Journal of Behavioral and Experimental Finance 32 (2021) 100577

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Review article

Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis

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ARTICLE INFO

Article history:
Received 7 June 2021
Accepted 26 August 2021
Available online 30 August 2021

JEL classification:
B16
B41
C13
C40
C44

Keywords:
Artificial intelligence
Bibliometric analysis
Finance
Machine learning
Review

ABSTRACT

Artificial intelligence (AI) and machine learning (ML) are two related technologies that are emergent in financial scholarship. However, no review, to date, has offered a wholistic retrospection of this research. To address this gap, we provide an overview of AI and ML research in finance. Using both co-citation and bibliometric-coupling analyses, we infer the thematic structure of AI and ML research in finance for 1986–April 2021. By uncovering nine (co-citation) and eight (bibliometric coupling) specific clusters of finance that apply AI and ML, we further identify three overarching groups of finance scholarship that are roughly equivalent for both forms of analysis: (1) portfolio construction, valuation, and investor behavior; (2) financial fraud and distress; and (3) sentiment inference, forecasting, and planning. Additionally, using co-occurrence and confluence analyses, we highlight trends and research directions regarding AI and ML in finance research. Our results provide assessment of AI and ML in finance research.

Contents

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https://doi.org/10.1016/j.jbef.2021.100577
2214-6350/

1. Introduction

The emerging use of artificial intelligence (AI) and machine learning (ML) within financial systems is disrupting and transforming industries, and societies (Li and Tang, 2020; Wall, 2018). From traditional hedge fund management firms and investment and retail banks, to contemporary financial technology (FinTech) service providers, many financial firms today are heavily investing in the acquisition of data science and ML expertise (Holzinger et al., 2018; Wall, 2018). The generation of machine-readable data throughout the financial system, backed by a persistent growth in computation power and storage, has had major implications for the financial industry. Concomitant with this 'drive for data' is a constant need to reprise regulatory systems. As a specific example, the global financial crisis of 2007–2008 motivated structural changes in the regulation of the financial industry to focus on 'data-driven' regulation. This led to reassessment of the procurement and analysis of contractual terms for bank loans and trading book stress-testing programs implemented throughout Europe and the United States (Flood et al., 2016).

Finance industry professionals are increasingly interested in 'alternative data' that is outside the purview of standard company fundamentals, security prices, and macroeconomic indicators. This includes voice recordings, news articles, posts in social media, and satellite images. Such sources of exceptionally large data now have significant influence on trading decisions (In et al., 2019). Exploring the properties of such datasets, de Prado (2019) observes that such large data sources are characteristically awkward for traditional approaches, being often non-numerical, unstructured, replete with missing values, and/or non-categorical. Therefore, such data are typically high-dimensional, with the number of variables (features) often exceeding the number of observations (see also Duan et al., 2021; Makarius et al., 2020).

Given these anomalies, classical econometrics, predicated on linear modeling, have little utility to derive predictive and deterministic models using alternative data (de Prado, 2019). Much subtle, but economically important, information inherent in large data sets remains undetected by such traditional modeling (Coulombe et al., 2020). For example, geometric constructs such as the covariance matrix cannot distinguish the topological interrelations that characterize networks in alternative datasets. On the other hand, ML models offer the computational power and functional flexibility required to decipher complex patterns in a high-dimensional data environment. Furthermore, recent advances in ML have made plausible the application of scientific theories to determine the (inter)relations among features of variables for deeper exploration, prediction, causal inferencing, and visualization (Dixon et al., 2020).

ML is a suitable remedy to overcome the shortcomings of classical econometric models in detecting outliers, extracting features, and performing classification and regression of complex data. For instance, $2^n - n - 1$ multiplicative interaction effects can exist in the midst of 'n' features, and thus, one interaction effect (f_1f_2) can manifest for two features (f_1 and f_2), whereas four interaction effects (f_1f_2, f_1f_3, f_2f_3, and $f_1f_2f_3$) can unfold with three features (f_1, f_2, and f_3), and a total of 1013 interaction effects can avail for a case as small as 10 features. Unfortunately, unlike ML, classical econometric models fail to 'read and learn' the underlying interactions leading to dramatic outcomes (Dixon et al., 2020). As an illustration, consider that fitting $Y_t = X_{1,t} + X_{2,t} + \varepsilon_t$ against $Y_t = X_{1,t} + X_{2,t} + X_{1,t}X_{2,t} + \varepsilon_t$ is simply not possible. However, an ML algorithm, such as a decision tree, can easily partition a complex dataset into subsets with identifiable linear patterns. Therefore, unlike classical linear regression, the decision tree algorithm in ML can quickly recognize patterns, and in this case, the $X_{1,t}X_{2,t}$ effect, thereby producing plausible outcomes for complex situations.

The power of AI over traditional econometric models has ignited significant research interest in ML application for algorithmic trading (Martínez et al., 2019), asset and derivative pricing (Houlihan and Creamer, 2021), automation (Kokina et al., 2020), financial modeling (Chan and Hale, 2020), fraud detection (Teng and Lee, 2019), loan and insurance underwriting (Bee et al., 2021), prevention of financial risk (Gao, 2021), risk management (Li et al., 2021), sentiment analysis (Chen et al., 2020), and trade settlement (Omarova, 2019), etc.

Though the popularity of AI and ML has sparked a recent plethora of literature, there is still a paucity of academic summaries regarding AI and ML for finance. Exceptions to this (Das, 2014; Li, 2020; Loughran and McDonald, 2020) are largely skewed toward exclusively focusing on the application of textual analysis in finance. No review, to date, presents a state-of-the-art overview of AI and ML application in finance. Reviews that provide retrospection of emergent areas are important as they facilitate scholars to acquire an overview of the structure and taxonomy of research areas (Donthu et al., 2021).

Given the importance of AI and ML, together with the paucity of research that consolidates the extant literature pertaining to the financial application of these technologies, we offer a retrospection of the extant literature on AI and ML application in finance. To do so, we employ bibliometric methodologies which encapsulates a host of quantitative techniques capable of handling large datasets relating to the literature (Donthu et al., 2021). In doing so, our bibliometric review of the extant literature identify themes and foundations of scholarly areas in which AI and ML have been applied in finance research, providing frameworks for future investigation.

Using both co-citation and bibliometric-coupling analyses, we infer the knowledge and thematic structure of AI and ML research in finance for 1986–April 2021. By uncovering nine (co-citation) and eight (bibliometric coupling) specific areas of finance that apply AI and ML, we further identify three clusters of finance scholarship that are roughly equivalent for both forms of analysis: (1) portfolio construction, valuation, and investor behavior; (2) financial fraud and distress; and (3) sentiment inference, forecasting, and planning. Additionally, co-occurrence and confluence analyses highlight trends and research directions regarding AI and ML in finance research. Our results provide guidance for future researchers, as well as focus for assessing the growing emphasis on AI and ML in finance research.

2. Background on AI and ML

The concept of AI originates from a 1955 Dartmouth Summer Research Project Proposal (McCarthy et al., 2006).[1] Later evolutions of this cohort posited that "every aspect of learning or any

[1] Members of this cohort included John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon.

other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it'' in an endeavor to ''find how to make machines use language, form abstractions and concepts, solve problems now reserved for humans, and improve themselves'' (McCarthy et al., 2006).[2] Since then, AI has evolved into a field of inquiry dedicated to enabling machines to have abilities to handle complex tasks. From this a pattern of success has gradually emerged. Turing tests, which assess the ability of machines to demonstrate intelligent behavior (Turing, 1995), show that machines often outperform humans in solving complex judgment-related problems, such as the identification of decision variables out of a very large number of candidates constrained within a high-dimensional space (DeepMind, 2016; Saygin et al., 2000). Indeed, ML, when informed by deep learning, has been remarkably successful for a variety of tasks (Dixon et al., 2020).

Yet, AI, ML, and associated concepts such as deep learning and data science, are often confusing to many people (Wall, 2018). In essence, ML is a specific manifestation of AI that develops techniques that enable machines to recognize patterns in datasets. By comparison, deep learning is a subset of ML that equips machines with those techniques required to resolve complex problems, Data science is a separate branch of study that applies AI, ML, and deep learning to arrive at actionable conclusions.

ML broadly covers facets of algorithms for recognizing patterns and making decisions. Supervised ML deals with labeled data, such as data that appear as pairs (X_1, Y_1 … X_n, Y_n, where $X_1 \dots X_n \in X$ and $Y_1 \dots Y_n \in Y$), wherein each feature vector (X_1) is labeled to a response (Y_1). In contrast, unsupervised ML deals with unlabeled data (X_1, X_2, X_3 … X_n), wherein the goal is to gather exploratory information and uncover hidden patterns by grouping observations into different clusters. Thus, unsupervised ML deals with clustering algorithms such as hierarchical clustering, *k*-means clustering, Gaussian mixture, self-organizing maps, and hidden Markov models frequently termed as data mining. For both supervised and unsupervised ML in finance, the suitable data can come from financial documents, financial time series, news reports, social media postings, or textual content on important events.

Unsupervised ML can also be informed through reinforcement learning. This is an algorithmic approach to defining the states and actions in response to a change in regime so that cumulative reward is maximized.[3] In contrast to supervised learning that is concerned with a single action at a point in time, unsupervised ML through reinforcement learning is concerned with an optimal sequence of actions, and thus, belongs to a form of dynamic programming that can be used in such situations as optimal portfolio allocation, optimizing liquidation of assets over a given horizon, and optimal trade execution.

3. AI and ML in finance research

The flourishing literature on AI and ML in finance has attracted previous scholarly review. For example, Das (2014) explores research on predictive analytics and text mining in finance. de Prado et al. (2016) evaluate studies on credit risk and bankruptcy, observing a growing tendency of finance research to move toward the employment of hybrid models that combine traditional modeling (e.g., discriminant analysis, logistic regression) with AI, neural networks, and other ML techniques. West and Bhattacharya (2016) offer a comprehensive analysis of literature on financial fraud detection between, classifying this literature based on the types of frauds indicated, the algorithms used, and the performance of detection methods.

Elliott and Timmermann (2016) analyze the forecasting methods deployed in economic and finance research, concluding that no one method is sufficient alone. They posit that appropriate forecasting methods should be chosen by accessing the economics of respective loss functions. Currie and Seddon (2017) expose the 'dark art' of high-frequency algorithmic trading following the 'Flash Crash' of 2010, providing conceptual tools for analyzing high frequency trading. Sangwan et al. (2019) highlight prevalent themes in FinTech research.

More recent reviews have focused on textual analysis. Li (2020) highlights the limitations of financial literacy measurement models, while Loughran and McDonald (2020) offer an updated review of textual analysis in finance. Bhatia et al. (2020) explore the advantages of robo-advisory services, while Königstorfer and Thalmann (2020) review the benefits and challenges of AI in commercial banks. Ciampi et al. (2021) evaluate over 100 studies on SME-default prediction models, endorsing the adoption of AI and ML for default prediction.

Taken collectively, existing reviews of AI and ML in finance are generally narrowly focused, with differing aspects presented separately rather than collectively. Of note, none of these past reviews present a comprehensive classification of AI and ML with respect to applications in finance. Therefore, in this review, we adopt a holistic and inclusive approach, while narrating a comprehensive overview of the adoption and implementation of AI and ML in finance.

4. Methodology

We adopt a bibliometric methodology that involves the use of quantitative tools for the analysis of bibliometric and bibliographic information (Pritchard, 1969). Unlike classic systematic literature reviews, a bibliometric review has facility to provide information over domains characterized by large amounts of bibliometric and bibliographic information. Specifically, we follow Donthu et al.'s (2021) four-pronged procedure for bibliometric reviews: (1) defining the aims and scope for review; (2) choosing the techniques for analysis; (3) collecting the data for analysis; and (4) conducting the analysis and reporting the findings.

We seek to infer the intellectual formation of AI and ML in finance research by examining the bibliometric structure encapsulating the publication trends of articles, journals, authors, institutions, and countries. The scope of review is sufficiently large as both AI and ML are transformative technologies that are widely present in today's global society, and particularly in finance applications.

4.1. Choosing the techniques for analysis

We adopt a range of bibliometric analysis techniques to unpack the structure of AI and ML in finance research. Besides an ability to handle a large corpus (Donthu et al., 2021), bibliometric analysis identifies publication trends, discerns progressive topics, and establishes visualizations of thematic evolution. This allows for both retrospection and the envisaging of future research directions (Ciampi et al., 2021; de Prado et al., 2016; Kumar et al., 2021a,b; Pattnaik et al., 2021). In line with Donthu et al. (2021), we conduct a performance analysis of the review corpus, selecting bibliometric analysis techniques of co-citation analysis, bibliographic coupling, and co-occurrence (or co-word) analysis.[4]

Co-citation analysis is effective for the demarcation of foundational knowledge (Boyack and Klavans, 2010; Small, 1973),

[2] This cohort included Trenchard More, Oliver Selfridge, Herbert Simon, and Ray Solomonoff.

[3] I.e., to enforce Bellman optimality on Markov decision processes.

[4] Akin to an analysis of the profile of respondents in empirical research.

whereas bibliographic coupling is useful for explicating the themes in the body of knowledge (Andersen, 2019; Waltman et al., 2010), and co-occurrence (co-word) analysis has utility for unveiling topical trajectories (Andersen, 2019; Cheng et al., 2018; Pattnaik et al., 2020a,b; Zupic and Čater, 2015). The co-citation of cited references, bibliographic coupling of clusters of articles, and co-occurrence of words are identified using the modularity of networking nodes predicated on the Louvain algorithm (Blondel et al., 2008). In this algorithm, nodes respectively represent referred citations, articles in the review, and author-specified keywords.

In simple terms, modularity is a measure of the strength of the division of a network into different module *alias* groups, communities, or clusters (Blondel et al., 2008). Networks with high modularity have dense connections among the nodes within a module but sparse connections outside that module (i.e., between nodes in different modules). Modularity is also an optimization method used for detecting communities with values ranging between −0.5 to +1. In a weighted network, with identifiable number of links such as the number of times an article is referred to by the articles in the review, the number of times two articles are co-cited, or the number of times two keywords co-appear is referred to as modularity (Q), and is defined as

$$Q = \frac{1}{2m}\sum_{i,j}[A_{ij} - \frac{k_i k_j}{2m}]\delta(c_i c_j) \tag{1}$$

where, A_{ij} indicates the weight of the edge (link) between i and j; $k_i = \sum_j A_{ij}$ represents the sum total of weights of the edges attached to vertex I; c_i is the class or community to which vertex i is assigned; δ function $\delta(u,v)$ is assigned '1' if u = v and '0' otherwise; and m $= \frac{1}{2}\sum_j A_{ij}$.

The Louvain method for community detection allows for progressive modularity optimization (Blondel et al., 2008), wherein each node within the network is first assigned its own community, and then, for each node i, the change in modularity (Δ) is calculated by replacing i from its own community to each of the neighboring communities j to which i is linked. The resulting change in modularity is calculated as

$$\Delta Q = [\frac{\sum_{in} + 2k_{i,in}}{2m} - (\frac{\sum_{tot} + k_i}{2m})^2] - [\frac{\sum_{in}}{2m} - (\frac{\sum_{tot}}{2m})^2 - (\frac{k_i}{2m})^2] \tag{2}$$

where $\sum_{in}$ is the sum total of the weights of the links within the community to which node i is moving into; $\sum_{tot}$ is the sum of all the weights of the links to nodes in the community i is moving into; k_i is the weighted degree of i, where degree is an indicator of the number of links associated with the node i; $k_{i,in}$ is the sum of the weights of the links between i and other nodes in the community that i is moving into; and m is the sum total of the weights of all links in the network. Once ΔQ is calculated for all respective community nodes that i is connected to, i is placed into the community that results in the greatest modularity increase.

4.2. Data collection

We elect to acquire data from Scopus, as this is the database that offers widest coverage of peer-reviewed research in finance (Pattnaik et al., 2020a,b)—as compared, for instance, to the Web of Science (Valtakoski, 2019). Following recent reviews (e.g., Garg et al., 2021; Mustak et al., 2021; Toorajipour et al., 2021), we apply a broad spectrum of search terms. Table 1 illustrates the systematic procedure we adopt to arrive at a final corpus of 283 articles.

Data obtained from Scopus, or any other search engine, is prone to erroneous bibliometric and bibliographic information arising from the reporting of the original manuscript in later manuscripts (Baker et al., 2021). Therefore, direct processing of such records without data cleaning risks inappropriate assessment. Therefore, we clean the data by introspecting its references. Such a strategy leads to an appropriate exploration of the bibliometric and bibliographic data, its visualization, and interpretation of results, as recommended by Donthu et al. (2021) and Zupic and Čater (2015).[5]

We also clean many terms appearing in the titles, abstracts, and author-specified keywords to carry out an accurate topical analysis using the natural language processing (NLP) function embedded in *VOSviewer*. For example, we convert many plural terms to their singular form (e.g., 'options' to 'option', 'bankruptcies' to 'bankruptcy', 'reports' to 'report', 'SMEs' to 'SME', etc.). Multiple representations of similar terms are also unified (e.g., 'peer-to-peer', 'peer to peer', and 'P2P' unified to 'P2P'; 'value-at-risk' and 'value at risk' unified to 'value at risk', etc.). Similarly, short forms and their expanded versions are also integrated (e.g., 'small and medium enterprises' and 'SME' unified as 'SME'; 'value at risk' and 'VAR' unified as 'value at risk', etc.). These cleaning strategies enable obtaining a uniform set of terms for topic exploration.[6]

5. Findings

5.1. Performance analysis of AI and ML research in finance

5.1.1. Publication activity of AI and ML research in finance

The publication trend of AI and ML research in finance is presented in Fig. 1, wherein the total number of articles is mapped against their respective year of publication. Fig. 1 indicates that AI and ML in finance are not new, occurring since 1986. However, finance research in these areas has proliferated only in recent years following the emergence of the fourth industrial revolution. The most prolific year are 2020 (64 articles), 2019 (43 articles), 2018 (21 articles), 2017 (18 articles), and 2016 (15 articles). This rising trend is expected to continue past 2021, with 25 articles (or 39% of 2020's total number of articles) already published by the end of the first quarter of 2021.

5.1.2. Top authors, institutions, and countries of AI and ML research in finance

The top authors, in AI and ML research in finance, along with their institutions and countries at time of authorship, are presented in Table 2. Based on number of citations, Wen-Tsao Pan emerges as the most impactful and influential author in AI and ML research in finance with 950 citations, followed by Sanjiv R. Das with 638 citations. In terms of number-of-publication productivity, Ashraf M. Elazouni is the most productive author with three publications. Among institutions, based on collected citations, the Oriental Institute of Technology and Santa Clara University are the most influential institutions with 950 and 638 citations, respectively. Based on number of the publications, the University of Hong Kong is the most productive institution with eight publications. Among countries, the United States has the most intellectual contributions in AI and ML research in finance (80 publications), with the highest number of citations (1997).

[5] For example, we find Antweiler and Frank (2004) referenced in four different ways in the articles in the review: "Antweiler, W., Frank, M.Z., Is all that talk just noise? The information content of internet stock message boards (2004) J. Financ., 59 (3), pp. 1259–1294"; "Antweiler, W., Frank, M.Z., Is all that talk just noise? The information content of internet stock message boards (2004) J. Finance, 59 (3), pp. 1259–1294"; "Antweiler, W., Frank, M.Z., Is all that talk just noise? The information content of internet stock message boards (2004) J. Finance, 59, pp. 1259–1294"; and "Antweiler, W., Frank, M.Z., Is all that talk just noise? The information content of internet stock message boards (2004) The Journal of Finance, 59 (3), pp. 1259–1294". As noted in the example, the differences are due to multiple representation of the journal (e.g., J. Financ., J. Finance, The Journal of Finance) and the publication information regarding the absence or presence of the issue number (e.g., 59(3) or 59).

[6] To run and analyze the bibliometric analysis techniques in Step 2 on the bibliometric and bibliographic data retrieved in Step 3, we use the Bibliometrix package in *R*, *VOSviewer*, and *Gephi*.

Table 1
Search criteria and article selection.

Filtering criteria	Reject	Accept
Search criteria		
Search engine: Scopus		
Search date: 14 April 2021		
Search term: ("AI" OR "artificial intelligence" OR "machine learning" OR "data mining" OR "data science" OR "algorithm" OR "analytics" OR "robot" OR "automation" OR "big data" OR "text mining" OR "natural language processing" OR "soft computing") AND ("finance" OR "financ* manag*")		11,357
Subject area: "Business, management and accounting", "Economics, econometrics and finance", "Social sciences", and "Arts and humanities"	9061	2,296
Document type: "Articles", "Conference papers", and "Reviews"	285	2,011
Article selection		
Erroneous records screening: Include documents with valid author information only	20	1,991
Language screening: Include documents in English only	44	1,947
Quality screening: Include documents in journals ranked "A*", "A", or "B" in the Australian Business Deans Council (ABDC) 2019 Journal Quality List only	1274	673
Content screening: Include articles if "Titles, abstracts, and keywords" indicate relevance to scope of study (i.e., AI and ML in finance) only	390	283

Note(s): This table discloses the systematic procedure adopted to arrive at the final corpus of (283) articles for review. The search terms were derived through a brainstorming among the authors consisting of subject-matter and methodological experts.

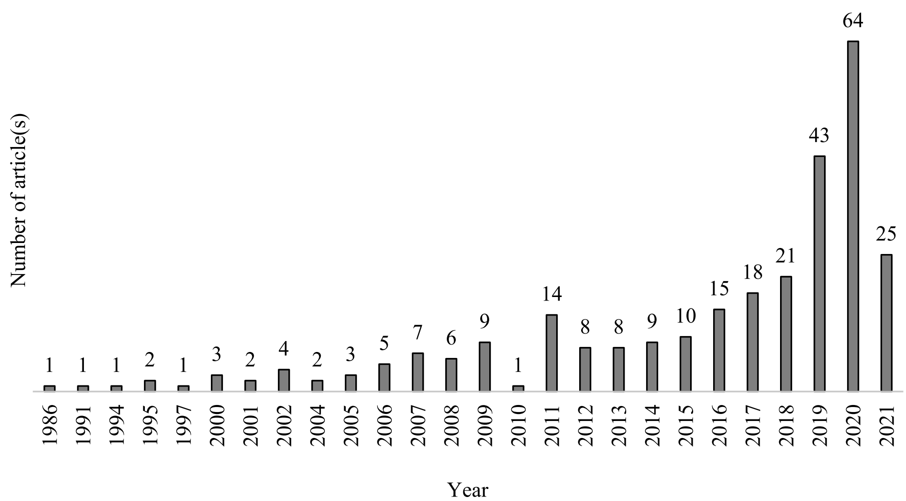

Fig. 1. Publication trend of AI and ML research in finance.

Table 2
Top authors, institutions, and countries of AI and ML research in finance.

TC	Author	TP	TC	Institution	TP	TC	Country	TP
950	Pan W.-T.	1	950	Oriental Institute of Technology	1	1997	United States	80
638	Das S.R.	2	638	Santa Clara University	2	1110	Taiwan	14
615	Chen M.Y.	1	615	Ludic Labs—San Mateo	1	751	United Kingdom	35
295	Ravi V.	2	615	Santa Clara University—Santa Clara	1	447	India	7
213	Beynon M.J.	1	266	University of Hong Kong	8	359	Australia	18
213	Peel M.J.	1	213	Cardiff Business School—Cardiff	1	335	China	44
198	Bose I.	1	203	Cornell University	2	294	Germany	21
198	Raghava Rao G.	1	198	Institute for Development Research in Banking Technology—Hyderabad	1	274	Hong Kong	11
198	Ravisankar P.	1	195	University of Minnesota—Minneapolis	1	256	France	22
195	Lee C.M.C.	1	147	King Fahd University of Petroleum and Minerals—Dhahran	3	147	Saudi Arabia	3
195	Radhakrishna B.	1	142	University of Arizona	1	143	Japan	4
147	Elazouni A.M.	3	117	Charles Sturt University—Albury	1	126	Portugal	4
142	Burgoon J.K.	1	115	University of Wisconsin—Madison	1	124	Switzerland	7
142	Burns M.B.	1	103	University of the West of England—Bristol	1	93	Czech Republic	4
142	Felix W.F.	1	103	University of York—York	1	82	South Korea	5
142	Humpherys S.L.	1	96	Tokyo Institute of Technology—Tokyo	2	75	Canada	9
142	Moffitt K.C.	1	93	London School of Economics—London	1	62	Netherlands	5
117	Bhattacharya M.	1	91	National Central University	2	60	Italy	13
117	West J.	1	91	Reserve Bank of India—Mumbai	1	55	Spain	4
115	Odders—White E.R.	1	83	University of Florida—Gainesville	2	52	Brazil	5
112	Metwally F.G.	2	82	Lindenwood University—Saint Charles	1	51	Belgium	4
109	Muniesa F.	1	82	Texas Tech University—Lubbock	1	43	Denmark	3
103	Brooks S.	1	81	Hunan University—Changsha	3	43	Singapore	4
103	Gabor D.	1	80	Korea University	3	41	Iran	3

Note(s): TC = total citations. TP = total publications. The research constituent (i.e., author, institution, country) appear according to total citations in this table.

Table 3
Top journals for AI and ML research in finance.

Journal	TC	FIN	ABDC	TP	1991–1995	1996–2000	2001–2005	2006–2010	2011–2015	2016–2021
Knowledge-Based Systems	1356		A	14					8	6
Decision Support Systems	790		A*	17			1		7	9
Management Science	615		A*	1				1		
Journal of Financial Markets	359	X	A*	4		2		1		1
Quantitative Finance	282	X	A	29			2	4	8	15
Omega	213		A	1			1			
Economy and Society	198		A	6				1		5
Computers and Security	141		A	2						2
Journal of Construction Engineering and Management	137		A*	3			1	1		1
International Journal of Information Management	131		A*	5			1			4
Journal of the Operational Research Society	126		A	8			1		2	5
Computational Economics	109		B	18		1		1	2	14
Accounting and Business Research	104		A	2					1	1
New Political Economy	103		A	1						1
Journal of Forecasting	101		A	6			1			5
Applied Mathematical Finance	86	X	B	4	3			1		
Journal of Economic Behavior and Organization	79		A*	2					1	1
International Journal of Electronic Commerce	59		A	2					1	1
Finance and Stochastics	58	X	A	3				2	1	
Journal of Behavioral and Experimental Finance	53	X	A	6						6
Computational Management Science	50		B	1				1		
International Journal of Theoretical and Applied Finance	50		B	4				2	1	1
Journal of Accounting Literature	48		A	1						1
Energy Economics	47		A*	3						3
International Journal of Production Economics	46		A	3					1	2

Note(s): ABDC = Australian Business Deans Council 2019 Journal Ranking List. TC = total citations. TP = total publications. FIN = X if a journal as classified as 'finance' by the 2018 *Academic Journal Guide*. The journals appear according to total citations in this table.

5.1.3. Top journals for AI and ML research in finance

The top journals that publish AI and ML research in finance are presented in Table 3. In terms of citations, *Knowledge-Based Systems* and *Decision Support Systems* are the two most influential journals with 1356 and 790 citations, respectively. However, in terms of publications, *Quantitative Finance* and *Computational Economics* are the two most productive journals with 29 and 18 publications, respectively.

The mapping of publication productivity against differing time periods indicates a recent rising trend of publication on the topic of this review. This is particularly true for both *Quantitative Finance* and *Computational Economics*. Interestingly, about 84% of the most significant journals for emphasizing AI and ML in finance are ranked 'A*' or 'A' in the Australian Business Deans Council (ABDC) 2019 Journal Quality List. This suggests that premier journals are receptive to publishing AI and ML research in relation to finance. As publications in premier journals motivate scholarly interest (Baker et al., 2021; Pattnaik et al., 2020b), these trends suggest future increasing research emphasis involving AI and ML in finance research.

However, if we examine Table 3 focusing on finance-classified journals versus non-finance-classified journals (as classified by the 2018 *Academic Journal Guide*) we see that finance journals have been, so far, relatively less active with publishing AI and ML articles. Exceptions include *Quantitative Finance*, which has published 29 articles on AI or ML and finance,[7] the *Journal of Behavioral and Experimental Finance.*[8] which has published six articles, all in the most recent of our subperiods, and the *Journal of Financial Markets*[9] which published a few highly cited articles.

5.1.4. Top articles on AI and ML research in finance

The top-cited publications on AI and ML research in finance are presented in Table 4. Pan (2012) is the most impactful and influential article with the highest number of citations in Scopus (950), followed by Das and Chen (2007) with 615 citations. Pan (2012) proposes a simple yet robust optimization algorithm termed "Fruit Fly Optimization" to address the problem of optimization that is frequently debated among scholars. While testing this algorithm on a financial distress data of Taiwanese enterprises, the author finds that the root mean square error value of the General Regression Neural Network model parsimoniously achieves the desired threshold while demonstrating high convergence, classification, and prediction abilities. Das and Chen (2007) develop a methodology to classify small investor sentiment from stock message boards. Offering several classifier algorithms, coupled with a voting scheme, the authors demonstrate that the sentiment accuracy of their algorithms is comparable to more popular Bayes classifiers, however, with a lower number of false positives. These proposed algorithms are useful for impact assessment of investors' opinions on management announcements, third-party news, press releases, and regulatory changes.

Further scrutiny of the top-cited publications on AI and ML in finance reveals that research in the areas of financial distress prediction (e.g., Liang et al., 2015; Pan, 2012;) and sentiment analysis (e.g., Chan and Franklin, 2011; Das and Chen, 2007; Kim and Kim, 2014; Kumar and Ravi, 2016; Oliveira et al., 2016) are particularly impactful and influential. More recently, AI and ML research on financial fraud prediction has attracted significant scholarly attention (e.g., Glancy and Yadav, 2011; Hajek and Henriques, 2017a; Humpherys et al., 2011; Ravisankar et al., 2011; West and Bhattacharya, 2016; Zhou and Kapoor, 2011). Other impactful and influential areas of research, as indicated by the list of top-cited publications, include access to financial services (Kshetri, 2016), asset pricing (Muniesa, 2007), corporate failure prediction (Beynon and Peel, 2001), credit scoring (Liu and Schumann, 2005), derivative pricing (Ninomiya and Victoir, 2008), FinTech (Gabor and Brooks, 2017), forecasting foreign exchange rates (Nag and Mitra, 2002), investor behavior analysis (Lee and Radhakrishna, 2000), management accounting information (Bhimani and Willcocks, 2014), scheduling (Elazouni and Metwally, 2005), trade classification (Odders-White, 2000), and volatility forecasting (Arroyo et al., 2011).

7 See especially Buehler et al. (2019); De Spiegeleer et al. (2018); Sirignano (2019); and Sirignano and Rama Cont (2019).

8 See especially, Aggarwal et al. (2020); Königstorfer and Thalmann (2020).

9 For very recent papers, see especially, Tobek and Hronec (2020).

Table 4
Top articles on AI and ML research in finance.

Author(s)	Title	TC
Pan (2012)	A new Fruit Fly optimization algorithm: Taking the financial distress model as an example	950
Das and Chen (2007)	Yahoo! for Amazon: Sentiment extraction from small talk on the web	615
Beynon and Peel (2001)	Variable precision rough set theory and data discretization: An application to corporate failure prediction	213
Ravisankar et al. (2011)	Detection of financial statement fraud and feature selection using data mining techniques	198
Lee and Radhakrishna (2000)	Inferring investor behavior: Evidence from TORQ data	195
Humpherys et al. (2011)	Identification of fraudulent financial statements using linguistic credibility analysis	142
West and Bhattacharya (2016)	Intelligent financial fraud detection: A comprehensive review	117
Odders-White (2000)	On the occurrence and consequences of inaccurate trade classification	115
Muniesa (2007)	Market technologies and the pragmatics of prices	109
Gabor and Brooks (2017)	The digital revolution in financial inclusion: International development in the Fintech era	103
Kumar and Ravi (2016)	A survey of the applications of text mining in financial domain	97
Bhimani and Willcocks (2014)	Digitization, big data and the transformation of accounting information	93
Nag and Mitra (2002)	Forecasting daily foreign exchange rates using genetically optimized neural networks	91
Glancy and Yadav (2011)	A computational model for financial reporting fraud detection	82
Liang et al. (2015)	The effect of feature selection on financial distress prediction	79
Kim and Kim (2014)	Investor sentiment from internet message postings and the predictability of stock returns	78
Elazouni and Metwally (2005)	Finance-based scheduling: Tool to maximize project profit using improved genetic algorithms	76
Zhou and Kapoor (2011)	Detecting evolutionary financial statement fraud	76
Ninomiya and Victoir (2008)	Weak approximation of stochastic differential equations and application to derivative pricing	70
Oliveira et al. (2016)	Stock market sentiment lexicon acquisition using microblogging data and statistical measures	69
Liu and Schumann (2005)	Data mining feature selection for credit scoring models	63
Kshetri (2016)	Big data's role in expanding access to financial services in China	60
Hajek and Henriques (2017a)	Mining corporate annual reports for intelligent detection of financial statement fraud — A comparative study of machine learning methods	55
Chan and Franklin (2011)	A text-based decision support system for financial sequence prediction	53
Arroyo et al. (2011)	Different approaches to forecast interval time series: A comparison in finance	53

Note(s): TC = total citations.

Table 5
Top references for AI and ML research in finance.

LC	Author(s)	Title	GC
18	Antweiler and Frank (2004)	Is all that talk just noise? The information content of internet stock message boards	800
15	Loughran and Mcdonald (2011)	When is a liability not a liability? Textual analysis, dictionaries, and 10-ks	1089
11	Tetlock (2007)	Giving content to investor sentiment: The role of media in the stock market	1399
9	Black and Scholes (1973)	The pricing of options and corporate liabilities	13,056
8	Das and Chen (2007)	Yahoo! for Amazon: Sentiment extraction from small talk on the web	620
7	Bollen et al. (2011)	Twitter mood predicts the stock market	2364
7	Kirkos et al. (2007)	Data mining techniques for the detection of fraudulent financial statements	324
6	Breiman (2001)	Random forests	37,830
5	Demšar (2006)	Statistical comparisons of classifiers over multiple data sets	9797
5	Fama (1970)	Efficient capital markets: A review of theory and empirical work	30,430
5	Groth and Muntermann (2011)	An intraday market risk management approach based on textual analysis	88
5	Hagenau et al. (2013)	Automated news reading: Stock price prediction based on financial news using context-capturing features	161
5	Heston (1993)	A closed-form solution for options with stochastic volatility with applications to bond and currency options	9708
4	Altman (1968)	Financial ratios, discriminant analysis and the prediction of corporate bankruptcy	19,940
4	Belleflamme et al. (2014)	Crowdfunding: Tapping the right crowd	877
4	Bollen et al. (2011)	Twitter mood predicts the stock market	2364
4	Borch et al. (2015)	Markets, bodies, and rhythms: A rhythm analysis of financial markets from open-outcry trading to high-frequency trading	35
4	Carhart (1997)	On persistence in mutual fund performance	18,281
4	Cecchini et al. (2010)	Making words work: Using financial text as a predictor of financial events	93
4	Fang and Peress (2009)	Media coverage and the cross-section of stock returns	582
4	Humpherys et al. (2011)	Identification of fraudulent financial statements using linguistic credibility analysis	142
4	Kraus and Feuerriegel (2017)	Decision support from financial disclosures with deep neural networks and transfer learning	83
4	Tetlock et al. (2008)	More than words: Quantifying language to measure firms' fundamentals	820
4	Wang et al. (2011)	A comparative assessment of ensemble learning for credit scoring	249

Note(s): LC = local citations. GC = global citations.

5.1.5. Top references on AI and ML research in finance

In this section we examine more closely the most frequently cited publications in the corpus of AI and ML research in finance to uncover the foundational inquires of research in AI and ML. This analysis also provides an opportunity to acknowledge important articles that may have been overlooked in our main search because they are niche topics or non-finance topics.

The top-cited publications based on local and global citations are presented in Table 5. Local citations denote the number of times an article is cited by other articles in AI and ML research in finance. Global citations refer to the number of times an article, perhaps outside the area of AI and ML in finance, is cited by articles in AI and ML in finance. Among the top-cited publications are Antweiler and Frank (2004) and Loughran and Mcdonald (2011) with 18 and 15 citations respectively. Breiman (2001) and Fama (1970) dominate our list of globally cited research with 37,830 and 30,430 citations, respectively. Regarding the seminal article on market efficiency, While obviously tangential, the seminal market efficiency article Fama (1970) is widely cited by researchers investigating AI and ML in finance when formulating hypotheses on pricing and valuation (e.g., Feuerriegel and Gordon, 2018; Li et al., 2018; Yang et al., 2018).

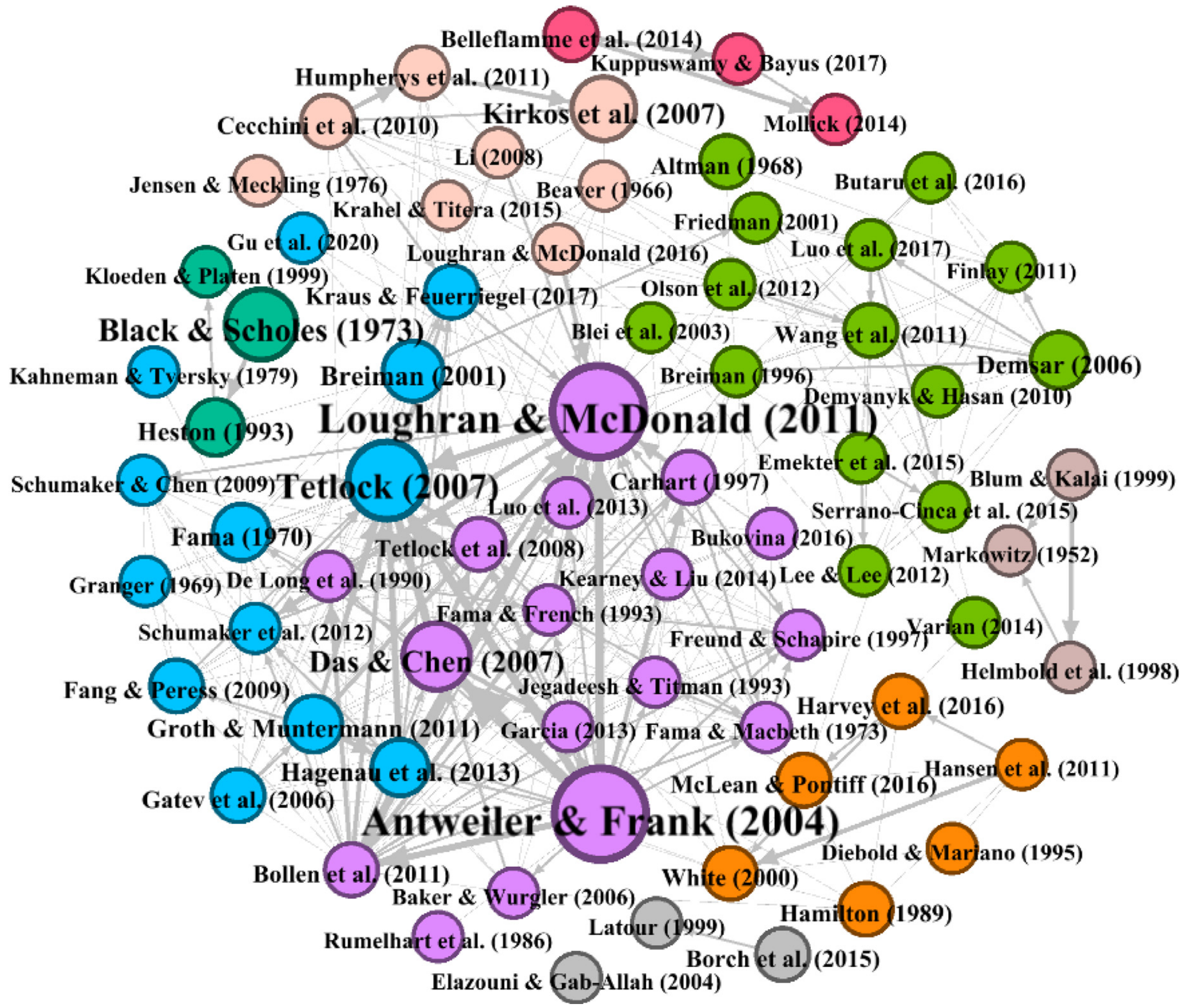

Fig. 2. Co-citation of references cited by articles on AI and ML in finance research. **Note(s)**: Each node represents a cited reference. Each color of nodes represents a semantic cluster of references based on thematic similarity. The size of nodes represents the degree of local citations wherein larger nodes reflect greater intensity of local citations. The link between nodes represents co-citations. The size of the link between nodes represents the degree of co-citations wherein thicker links reflect greater co-citation intensity.

Antweiler and Frank (2004) conduct a sentiment analysis of more than 1.5 million internet stock messages posted in Yahoo! Finance and Raging Bull regarding 45 companies listed in the Dow Jones Industrial Average. The authors find that higher message postings about a stock can predict its subsequent negative return, leading to market volatility, even though the impact is economically small. Their research has also successfully motivated new research that analyzes the sentiments featured in their study (e.g., Das and Chen, 2007; Hill and Ready-Campbell, 2011; Kim and Kim, 2014; Kumar and Ravi, 2016; Oliveira et al., 2016).

Loughran and Mcdonald (2011) demonstrate that negative words, as denoted in the Harvard Dictionary, are functionally non-negative within the specialized context of financial economics. They establish a classification of correspondence of such negative words with financial sentiments. This new classification proposed by the authors has been applied in stock index forecasting research (Feuerriegel and Gordon, 2018), natural language processing research on corporate reporting (Lewis and Young, 2019), and financial distress prediction research (Tang et al., 2020) in the corpus of the present review.

Breiman's (2001) article, which tops our list with the highest global impact, is an extension of the concept of bootstrap aggregation. The author proposes a novel random forest algorithm to overcome the problem of classification accuracy, which is an idea that has been widely applied in finance, especially in research dealing with classification problems such as the detection of financial fraud (e.g., Hajek and Henriques, 2017a) and the prediction of customer churn (e.g., Shirazi and Mohammadi, 2019).

5.2. Intellectual and influence structure of AI and ML research in finance

5.2.1. Knowledge foundations of AI and ML research in finance through co-citation analysis

The semantic associations of co-cited references uncovered through co-citation analysis depict the knowledge foundations of a field (Donthu et al., 2021; Small, 1973). The co-citation map of references that are cited at least three times by the articles in the review corpus is presented in Fig. 2.

Overall, co-citation analysis of co-cited references reveals that AI and ML research in finance draws upon existing research from nine foundational clusters, namely *asset pricing and valuation* (purple nodes), *text mining and sentiment analysis* (blue nodes), *option pricing and valuation* (deep green nodes), *financial fraud detection analytics* (pink nodes), *crowdfunding* (red nodes), *financial risk, credit risk, corporate failure, and bankruptcy* (bottle green nodes), *portfolio optimization* (peach-colored nodes), *forecasting and predictive analysis* (orange nodes), and *algorithmic*

Table 6
Thematic clusters of AI and ML research in finance.

Theme	Author(s)	Title	TC
Financial distress and corporate failure	Pan (2012)	A new fruit fly optimization algorithm: Taking the financial distress model as an example	950
	Beynon and Peel (2001)	Variable precision rough set theory and data discretization: An application to corporate failure prediction	213
	Liang et al. (2015)	The effect of feature selection on financial distress prediction	79
Algorithmic and high-frequency trading	Muniesa (2007)	Market technologies and the pragmatics of prices	109
	Coombs (2016)	What is an algorithm? Financial regulation in the era of high-frequency trading	27
	Borch (2016)	High-frequency trading, algorithmic finance and the flash crash: Reflections on eventalization	21
Forecasting and predictive analysis	Nag and Mitra (2002)	Forecasting daily foreign exchange rates using genetically optimized neural networks	91
	Arroyo et al. (2011)	Different approaches to forecast interval time series: A comparison in finance	53
	Künzi-Bay and Mayer (2006)	Computational aspects of minimizing conditional value-at-risk	50
Text mining and sentiment analysis	Das and Chen (2007)	Yahoo! for Amazon: Sentiment extraction from small talk on the web	615
	Kumar and Ravi (2016)	A survey of the applications of text mining in financial domain	97
	Kim and Kim (2014)	Investor sentiment from internet message postings and the predictability of stock returns	78
Financial fraud	Ravisankar et al. (2011)	Detection of financial statement fraud and feature selection using data mining techniques	198
	Humpherys et al. (2011)	Identification of fraudulent financial statements using linguistic credibility analysis	142
	West and Bhattacharya (2016)	Intelligent financial fraud detection: A comprehensive review	117
Pricing and valuation	Ninomiya and Victoir (2008)	Weak approximation of stochastic differential equations and application to derivative pricing	70
	Broadie and Cao (2008)	Improved lower and upper bound algorithms for pricing American options by simulation	43
	Černý and Kyriakou (2011)	An improved convolution algorithm for discretely sampled Asian options	35
Scheduling	Elazouni and Metwally (2005)	Finance-based scheduling: Tool to maximize project profit using improved genetic algorithms	76
	Elazouni and Metwally (2007)	Expanding finance-based scheduling to devise overall-optimized project schedules	36
	Ali and Elazouni (2009)	Finance-based CPM/LOB scheduling of projects with repetitive non-serial activities	35
Investor behavior and trade classification	Lee and Radhakrishna (2000)	Inferring investor behavior: Evidence from TORQ data	195
	Odders-White (2000)	On the occurrence and consequences of inaccurate trade classification	115
	Boehmer et al. (2007)	Estimating the probability of informed trading-does trade misclassification matter?	49

Note(s): TC = total citations.

and high-frequency trading (gray nodes). Interestingly, the biggest foundational clusters relate to asset pricing and valuation (purple nodes), text mining and sentiment analysis (blue nodes), and financial risk, credit risk, corporate failure, and bankruptcy (bottle green nodes).

Examining these topic groupings further, we observe that the nine foundational clusters converge into three overarching foundational clusters. Specifically, the deep green, gray, purple, red, and peach nodes converge as *financial asset sources, valuation, and optimization*, whereas the bottle green and pink nodes converge as *financial fraud, risk, and failure*, and the blue and orange nodes converge as *inferring sentiment, and forecasting*. These overarching foundational clusters represent the knowledge foundations of AI and ML research in finance.

5.2.2. Thematic clusters of AI and ML research in finance through bibliographic coupling

Building on the knowledge foundation discovered in the previous section, we further examine the body of knowledge relating to AI and ML research in finance through bibliographic coupling. Unlike co-citation analysis, which considers cited publications and thus reflects seminal knowledge focusing on highly cited publications in the domain (Donthu et al., 2021), bibliographic coupling relies on citing publications to explain the extant knowledge in the field (Kessler, 1963). In this sense, bibliographic coupling encapsulates seminal, niche, and recent knowledge. Therefore, it highlights works which understandably have not yet received many citations and are thus likely overlooked in co-citation analysis (Donthu et al., 2021). Bibliographic coupling has become an established technique in bibliometric reviews on finance research (e.g., Baker et al., 2021; Pattnaik et al., 2020a,b). The overview of the nine thematic clusters that underpin the knowledge structure of AI and ML research in finance revealed through bibliographic coupling is presented in Table 6.

Cluster 1 consists of 50 articles on *financial distress and corporate failure* that have been cited 1,874 times according to Scopus. The top-three cited articles in this cluster are Pan (2012), Beynon and Peel (2001), and Liang et al. (2015) with 950, 213, and 79 citations, respectively. As described previously, Pan (2012) develops applies a Fruit Fly optimization algorithm to financial distress data. Beynon and Peel (2001) examine the prediction of UK companies' failure via a modified variable precision rough set (VPRS) model. Interestingly, while the rough set theory is a based decision-making technique that has been around since 1982, little was previously known about its empirical validity in finance research. Importantly, the comparative results of VPRS alongside the classical logit multivariate discriminant rule analysis and the non-parametric decision tree methodology demonstrate its practicability in predicting problems involving classifications.

Liang et al. (2015) investigate the impact of filter- and wrapper-based feature selection methods in the context of financial distress prediction. By including three filter- and two wrapper-based feature selection methods along with six other prediction models, the authors compare the effect of feature selections on prediction models. Analysis of results over four different datasets indicates that there is no best combination in feature selection methodologies. Conducting feature selection does not necessarily improve prediction performance, even though logistic regression and genetic algorithms appear to provide better predictions over the datasets.

Cluster 2 consists of 23 articles on *algorithmic and high-frequency trading* that have been cited 275 times according to Scopus. The top-three cited articles in this cluster are Muniesa (2007), Coombs (2016), and Borch (2016) with 109,

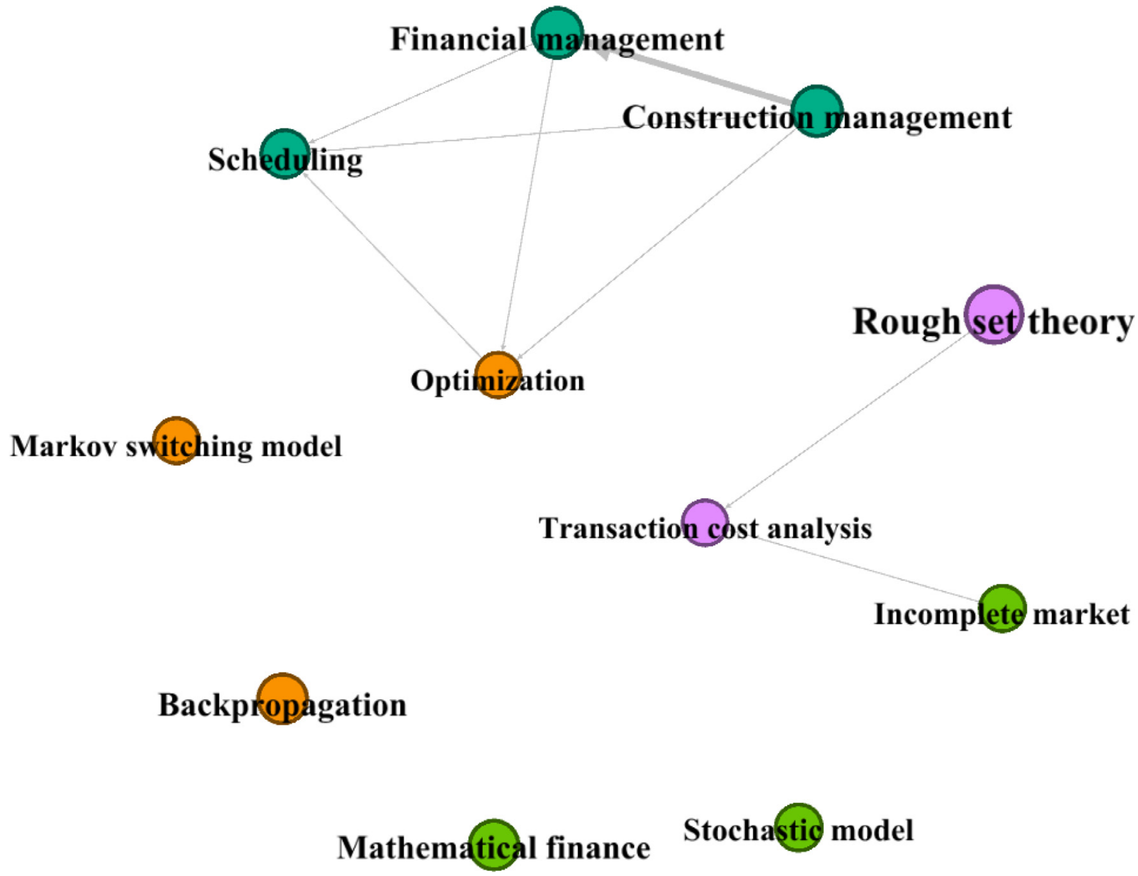

Fig. 3. Influential topics with APY between 1986.0 and 2009.0. **Note(s)**: Node = topic represented by keyword. Color of nodes = thematic cluster of nodes. Size of nodes = citations garnered by a topic. Link = co-occurrence between nodes. Thickness of link = occurrence of co-occurrences between nodes. Bottle green nodes = pricing and valuation. Deep green nodes = algorithmic and high-frequency trading. Orange nodes = portfolio optimization. Purple nodes = text mining and sentiment analysis.

27, and 21 citations, respectively. In particular, Muniesa (2007) extends Peirce's theory of the signs of closing prices by examining the technological configuration that produces closing prices. The author advocates for the pragmatic adoption of algorithms for pricing and valuation—similar high-frequency trading algorithms that are often blamed for market manipulations, and the repeated flash crashes. Coombs (2016) suggests that rules tagging algorithms establish ethical guidelines for trading firms. Such regulations may impede flash-crash incidents Borch (2016) delves into the criticalities of flash-crash episodes causing aversion to technology among retail investors.

Cluster 3 consists of 67 articles on *forecasting and predictive analysis* that have been cited 631 times. The top-three cited articles in this cluster are Nag and Mitra (2002), Arroyo et al. (2011), and Künzi-Bay and Mayer (2006) with 91, 53, and 50 citations, respectively. Acknowledging the failure of various classical econometric models in forecasting currency exchange rates, Nag and Mitra (2002) advocate the adoption of a hybrid artificial intelligence technique based on a neural network and genetic algorithm. This algorithm is evidenced to be superior in comparison with various non-linear statistical models. Arroyo et al. (2011) propose a new method to forecast volatility in interval time series following a comparison of VAR, exponential smoothing, multilayer perceptron, and K-NN algorithm approaches. Considering the problem of optimization via minimizing the conditional value at risk, Künzi-Bay and Mayer (2006) suggest a two-stage recourse of stochastic programming. Their proposed algorithm outperforms expectations in a portfolio optimization problem involving five random variables. Its comparative efficacy is demonstrated by a randomly generated test involving 50 variables.

Cluster 4 consists of 33 articles on *text mining and sentiment analysis* that have been cited 1,260 times. The top-three cited articles in this cluster are Das and Chen (2007), Kumar and Ravi (2016), and Kim and Kim (2014) with 615, 97, and 78 citations, respectively. Das and Chen (2007) propose an algorithm combined with a voting scheme to extract sentiments from stock message boards. The algorithm achieves an accuracy level similar to the widely used Bayes classifiers coupled with a lower level of false positives. Kumar and Ravi (2016) provide a comprehensive review of the various applications of text mining in finance such as forex trading, prediction of stock markets, customer relationship management, and cyber security. Kim and Kim (2014) analyze 32 million messages reported in Yahoo! Finance to examine if such messages can predict stock returns, trading volume, and volatility. The authors establish that investor sentiment is positively relate to stock price performance.

Cluster 5 consists of 29 articles on *financial fraud* that have been cited 903 times (Scopus). The top-three cited articles in this cluster are Ravisankar et al. (2011), Humpherys et al. (2011), and West and Bhattacharya (2016) with 198, 142, and 117 citations, respectively. Ravisankar et al. (2011) apply a series of data mining methods (Multilayer Feed Forward Neural Network, Genetic Programming, Support Vector Machines, Group Method of Data Handling, Probabilistic Neural Network, Logistic Regression) to track firms conducting financial statement frauds. The authors conclude that Probabilistic Neural Network is superior against techniques that do not involve feature selection while Genetic Programming and Probabilistic Neural Network outperform all others with feature selection. Humpherys et al. (2011) examined

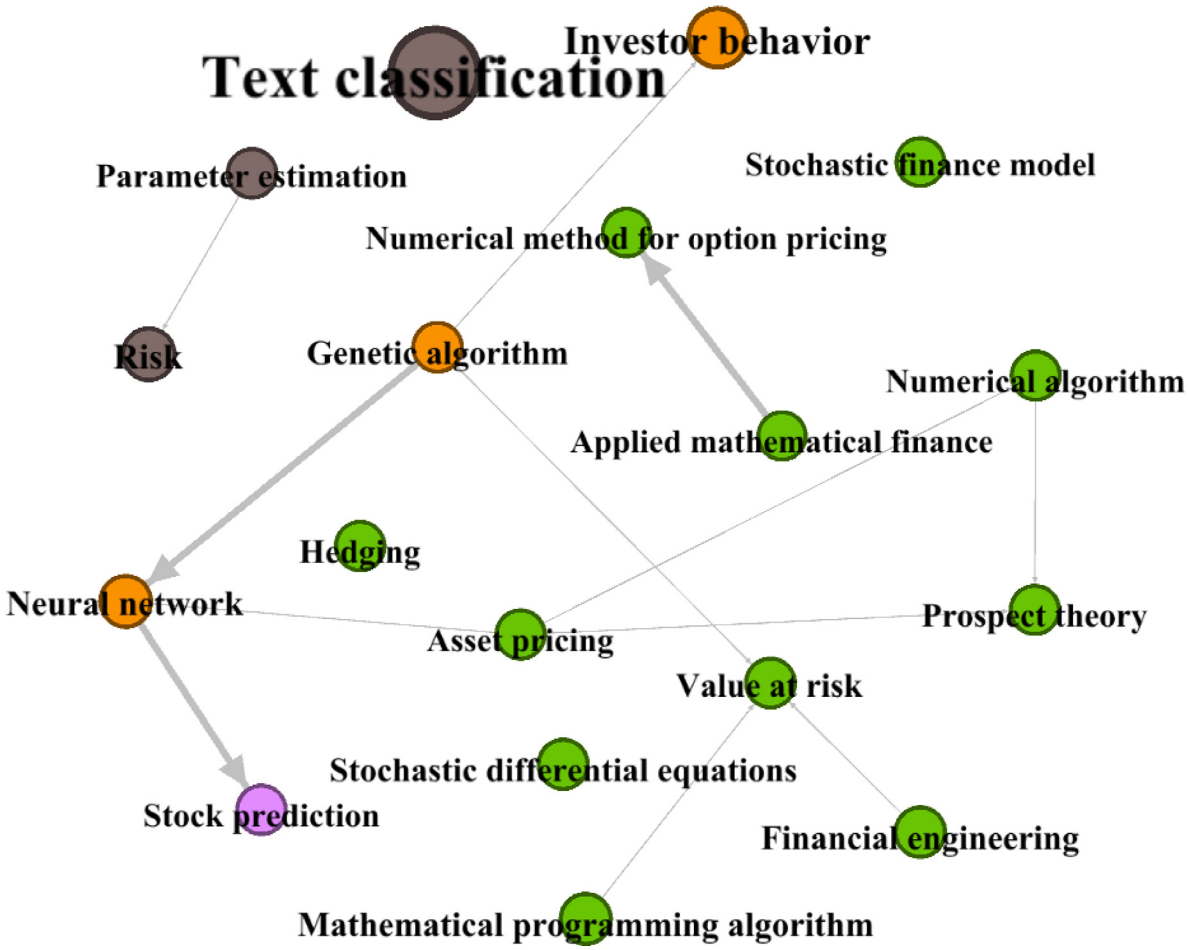

Fig. 4. Influential topics with APY between 2009.1 and 2012.0. **Note(s)**: Node = topic represented by keyword. Color of nodes = thematic cluster of nodes. Size of nodes = citations garnered by a topic. Link = co-occurrence between nodes. Thickness of link = occurrence of co-occurrences between nodes. Black nodes = forecasting and predictive analysis. Bottle green nodes = pricing and valuation. Orange nodes = portfolio optimization. Purple nodes = text mining and sentiment analysis.

the linguistic cues in managerial financial fraud, finding that fraudulent disclosures are often wordy, imagery, associated with less lexical diversity, and use more activation language. West and Bhattacharya (2016) shed light on computational intelligence-based techniques to detect financial fraud through a review of financial fraud detection research.

Cluster 6 consists of 39 articles on *pricing and valuation* that have been cited 423 times in Scopus. The top-three cited articles in this cluster are Ninomiya and Victoir (2008), Broadie and Cao (2008), and Černý and Kyriakou (2011) with 70, 43, and 35 citations, respectively. Ninomiya and Victoir (2008) proposed an order two algorithm and found that the algorithm effectively approximates the weakly stochastic differential equations using the pricing of Asian options under the Heston stochastic volatility model. In contrast, Broadie and Cao (2008) introduced a new variance reduction algorithm and offered computational improvements to the Monte Carlo methods for the pricing of American-styled options. Whereas, Černý and Kyriakou (2011) suggested an improved FFT pricing algorithm for the pricing of Asian options benchmarked against the finite difference, forward density convolution algorithms, and Monte Carlo simulations.

Clusters 7 and 8 are minor clusters comprising three articles each on *scheduling* and *investor behavior and trade classification* that have been cited 147 and 359 times in Scopus, respectively. The top-cited articles from these clusters are Elazouni and Metwally (2005) and Lee and Radhakrishna (2000). Elazouni and Metwally (2005) apply a genetic algorithm technique to develop finance-based schedules to maximize profitability of construction projects via minimization of their financing and indirect costs. Lee and Radhakrishna (2000) calibrate several techniques to infer investor behavior from transactions data. They developed a firm-specific proxy for trade size that is evidenced to be highly effective in segregating trading activities of institutional versus individual investors. Their findings are useful for considering buy and sell decisions while analyzing market transactions.

Interestingly, we observe that the eight thematic clusters that we identify with bibliographic coupling converge toward three overarching thematic clusters that are quite similar to those identified as foundational clusters using co-citation analysis. Specifically, Clusters 2, 6, and 8 converge as *financial asset and investor behavior*, whereas Clusters 1 and 5 converge as *financial distress, fraud, and failure*, and Clusters 3, 4, and 7 converge as *inferring sentiment, forecasting, and planning*. Taken collectively, these overarching thematic clusters represent the body of knowledge and themes of AI and ML research in finance.

5.2.3. Thematic trends of AI and ML research in finance through co-occurrence analysis

Building on the foundations and themes revealed through co-citation analysis and bibliographic coupling, in this section we further explore thematic trends in AI and ML research in finance through co-occurrence analysis. Co-occurrence analysis is conducted using author keywords (i.e., keywords that authors list in their articles). Such keywords are passed through a temporal lens

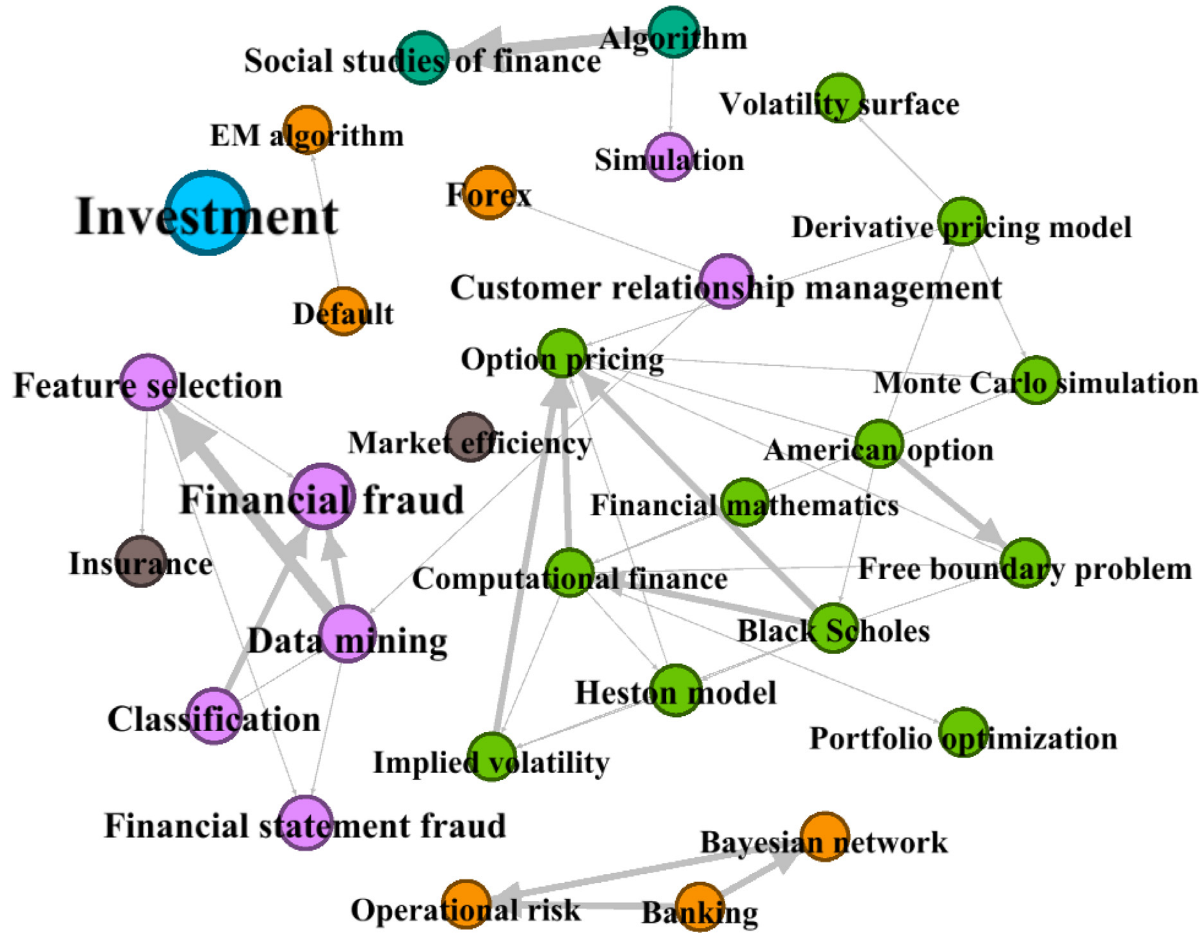

Fig. 5. Influential topics with APY between 2012.1 and 2015.0. **Note(s)**: Node = topic represented by keyword. Color of nodes = thematic cluster of nodes. Size of nodes = citations garnered by a topic. Link = co-occurrence between nodes. Thickness of link = occurrence of co-occurrences between nodes. Black nodes = forecasting and predictive analysis. Blue nodes = big data analytics and FinTech. Bottle green nodes = pricing and valuation. Deep green nodes = algorithmic and high-frequency trading. Orange nodes = portfolio optimization. Purple nodes = text mining and sentiment analysis.

to uncover the thematic evolution of finance topics appearing in at least two articles in our review corpus. This thematic evolution is reported in Figs. 3–7. In these figures, the themes (topics) are presented in tandem with the average publication year (APY), which is considered an indicator of topical trend (Andersen, 2019; Pattnaik et al., 2021). Specifically, APY is expressed as

$$\mathrm{APY}_t = \frac{\sum_{i,j} t_i y_j}{\sum_i t_i} \tag{3}$$

where if a topic t appears in two articles in 2019, three articles in 2020, and four articles in 2021, then its APY value is 2020.2 [i.e., $\frac{(2X2019)+(3X2020)+(4X2021)}{9}$].

Examining Figs. 3–7, we see that between APY 1986.0 and 2009.0 (Fig. 3), AI and ML research in finance concentrated on *algorithmic and high-frequency trading* consisting of construction management, financial management, and scheduling (deep green nodes); *pricing and valuation* involving incomplete markets, mathematical finance, and stochastic models (bottle green nodes); *portfolio optimization* using backpropagation and the Markov switching model (orange nodes); and *text mining and sentiment analysis* in tandem with rough set theory and transaction cost analysis (purple nodes).

Between APY 2009.1 and 2012.0 (Fig. 4), AI and ML research in finance mainly focused on a range of *pricing and valuation* topics such as asset pricing, hedging, option pricing, and value at risk using applied mathematical finance, mathematical programming algorithm, numerical algorithm, prospect theory, stochastic differential equations, and stochastic finance model (bottle green nodes). Research in this period also sheds light on *portfolio optimization* based on genetic algorithms, investor behaviors, and neural networks (orange nodes); *forecasting and predictive analysis* on risk using parameter estimation and text classification (black nodes); and *text mining and sentiment analysis* for stock prediction (purple node).

Between APY 2012.1 and 2015.0 (Fig. 5), AI and ML research in finance emphasized *pricing and valuation* topics such as American options, option pricing, and portfolio optimization, as well as a range of techniques such as the Black Scholes and other derivative pricing models, financial mathematics, free boundary problems, Heston modeling, Monte Carlo simulation, and volatility surface problems (bottle green nodes). Research in this period highlights *portfolio optimization* with regard to banking, forex, defaults, and operational risk using Bayesian network and EM algorithms (orange nodes); *text mining and sentiment analysis* of financial fraud and financial statement fraud, as well as customer relationship management using classification, data mining, feature selection, and simulation techniques (purple nodes); *algorithmic and high-frequency trading* through a social lens in conjunction with algorithms (deep green nodes); *forecasting and predictive analysis* for insurance and market efficiency (black nodes); and *big data analytics and FinTech* for investment (blue node).

Between APY 2015.1 and 2018.0 (Fig. 6), AI and ML research in finance focused mainly on *text mining and sentiment analysis* of

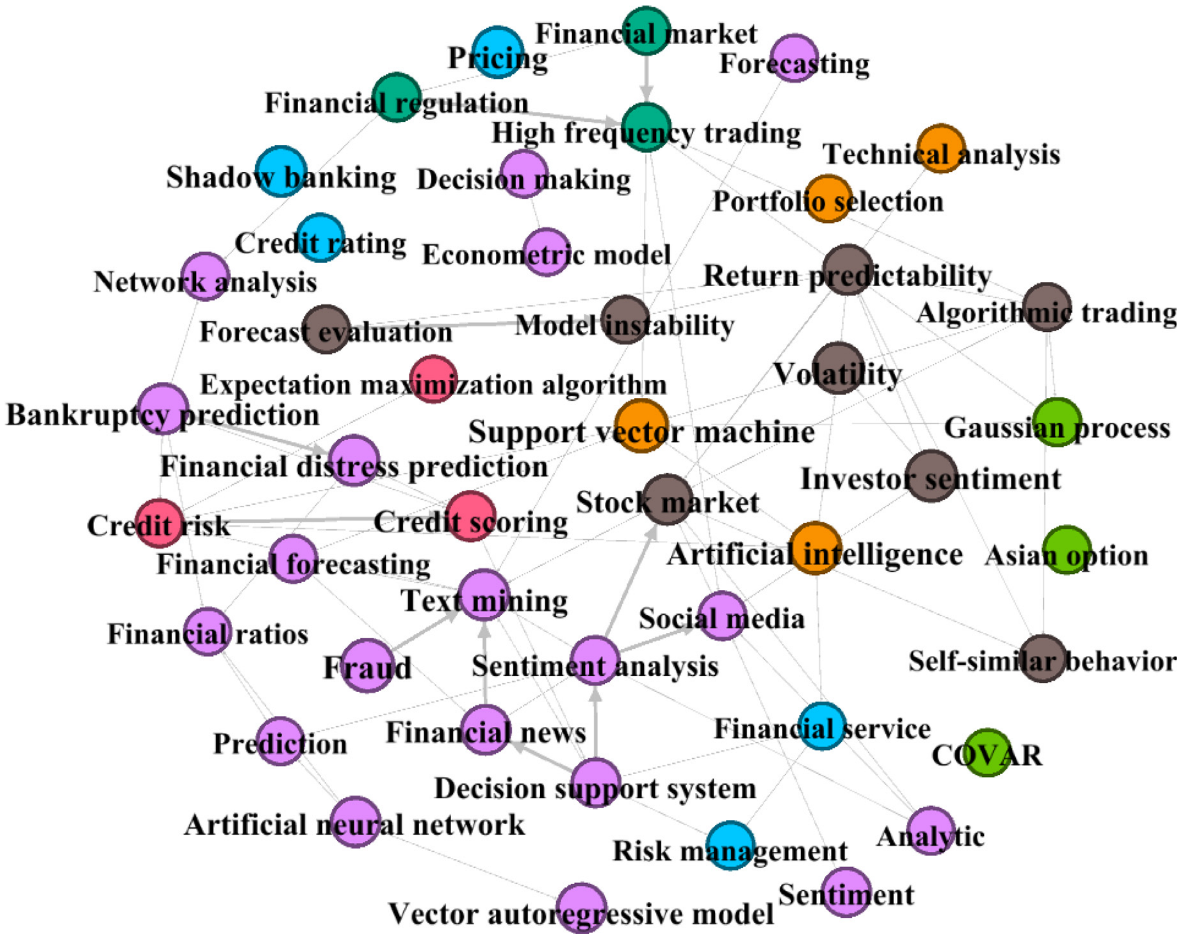

Fig. 6. Influential topics with APY between 2015.1 and 2018.0. **Note(s)**: Node = topic represented by keyword. Color of nodes = thematic cluster of nodes. Size of nodes = citations garnered by a topic. Link = co-occurrence between nodes. Thickness of link = occurrence of co-occurrences between nodes. Black nodes = forecasting and predictive analysis. Blue nodes = big data analytics and FinTech. Bottle green nodes = pricing and valuation. Deep green nodes = algorithmic and high-frequency trading. Orange nodes = portfolio optimization. Pink nodes = financial risk, credit risk, corporate failure, and bankruptcy. Purple nodes = text mining and sentiment analysis.

financial news, financial ratios, and social media on topics such as bankruptcy prediction, financial distress prediction, fraud, and decision making in conjunction with artificial neural network, econometric modeling, and network analysis (purple nodes). Research in AI and ML in finance in this period also investigates *forecasting and predictive analysis* of investor sentiment, stock markets, return volatility related to algorithmic trading, forecast evaluation, and self-similar behavior (black nodes); *big data analytics and FinTech* involving credit ratings, financial services, pricing, risk management, and shadow banking (blue nodes); *pricing and valuation* of Asian options using COVAR and the Gaussian process (bottle green nodes); *algorithmic and high-frequency trading* in the contexts of financial markets and financial regulation (deep green nodes); and *portfolio optimization* using AI, support vector machines, and technical analysis (orange nodes).

Between APY 2018.1 and 2021.0 (Fig. 7), AI and ML research in finance emphasized *big data analytics and FinTech* involving behavioral finance, blockchain, commercial banks, corporate finance, crowdfunding, cryptocurrency, digitalization, digital transformation, initial coin offerings, innovation, financialization, financial inclusion, funding success factors, Internet finance, P2P lending, soft information, supply chain finance using Bayesian methods, big data, and data analytics (blue nodes); as well as *text mining and sentiment analysis* of annual reports, economic policies, and stock indices using data visualization, deep learning, high frequency data, Lévy process, natural language processing, ML, network analysis, reinforcement learning, statistical arbitrage, and textual analysis for consumer finance, early warning, financial risk evaluation, and trading strategy (purple nodes). Research in this period focused on *portfolio optimization* of online and universal portfolios using GDPR, online ML, particle swarm optimization, robo advisors, and weak aggregating algorithms. Among other areas, *financial risk, credit risk, corporate failure, and bankruptcy* involved default prediction, microcredits, and SMEs using bibliometric analysis (pink nodes); and *forecasting and predictive analysis* used agent-based modeling (black nodes).

Results suggest early AI and ML research in finance was sporadically spread across the themes of algorithmic and high-frequency trading, portfolio optimization, pricing and valuation, and text mining and sentiment analysis (APY 1986.0 and 2009.0). Later, over more recent periods, research involving AI and ML and finance focused more on pricing and valuation (between APY 2009.1 and 2015.0), text mining and sentiment analysis (between APY 2015.1 and 2021.0), and big data analytics and FinTech (between APY 2018.1 and 2021.0).

5.2.4. Confluence of topics and methods in AI and ML research in finance

Building on the mapping of AI and ML research in finance through the lens of co-citation analysis, bibliographic coupling, and co-occurrence analysis, this section examines the juxtapositions of research topics and study methods. The cross-tabulation

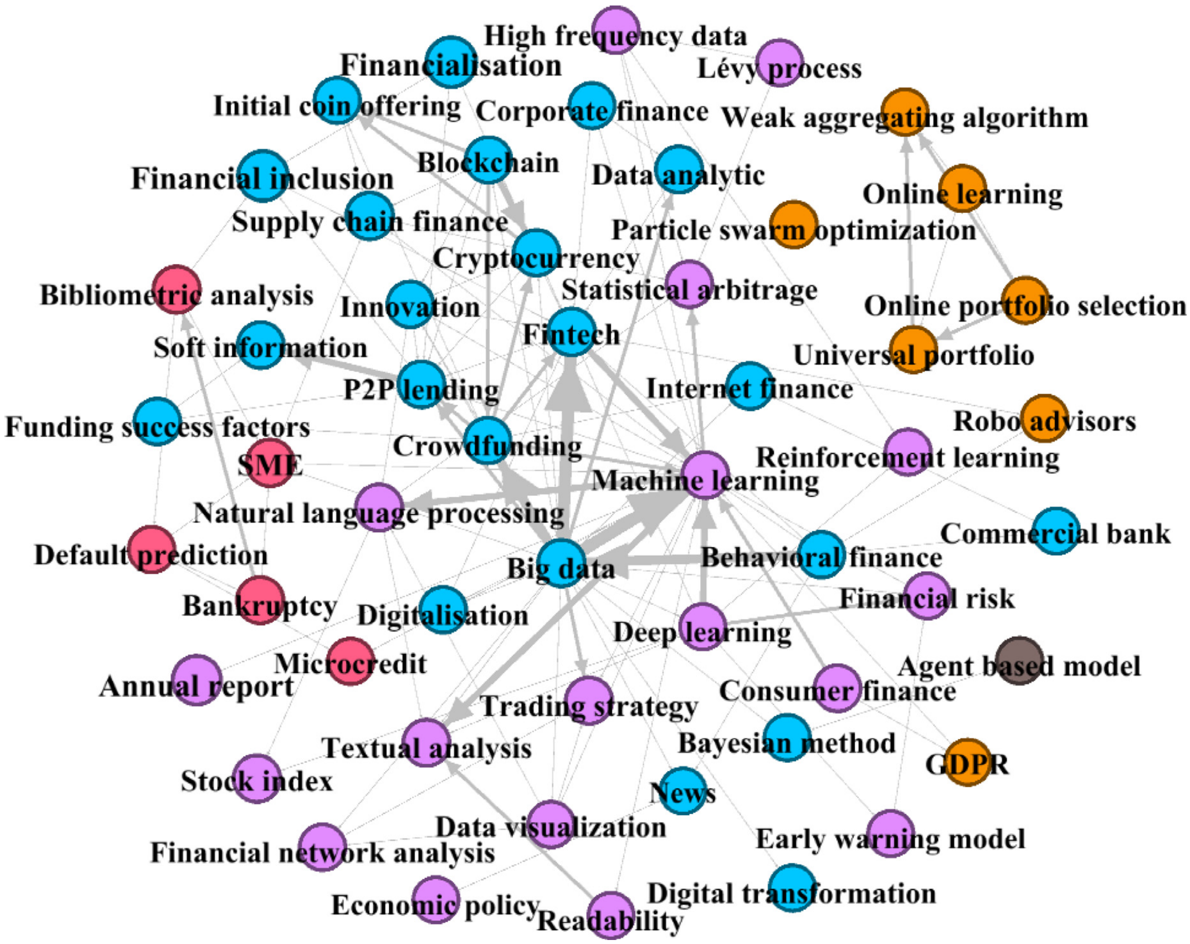

Fig. 7. Influential topics with APY between 2018.1 and 2021.0. **Note(s)**: Node = topic represented by keyword. Color of nodes = thematic cluster of nodes. Size of nodes = citations garnered by a topic. Link = co-occurrence between nodes. Thickness of link = occurrence of co-occurrences between nodes. Black nodes = forecasting and predictive analysis. Blue nodes = big data analytics and FinTech. Orange nodes = portfolio optimization. Pink nodes = financial risk, credit risk, corporate failure, and bankruptcy. Purple nodes = text mining and sentiment analysis.

of frequently researched topics in finance and AI and ML with study methods is presented in Table 7. In Table 7, topics are identified based on our results of the previous sections. The frequencies denoted in this table are not mutually exclusive as it is not uncommon to apply a number of ML techniques within a single study to evaluate the superiority of one technique over another.

In general, we observe that AI, supervised ML, and NLP have been widely applied for predictive analysis and forecasting, though this trend is more recently shifting toward big data analytics and deep learning (e.g., Craja et al., 2020; Li and Tang, 2020; Tang et al., 2020; Uthayakumar et al., 2020). Craja et al. (2020) apply a hierarchical attention network (HAN) to analyze the text features in the management discussion section of annual reports, wherein the architecture of the model captures both the content and context of managerial comments, and thus, serving as a supplementary predictor for detecting fraudulent reporting. Li and Tang (2020) propose an integrated wavelet transform, filter cycle decomposition, and multilag neural network (WT-FCD-MLGRU) model that produces minimum forecasting error in stock index prediction modeling.

Uthayakumar et al. (2020) suggest an Ant Colony Optimization (ACO) financial crisis prediction (FCP) model that incorporates both feature selection and data classification algorithms to perform predictions. The model was tested on five distinct qualitative and quantitative datasets with the experimental outcome establishing the superiority of the algorithm against alternative AI and traditional econometrics techniques. Tang et al. (2020) employ the wrapper-based feature selection framework, which is a hybrid form of textual analysis, to reveal financial distress features among listed Chinese companies to provide early signals of financial risk.

Additionally, we report in Tables 8–10 research topics in finance enlisted against supervised and unsupervised ML and NLP. In general, we observe that supervised ML is more popular than unsupervised ML techniques in finance research. We also observe that artificial neural network (ANN) algorithms have been widely applied in finance research involving forecasting and predication. For example, as already mentioned, Pan (2012) apply a Fruit Fly optimization algorithm for financial distress prediction, Feuerriegel and Gordon (2018) exploit the forecasting power of news related to regulatory disclosures for the prediction of share valuation. Interestingly, NLP techniques have also been widely applied in predictive analytics and sentiment analysis of financial news and media reports (e.g., Chan and Franklin, 2011; Feuerriegel and Gordon, 2018; Hill and Ready-Chambell, 2011).

Taken collectively, confluence analysis suggests that although AI and ML have indeed been widely applied in finance research, avenues for future research remain plentiful, as seen by the research topic and method gaps illustrated in Tables 8–10.

Table 7
AI and ML techniques in finance.

Topic	TP	TC	AI	DL	BD	SML	UML	RL	NLP
Algorithmic trading	8	78	1		1	1	1	1	3
Arbitrage	7	70		1	1	5	1	1	2
Asset pricing	19	223	2	1	4	1			7
Asset return	5	25	1	1	1	3			1
Automation	8	114			1	1			1
Bankruptcy	9	174	4	1	1	6			2
Blockchain	6	16			1	1			2
Chatbot	2	4	2						
Credit rating	4	30			1	1			
Credit risk	15	158	5		1	7			2
Credit score	8	158	2		1	6	1		1
Crowdfunding	10	52			4	4			5
Cryptocurrency	4	15			1	3			1
Default prediction	14	93	2		1	8	1		2
Derivative pricing	7	115		1		1		1	
Feature selection	8	466	1	1		7			2
Financial crisis	16	140	5	2	1	6			1
Financial distress	7	1147		1	1	4	1		1
Financial inclusion	5	119	3		1				
Financialization	5	163			2	2			
Fintech	15	177	4	1	6	4			1
Forecasting	50	672	8	2	8	19	1	1	11
Forex	4	192	1			1			1
Fraud detection	16	756	2	1	3	9	1	1	9
Hedging	5	52		1		1		1	
High frequency Trading	9	126				3	1	1	1
Implied volatility	5	68				2			1
Insurance	10	93				4			1
Loan/credit	12	81	1		3	5	1		4
Market efficiency	4	47			1	2			1
News/media reports (sentiment)	17	1059	3		3	5		1	17
Optimization	31	1390	1	2	1	10	2	3	1
Option pricing	34	359	1	2	1	7	1	1	2
P2P lending	11	125	2		5	3	1		3
Portfolio management	4	46	1		1	2			0
Portfolio optimization	4	59							0
Predictive analysis	80	2415	11	3	12	34	3	2	26
Risk management	19	149	3		7	2			4
Robo-advisory	9	33	6						
SME	11	135	1		3	3			1
Social media/Twitter/Facebook (sentiment)	24	251	2		10	5	1		24
Supply chain finance	4	57			1	2			1
Trading strategy	11	79	1		3	6	1	1	4
Value at risk	5	67				1			

Note(s): TP = total publications. TC = total citations. AI = artificial intelligence. SML = supervised machine learning. UML = unsupervised machine learning. RL = reinforcement learning. NLP = natural language processing. DL = deep learning. BD = big data, P2P = peer-to-peer. SME = small and medium enterprises.

5.3. Suggestions for future research

Key summaries and findings for each of our above analyses are presented in Table 11. We hope our findings and retrospective will facilitate meaningful progression of AI and ML research in finance. In the next sections, we outline several potential directions for future research.

According to Dixon et al. (2020), aspects of AI and ML in finance are placed at the crossings of several emerging and established disciplines such as dynamic programming, financial econometrics, pattern recognition, probabilistic programming, and statistical computing. Facilitated by increases in computation abilities regarding larger datasets, ML has evolved into a core computational engineering field that democratizes plug-and-play algorithms through open-sources (Corbet et al., 2021). Clearly, with AI and ML penetrating across vast swathes of the finance industry, there is both considerable need and wide opportunity for scholarly research.

5.3.1. AI, ML, and asset pricing

Finance research in asset pricing is moving toward empirically driven models that encompass application of richer sets of firm-specific factors. Contexts for this include modeling the dynamics of market equity risk premia by performing a comprehensive analysis of expected returns (Gu et al., 2020). Harvey et al. (2016) explore 316 common and firm specific factors to describe stock return behavior. As the assessment of risk premia or the measuring of expectation of an excess future return is a fundamental problem of predictive analysis, methodologies that can dependably attribute excess returns provide utility. In this regard, ML offers non-linear empirical approaches to modeling realizable asset returns on firm characteristics. Casting neural networks in canonical asset pricing research, there are opportunities for future research to construct asset pricing models.

5.3.2. AI, ML, and FinTech

The rise of AI and ML along with big data has led to the birth of a FinTech sector that comprises digital innovations and technology-backed innovative business models for finance (Dixon et al., 2020). Examples of innovations central to FinTech include blockchain and cryptocurrencies, digital advisory and trading systems, equity crowdfunding, peer-to-peer lending, and mobile payment services. Further, innovations such as robo-advisors, can provide portfolio management services and financial advice without significant human invention. However, more research is required to understand the myriad aspects of FinTech and the impact of AI and ML in this new area.

5.3.3. AI, ML, and financial fraud

It is well known that financial crime is a global problem of immense economic significance. The detection of financial fraud, or its prevention through the design of alert models offers AI and ML enormous utility for financial systems. Naïve Bayes models and support vector machines are two of the methods for efficacy in fraud detection (Ravisankar et al., 2011). Further, the rise of electronic trading will likely lead to newer forms of market manipulation and financial fraud. Consequently, electronic exchanges and transactions will need to be scrutinized to effectively counter new threats of financial fraud. New developments in this area will also likely include research into the securing, and perhaps the oversight, of blockchains. FinTech development will no doubt motivate research using AI and ML to investigate topics in financial fraud.

6. Conclusions

Understanding application of machine-readable data impacts both financial systems and financial research. For instance, the financial services industry increasingly relies on computational methods, with high-power computation backed by sophisticated hardware and software advances empowering machines to develop high-dimensional complex models leading to robust evaluation of new information. In particular, the adoption of AI and ML are radically transforming trading and investment decisions. Concomitantly, finance research is responding to the need to understand better the economic impacts of AI and ML. Further, finance research is also discovering the utility of AI and ML procedures as tools for further investigation of established topics and research questions.

Artificial intelligence (AI) and machine learning (ML) are two related technologies that are emergent in financial scholarship. However, no review, to date, has offered a wholistic retrospection of this research, despite an important need to encourage finance scholarship to improve our understand of the impacts of AI and ML on financial systems. To address this gap, we overview AI and

Table 8
Supervised ML techniques in finance.

Topic	LR	LASSO	RIDGE	EN	Log. R	LDA	K-NN	DT	CART	SVM	Ensemble	RF	ANN	DNN	ARIMA	RNN	LSTM
Algorithmic trading										1							
Arbitrage										1		1	4				
Asset pricing				1													
Asset return				1									2				
Automation													1				
Bankruptcy					2		1				2		2				
Blockchain													1				
Credit rating					1			1		1	1			1			
Credit risk			1		2		1	2		2	3	1	1	1			
Credit score			1		2		1	1			1	1	1				
Crowdfunding		1			1						1		3				
Cryptocurrency										1	1		2				
Default		1	1				1	2		1	1	1	3				
Derivative pricing													1				
Feature selection					3		1			2	3	1	1				
Financial crisis	1				2			1	1	1	2		1	1			
Financial distress					1		1				1		2				
Financialization								1		1	1	1	1				
Fintech		1		1							1		3				
Forecasting	1						1	1		2	4	1	13		3	3	2
Forex															1		
Fraud detection		1			1		1	2		3	1		4				
Hedging													1				
High frequency Trading										2			1				
Implied volatility													3				
Insurance					1		1	1				1	2				
Loan/credit		1				1		2		1	2	1	1				
Market efficiency													2				
News/media reports (sentiment)					1					1			4				
Optimization		1								2	2		5	1			
Option pricing			1										6	1			
P2P lending		1				1		1			1						
Portfolio management			1				1	1		1							
Predictive analysis	1			1	3		3	6		5	7	4	16	1	1	3	2
Risk management			1				1	1		1							
SME								1			5	1	1				
Social media/Twitter/Facebook										1	1	1	5				
Supply chain finance											1		2				
Trading strategy										2			4				
Value at risk			1														

Note(s): LR = linear regression. EN = elastic net. Log. R = logistic regression. LDA = linear discriminant analysis. K-NN = k-nearest neighbor. DT = decision tree. CART = classification and regression trees (also known as decision tree classifiers). SVM = support vector machine. RF = random forest. ANN = artificial neural network. DNN = deep neural network. ARIMA = autoregressive integrated moving average. RNN = recurrent neural network. LSTM = long short-term memory. Ensemble includes both boosting and bagging methods such as adaptive boosting, gradient boosting, and ensemble bagging.

Table 9
Unsupervised ML techniques in finance.

Topic	Reinforcement learning	Markov decision
Algorithmic trading	1	1
Arbitrage	1	
Derivative pricing	1	
Forecasting	1	
Fraud detection	1	1
Hedging	1	
High frequency trading	1	1
News/media reports (sentiment)	1	
Optimization	3	1
Option pricing	1	
Predictive analysis	2	
Trading strategy	1	1

Table 10
NLP in finance.

Topic	Text mining	Naïve Bayes	LSA	LDA
Arbitrage	1			
Asset pricing	2	1		
Automation	1			
Bankruptcy		2		
Blockchain	1			
Credit risk	1	1		
Crowdfunding	3			
Default	1			
Financial crisis	1			
Financial distress		1		
Forecasting	7	3		
Forex	1			
Fraud detection	7	3		
High frequency trading	1			
Implied volatility		1		
Insurance	1			
Loan/credit	4			1
News/media reports (sentiment)	8	1		
Optimization	1			
Option pricing	1	1		
P2P lending	3			1
Predictive analysis	9	5		
Risk management	1	3		
Social media/Twitter/Facebook	4			
Supply chain finance		1		
Trading strategy	1			

Note(s): LSA = latent semantic analysis. LDA = latent dirichlet analysis.

ML research in finance. Using a bibliometric approach, for the period 1986–April 2021, analyzing 283 articles published in leading international journals, we infer the intellectual structure of AI and

Table 11
Summary of bibliometric review on AI and ML research in finance.

Performance analysis • Based on bibliometric data • Reflect research performance	*Co-citation analysis* • Based on cited publications • Reflect knowledge foundation	*Bibliographic coupling* • Based on citing publications • Reflect the body of knowledge	*Co-occurrence (co-word) analysis* • Based on author keywords • Reflect the body of knowledge	*Confluence of research topics in finance and AI and ML study methods* • Provides post-hoc scrutiny
Publication activity • Total of 283 articles published in ABDC A*, A, or B journals between 1986 and April 2021. • 2020 was the most prolific year with 64 articles. *Top authors* • Most citations: W.-T. Pan (950 citations) • Most publications: A. M. Elazouni (three publications) *Top institutions* • Most citations: Oriental Institute of Technology (950 citations) and Santa Clara University (638 citations) • Most publications: University of Hong Kong (eight publications) *Top countries* • Most citations: United States (1,997 citations) • Most publications: United States (80 publications) *Top journals* • Most citations: *Knowledge-Based Systems* (1,356 citations) and *Decision Support Systems* (790 citations) • Most publications: *Quantitative Finance* (29 publications) and *Computational Economics* (18 publications) *Top articles* • Pan (2012): 950 citations • Das and Chen (2007): 615 citations *Top references* • Local citations: Antweiler and Frank (2004) (18 citations) and Loughran and Mcdonald (2011) (15 citations) • Global citations: Breiman (2001) (37,830 citations) and Fama (1970) (30,430 citations)	*Themes* 1. Financial asset sources, valuation, and optimization (a) Algorithmic and high-frequency trading (gray nodes) (b) Asset pricing and valuation (purple nodes) (c) Crowdfunding (red nodes) (d) Option pricing and valuation (deep green nodes) (e) Portfolio optimization (suave nodes) 2. Financial fraud, risk, and failure (a) Financial fraud detection analytics (pink nodes) (b) Financial risk, credit risk, corporate failure, and bankruptcy (bottle green nodes) 3. AI and ML for finance (a) Forecasting and predictive analysis (orange nodes) (b) Text mining and sentiment analysis (blue nodes)	*Themes* 1. Financial asset and investor behavior (a) Algorithmic and high-frequency trading (Cluster 2) (b) Pricing and valuation (Cluster 6) (c) Investor behavior and trade classification (Cluster 8) 2. Financial distress, fraud, and failure (a) Financial distress and corporate failure (Cluster 1) (b) Financial fraud (Cluster 5) 3. AI and ML for finance (a) Forecasting and predictive analysis (Cluster 3) (b) Text mining and sentiment analysis (Cluster 4) (c) Scheduling (Cluster 7)	*Themes* APY 1986.0 and 2009.0 • Algorithmic and high-frequency trading • Portfolio optimization • Pricing and valuation • Text mining and sentiment analysis APY 2009.1 and 2012.0 • Forecasting and predictive analysis • Portfolio optimization • Pricing and valuation[a] • Text mining and sentiment analysis APY 2012.1 and 2015.0 • Algorithmic and high-frequency trading • Big data analytics and FinTech • Forecasting and predictive analysis • Portfolio optimization • Pricing and valuation[a] • Text mining and sentiment analysis APY 2015.1 and 2018.0 • Algorithmic and high-frequency trading • Big data analytics and FinTech • Financial risk, credit risk, corporate failure, and bankruptcy • Forecasting and predictive analysis • Portfolio optimization • Pricing and valuation • Text mining and sentiment analysis[a] APY 2018.1 and 2021.0 • Big data analytics and FinTech[a] • Financial risk, credit risk, corporate failure, and bankruptcy • Forecasting and predictive analysis • Portfolio optimization • Text mining and sentiment analysis[a]	*Insights* • AI, supervised ML and NLP have been widely applied for predictive analysis and forecasting. • Big data analytics and deep learning are on the rise in finance research. • Supervised ML is more popular than unsupervised ML in finance research. • NLP is highly popular in finance research.

Note(s):
[a]Major theme(s) in co-occurrence (co-word) analysis.

ML research in finance. Using both co-citation and bibliometric-coupling analyses, we infer the knowledge and thematic structure of AI and ML research in finance for 1986–April 2021. By uncovering nine (co-citation) and eight (bibliometric coupling) specific areas of finance that apply AI and ML, we further identify three clusters of finance scholarship that are roughly equivalent for both forms of analysis: (1) portfolio construction, valuation, and investor behavior; (2) financial fraud and distress; and (3) sentiment inference, forecasting, and planning. Additionally, using co-occurrence and confluence analyses, we highlight trends and research directions regarding AI and ML in finance research. Our results provide guidance for researchers to assess the growing emphasis on AI and ML in finance research.

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