, cross-product, cross-service, cross-indicator, cross-platform and cross-network analysis, modelling and hologram generation for whole-of-market, whole-of-enterprise and whole-of-business understanding and management of economic-financial status, risk, opportunities, and innovations; (21) analyzing, modeling, monitoring, managing and intervening economic-financial crisis, exception, emergence, uncertainty, and ill- to un-structured systemic risk; (22) inventing data-driven theories and tools for creating digital assets and their valuation, risk analysis and management; (23) inventing new blockchain theories, mechanisms, products and services for cryptocurrency, digital asset pricing, trading, mechanism design, smart contract, open banking, and investment; (24) creating intelligent algorithms, mechanisms, interfaces and systems for digital, mobile, virtual and Internet-based banking, financing, capital markets, regulation, insurance, and payment; (25) inventing data-driven and intelligent technologies, including processes, systems, services and tools, for regulation, compliance, security, and risk management and innovations (so-called RegTech); (26) inventing data-driven and intelligent technologies, including processes, systems, services and tools, for insurance operations, compliance, security, and risk management and innovations (so-called InsurTech); (27) inventing data-driven and intelligent technologies, including processes, systems, services and tools, for payment operations, compliance, security, and risk management and innovations (so-called PayTech); (28) analyzing, modeling, monitoring, managing and intervening trust, privacy, security, compliance, explainability and general ethics in EcoFin, FinTech and AIDS-enabled EcoFin; (29) benchmarking, evaluating and optimizing better practice in AIDS-enabled FinTech and EcoFin into implementation and productization; and (30) other important aspects, issues and progress associated with AIDS in FinTech and EcoFin.

These aspects and objectives are applicable to every aspect of the diversified economic-financial entities, activities and forms [20, 49, 75, 172]. In addition, AIDS techniques can be integrated into other non-intelligent systems and technologies, e.g., software engineering of economic-financial

systems and infrastructure, quality of service, operating systems and governance system, which are also important for engineering economic-financial infrastructure and systems [113]. The synergy of AIDS and EcoFin complement, strengthen and transform each side of roles, functions and performance toward more advanced, smart, personalized, efficient, transparent, globalized, virtual and novel economic-financial systems and services. As a result, the new-generation AIDS technologies are transforming modern economy and finance and enabling a new-generation of economy and finance, e.g., data economy, virtual economy, game economy, entertainment economy, social media economy, sharing economy, Internet finance, and mobile finance [19, 102].

Expanding the above overview of AIDS for smart EcoFin and FinTech, the following sections further summarize and categorize major business areas, problems, tasks and applications of AIDS for smart EcoFin and FinTech. They are structured in terms of several major research areas, which are selected, summarized and articulated in terms of three AI research directions: (1) classic research on AI in EcoFin, and (2) modern research on AIDS in EcoFin[‖]. Fig. 3 summarizes the main economic-financial business areas, research areas of AI in EcoFin, and some of the respective AIDS techniques.

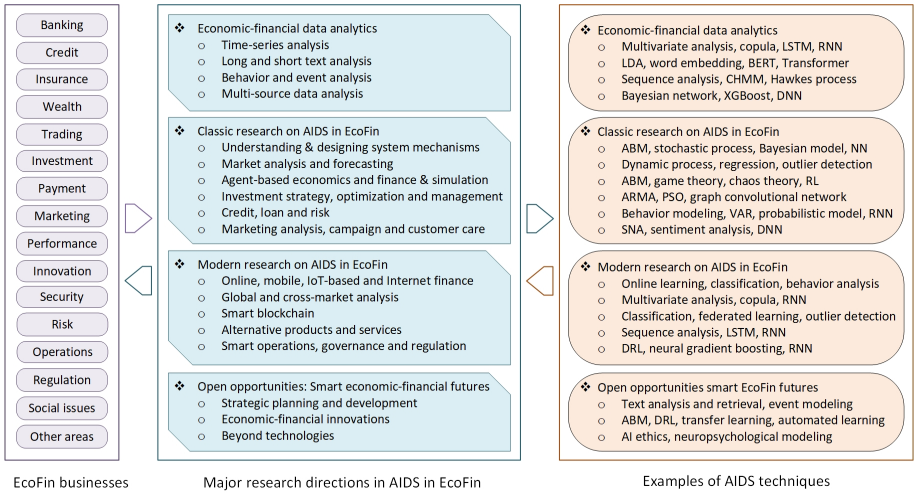

Fig. 3. The research areas of AIDS for smart EcoFin and FinTech. The left box lists major business areas, the middle one summarizes four research directions, and the right one illustrates some typical AIDS techniques. The problems in an economic-financial system may be addressed by one to multiple AIDS areas and techniques.

3 CLASSIC RESEARCH ON AI IN FINANCE

AI in economics and finance has been explored for over decades as a typical application of AI [5, 68, 75, 131]. In the literature, there are many relevant publications, which can be grouped into the following families: modeling economic-financial system mechanisms; financial market analysis and forecasting; agent-based economics and finance; smart investment, optimization and management; smart credit, loan and risk management; and smart marketing analysis, campaign and customer care. We briefly discuss each of them below. Table 1 summarizes their typical application domains and problems in finance and the corresponding AI methods. In the following sections, we expand the discussion on each of the above areas.

[‖]Due to space limit, the other review on AI techniques for economic-financial modeling and analytics is in [21]

Table 1. Classic AI Techniques and Their Representative Applications in Finance.

AI areas	Financial areas	Typical financial problems	Typical AI methods
Modeling economic-financial mechanisms	Understanding financial systems	Modeling market ecosystem, pricing, hypotheses, relations, interactions, trading, movement, and marketing mechanisms, processes, and effect, etc.	Mathematical modeling, statistical modeling, quantitative analysis, game theories, theories of complex systems, simulation, machine learning, etc.
	Artificial financial markets	Simulating and testing market mechanisms, models, policies, new products and services, trading rules, regulation, stakeholder relations and interactions, etc.	Computer simulation, agent-based modeling, game theories, theories of complex systems, human machine interaction, optimization methods, reinforcement learning, etc.
Financial market analysis and forecasting	Market complexities and dynamics	Modeling financial system characteristics; macro, meso and micro indicators and variables; interactions, information and influence propagation and effect; etc.	Quantitative and quantitative modeling, complex systems, information theory, network theories, data analytics, machine learning, etc.
	Financial time-series analysis	Modeling and predicting market movement, trend, volatility dynamics, exceptions, events, etc.	Time-series analysis, sequence analysis, pattern mining, dynamic process and programming, machine learning, and deep models, etc.
	Trading design and optimization	Discover and optimize strategies, signals and movements for pricing, trading, portfolio, and risk management, etc.	Quantitative analysis, data mining, machine learning, behavior analysis, risk analytics, and optimization methods, etc.
	Financial relation and interactions	Characterizing and analyzing diversified, hierarchical and multidimensional relations and interactions in financial variables and participants, etc.	Mathematical modeling, statistical modeling, relation learning, interaction learning, network theories, graph theories, etc.
	Market anomaly analysis	Recognize and predict abnormal movements, trends, behaviors, events inside/outside markets and of participants, etc.	Outlier detection, novelty/exception/change detection, behavior analytics, pattern mining, event modeling, probabilistic modeling, clustering, and classification, etc.
Agent-based economics and finance	Agent-based modeling	Modeling and simulating markets, supply and demand, participant behaviors and relations, mechanisms, policies, strategies, emergence and effect, etc.	Multiagent systems, simulation theories, human computer interaction, user modeling, behavior modeling, visualization, etc.
	Agent-based economics	Simulating macro/micro-economic hypotheses, policies, protocols, mechanisms and their effect in multiagent systems, etc.	Multiagent systems, computational economics and finance, and computational experiments, etc.
Intelligent investment, optimization and management	Automated and smart investment	Developing and optimizing intelligent investment models, algorithms, platforms and services with market forecasting and risk-averse management, etc.	Market representation, forecasting, portfolio optimization, learn to rank, reinforcement learning, recommender systems, behavior analysis, deep models, game theories, optimization methods, etc.
	Online and offline portfolio optimization	Selecting, optimizing and managing online or offline diversified forms and products of portfolios with market prediction and risk management, etc.	Market representation, prediction, learn to rank, game theories, reinforcement learning, recommender systems, behavior analysis, deep models, portfolio optimization, optimization methods, etc.
Intelligent credit, loan and risk management	Credit management	Estimating, predicting and optimizing credit rating, limit, valuation, scheduling, and risk and fraud management, etc.	Profiling, forecasting, prediction, sequential and recurrent modeling, game theory, reinforcement learning, behavior analytics, risk analytics, optimization, etc.
	Loan management	Estimating, predicting and optimizing loan value, default, refund, repayment, refinance, risk and fraud management, etc.	Profiling, forecasting, prediction, behavior informatics, sequence analysis and modeling, game theory, reinforcement learning, risk analytics, and optimization, etc.
	Risk management	Modeling, predicting and managing risk factors, effect and its severity, fraud, crime, security-related events and money laundering associated with diversified financial products, mechanisms, markets and participants, etc.	risk analytics, probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, deep neural models and reinforcement learning, etc.
Intelligent marketing	Marketing analysis and campaign	Analyzing marketing performance, product/company competitiveness, campaign effect, competitor advantage and strategies, market share change, recommending and optimizing marketing campaign strategies, actions, and target, etc.	Numerical modeling, econometrics, forecasting, prediction, event analysis, behavior analysis, interaction analysis, game theories, reinforcement learning, recommender systems, optimization methods, etc.
	Customer management	Understanding and predicting customer needs, sentiment, satisfaction, concerns, complaints, circumstance change, new demand, potential churning, mitigation strategies, etc.	Profiling, prediction, interaction modeling, behavior analytics, change analysis, social media analysis, text analysis, and recommender systems, etc.

3.1 Modeling economic-financial mechanisms

A major challenge in economic and financial research is to build a genuine, deep and comprehensive understanding of the intrinsic yet often intricate working mechanisms of an economic-financial system [42, 79, 99, 129], e.g., a product, service, market, or company. This involves both fundamental AI research areas and topics and specific ones.

The *fundamental AIDS research in understanding financial systems* includes but is not limited to:

- Modeling the whole market ecosystem including market participants, financial assets, services, processes and regulatory mechanisms in an orchestration way; building a comprehensive and benchmarkable representation of a security, an asset, a portfolio, a market, a company or even a trading network to capture and interpret their fundamental factors, characteristics, interactions and relations, structures and distributions, and working processes;

- Modeling the pricing formation, evolution and strategies in a financial derivative market by involving on-market data such as instrument prices and trading volumes and the influence of off-market data such as financial news and underlying equity prices;
- Studying different hypothesis of market such as prophet inequality, efficient market, bounded rationality and their applicability in market design and influence on market investment, governance and regulation;
- Understanding the linear and nonlinear relations between trading behaviors, performance and market dynamics, modeling the causal inference between market and intervention policies and the confounders;
- Identifying high-frequency trading behaviors, market marking strategies and high-performing signals by modeling their actor profiles and trading frequencies, actions and states, etc.;
- Modeling the market movement and trend coupled with investor's trading behaviors and patterns in stock market trading and with the connectivity and transparency between equity and derivative markets;
- Modeling the impact of no, bounded or variable transaction costs on portfolio optimization by optimizing the relationship between the market return of a portfolio, frequent portfolio rebalancing, and transaction cost scenarios;
- Detecting contradictory opinions from market stakeholders, industry and academia, detecting contradictory signals from different markets and contradictory opinions from multiple modalities and analyzing their formation cause and influence on market;
- Extracting data from financial news and statements about a firm's profile, activities, operation efficiency, business performance, customer feedback and market reputation; comparing a company with peers in its industry sector; quantifying fundamental aspects of the company; building measures about a company fundamental, indexing the firm and its position in the industry per the financial fundamentals; and benchmarking firms and sectors for comparison;
- Developing optimal trading strategies of market making w.r.t. objective (e.g., expected net profit with constrained risk, e.g., by DRL such as Q-learning, in limit order book; modeling the impact of market making mechanisms and market makers on equality and fairness of a market and their consequences, and designing the corresponding market compliance and regulation policies;
- Simulating financial business processes towards automated composition of assets and portfolio, designing reinforcement learning systems for optimizing market making strategies and enabling predictive market making by predicting future market prices, and developing the corresponding regulatory and surveillance intervention;
- Simulating market manipulation and insider trading methods in markets, e.g., market-making by techniques such as game theories and adversarial learning to mimic and distinguish regular trader behaviors, manipulator behaviors, and market-maker behaviors; and
- Visualizing the multi-resolution trading charts and trading patterns in market replay to understand the micro-level market working mechanisms, and creating snapshots and tracing the scene of trading for trading training or surveillance.

Techniques for understanding the nature of economic-financial systems are various, including mathematical modeling such as linear programming, stochastic processes and time series; statistical modeling [137] such as frequentist and Bayesian theories; economic-financial theories such as quantitative analysis methods and efficient and rational market hypothesis; game theories and simulation methods [115]; and various machine learning and knowledge discovery methods [10] such as network modeling [74], graph theory, and NNs. A typical and lasting research area is to simulate real-life market mechanisms by building artificial financial markets and testing hypotheses,

market mechanisms, and strategies and rules in such a market, and compare and evaluate the artificial markets with the real ones for improving understanding and further development.

Artificial financial markets (or artificial stock markets) [95, 153, 166] are typically built in computerized simulation software with user interfaces, e.g., a computer or online game, which is incorporated with simulated market participants, interactions, rules, evaluation and human interference to simulate real-life markets. ABM is a cheap, controllable, repeatable and user-friendly tool popularly used to build such artificial markets to undertake various tasks and research agenda, e.g.,

- Studying complicated real-life market problems such as the robustness, uncertainty and emergence of risk-averse behaviors, releasing constraints and domain-specific penalties by considering adversary to simulate the competitive, contrastive or contradictory behaviors, beliefs and objectives in the context of Nash equilibrium;
- Verifying and optimizing new product, service, policy and regulation rules in an artificial market that is highly similar and synchronized with real-life environment, e.g., modeling and intervening the influence of shadow leverage on corporate bond pricing;
- Optimizing market mechanisms and trading strategies by reinforcement learning and optimization theories and verifying them in the correspondingly set artificial markets;
- A single agent to simulate and evaluate market mechanisms such as marketmaking strategies and pricing enabled by multiagent reinforcement learning, e.g., discrete-time zero-sum game;
- Financial market simulation, backtesting and market replay study by verifying, optimizing and generating various trading rules (e.g., by learning trading behaviors as trading patterns) in limit order books against market portfolio theories;
- In an artificial market incorporated with historical trading data, machine learning-enabled trading agents can learn the trading patterns and behaviors of historical actual traders and generate simulated but smart trading strategies on the fly while the agents compete with each other in the market for portfolio optimization;
- In coping with the need of high frequency and algorithmic trading, machine learning methods can be learned to automate asset selection, asset pricing, trading signal and position generation and order placement, which can be tested in the artificial markets instantly updated with near-real-time data from a real target market;
- In blockchain, autonomous trading agents extract and analyze distributed data about a cryptocurrency (a digital asset) and then forecast its price before investment is made.

3.2 Financial market analysis and forecasting

Financial market analysis applies typical AIDS techniques to understanding market complexities and dynamics, financial time series analysis, trading strategy design and optimization, financial relation learning, financial objective optimization, abnormal market movement analysis, etc.

First, *understanding market complexities and dynamics* [17, 19, 74, 165] applies modeling and computational techniques such as theories of complex systems, quantitative and quantitative modeling, information theory, knowledge representation and network theory to model financial system characteristics, e.g., dynamics, chaos, uncertainty and evolution; macro, meso and micro market and economic/financial indicators and variables and their distributions, structures and relations; and interactions, information and influence propagation and effect formation within and between financial assets and markets. Second, *financial time series analysis* [116, 149] applies techniques such as time series analysis, sequence analysis, dynamic process and programming, and RNN for modeling the movement, dynamics and exceptions of financial indicators and variables [87, 171, 175]; the quantification, representation, regression, categorization, forecasting and prediction of individual and collective assets, markets, systems and networks; volatility clustering and return distributions; and the detection of abnormal movement, change, and events. Third, *trading strategy*

design and optimization [22, 46, 77] applies techniques such as data mining, machine learning, behavior analysis and optimization methods to discover, design, integrate and optimize high-performing strategies, signals and movements for algorithmic trading, asset management, portfolio management and risk management in equity markets, foreign exchange markets, derivative markets, and across equity and other markets (e.g., derivatives and money markets). Further, *financial relation learning* [28, 91, 170, 174] quantifies, represents, models, analyzes and evaluates the dependency and its degree and structures, high-dimensional dependency, correlation and its structures, and other relations such as association, causality and influence between financial variables and indicators; such research is often conducted in the context of stylized fact, fat tail, and asymmetric underlying market conditions. Typical techniques for *financial objective optimization* [40, 64, 128, 131] include evolutionary computing, linear programming, NN, fuzzy logic and numerical optimization for single and multiple-objective optimization, which may be applied to different assets, markets, optimization targets, and objective functions. Lastly, *abnormal market movement analysis* [24, 38, 160] involves techniques including outlier detection, novelty detection, exception analysis, change detection, behavior analytics, sequence analysis, pattern mining, event modeling, probabilistic graphic modeling, clustering and classification methods to recognize, detect, predict and analyze abnormal movements, trends, events and trading activities of market, asset price, volatility, return on investment and consequences; traders, stakeholders and associated accounts and their abnormal behaviors; abnormal trading behaviors such as long-term and short-term manipulations, pool manipulations, insider trading, and abnormal cross-market arbitrage.

3.3 Agent-based economics and finance

Agent-based economics and finance refer to the research areas that complement the theories and methods in finance and economics with the approaches of Agent-based modeling [42].

Agent-based modeling (ABM) [53] refers to techniques that model a system and its objects as a multiagent system and apply such theories as complex systems and game theories to the multiagent system to simulate the target system and its problems. In economics and finance, ABM models economic/financial participants as agents, economic systems and financial markets as multiagent systems, and the underlying working mechanisms, relations and complexities as rules, protocols, policies, actions, utility, agent interactions, self-organization and emergence, etc. in a bottom-up approach. The bottom-up ABM working mechanisms complement the top-down economic/financial theories and tools in particular in addressing uncertain, stochastic, self-organizing and evolutionary nature of markets; potential issues and limitations of specific economic/financial hypotheses, involving limited observations and incomplete modeling of all possible entities and mechanisms; and costly testing on large scale and complex settings.

In ABM, economic/financial hypotheses, principles and theories, etc., are decoded as properties, rules and constraints and applied to the simulated agents and their behaviors, group behaviors and functions including interactions, communications, cooperation, competition and coalition, and agent interactions with environment. In general, a multiagent simulator implements the above settings and presents emergent outcomes of agent interactions to understand the underlying systems, phenomena and problems. ABM has been applied to many economic and financial problems, e.g., modeling stock markets and their trading strategies and market mechanisms where agents trade on the orderbook of an instrument, simulating the impact of trading tax and regulation policies on macro-economy, understanding the roles of central banks, testing property market and household policies, conducting multi-objective optimization of asset allocation and portfolio management, modeling the supply and demand and the effect of relevant market campaign activities for new product and pricing, and observing macroeconomic effect of new financial models and activities such as peer-to-peer lending and Internet finance.

Agent-based economics [70, 156] builds multiagent systems incorporated with economic/financial hypotheses and principles to interpret economic/financial and policy-related problems, complexities, design and phenomena in terms of multiple economic/financial agent interactions, self-organization, emergence, behaviors and states with their environment in terms of micro-level variables, rules, protocols, and mechanisms. Agent-based economics and finance form areas such as ABM, agent-based macroeconomics, computational economics and finance, and computational experiments.

In particular, agent-based economics integrates the mainstream (dynamic) equilibrium models and economic/financial and policy assumptions for economic/financial studies and policy analysis in terms of macro-, meso- and micro-economic variables with agent-based models typically by multiagent simulators and games (such as the Santa-Fe complex adaptive systems) [156]. One area is to *study macro-level problems, properties, effect, dynamics, and solutions* such as modeling the demand for the consumption goods and financial assets and the labor supply for households; modeling the supply of consumption goods, the impact of technology, the demand and supply of capital goods, and the demand for labor and credit for firms; and modeling the credit risk, interest rate, and the supply of loans for banks. Another direction is to *conduct policy analysis* for fiscal policies, monetary policies, financial regulation, crisis resolution mechanisms, labor market policies, policies about regional growth, convergence and cohesion. In addition, *agent-based finance* [22] models the interactions, dynamics and relations within individual asset markets or between multiple asset markets; the systemic risk, endogenous dynamics, market impact, volatility, stability, contagion and stress test in financial systems and networks; the demand and supply, pricing and contract design for energy markets.

3.4 Intelligent investment, optimization and management

The study on effective and efficient investment strategies and portfolio selection and optimization has been a mainstream direction in AIDS for EcoFin. This involves areas such as modeling factors, factor relations and contextual factors in investment decision-making, designing and optimizing investment strategies and management, and evaluating constraints and risk in investment. In a more general sense, AIDS enables automated and smart investment. *Automated and smart investment* involves many research topics and tasks [88, 135] that are enabled by AIDS, e.g.,

- Designing and implementing intelligent trading and investment decision-support platforms, online services and mobile applications to support quantitative investment, investment portfolio formation and selection, evaluation of investment strategies and portfolio, and high-frequency algorithmic trading;
- For quantitative investment, designing quantitative models such as multifactor models by techniques e.g. evolutionary algorithms to learn optimal alpha factors for quantitative investment and to rank models, models generated are then to create portfolios for investment;
- Predicting trends of stock-wise fundamental and technical factors associated with each security for stock movement and price trend forecasting, modeling stock movement trend in terms of multi-scale stock data, e.g., trading transactions, market data, and external economic and fundamental data;
- Predicting price and market trend of a financial asset by time series analysis techniques such as autoregressive moving average (ARMA), optimization algorithms such as swarm intelligence-based PSO and sequence modeling techniques such as recurrent neural models, and recommending trading signals and positions;
- Predicting stock price and movement at specific scenarios, e.g., on ex-dividend day by specific events on that day and ex-dividend period, and forecasting overnight movements before the dividend day;

- Predicting the movement and price of a financial asset (e.g., a stock or a forex currency) by involving the influence of external and contextual market factors, e.g., by extracting market-sensitive financial events in financial news;
- Optimizing the selection and combination of trading positions such as buy, sell, trade and hold on multiple products (e.g., trading multiple foreign exchange currencies) by optimization techniques such as evolutionary computing or reinforcement learning;
- Learning a causal representation of a limit order book market by reinforcement learning to minimize the risk and monetary loss, then predicting market movement and risk by deep neural models on the learned representations;
- Modeling stock dependency in a portfolio by techniques such as statistical dependency modeling, e.g., copula methods or sequential modeling techniques such as stacked RNN or graph convolutional networks for portfolio selection and optimization;
- Designing cross-sectional investment strategies and portfolios by modeling the relations between sections and the influence of sectional factors on portfolio selection;
- Recommending financial products and services, e.g., personalized stock recommendation by considering investor's preference, capability, behaviors and past performance; and recommending peer-to-peer (P2P) lending loans by analyzing loan supply-demand equilibrium and risk-return balance between P2P borrowers and lenders by techniques such as machine learning-enabled recommenders and game theory;
- Enabling algorithmic trading toward optimal order execution by optimization techniques such as actor-critic-based proximal policy optimization and generative adversarial networks, optimizing trading strategies by imitation learning of historical trading behaviors on multimodal data including historical stock prices and trading actions, and discriminating the learned plans against expert plans for stock and action selection;
- In institutional trading, learning policies for trading signals in a simulated market environment and optimizing the reward per reinforcement learning or optimization theories for optimal trade execution;
- Combining reinforcement learning-based simulation and real market data-driven trading strategies for actionable optimal trade execution in real markets by modeling market impact, e.g., using the real market data to learn candidate trading signals by learning high-performing trading behaviors, low market impact and weak constraints, and then selecting the optimal trading strategies through reinforcement learning;
- Optimizing and scheduling the investment order, e.g., the asset order in a portfolio or a credit order, by techniques such as reinforcement learning and sequence modeling such as recurrent neural models to predict the order and next profitable assets or portfolio; and
- Informing early-stage and cold-start investment strategies and portfolio by analyzing the similarity and relations between novel and cold-start assets and existing market products using various techniques in machine learning and recommender systems.

Specifically, *online and offline portfolio selection, optimization and management* [58, 62, 71, 97, 128, 131, 138, 142] has been a critical task in investment management. Both financial theories and AIDS techniques are widely explored for selecting, optimizing and managing online or offline portfolios. We show the following examples and case studies.

- Conducting mean-variance portfolio selection and optimization by optimizing the expectation (mean) and variability (variance) of investment return and conditional VaR, and modeling the sensitivity between the optimization objective and the resultant portfolio structures;
- Conducting momentum analysis, and learning market conditions and momentum and conducting reversal predictors of portfolio for portfolio optimization;

- In high frequency trading, learning online portfolio selection strategies and optimization with cardinality constraints and transaction costs, and involving historical data by optimization methods such as exponential gradient with momentum;
- Applying traditional multiagent reinforcement learning and current DRL networks to portfolio optimization, modeling asset relations in a portfolio and predicting asset movement as action or trading strategy candidates, and selecting actions toward maximizing return and minimizing risk as reward under the sequences of asset states;
- In a multiagent-based multiple-portfolio optimization setting, by incorporating risk into proximal policy optimization, each agent is modeled to form a portfolio toward self maximal return and minimal loss, while multiple agents coordinate for the collective return maximization and loss minimization;
- Recommending assets and alternative investments in a portfolio by modeling the asset relations (e.g., on historical price series) and the influence of external asset-related information by techniques such as attentive graph CNN;
- Selecting portfolio and optimizing trading strategies by learning sequential behaviors of trading assets, modeling the multi-asset relations and dependency between multiple time series in a portfolio, and modeling the dynamic portfolio management in a time period to learn optimal policies for assets such as stocks and cryptocurrencies and their effective trading strategies and price prediction;
- Analyzing the risk and enabling risk aversion in portfolio selection and optimization by techniques such as risk-based reinforcement learning, and controlling the return variance and risk of portfolio positions;
- Detecting exceptional decoupling scenarios in portfolio assets for managing exceptional event-related risk and risk-averse portfolio optimization, e.g., the structural breaks, correlation changes and simultaneous asset shocks between time series in a portfolio; and
- Modeling the within and between portfolio relations and influence in multiple sequential portfolios in terms of multiple RNN and multi-head attentions to model the importance of portfolio assets at each time point.

3.5 Intelligent credit, loan and risk management

Credit, loan and risk are three of major financial activities that involve almost all economic-financial systems and services, including investment, financing, banking, Internet finance, insurance, and wealth management. Accordingly, there are many aspects and issues that can benefit from or require the application of AIDS techniques.

Credit refers to a contractual agreement by which a leader (creditor) provides something of value to a borrower (debtor) now and the borrower will repay or return the value to the lender at an agreed later time plus certain interest charged. Financial credit may be applied to a financial instrument, e.g., bond, private credit or bank credit, and attached to a credit-carrying device or tool, e.g., a bank credit card or a coupon. AIDS techniques such as forecasting and prediction, optimization, sequential and recurrent modeling, reinforcement learning and behavior analytics may be used for managing, optimizing, planning and securing credit services and their sustainability, trust and healthy growth on general and specific topics [1, 66, 92, 105], e.g.,

- Estimating, adjusting and managing credit limit by jointly analyzing consumer need, consumption behaviors and transactions, repayment history, circumstance and changes, etc.;
- Analyzing the relations between credit limit and the consumed credit amount, expense and repayment transactions, and requests of credit limit change for credit limit adjustment;
- Compromising card, e.g., by ID theft, card theft, card stolen, card lost, and the ID information stolen through installed cameras at ATM areas;

- Estimating credit (card) risk rating and detecting and predicting fraud by sequentially modeling credit (card) transactions and consumption behaviors;
- Jointly modeling credit risk and limit and forecasting credit risk and limit by involving financial information, credit loan information and repayment data under certain limit scenarios, prior knowledge and heuristic strategies into limit estimation;
- Analyzing risk of overdraft approvals and predicting repayment capability, and detecting and preventing malicious credit overuse behaviors; and
- Optimizing credit order scheduling in credit factory for investment such as loan applications.

Loan refers to the lending of value (money, property, or other goods) to a party who will repay it with interest. Different financial loan can be created, e.g., personal loans, mortgage loan, and business loan. AIDS techniques such as models for forecasting, prediction, behavior informatics, sequence analysis and modeling, game theory, risk analytics, optimization and reinforcement learning can be used for operating, planning, predicting, automating, optimizing and securing loan services by involving loan-related lenders, debtors, loan information, context and their data characteristics [48, 59, 69, 150, 158], e.g.,

- Estimating loan value and loan default for cohort or specific customer groups by considering the debtor's circumstance and valuation of credit;
- Estimating credit scoring and financial credibility rating by involving debt obligations, customer profiling, loans, interest rate, customer behaviors, and circumstance changes, etc.;
- Detecting loan repayment risk and loan fraud of single loan product owner or cross-loan risk and fraud by analyzing circumstances, behaviors and repayments on all loans;
- Extracting evidence and rating risk for loan denials and approvals from application documents, borrower's demographics, history, debt, income, property and asset related information;
- Predicting loan refunding and repayment capability for credit scoring by analyzing borrower's repayment sequences and external data about income, debt and asset etc.;
- Predicting loan refinance by analyzing borrower's communications with the lender, complaints, feedback and circumstance change update, and recommending intervention strategies for retention or risk mitigation;
- Analyzing risk and debt obligation of guaranteed loan;
- Analyzing the competition, quality and feedback of market loan products and loan provision, and benchmarking and scoring the risk of multi-providers and loan issuers;
- Predicting online lending credit risk and limit by analyzing borrower's expenses, repayments, income, assets and risk factors; and
- Explaining credit scoring w.r.t. underlying explanatory variables and financial indicators.

Risk refers to the potential, probability or threat of loss of value, damage or liability, or the lower return on investment than expected. Financial risk is associated with any financial systems, products and services, and can be categorized into many types, e.g., capital risk, economic risk, interest rate risk, liquidity risk, payment risk, loan risk, credit risk, and investment risk. Accordingly, risk analytics and management have been a fundamental and challenging task in EcoFin, are customized for specific financial instrument and services, and evolve over time and contextual change. AIDS techniques including risk analytics, probabilistic modeling, classification, clustering, semi-supervised learning, behavior modeling, sequential modeling, event analysis, deep neural models and reinforcement learning have been widely explored for managing financial risk associated with financial instruments, services, systems, markets and participants in terms of general and specific business objectives, tasks and problems [14, 80, 88, 133, 138, 145, 155], e.g.,

- Conducting systemic risk modeling, factor analysis and simulation of a company or a market by jointly analyzing financial indicators, market data, news and client sentiment (e.g., through

social media etc.) as well as data across the relevant markets (e.g., index, derivative products, commodity and exchange rates);
- Modeling the systemic risk of a bank (or other financial service provider or investment company) by considering financial indicators of the bank across all major business lines and products, its investment performance (trading in stock markets) and operational performance;
- Modeling investment and trading risk in underlying and derivative markets with transaction costs, and modeling investment and market risk across financial derivative markets;
- Analyzing and improving payment accuracy for credit, loan, funding and other relevant economic-financial payment services by detecting, predicting and managing overpayments, over or under-claims, overpricing or underpricing, over or under-declaration of capabilities or revenue, and delayed lodgment, etc. on data related to these aspects, their payers and payees, their interactions, and behaviors;
- Predicting debt occurrences and incorrect payments in credit, loan, funding, lending, investment, insurance, taxation and government services by involving debtor's circumstances, declaration, lodgment and repayment behaviors, debt information, service information about the providers or payers, and recommending strategies for debt recovery and intervention;
- Analyzing the performance, productivity and market competitivity of multi-product and multi-policy financial services associated with a financial service provider or a financial service customer, detecting fraudsters associated with multi-product and multi-policy customers;
- Analyzing financial system vulnerability by analyzing the resilience to malicious attackers and attacking behaviors and detecting, predicting and intervening malicious attacks;
- Estimating and predicting financial risk rating and volatility of a financial instrument (e.g., cryptocurrency) by extracting and detecting risk factors in its financial reports, bank statements, Q/A dialogue transcripts, and short texts;
- Predicting P2P lending risk and interpreting the risk in terms of risk factors, scenarios and potential effect, and recommending intervention strategies to be taken on mitigating the risk; predicting the overdue risk of P2P lending on call detail records, personal information, credit information, loan history and repayment information, etc.;
- Predicting dynamic credit risk by modeling sequential behaviors of credit debtors, lending and repayment behaviors and time intervals and relevant debt information; generating automated and interpretable credit risk modeling by involving expert knowledge and converting risk management as business rules;
- Automating the compliance check of financial review reports about violations of terms and conditions in financial contracts, investment, operations, trademarks and regulations by undertaking text analysis;
- Detecting online business, payment and banking-related online fraud, web phishing and malware to compromise accounts, ID takeover and possible account information theft by analyzing data related to online customer's behaviors, suspicious transactions, unexpected behaviors, and the difference between normal behaviors and suspicious behaviors;
- Detecting financial fraud associated with a financial institution, product, service or customer by considering the real-life data and business complexities, e.g., with imbalanced minority class and overlapped classes of fraud; detecting specific types of fraud such as associated with cash flow, credit card, home loan, cryptocurrency, and market trading;
- Detecting financial crime and criminal behaviors, events and their consequences and outcomes associated with a financial system, market, product, service or participant;
- Detecting money laundering associated with a banking or online payment institution by learning the traces and connections between relevant transactions, behaviors, actions, states, context, changes and exceptions; when financial statements and activities related to target

financial systems or entities are collected, reasoning and knowledge graph can be built on them for detecting money laundering activities and entities;
- Detecting money laundering in financial systems by analyzing the direct and indirect couplings and sequential cross-system movements in transactional data and information from banking, gaming and gambling venues, e-commerce, property market, capital markets and government compliance and regulation bodies to enforce financial integrity, transparency, security, compliance and privacy;
- Analyzing risk associated with small and medium-sized enterprises (SME) on the supply chain relations between SMEs.

3.6 Intelligent marketing analysis, campaign and customer care

In EcoFin, marketing analysis, campaign and customer care not only share the same or similar objectives, tasks and methods as in 'real economy' such as physical manufacturing, food and logistics industry but also distinct missions, settings, problems and opportunities in its 'virtual' and 'real + virtual' economic forms and financial services. The 'real' nature is indicated by the physical entities, facilities, activities, media, processes and consequences; the 'virtual' nature is reflected through digitized, computerized, networked and ICT-enabled intermediaries, products, services, communications, and marketing. AIDS contributes significantly to intelligent marketing and customer relationship management in finance and beyond [4, 61, 94, 152, 154], e.g.,

- Selecting and promoting the translation of classic real and physical marketing and customer care toward virtual and digital marketspace and residence, and developing and expanding targeted marketing and customer services for digitized clients;
- Identifying and promoting the change of digitization and digital life quality of customers (e.g., elders and rural area customers) for more cost-effective, instant, personalized and modernized services and well-being, and discovering new growth opportunities of economic-financial services for those customers with undeveloped and less-developed services;
- Analyzing customer usage, location and trajectory of mobile and social media applications and services for recommending personalized, mobile and social media-based marketing campaigns and customer care;
- Identifying and forecasting the fast and evolving change and progression of customer profile, financial circumstance, demand and requirements, and intent and expectation, and recommending more appropriate, timely and needed products, services and advice, e.g., predicting those customers who may turn from inactive to active mobile payment users, from poor or regular financial circumstance to rich class, from economic to luxurious service requirements, and from individual to family-oriented demand;
- Characterizing and representing customer intent on subscribing specific financial products and services, capturing their intent change for new, more advanced, diversified and better-served financial products and services, and for higher return but lower maintenance cost;
- Modeling and forecasting customer consumption and spending demand, preferences, behaviors, sentiment, emotion and satisfaction, as well as their changes w.r.t. data such as in social media and questionnaires, and recommending the relevant, sequential and evolving products and services under the context;
- Analyzing transactions, profile and dynamics of cohort, business or problem-specific call centre and customer services for more planned, cost-effective, personalized and tailored services, e.g., predicting inbound calls and customer service and allocation of phone agents;
- In online and mobile payment etc. financial services, recommending marketing campaigns within a limited budget, quantifying customer sensitivity to specific types of incentives, predicting incentive-induced consumption and pricing, and optimizing incentive strategies

(e.g., coupons, discounted rates, and commissions) for customers and merchants; in chain-based campaigning, recommending and optimizing sharable and joint incentive strategies for balancing the customer-merchant incentives by considering their interactions, respective characteristics, aims, conflict, cooperation and alliance for mutual benefit and growth;
- Conducting financial company comparison and performance benchmarking by analyzing the similarity and difference between company's profile, accounting data, profitability, vision and strategies, company news, growth, products and services and their performance, etc., the resultant findings can inform the portfolio selection, investment analysis, regulation and compliance, and risk management;
- Predicting the performance, return on investment and value of online customers, and product- and domain-specific customers;
- Understanding customer needs and problems associated with specific products and services through analyzing contextual human conversations such as by chatbot and online Q/A, supporting personalized Q/A and enquiries, and making corresponding recommendations;
- Forecasting new market opportunities and taking targeted marketing activities and promotional campaigns on inactive, busy, time-poor, technologically disadvantaged, elder and disabled customers; understanding and quantifying the different profiles, patterns, behaviors, preferences and intent; and building unified representations of contrastive groups and their associated contrast factors, behaviors and performance;
- Customizing and predicting targeted customer services and recommendations in marketing, expanding the market share and target customers, and predicting next financial products and services through customizing marketing campaign strategies and considering challenges and scenarios such as in dynamic and uncertain markets, where supply and demand, customer circumstances and market competitive nature, and financial products and services in market evolve over time; innovations emerge in market in an increasingly competitive and fast-approaching way; and where market demand is affected by marketing competitor's campaign and incidental events such as severe social and public disasters or events.

4 MODERN RESEARCH ON AI IN FINANCE

This section further discusses some of major directions in the modern research on AIDS in EcoFin and FinTech [9, 20, 43, 67, 71, 102, 118]. We focus on the following five areas: smart online, mobile, IoT-based and Internet finance; global and cross-market analysis; smart blockchain; smart alternative economic-financial products and services; and smart operations, governance and regulation. Table 2 summarizes the typical financial domains and problems applicable to each of the above areas and the representative modern AI methods. More discussion is in the following sections.

4.1 Intelligent online, mobile, IoT-based and Internet finance

In addition to traditional online banking and financial services typically offered by banks, new finance, banking and payment services increasingly run through mobile networks, IoT, wifi networks and Internet. Such finance applications and platforms play increasingly wider and more important roles in e-commerce, online businesses and various contactless payment-based businesses, as well as triggering more and more new opportunities and problems. Examples include supporting intelligent financial services, ensuring risk-free and secure management and regulation, and creating new and smarter financial services. Below, we summarize some of the relevant areas in e-commerce, online banking and payments, mobile banking and payment [146], and broad Internet finance [97, 134].

E-commerce widely involves conventional online businesses, shopping and payments, and further evolves toward a new-generation integrative and ubiquitous ecosystem that connects and communicates with Internet services, mobile devices, IoT devices and wifi devices, as well as the users of

such devices. Accordingly, AIDS techniques can be applied to address many existing and emergent problems and needs in e-commerce [3, 26, 84, 181].

Table 2. Modern AI Techniques and Their Representative Applications in Finance.

AI areas	Financial areas	Typical financial problems	Typical AI methods
Intelligent online, mobile, IoT-based and Internet finance	Intelligent e-commerce	Estimating, predicting and optimizing online pricing, demand, supply, production, storage, logistics, delivery, marketing, risk, fraud, security, etc.	Profiling, predictive modeling, network analysis, web analysis, social media analysis, text analysis, distributed learning, behavior analytics, user modeling, interaction modeling, trajectory modeling, recommender systems, risk analytics, etc.
	Smart banking and payment	Supporting smart, secure and risk-averse online/mobile and other banking and payment methods, tools, behaviors and services; analyzing and predicting banking and payment demand, trend, growth, risk, fraud, security, malfunctions, etc.	Various methods of data mining, machine learning, deep learning, distributed learning, recommender systems, behavior informatics, risk analytics, security informatics, etc.
	Internet finance	Automating, predicting, securing and optimizing Internet-based financing, investment, wealth management, trust, credit, insurance, payment, etc.	Online/web/network analysis, online user modeling, interaction modeling, behavior analytics, text analysis, prediction, distributed learning, recommender systems, outlier detection, risk analytics, etc.
Global and cross-market analysis	Macro/micro-economic analysis	Coupling and analyzing the interactions, relations and influence between macroeconomic variables/markets and micro-financial variables; and modeling and predicting the influence of one level on the movement of the other level of financial markets or variables, etc.	Mathematical modeling, statistical modeling, multi-source/modal/view analysis, coupling learning, hybrid methods, event analysis, behavior analysis, interaction learning, etc.
	Cross-market analysis	Modeling relations, interactions and influence between financial (e.g. underlying-derivative) markets, regions, countries, companies and financial indicators; modeling relations and influence of economic, social, cultural and political aspects on financial markets; modeling financial crisis, influence and contagion; etc.	Multivariate analysis, dependence modeling, coupling learning, relation learning, interaction learning, multi-source/modal/view analysis, event modeling, behavior analysis, sequence modeling, hybrid methods, etc.
Intelligent blockchain	Blockchain systems and mechanisms	Modeling blockchain system complexities to optimize blockchain mechanisms and design; evaluating and optimizing bitcoin and cryptographic contracts and models; optimizing pricing and portfolio; etc.	Theories of complex systems, game theories, representation learning, agent-based modeling, reinforcement learning, machine learning, deep learning, distributed learning, online learning, behavior analytics, prediction, semantic web, optimization methods, etc.
	Blockchain security	Enabling secure, privacy-preserving, risk-averse and anti-attack blockchain systems and smart contracts; detecting and mitigating malicious attacks and criminal activities; assuring active governance and regulation; etc.	Process analysis, event analysis, behavior analytics, outlier detection, change detection, distributed learning, risk analytics, security data analytics, fraud detection, and benchmarking, etc.
Smart alternative finance	Property market	Estimating and predicting property valuation, pricing, demand, supply, recommendation and site selection; evaluating and optimizing property policies and governance; etc.	Numerical computing, machine learning, statistical learning, data mining, knowledge discovery, evolutionary computing, text analysis, social media analysis, behavior analytics, recommender systems, etc.
	Insurance	Estimating, predicting, optimizing and recommending insurance products and services and their pricing and market positioning; personalized product customization and recommendation; detecting fraud and risk; etc.	Profiling, classification, statistical modeling, mathematical modeling, outlier detection, behavior analysis, sequence modeling, interaction learning, and document analysis, social media analysis, risk analytics, recommender systems, deep learning, etc.
	Foreign exchange market	Predicting currency rating and movement; optimizing currency portfolio and cross-marketing trading; analyzing cross-market movement and influence; etc.	Multivariate time series, artificial neural network, evolutionary computing, coupling learning, multi-source/modal analysis, cross-market analysis, influence modeling, behavior analysis, and event analysis, etc.
	Energy	Estimating, predicting and optimizing the pricing, movement, supply, demand of electricity, oil, solar, gas, wind, nuclear and water power; optimizing energy pricing, marketing, service and portfolio; etc.	Machine learning, optimization methods, knowledge discovery, forecasting and prediction techniques, anomaly and exception analysis, coupling learning, and dependency modeling, etc.
	Wealth management	Discovering wealthy people and demand; recommending personalized products, services and customer care; detecting circumstance change and new requirements; customizing risk management, training and social trading services; etc.	Customer profiling, behavior analysis, sentiment analysis, prediction, active learning, intent learning, capability and propensity modeling, personalized recommendation, knowledge engineering, etc.
Optimal operations, governance and regulation	Smart operations and regulation	Evaluating and optimizing operation, governance and regulation performance; discovering factors, problems, failures, low-performing areas, risk and loss of operations and governance; analyzing operational, financial, regulatory, personnel and service risk; etc.	Process analysis, risk analytics, behavior analytics, event analysis, interaction modeling, relation learning, multi-source/modal analysis, prediction techniques, outlier detection, etc.
	Corporate finance	Analyzing, predicting and optimizing corporate financial budget, balance, accounting integrity, auditing issues, and payment accuracy; detecting and mitigating financial fraud, overpayment, irregular behaviors and activities, and risk; etc.	Financial time series analysis, numerical optimization, anomaly detection, probabilistic learning, relation learning, risk analytics, representation learning, and supervised and unsupervised learning, etc.

- Personalized estimate of demand, supply, production, storage and delivery as well as their balancing and Nash equilibrium of specific products for target customers, customer groups

and corporate users at particular time or time interval and at a target region or geographical location under certain situations;
- Personalized and dynamic pricing and market campaigning of specific products for target customers and particular circumstances;
- Predicting demand, supply and their balance of specific products under extreme and special circumstances, e.g., sudden extreme weather and climate conditions, high-impact political, social and cultural accidents, or significant natural disasters;
- Predicting the demand, supply and balance of logistics and delivery services and facilities for specific products, customers, regions and requirements; planning and optimizing the trajectory and scheduling of logistics and delivery personnel, facilities and services; catering for emergent businesses and delivery services such as peer-to-peer selling or exchange of second-hand goods and services and their door-to-door delivery;
- Analyzing and predicting payment distribution, trend and growth in terms of different access interfaces and channels, e.g., online, mobile, IoT devices, with different profiles of customers and for various purposes; the learned results could further inform better risk management, surveillance, marketing and recommendations;
- Detecting and predicting risk, fraud and cybersecurity related accidents, risk factors and scenarios and recommending intervention strategies for mitigating the risk, preventing fraud and cybersecurity accidents;
- Extracting the change of e-commerce intention, requirements, preference, sentiment and interest of specific customers, on different products, and for various purposes; developing tailored marketing strategies, personalized recommendations, and targeted campaigns;
- Enabling automated online matching of customer business need, preferences and next expense demand with the most suitable products and services available; and supporting follow-up promotions and interventions by tracing the sequential customer demand, intention, behaviors, preferences and circumstance change.

Online banking services are typically made through banking facilities and support payments such as by online transfer and BPay. *Online payment* instead uses merchant's facilities and online payment interfaces to support payment made by credit cards, Internet financing such as Alipay, BPay and online transfer, etc. Online and mobile banking and payment and other e-payment systems require intelligent systems and facilities to support the services and processes, generate a large number of online payment transactions [31, 34, 41, 56, 86, 111, 146]. They also face existing and emergent opportunities and challenges and require smart innovation, compliance and decision-support. Below, we list a few such examples of developing AIDS techniques for smart, secure and risk-free online banking and payments. These may involve data about online transactions, the settings of services and facilities, payer and payee information and their behaviors, the interactions between payers and payees, device-based information such as the use log of applications, the location information, the results and consequences of services, and customer care, complaints and feedback-related data.

- Predicting the banking and payment demand, trend and growth dynamics on each type of services and the corresponding service and supporting requirements, identifying gaps in satisfying consumer's need and change of intent and interest, and forecasting new product and service opportunities;
- Exploring the opportunities of applying new mobile, online, IoT and cloud etc. based techniques and facilities in online banking and payment for more personalized, ubiquitous and convenient banking and payment services;

- Analyzing and predicting the demand, money flow and activity sequence of merchant's payment transactions, and predicting and optimizing the staffing workload, facility and resource demand and planning, fraud and risk management, and growth development;
- Analyzing the expense and payment trajectories, characterizing habitual, aggressive and conservative expense and payment behaviors and customers, recognizing genuine needs and firing instant alerting on over-spending and suspicious or fraudulent spending, debt and credit imbalance, and recommending strategies and alerts for cost management and avoiding unnecessary interest charged;
- Detecting online banking and payment fraud, suspicious banking and payment behaviors and accounts, money-laundering suspicions and cybersecurity-related accidents associated with specific payment methods and criminal tools such as ID taken-over, account theft, credit compromising, phishing or malware attacks in long-range sequential interactions between a customer and the online facility, customer behavioral profiling and contextual information, tracking and detecting money transfers and money-laundering to safeguard banking and payment services;
- Analyzing complaints, accidents, failures and malfunctions that happen in online banking and payment services and facilities, predicting better and more instant monitoring, checking and repairing planning and resource planning, automating the backup and replacement and suggesting the use of most nearby services;
- Analyzing suspicious mobile, contactless and online payment behaviors and trajectories, the level of activeness, unusual consumption behaviors and expenses, the behaviors and activities of service providers, shops and merchants, the relations and interactions between consumers and merchants, detecting malicious, suspicious and fraudulent behaviors in online, credit card, mobile, contactless and other payment related apps and services, and detecting cybersecurity, money-laundering, risk and fraud etc. related activities and entities.

Internet finance has become very popular in countries such as China. Internet finance is a new financial model that applies Internet and new ICT technology to support Internet-based financing, investment and wealth management, including capital borrowing, online lending and peer-to-peer lending, direct sales of funding, money market funds, and equity crowdfunding, Internet insurance, credit rating and Internet trust; online and third-party payment; banking services; and information and communication services. Internet finance not only forms a revolutionary substitute to traditional banking and financial services but also enormously expands the scope, coverage, channel and intermediary, format and accessibility of novel, anywhere, anytime, anybody and any-form of financial services. Accordingly, Internet finance is a product and a result of technology-driven revolution of new-generation financing systems and services and is probably the most iconic landmark of FinTech, where AIDS plays the most important roles [76, 81, 173], in areas and opportunities such as

- Inventing new forms of financing, investment, payment and banking models and services for individual, institutional, event-oriented, specific plan and campaign-based, ad hoc and open domain financial services, e.g., novel crowdfunding campaigns, Internet trust, and cryptocurrency-based wealth investment products;
- Connecting and integrating channels and services across living, entertaining, working, traveling, spending and investment entities and their activities and contexts and fusing networks and communications through mobile, Internet, IoT, cloud, wifi and other instant messaging facilities to generate new anytime, anywhere, anybody, and any-form financial services;
- Building more efficient, secure and on-the-fly individual (agent)-based, large-scale, distributed, decentralized, parallel, Internet-to-door, end-to-end and peer-to-peer Internet, mobile, cloud, IoT and wifi-based financial services, e.g., investment on mobiles; and

- Enabling active and on-the-fly cybersecurity, risk, fraud and regulation management of Internet finance, developing intelligent algorithms and systems for real-time, short to long-ranged, dynamic and evolving risk and compliance checking, detection, prediction and mitigation recommendation, e.g., predicting institutional and public risk of P2P lending services and estimating credit rating.

Techniques usable for modeling, automating, optimizing and transforming the above mentioned mobile, IoT-based and Internet finance spread almost all areas of AIDS, as well as the synergy with new theories and tools in finance and economics. Examples are behavior informatics and analytics for handling behavioral profiling, risk rating, positive and negative behavior detection, behavior impact prediction, and future behavior forecasting and consequence intervention; dynamic, sequential, on-the-fly and contextual modeling, analysis, monitoring and prediction of new financial service demand, supply, gaps, market share, growth and opportunities; and personalized, sequential and proactive recommendation of financial services and products and client-side risk and security alerting and mitigation; and incorporating multimodal and multisource data and cross-platforms and systems into business analytics, risk analytics, opportunity forecasting, and target recommendation.

4.2 Global and cross-market analysis

Global and cross-market analysis refers to the analysis of economic-financial systems, products, services, activities and events in a highly globalized market or across multiple relevant markets. With the ubiquitous and increasing globalization of economy, human social and cultural activities, climate issues, social and political issues such as counter-terrorism and anti-money laundering, biogeographical issues such as global virus spreading, global and cross-market analysis plays an increasingly important role in promoting local, regional and global socioeconomic, cultural, environmental and political developments and addressing local, regional and global issues. Such global and cross-market issues involve significant complexities and challenges associated with global and cross-market cultural, regional, political and economic difference and often distributed, hierarchical, heterogeneous, inconsistent and cross-time zone and season businesses, data, information systems, working mechanisms, etc. AIDS techniques are crucial for addressing these complexities and challenges that may not be resolvable before or well understandable; AIDS can also detect often hidden, interactive, complicated, evolving global and large-scale events and disclose their driving factors and consequent transfer effect to other systems and markets [29, 30, 65, 73, 162, 174]. In the following, we illustrate several of such examples and case studies.

- Learning the influence of macroeconomic variables and factors on micro-level financial indicators and factors (e.g., an asset price and its movement), and modeling the influence propagation across financial indicators, markets, instruments and companies, e.g., by integrating financial time series analysis, dependence models such as copula with sequential modelers such as recurrent or graph neural models;
- Modeling global market couplings in terms of the linear and nonlinear correlations, sequential and static dependency, observable and latent variables, macro and micro-level variables, and their structures and degrees;
- Modeling the influence propagation and directions of market coupling and dependency transfer from one financial entity or participant to another; detecting correlation evolution, structural changes and breakdowns of dependency, new dependency between previously less coupled assets, new dependency structures, and dependency level changes; identifying reasons and triggers causing the dependency transformation, e.g., extreme events, epidemic emergence and disease, travel bans, financial crisis, and global geopolitical emergency;
- Modeling the cross-country economic dependency and the political dependency of one country on third-party organizations and their economy and political systems;

- Modeling the couplings between markets, countries, regions and companies, modeling the influence of couplings on their economic, social, cultural, health and political systems, and estimating the impact and consequence of their decouplings;
- Modeling the change of couplings and dependency between markets, countries, regions and companies and their influence on the performance, operations, developments and future of these entities;
- Representing and quantifying financial stability, soundness and vulnerability of global economic systems based on indicators of banks, shadow banks, mutual funds, hedge funds, insurance companies, and pension funds and modeling their mutual influence and relations;
- Modeling the goal-oriented, operational and performance-related effectiveness and efficiency of multinational companies, regional and global institutions, and international alliances by reviewing their settings, policies, operations, resources and consumption, financial data, auditing and compliance, etc.;
- Estimating and analyzing global financial crisis and crisis contagion across companies, banks, financial markets, countries and economic entities by involving financial indicators about these entities and their financial statements, news, and social media information;
- Predicting economic indicators such as the GDP of a country and the world by modeling the influence of significant external, regional and global economic, social, cultural and political events on the indicators;
- Modeling the propagation and spreading of significant global emergency (e.g., epidemic COVID-19) from one place to global places and their influence and consequences on other aspects, e.g., economic conditions, growth and future development;
- Designing, automating, optimizing and securing cross-market trading and investment assets, products, services and platforms (e.g., commodity, cryptocurrency and foreign currency);
- Designing, automating, optimizing and securing high-frequency trading across equity and derivative markets and across commodity, foreign exchange, and capital markets.

4.3 Intelligent blockchain

For **blockchain**, both classic and modern AIDS techniques can contribute to smart blockchain and blockchain developments. For example, both classic AIDS techniques such as random forest, regression, time series forecasting, and shallow clustering and classification learners and modern AIDS approaches including Bayesian graphical models, CNN, RNN, and reinforcement learning models are applicable to blockchain systems. Examples include understanding and designing blockchain systems; the enhancement of blockchain infrastructure; enabling semantic blockchain; blockchain privacy and security preserving and enhancement; detection, identification and classification of blockchain entities, attacks and behaviors; price prediction and portfolio management of bitcoin and cryptocurrencies; and evaluating and enhancing blockchain system performance, etc. [15, 32, 36, 37, 47, 52, 121, 136, 159, 164, 169, 177].

Specifically, to *understand and design blockchain systems and problem-solving* driven by handcrafted and design-based nature, AIDS understand, represent, simulate and quantify the complexity of blockchain systems, e.g., their order, hierarchy, self-organizing, interactions, decentralization, emergence, uncertainty, and nonlinearity. For *enhancing blockchain infrastructure* [15], AIDS design, evaluate and optimize bitcoin and cryptographic protocols [52, 164], e.g., more robust and efficient blockchain consensus mechanisms and cryptographic hash functions; address the Byzantime general problems for more trusted conversation and consensus decision [108, 169]; and detect and analyze artificial cycle and instability by design (e.g., the block reward halving design). AIDS techniques such as logic programming, semantic web and computation semantics can be integrated with blockchain to form procedural and declarative *semantic blockchain* [164]. Semantic

blockchain ensures easier, smarter and more explainable, robust, secure and validatable smart contracts, communications, computation, functional and logic programming, and fault tolerance for and between blockchain participants (e.g., blockchain ledgers, buyers, sellers, validators, and regulators). To *preserve and strengthen blockchain privacy and security*, AIDS applies to the collection, storage, updating, auditing, sharing, changing, processing and validation of blockchain data and transactions [98]; developing more secure blockchain frameworks and smart contracts; and for specific applications such as IoT systems and mobile applications [136]. In addition, for *blockchain entity, attack and behavior detection, identification and classification*, AIDS detect, identify and classify malicious attacks and criminal (including cybercriminal) and dishonest blockchain transactions, activities and behaviors, and different types and categories of entities (e.g., service, exchange, and gambling, etc.), etc. Further, regarding *price prediction and portfolio management of bitcoin and cryptocurrencies*, AIDS analyze and predict the price, price formation, portfolio, value of unspent transaction outputs, and their dynamics and trends of bitcoins, cryptocurrencies, and digital cash; analyze the topological structures of chain transition; and design trading strategies for buying and selling bitcoins and cryptocurrencies [9]. Lastly, AIDS techniques are applied to *analyzing and improving blockchain system performance* [36], e.g., allocating computational power and distributed computing power for bitcoin mining processes, mobile bitcoin mining activities, IoT, etc.; reducing computational costs and power consumption in bitcoin mining; designing energy-saving and efficient bitcoin mining processes, hardware-dependent distributed and parallel mining systems, algorithms and strategies, and data-rich message passing and transaction compression; and maximizing the efficacy of blockchain data collection, storage, sharing and processing, etc.

More specifically, we illustrate some of the opportunities where AIDS techniques can significantly contribute to smart blockchains below:

- Modeling and representing blockchain systems e.g. by graphs, networks and knowledge graphs, and involving techniques e.g. knowledge reasoning and graph analysis to predict the price movement of cryptocurrencies and the problems e.g., the money laundering;
- Building more efficient and energy-efficient blockchain consensus mechanisms such as improved proof-of-work and proof-of-stake, and modeling the profitability, computational costs and risk of blockchain trading for consensus building in the blockchain ecosystem;
- Designing strategies for blockchain-based crowdsourcing with distributed platforms and consensus protocols such as proof-of-strategy for fork issue and malicious behaviors, and enabling quality rating and quality of service;
- Efficiently building trustless, transparent and decentralized oracles in blockchain by involving truthful and multimodal information and controlled gas cost etc. for blockchain optimization;
- Developing the performance evaluation systems and measures of the business performance and impact of blockchain systems and businesses;
- Modeling the state transitions in blockchain systems, modeling the operational behaviors in blockchain businesses, and detecting suspicious and fraudulent states and behaviors that may violate the security, privacy and compliance of blockchain;
- Developing, detecting and evaluating models and measures for blockchain governance and regulations, developing models and rules for the compliant blockchain operations;
- Developing privacy-preserving systems, methods and measures for ensuring the privacy preserving in blockchain, and detecting violations of privacy in blockchain businesses;
- Optimizing blockchain systems e.g. decentralization, robustness, efficiency, scalability and security in mixed-type, multimodal and dynamic and uncertain blockchain data and businesses, supporting cross-chain extensions and smart contracts in blockchain businesses;
- Evaluating and supporting the balance between blockchain scalability, security and decentralization in blockchain businesses and processing;

- Designing the support to hierarchical, distributed, satellite and side blockchains and their communications and security assurance for large-scale blockchain business and operations;
- Designing smart misbehavior screening algorithms and systems to filter and alert on misbehaviors in blockchain networks;
- Designing more efficient and accurate algorithms for discovering cryptocurrency, and predicting the cryptocurrency price and market movement such as by learning relevant opinions and indications from news and social media discussions;
- Recommending and predicting blockchain financing such as initial coin offerings and cryptocurrency portfolios; and
- Detecting and predicting existing and novel ransomware and hacking behaviors in bitcoin and cryptocurrencies, and detecting phishing scams and accounts in blockchain transactions, e.g., with Ethereum;

4.4 Smart alternative economic-financial products and services

In EcoFin, creating new and novel investment opportunities beyond financial products and services in capital markets is critical for new business, financial, economic and investment developments. Such opportunities may include those innovations and transformations in the conventional economic-financial systems, products and services and creating new economic-financial systems, products and services beyond financial markets, e.g., in property markets, energy markets, healthcare markets, insurance markets, foreign exchange markets, blockchain, and wealth management businesses [183]. Here, we illustrate such opportunities in some of these markets, but leave the discussion on blockchain to Section 4.3 and new economic-financial innovations to Section **??**.

The investment in property markets can significantly benefit from AIDS techniques [13, 101, 106, 148, 163, 180], for example, customizing numerical computing, machine learning, statistical learning, data mining and knowledge discovery, evolutionary computing, and NLP for

- Predicting property price and developing valuation models for property pricing by analyzing historical data of real estate, environmental data, buyer and seller data, and macroeconomic and microeconomic data related to property policies, availability, taxation, commissions, and stamp duty policies, etc.;
- Analyzing factors that determine who will buy what types of properties, e.g., between the purchase decision and property location, property conditions, price, land conditions, environmental factors (e.g., nearby parks, rivers and entertaining facilities), public services and facilities (e.g., schools, shops, train and bus stations);
- Recommending property sites and existing property ranking in terms of property conditions and prices, site information, council services, residential facilities, suburb profile, resident feedback in social media, and property market data;
- Predicting property pricing trend and movement by analyzing opinions and sentiment in public news (e.g., commentaries and survey reports about property markets), social media, and third-party analysis reports;
- Predicting the property demand in terms of varied categories of purchaser profiles, preferences and sentiments at each suburb and area, evaluating the government policies and property construction plans, and recommending strategies and policies for addressing market demand;
- Building evidence and estimation for new construction site selection and site landscape design by analyzing data related to buyer's preferences, market demand, target residents, etc., and discovering sensitive factors and measures that affect site selection and property market;
- Predicting the influence of property policies (e.g., on tax, stamp duty, first buyer), land value change, investment market conditions, foreign investment, external accidents and events (e.g., air and water quality pollution) on property price movement and property sales.

Insurance spreads to very broad areas and aspects, e.g., insurance for income protection, unique and important characters and assets, property care and wealth, in addition to traditional focus on vehicles, properties and healthcare. Such additional insurance products and services bring about new investment opportunities, where AIDS techniques such as classification, outlier detection, behavior analysis, sequence modeling, interaction learning and document analysis can play valuable roles [54, 82, 117, 126, 151, 161], e.g.,

- Evaluating the design, market positioning, market share, market competition, and long-term market growth trend of a new insurance product and service, predicting the target clients and their sensitivity to the new product and service, and suggesting marketing campaign strategies and activities;
- Recommending new insurance products to existing insurance clients who may likely purchase, and developing multi-product policies and campaign strategies and activities;
- Modeling the fraud and risk associated with specific insurance products and services, customers and their interactions and communications with the insurers, over or under-services, over and under-claims, and accident information;
- Estimating the value of insurance, pricing of premiums, excess values, and refund limits of each insurance product, developing personalized pricing and limit settings for high-value and high-potential customers and corporate customers;
- Evaluating the impact of purchased insurance on customers, particularly for non-compulsory insurance products and selective customers, providing review evidence for national and corporate policy-making and regulation of insurance businesses;
- Analyzing the healthy partnership between insurance providers and insured customers, analyzing their interactions, communications, trajectories, claimed services and expenses, and identifying and tracking suspicious and fraudulent activities and collaborations.

Investment in *foreign exchange markets* can benefit from AIDS techniques such as multivariate time series, artificial neural network, evolutionary computing, coupling analysis of cross-market indicators, influence modeling, and behavior and event analysis [29, 78, 100, 132, 170, 173, 178], with examples such as

- Predicting the trend and movement of exchange rates of a foreign currency by learning its relations with other macro- and micro-economic indicators and the influence of these indicators on exchange rates;
- Predicting the exchange rate dynamics against relevant foreign currencies by learning the sequential dependency between the currencies;
- Selecting foreign currencies and their investment composition in a portfolio by learning their high-order couplings and individual heterogeneity (such as distributions and dynamics) and the market risk of such portfolios;
- Analyzing the influence of market events, exceptional accidents, political and other events on foreign exchange rates, and recommending intervention strategies, timing and actions to maintain the stability of exchange rate;
- Detecting the manipulation of exchange rates and factors by a company or a country to explain the manipulation and discovering manipulative behaviors;
- Analyzing the couplings between exchange rates, equity market index, and other financial indicators such as petrol price and gold price and their influence on each other's dynamics;
- Detecting opportunities and portfolio construction for cross-market investment, e.g., portfolio selection of foreign currencies, commodity products, and stocks by analyzing their influence and movement.

Energy becomes increasingly important in investment. Energy market is diversified by electricity, oil, solar, gas, wind, nuclear, and water power, etc. By developing energy-oriented machine learning,

optimization, knowledge discovery, forecasting and prediction techniques, anomaly and exception analysis, coupling learning and dependency modeling, etc. AIDS techniques, we are able to significantly address various issues of energy markets including electricity, wind, solar, nuclear and water energy and improve the different aspects of energy investment [11, 55, 103, 119, 167, 168], e.g.,

- Analyzing and predicting short to long-term price trend and movement of different forms of energy and price sensitivity to the demand and supply of other forms of energy, cost and performance, and impact on air quality and environment;
- Analyzing and predicting the market share, roles, demand and supply of different types of energy across different countries and regions;
- Analyzing the quality and market reputation and performance of specific energy, and detecting problems with the energy quality and suggesting improvement strategies;
- Analyzing and minimizing the cost, risk, and accidents associated with a type of energy in terms of the energy packaging, transportation, storage and distribution as well as the related transport tools, pipes or networks, devices and vehicles, weather conditions, human mistakes and damages, etc.;
- Analyzing the positive and negative impact of a type of energy on business and residential conditions and quality, air quality, human health, and economic effect;
- Designing the portfolio of energy products for a country or a large organization by considering short to long-term price dynamics and demand and supply relations;
- Developing new energy product, e.g., electricity trading such as enabling vehicle-to-vehicle electricity trading based on blockchain techniques to build a distributed Internet of vehicles through blockchain and then determine the pricing of electricity, preserving the information privacy of vehicles, security and reliability of trading, and analyzing and managing risk.

The significant growth of middle-class and wealthy people in the global society urges the booming of *wealth management*. AIDS techniques including personalized, active, risk-tolerant and tailored analysis, prediction and recommendations of wealthy groups and individual institutions play unique and complementary roles in driving the design, implementation, optimization and evaluation of smart and personalized wealth management [45, 109, 114], e.g.,

- Developing personalized products and portfolios for wealthy people, e.g., alternative investments of private equity, private credit, hedge funds and real estate that best suit target profiles of wealthy people;
- Understanding a client's personal wealth situations and investment goals and constraints, and developing personalized investment plans and portfolio proposals for each client;
- Conducting personalized care and follow-ups, analyzing the interactions and communications with wealthy people for better customizing the investment products, portfolios and services for suiting their circumstances, expectations and long-term strategic plans;
- Analyzing enquiries regarding the updates of recent and legacy investment products and services, funds, assets and real estate, and discovering opportunities for improving the services and tailoring upgrades for specific clients;
- Customizing training courses to address wealthy people's investment needs, analyzing and improving personalized customer relationships, and training clients with knowledge, risk and mitigation skills about specific products and significant investment and risk management;
- Conducting the analysis of due diligence, compliance, performance and strategy evaluation for significant investments made for wealthy people, identifying potential risk and exceptional accidents, and preventing the impact of unexpected events on investments and return;
- Predicting and explaining company mergers by the acquisitions and analysis of company-related external news, social media comments, media commentaries and intercompany activities, as well as their complementarity and emergent opportunities after the merger;

- Estimating the valuation of discounted cash flow of a company in terms of changing company value, market shares, wealth growth potential, business lifecycle, and chronological events;
- Estimating the value of patents and their relative values, and predicting the opportunity for patent trading and patent recommendation;
- Customizing financing strategies and opportunities, e.g., recommending crowdfunding campaign strategies of issuing equity and debt by analyzing the company's financial conditions, capital structures, growth momentum, funding need, business life cycle, business activeness, and cash flow health;
- Customizing and securing social trading to share investment strategies, experience and knowledge, characterizing expert experience of those demonstrated high-performing expert traders, ranking trader's performance, and recommending portfolios for trading settings.

4.5 Optimal operations, governance and regulation

Operations, governance and regulation are critical for economic entities, financial institutions, corporate, businesses, economy and the society. In the era of data and intelligence, conventionally domain knowledge-enabled, hypothesis-based and predefined rules-based theories, methods and systems for designing, implementing, validating, evaluating and optimizing operations, governance and regulation are transformed to be data-driven, intelligent, automated, dynamic and proactive. New-generation operations, governance and regulation are built on AIDS and related analytics and learning techniques, such as risk analytics, mixed data analysis, event analysis, activity and behavior analysis, interaction modeling, relation learning, and prediction techniques such as gradient boosting, tree-like boosting, neural gradient boosting, and deep neural models [6, 7, 39, 57, 83, 93, 110, 112, 120, 122, 124, 130, 147, 155, 176]. Smart operations, governance and regulation involve many aspects of both upgrading conventional operations, governance and regulation and enabling new-generation operations, governance and regulation. Here are some examples.

- Evaluating the quality and performance of operations, governance and regulation of an institution, its business units, a team or a market, and building benchmark indicators for monitoring, evaluating and comparing their operational, governance and regulatory practice, quality and performance;
- Detecting well or poorly operated, governed and regulated areas in an organization or its business units, analyzing factors and reasons affecting operational, governance and regulatory practice and performance, and suggesting strategies and actions to be taken for the poor-to-high-performing transformation of operations, governance and regulation;
- Quantifying the risk associated with operations, governance and regulation, predicting the risk severity, consequences and associated factors of operational risk, governance risk and regulatory risk in a financial organization by analyzing internal data and information associated with the corporate finance, human resources, staffing, workplace, corporate services, planning, review, property or other resources, and predicting new types of risk and evolving risk in operations, governance and regulation;
- Analyzing and predicting operational, governance and regulatory risk and extracting specific risk types and associated factors by analyzing relevant external data, e.g., financial news, events, public feedback, third-party auditing and review data, and accounting data;
- Predicting the operational loss of a company by modeling the loss transactions, account balance, expense sequence, revenue streams, and irrational and unreasonable expenses, and shortage of income, etc.;
- Analyzing and predicting the operational losses of a corporate's credit and loans by analyzing the corporate lending, expenses, loans, repayments, cancellations, and interests charged;

- Quantifying and benchmarking the performance of financial analysts, engineers and managers by analyzing their workplace activities, key performance indicators, leaves, corporate engagement, earnings, bonuses, shares, and their product knowledge, team work, communication and impact (such as writing high-impact financial reports, social media messaging, and public activities such as commentaries on TV and online media channels);
- Evaluating the qualifications and work capability of economic-financial analysts, engineers and managers, as well as their learning ability, teamwork and collaborations, marketing skills, communication skills, and core analytical skills and knowledge, capability in understanding broad markets, investment products, and financial regulations;
- Benchmarking the work capability of handling detailed, dynamic, multi-task-oriented and collaborative tasks in an evolving, uncertain, and interactive workplace;
- Predicting and planning staff travel and leave periods and their work backup, corporate facility bookings and usage, and operational consumption resources;
- Developing real-time risk management systems for screening, alerting and managing enterprise operations, governance and regulation;
- Evaluating the effectiveness, efficiency and business performance of teamwork, collaborative tasks, and business partnering across the finance, production, sales and marketing, R & D, and corporate service teams in a corporate, and identifying silos, gaps, and blocks preventing collaborations and partnership;
- Undertaking compliance check of corporate data governance and management, cybersecurity-related issues, ethics and privacy-related compliance issues such as GDPR privacy compliance by analyzing the rules and compliance settings for data governance, ethics, privacy, security, system settings, log and transactions of data management and protection, detecting privacy and security breaches, incompliant entities and behaviors, regulators, attacking accidents and attacking behaviors;
- Estimating and optimizing enterprise revenue, business credit and corporate credit rating, forecasting and managing the impact of credit rating changes made by credit-rating agencies and informed by external information including market sentiment.

Corporate finance including accounting and auditing is a critical component in operations, governance and regulation. Corporate finance is experiencing a paradigm shifting from rule and corporate-based accounting and auditing services, information management and governance to individualized mobile and cloud finance, and personal digital device-based finance. AIDS techniques such as financial time series analysis, numerical optimization, anomaly detection, probabilistic learning, relation learning, risk analytics, representation learning, and supervised and unsupervised learning such as deep neural models and Bayesian networks are playing increasing important roles in the shifting and smart corporate finance transformation and gaining real-time, proactive and dynamic visibility and insight into financial status, progress, exceptions and risk in a corporate [60, 123, 127, 144, 179]. Below, we present a few examples.

- Conducting accounting risk analytics associated with financial journals, account adjustments, reconciliations, account variances, intercompany exposure, and failed and overdue receivables and payables;
- Analyzing accounting process-related risk such as workload imbalance, inconsistencies in accounting processes, failed and overdue approvals and journal processing, efficiency and quality of accounting processing, etc.;
- Analyzing accounting indicators, balance sheets, budget and expense to measure the financial health and balance between account payables and receivables, between budget and expense, and between revenue and expense, etc.; predicting and scheduling accountable receivables and invoice payments; and evaluating accounting risk and identifying mitigation strategies;

- Analyzing historical account receivable and payment behaviors to detect abnormal and fraudulent financial activities and significant variances in a corporate institution, identifying triggers for further internal and external audit and investigation, and alerting on suspicions and anomalies for risk management actions;
- Evaluating and indexing corporate financial health by collecting and analyzing risks identifiable in narrative statements, periodical and annual financial statements and annual reports, and quantifying the statistics of corporate financial performance and scenarios;
- Learning the financial position, condition and soundness of a company by associating account balance with the textual information in financial statements about sector, company activities, and contextual economic and market conditions;
- Estimating the bankruptcy likelihood of companies and recommending intervention and change strategies;
- Detecting cause-effect entity relations and nested causality in financial statement disclosure by sentence segmentation, causality connective detection and segment matching;
- Conducting audit analytics to discover key indicators, period-to-period variances, quantifying benchmarks against typical and ordinary thresholds, comparing against business units, accounts, processes and products;
- Conducting benchmark analytics of typical financial and operational metrics (e.g., return on investment and profit margin) against similar (e.g., same-sector and same-sized) companies and of external, third-party-based and crowd-sourced accounting, auditing and financial comparisons and benchmarks;
- Evaluating accounting operational performance and benchmarks against comparatives such as completed accounting assignments, on-time completion rate, and average reconciliation rejection percent for the same industry and the similar company size and profile of companies;
- Analyzing real-time corporate financial transactions of corporate expenses, income, payments and their associated activities and entities to identify problematic accounting behaviors and entities, suspicious stakeholder relationships, abnormal procurement, etc. for real-time auditing and risk mitigation.

5 CONCLUSIONS

This review presents a comprehensive picture of AIDS-enabled smart economy and finance. The new generation of AIDS, in particular data science, machine learning, and deep learning, is driving the era of data and intelligence-driven economics and finance, which present tremendous opportunities of translating conventional economic-financial theories, research and tools and promoting smart and intelligent economic-financial practice, which also further advances AIDS to better tackle real-life significant economic-financial challenges and complexities and deliver actionable intelligence-driven economy and finance.

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