Financial Innovation

REVIEW

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Artificial intelligence in the service of entrepreneurial finance: knowledge structure and the foundational algorithmic paradigm

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Abstract

The study conducts a bibliometric review of artificial intelligence applications in two areas: the entrepreneurial finance literature, and the corporate finance literature with implications for entrepreneurship. A rigorous search and screening of the web of science core collection identified 1,890 journal articles for analysis. The bibliometrics provide a detailed view of the knowledge field, indicating underdeveloped research directions. An important contribution comes from insights through artificial intelligence methods in entrepreneurship. The results demonstrate a high representation of artificial neural networks, deep neural networks, and support vector machines across almost all identified topic niches. In contrast, applications of topic modeling, fuzzy neural networks, and growing hierarchical self-organizing maps are rare. Additionally, we take a broader view by addressing the problem of applying artificial intelligence in economic science. Specifically, we present the foundational paradigm and a bespoke demonstration of the Monte Carlo randomized algorithm.

Keywords: Bibliometrics, Artificial intelligence, Entrepreneurship, Finance, Randomized algorithm

Introduction

The continuous accumulation of computational knowledge consistently leads to the development of new methods, particularly those that are nature/data-driven (Tapeh and Naser 2022) and can effectively replace or improve upon older solutions that rely on traditional mathematical and statistical frameworks (Nazareth and Reddy 2023). This trend arises primarily from the limitations of conventional methods in addressing nonlinear, time-variant, and behaviorally uncertain problems, which are common in many real-life phenomena (Bahrammirzaee 2010). Artificial intelligence (AI) has proven to be effective for such problems across various fields (Tapeh and Naser 2022), including medicine (Hamet and Tremblay 2017), transport (Kouziokas 2017), manufacturing (Arinez et al. 2020), economics (Dirican 2015), and finance (Bahrammirzaee 2010). Although the field of finance might seem saturated, it has recently seen a surge in AI-related publications (Goodell et al. 2021). Similarly, the application of AI in entrepreneurship is particularly noteworthy, given its nascent stage (Obschonka and Audretsch 2020).

Along with its popularity in science, the momentum of AI in finance and related disciplines has recently been recognized in practice. According to the "Hired's 2023 State of Software Engineers" survey (Perry 2023), the AI industry has climbed to the top of the list of booming technology jobs in 2023. This rise is expected, given AI's recent surge in popularity following the public release of Dall-E 2 and ChatGPT. However, the financial technology industry (FinTech)[1] has now surpassed sectors such as health technology and cybersecurity.

This study is the first to map and perform a bibliometric analysis of the relationship between AI, entrepreneurship, and finance. It is also the first review to address AI methods in entrepreneurship. The study offers a bibliometric review of how AI is applied in two main areas: the entrepreneurial finance literature, and the corporate finance literature with implications for entrepreneurship. In addition to standard bibliometric indicators, a rigorous and temporal analysis of data identifies various AI methods within the subject literature. This analysis reveals the chronological development of the field and suggests potential future applications. This study provides rich insights into the research area, providing implications for various target groups involved with AI in entrepreneurial finance, including the scientific community, computer experts, entrepreneurs, and investors in entrepreneurship.

In Sect. 2, the study is positioned within the existing scientific body of work, and we present the scope and objectives of the research. Section 3 describes the bibliometric methodology, discussing the data search and screening procedures, and highlights the bibliometric tools used. Section 4 presents and interprets the bibliometric results, setting the stage for the discussions and research implications in Sect. 6. Section 5 presents the foundational paradigm of AI and various methods, emphasizing the practical aspect to help resolve the issues with AI results noted in Biju et al. (2023). Finally, Sect. 6 concludes the paper.

Background of the study

Overview of AI in entrepreneurship

The era of AI in entrepreneurship began recently (Obschonka and Audretsch 2020). Although the first scientific papers in this field appeared in the 1980 s, the total output published in the first 20 years was minimal, with only five papers listed in the Web of Science Core Collection (WoSCC) by 2003. After a period of slow growth from 2003 to 2016, the domain has been experiencing a publication explosion since 2017 (Li et al. 2022), not only quantitatively, but also in terms of the diversity of interests and topics that arise from "the reciprocity of the co-evolving fields of entrepreneurship research and practice" Obschonka and Audretsch (2020) (p. 529). Influential scholars note (Obschonka and Audretsch 2020; Chalmers et al. 2020; Nambisan 2017) that AI and technologies in general enrich and transform the field of entrepreneurship research and affect real-world entrepreneurial activity. Nambisan (2017) recognizes the dual transformative effects of new technology proliferation on entrepreneurial endeavors. First,

[1] Some aspects of FinTech are strengthening as a consequence of regulatory acts. For example, the Dodd-Frank Act constrained lending to small businesses, due to which "innovative new lending models gained a regulatory advantage" over traditional banks, and "the Peer-to-Peer lenders capitalized on this" Hamarat and Broby (2022).

technological advancements expand the scope of entrepreneurial processes and outcomes, making them more fluid and porous. For example, advances in FinTech enhance the sources of entrepreneurial finance available, without spatial and temporal boundaries within a specific entrepreneurial ecosystem (Nambisan 2017). Second, technology shifts the focus of entrepreneurial agency, creating dynamic sets of agents with varying characteristics, aspirations, and goals. An example of this is the development of new infrastructures such as crowdfunding systems, which have stimulated the emergence of more collective forms of entrepreneurial initiatives (Nambisan 2017; Iurchenko et al. 2023). These disruptive changes and innovations are reciprocally reflected in the agenda of entrepreneurship research, which is enhanced by new AI research tools and methods, and targets new subjects to analyze using these methods (Obschonka and Audretsch 2020).

AI in entrepreneurial finance is a particularly productive area of research, showing significant promise in decision-making support and business performance improvement (Giuggioli and Pellegrini 2022; Obschonka and Audretsch 2020). For example, AI methods are now being used to codify the communication behaviors of entrepreneurs and analyze crowdfunding presentation campaigns (Kaminski and Hopp 2020; Deng et al. 2022). These capabilities have the potential to enhance entrepreneurs' communication strategies and help investors make more rational decisions (Giuggioli and Pellegrini 2022). AI also plays an important role in managing entrepreneurial finance. Hybrid AI-blockchain platforms are revolutionizing financial accounting management in entrepreneurial ventures (Chalmers et al. 2020) and transforming audit processes by reducing reliance on traditional procedures such as sampling and confirmations (Giuggioli and Pellegrini 2022; Zemankova 2019). In broader business management, AI automation tools introduce a new paradigm for scaling businesses (Chalmers et al. 2020). AI is also being used to predict the success of entrepreneurial ventures (Krishna et al. 2016; Koumbarakis and Volery 2022), offering advantages over traditional methods, owing to its accuracy in prediction, ability to handle nonlinear effects in data, and detection of ambiguities (Koumbarakis and Volery 2022). Similarly, AI is valuable in business planning, particularly in forecasting sales, pricing products (Giuggioli and Pellegrini 2022; Syam and Sharma 2018), and predicting customer reactions to price changes (Chalmers et al. 2020).

Despite the increasingly frequent use of AI in entrepreneurship research and practice, along with numerous new scientific topics, the research focus on the types of AI methods applicable in the field and the possibilities of these methods remains relatively weak. Given the immaturity and newness of the area, this is not surprising. Currently, the intersection of AI and entrepreneurship is primarily addressed by entrepreneurship scholars, who have yet to seek partnerships with researchers who are experts in AI (Lévesque et al. 2020). Thus, multidisciplinary collaboration would produce more technical scientific insights on AI in entrepreneurship.

Overview of AI in finance

In contrast to AI research in entrepreneurship (Obschonka and Audretsch 2020), AI in finance is not a new field (Goodell et al. 2021). An examination of significant scientific databases, including Google Scholar, Scopus, and Web of Science, reveals that the first relevant journal articles on the intersection of AI and finance appeared in the 1970 s (Google Scholar) and 1980 s (Scopus). These articles focused primarily on the use of AI in banking and securities investment. Some of the early topics covered included assessing credit card applications (Tamai and Fujita 1989), predicting a firm's financial health (Elmer and Borowski 1988), evaluating credit (Shaw and Gentry 1988), selecting stock portfolios (Yamaguchi 1989), predicting stock market behavior (Loo 1989), and assigning ratings to corporate bonds (Dutta and Shekhar 1988). Since the mid-1980 s, a small group of authors has highlighted the use of expert systems in accounting and auditing (Shim and Rice 1988), addressing issues such as the auditor's assessment of uncollectible accounts (Dungan and Chandler 1985) and the assessment of company solvency (Dillard and Mutchler 1987). This domain continued to develop in the 1990 s and 2000 s when a larger number of relevant applications of AI methods appeared in corporate bankruptcy prediction (e.g., Zhang et al. 1999) and financial fraud detection (accounting fraud, (Cerullo and Cerullo 1999); fraud in credit approval process (Wheeler and Aitken 2000); and credit card fraud (Kim and Kim 2002)). Additionally, the field of financial forecasting based on sentiment analysis began to develop, with a rise following the notable publication of Das and Chen (2007). A few years later, the highly cited work of Pan (2012) paved the way for further advances in financial distress models (Pan 2012). Driven by the fourth industrial revolution, AI-finance research has experienced a strong proliferation that continues to this day (Goodell et al. 2021). Recently, new topic niches have begun emerging, such as AI in the context of FinTech innovations (cryptocurrencies and blockchain, crowdfunding, peer-to-peer lending, financial robo-advising, and mobile payment services (Goodell et al. 2021; Antonio et al. 2024; Piehlmaier 2022; Rjoub et al. 2023), and predicting financing success using new FinTech funding sources (e.g., Kaminski and Hopp 2020).

Expert systems represent the earliest form of AI in finance, initially applied in 1977 (Wong and Monaco 1995; Bahrammirzaee 2010). Despite the hardware limitations at that time, by the mid-1990 s, they had been pioneered in fields such as finance, investment, taxation, accounting, and administration (Wilson 1987) (as cited in Bahrammirzaee (2010)). A particularly notable work from this period was published by Shaw and Gentry in 1988 Shaw and Gentry (1988), who developed the MARBLE system to assess the riskiness of business loan applicants. Although ES were more practical than conventional statistical techniques, they were outperformed by other AI methods, such as artificial neural networks (ANN) and hybrid intelligent systems (HIS). ES were only capable of prescription, not prediction or improvement through experience, and they were ineffective at identifying nonlinear relationships (Bahrammirzaee 2010).

ANNs, first applied in bond ranking in the 1980 s, eliminate these deficiencies (Dutta and Shekhar 1988). As "nonparametric" methods, ANNs are data-driven and self-adaptive, and they are less sensitive to model misspecification than parametric methods are. They are well suited for models that do not require a priori assumptions about the data, which can be nonlinear and discontinuous (Kumar et al. 2021; Tay and Cao 2001). These characteristics have proven to be a significant strength over sophisticated statistical techniques in areas such as bankruptcy prediction and stock market prediction (Tay and Cao 2001; Kumar et al. 2021; Bahrammirzaee 2010), especially when dealing with a complex set of highly correlated, nonlinear, and unclearly related variables (Wong and Selvi 1998).

Despite their advantages, ANNs have some shortcomings. The most popular ANN in finance, the back-propagation neural network (BPNN), requires many control parameters, rarely provides a stable solution, and is prone to potential overfitting, which leads to poor generalization ability with out-of-sample data (Tay and Cao 2001). Therefore, it is often combined with classical statistical techniques or other intelligent methods, such as ES, fuzzy logic, genetic algorithms (GAs), and robotics (Wong and Selvi 1998). Hybrid Intelligent Systems (HIS) leverage the advantages of complementary methods and minimize their shortcomings, and can achieve multi-functionality, technical enhancement, and a multiplicity of application tasks. Although their performance is very sensitive to the correct choice of integration methods and the problem of parameterization, they have generally proven to be effective in solving problems in credit evaluation, portfolio management, and financial forecasting and planning (particularly various neuro-fuzzy systems and combinations of neural networks, fuzzy logic, and GAs) (Bahrammirzaee 2010).

In addition to hybridized methods, support vector machines (SVMs), introduced in 1998, have shown improved generalization performance. Compared with BPNNs, SVMs[2] consistently demonstrate significantly or at least slightly better results in financial time series forecasting (e.g., Huang et al. 2005), credit rating analysis (e.g., Huang et al. 2004), and financial distress evaluation (Hui and Sun 2006). The advantage of SVMs lies in their implementation of the structural risk minimization principle, which minimizes an upper bound of the generalization error, unlike previous ANN algorithms that are based on the empirical risk minimization principle (Tay and Cao 2001; jae Kim 2003). Another advantage of SVMs is that training them is equivalent to solving a linearly constrained quadratic programming problem, resulting in a unique, optimal solution without the issue of converging to a local minimum, a potential drawback of BPNNs (Tay and Cao 2001; Osuna et al. 1997; Bahrammirzaee 2010; Li et al. 2006). These factors have made SVMs one of the most common AI methods for addressing a range of (especially predictive) problems in finance (Goodell et al. 2021), whether used as a standalone method or as a component of HIS (Bahrammirzaee 2010).

Over the past 14 years, natural language processing (NLP) has gained increasing popularity in the field of finance (Fisher et al. 2016; Gupta et al. 2020). Advocates for these methods argue that much data cannot be effectively expressed numerically without losing its holistic meaning, endless variety, and nuances. Unstructured text documents often contain more timely information than quantitative financial data sets. Furthermore, texts from financial news, social networks, or auditor's reports include opinions, connections, and emotions, all of which are valuable in various financial classification and prediction problems (Das 2014; Fisher et al. 2016). According to Fisher et al. (2016), the most used AI tools for NLP-based research in finance are SVMs, followed by naive Bayes (NB) models, hierarchical clustering, statistical methods, and term

[2] There are also some exceptions to the majority of findings (e.g., Ecer 2013).

frequency–inverse document frequency (TF-IDF) weighting. NLP has also shown promising results in generating and validating prototype taxonomies and thesauri, enhancing corporate reports' readability, and particularly in areas such as financial fraud detection and recognizing stock price movements (Fisher et al. 2016). However, as recently as nine years ago, this domain was still in its early stages (Purda and Skillicorn 2014). Some of the research questions identified at that time focused on the extent to which NLP can function independently in accounting taxonomies and thesauri without manual interventions, and how to address the challenges posed by small data samples, the distributed location of text documents, and the evolving nature of accounting vocabulary (Fisher et al. 2016). More recent advancements include topic analyses of accounting disclosures and the expansion of deep learning research in areas such as quantifying the diversity of a firm's operations and locations, and labeling different types of corporate risks (Bochkay et al. 2022).

Research gaps and objectives of the study

In the domain of AI-entrepreneurship, the literature has been expanding recently, with significant contributions from Li et al. (2022); Giuggioli and Pellegrini (2022); Blanco-González-Tejero et al. (2023), and Gupta et al. (2023). In the AI-finance field, notable review contributions include works by Wong and Selvi (1998); Bahrammirzaee (2010); Das (2014); do Prado (2016); Shi and Li (2019); Kumar et al. (2021), and Goodell et al. (2021), among others. Most of the review papers in these areas are systematic literature reviews, and several bibliometric analyses have been conducted (Goodell et al. 2021; Ahmed et al. 2022; do Prado 2016; Shi and Li 2019; Li et al. 2022; Gupta et al. 2023; Blanco-González-Tejero et al. 2023; Chaklader et al. 2023; Chen 2023). A significant portion of the literature reviews focuses on specific subtopics, such as AI in banking (Fethi and Pasiouras 2010), bankruptcy prediction (do Prado 2016; Shi and Li 2019), and sustainable entrepreneurship (Gupta et al. 2023). Two bibliometric studies aim to provide a comprehensive view of the AI-finance field (Goodell et al. 2021; Ahmed et al. 2022). However, no bibliometric study offers an overview of AI methods in finance or entrepreneurship, with the exception of the study by Goodell et al. (2021), which examines groups of AI methods in finance. However, this study is based on a small sample of documents (N = 283) and does not include computer science literature in its corpus or focus on the entrepreneurship field. In fact, almost all bibliometric studies are conducted with a relatively small sample of documents (Donthu et al. 2021), and some have additional methodological limitations, such as excluding computer science literature from the data set, limited use of available bibliometric tools, and not performing data-screening procedures before analysis. Importantly, no existing studies have discussed the intersection of AI, entrepreneurship, and finance in relation to the entrepreneurial finance domain.

The present study aims to explore and review the conceptual and intellectual structure of scientific knowledge (Aria and Cuccurullo 2017) on the intersections of AI with two economic fields: entrepreneurship and finance. Specifically, this study focuses on the AI-entrepreneurial finance literature and AI-corporate finance literature with implications for entrepreneurship. Here, entrepreneurial finance is defined as "the art and science of investing and financing entrepreneurial ventures" (p. 9) (Alemany and Andreoli 2018). This includes two fundamental aspects: investing, or choosing the direction of an entrepreneur's investment, such as the purchase of physical assets or entering a new market, and financing, or securing money to realize an investment plan (Alemany and Andreoli 2018). Important topics within this domain include sources of funding for entrepreneurs (bank lending, equity capital, crowdfunding, business angels, etc.), investor-entrepreneur negotiation strategies, business planning (including financial planning and forecasting), understanding and analyzing financial statements, and valuation of new ventures and small businesses (Abor 2016). The concept extends beyond startups to include intrapreneurship, acquisitions of existing businesses, and new entrepreneurial ventures within corporations or family firms (Alemany and Andreoli 2018). Moreover, some authors expand the concept to include the financial and investment activities of all small and medium-sized enterprises (SMEs), distinguishing it from corporate finance, which is defined as the "financial decision-making of large corporate organizations" (p. 4) (Abor 2016).

The specific objectives of this study are as follows:

1. to determine the publication productivity and the evolution of scientific knowledge at the intersection of AI, entrepreneurship, and finance;
2. to identify the most influential journals and prominent themes at this intersection, and to track the chronological development of these themes;
3. to determine the AI methods (methods, algorithms, techniques) used in studying specific themes at this intersection;
4. to gain deeper insights into emerging research directions and promising AI methods in entrepreneurial finance, with implications for the scientific community, computer experts, entrepreneurs, and investors; and
5. to provide recommendations for future improvements in bibliometric methodology.

In Tables 1 and 2, we compare the characteristics of the current study with those of related bibliometric works.

Methodology

Preliminary search and initial screening of the field

The bibliometric methodology of this study is shown in Fig. 1. The bibliometric analysis (Donthu et al. 2021; Aria and Cuccurullo 2017) starts by defining the general objective and scope of the study (Subsection 2.3). This is followed by a preliminary search and initial screening of the research field. The goal of the preliminary search is to define an appropriate set of keywords and search queries, which serve as key inputs for the final data collection phase (Subsection 3.2). The proper selection of keywords is crucial, because even minor variations in terms and queries can change the data set, potentially yielding different results (Hire et al. 2021).

The preliminary search phase involved using the Google Scholar database, selected for its comprehensive coverage as the largest scientific database, to conduct searches with broadly defined keywords created by the researchers. Additionally, the WoSCC was searched to gain insight into the relevant literature of the field. Between March 16, 2023, and March 29, 2023, researchers searched and screened a total of 1,427 documents from

Table 1 Comparison of the present study against related bibliometric work—part I[a]

Intersection AI-finance

Topic scope	Methods	Database	Subject area	Sample	Review[b]
do Prado (2016)					
Credit risk and bankruptcy prediction	Multivariate Data Analysis Techniques	WoSCC	No limit	393	Credit risk and bankruptcy prediction multivariate techniques list and timeline
Shi and Li (2019)					
Corporate bankruptcy prediction	Intelligent Techniques	WoSCC	No limit	413	Only bankruptcy prediction intelligent methods list
Goodell et al. (2021)					
Finance	Artificial Intelligence	Scopus	Only Social Sciences, no Computer Science	283	AI methods list, in finance
Ahmed et al. (2022)					
Finance	Artificial Intelligence	Scopus	Only Economics and Finance, no Computer Science	348	None
Chaklader et al. (2023)					
FinTech companies	Artificial Intelligence	Scopus	No limit	302	None
Nazareth and Reddy (2023)					
Finance	Machine Learning	ScienceDirect	No limit	126	Machine learning in finance
Chen (2023)					
Finance	Explainable Artificial Intelligence	WoSCC	Only Business, Business Finance and Economics, no Computer Science	2, 733	None

Data has been grouped by publication year, in ascending order.

[a]Continuation of the analysis presented in the table can be seen in Table 2

[b] What kind of AI method review provided

Google Scholar (1,053 after removing duplicates) and 419 documents from the WoSCC. The search used 12 queries based on seven key expressions (artificial intelligence OR machine learning, finance OR funding, entrepreneur OR venture OR business) to provide a general overview of the area. The initial screening included various document types, such as journal articles, books, conference papers, theses, and reports. After reviewing the titles, keywords, and abstracts, we identified 266 relevant documents. These documents were then examined in detail by re-reading the abstracts and keywords and, in some cases, inspecting the full text to ensure the validity of the research.

The preliminary search and screening of the 266 relevant documents showed that the intersection of AI, entrepreneurship, and finance is a dynamic area with a large number of recent publications (within the previous three years), primarily within two research areas: computer science and business. Therefore, the scope of the research field is considered sufficient for conducting a bibliometric analysis. We identified the following intertwined topic niches:

1. AI as support for entrepreneurial financing decisions

Table 2 Comparison of the present study against related bibliometric work—Part II[a]

Topic scope	Methods	Database	Subject area	Sample	Review[b]
Intersection AI-entrepreneurship					
Li et al. (2022)					
Entrepreneurial management	Artificial Intelligence	WoSCC	No limit	123	None
Blanco-González-Tejero et al. (2023)					
Entrepreneurship	Artificial Intelligence	Dimensions.ai	No data	520	None
Gupta et al. (2023)					
Sustainable entrepreneurship	Artificial Intelligence	Scopus	No limit	482	None
Intersection AI-entrepreneurship-finance					
The present study					
Entrepreneurial finance and corporate finance with implications for entrepreneurship	Artificial Intelligence	WoSCC	No limit	1, 890	Artificial intelligence in entrepreneurial and corporate finance

Data has been grouped by publication year, in ascending order

[a] First part of the analysis presented in the table can be seen in Table 1

[b] What kind of AI method review provided

1.a Investment success/business performance and entrepreneur's behavior and presentation
1.b Sources of entrepreneurial finance
1.c Valuation of an entrepreneurial venture/Prediction of performance and/or bankruptcy

2. FinTech, in the context of entrepreneurship
3. Management of entrepreneurial finance

3.a AI and accounting, auditing, and detecting financial fraud
3.b Financial planning and other aspects of financial management

Within each topic niche, we defined different combinations of keywords and search queries as inputs for the subsequent stage of the literature search. Table 3 shows the keywords and queries, along with the ordinal numbers of the corresponding topic niches, as enumerated above.

Searching, collecting, and screening the data for bibliometric analyses

The data for the bibliometric analysis were gathered from the WoSCC. Clarivate PLC's database was chosen for the study, because it is one of the most relevant and comprehensive collections of peer-reviewed scientific material. The data export occurred on May 5, 2023. The search was performed using the criterion Topic (searching titles, abstracts, author keywords, and keywords plus, which are generated from references (Garfield and Sher 1993)). We applied the following search filters: (1) Document Type: Article, Review Article, Early Access; (2) Language: English; (3) Web of Science Index:

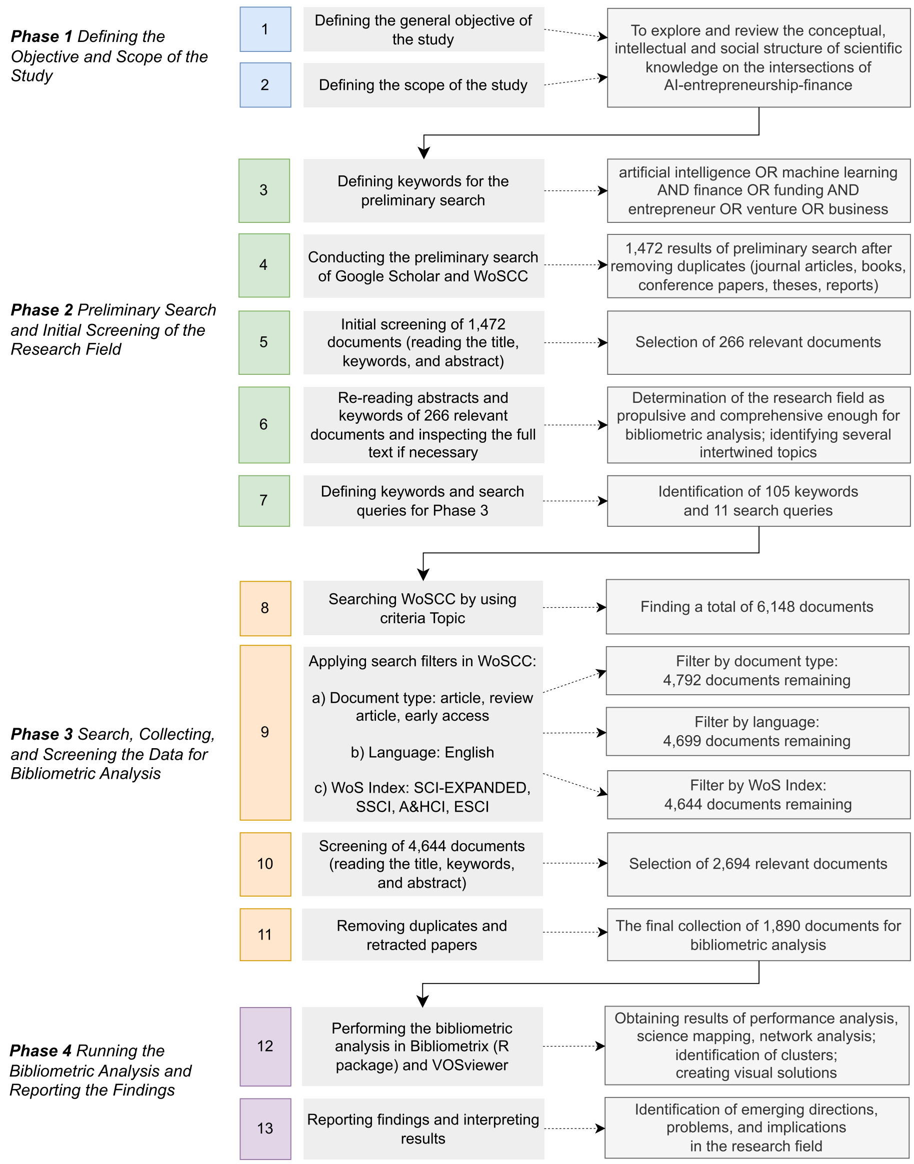

Fig. 1 Flowchart detailing the bibliometric methodology steps and procedures in the present study

Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (A&HCI), and Emerging Sources Citation Index (ESCI).

By limiting the search to the WoSCC and the listed indices and document types, we retrieved data only from journals that demonstrate high levels of editorial rigor and best practice (Web of Science Core 2023). We excluded papers published in conference proceedings and other forms of scientific material from the data set. Our goal was to form a corpus comprising only peer-reviewed and highest-quality scientific work (Kumari et al. 2023). To provide a comprehensive view of the research field, both temporally and disciplinarily (Shi and Li 2019), we did not use any filters on the time range and research areas.

Table 3 Search queries and number of records in procedures of searching, collecting, and screening the data for bibliometric analysis

Topic[a]	Search query[b]	Records[c]	Filtering procedure			
			Document type	Language english	WoS index[d]	Screening[e]
1 (a)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND (text OR emotion OR nonverbal OR facial OR speech OR signal* OR pitch OR persuasion OR present* OR video OR trait* OR narrat* OR motivat* OR impress*) AND ("SME" OR "SMEs*" OR "small business*" OR entrepreneur* OR crowdfund*)	555	385	377	369	121
1 (b)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("debt*" OR "loan*" OR "venture capital*" OR "venture fund*" OR "angel*" OR "equit*" OR "bootstrap financ*" OR "bootstrapping") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*)	736	563	556	552	277
1 (b)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("security token offer*" OR "initial coin offer*" OR crowdfund* OR kickstart* OR "peer-to-peer lending" OR "peer-to-peer loan")	196	146	145	143	120
1 (c)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("SME failure" OR "SMEs* failure" OR "enterprise* failure" OR "compan* failure" OR "business* failure" OR "firm* failure" OR "entrepreneur* failure" OR bankruptcy)	1, 184	1, 021	997	986	740

Table 3 (continued)

Topic[a]	Search query[b]	Records[c]	Filtering procedure			
			Document type	Language english	WoS index[d]	Screening[e]
1 (c)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("SME valuat*" OR "SMEs* valuat*" OR "enterprise* valuat*" OR "business* valuat*" OR "compan* valuat*' OR "firm* valuat*" OR "entrepreneur* valuat*" OR "SME success*" OR "SMEs* success*" OR "enterprise* success*" OR "business* success*" OR "compan* success*" OR "firm* success*" OR "entrepreneur* success*" OR "SME performance*" OR "SMEs* performance*" OR "enterprise* performance*" OR "business* performance*" OR "compan* performance*" OR "firm* performance*" OR "entrepreneur* performance*")	547	455	450	445	224
2	('artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND (fintech OR "financ* technology") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*)	166	129	124	121	39
3 (a)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND audit* AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm*)	375	301	295	288	162
3 (a)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("accounting" OR "accountant" OR "financ* statement*") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*)	696	540	524	519	370
3 (a)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("fraud detect*" OR "financ* fraud" OR "accounting fraud") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*) NOT "credit card*"	258	160	159	158	67

Table 3 (continued)

Topic[a]	Search query[b]	Records[c]	Filtering procedure			
			Document type	Language english	WoS index[d]	Screening[e]
3 (b)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("financ* management" OR "financ* planning" OR "financ* decision*" OR "financ* analys*" OR "financ* sustainability" OR "financ* distress" OR "financ* risk" OR "financ* constraints") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*)	745	617	606	602	442
3 (b)	("artificial intelligence" OR "machine learning" OR "deep learning" OR "soft computing" OR "neural network*" OR "natural language processing") AND ("demand predict*" OR "demand forecast*" OR "predict* demand" OR "forecast* demand" OR "price* predict*" OR "price* forecast*" OR "predict* price*" OR "forecast* price*" OR "salar* predict*" OR "salar* forecast*" OR "wage* predict*" OR "wage* forecast*" OR "predict* salar*" OR "forecast* salar*" OR "predict* wage*" OR "forecast* wage*") AND ("SME" OR "SMEs*" OR enterprise* OR business* OR compan* OR firm* OR entrepreneur*)	690	475	466	461	132
$\sum$		6, 148	4, 792	4, 699	4, 644	2, 694
$\sum D$						804
$\sum B$						1, 890

Sorted according to search query, in ascending order. D and B are representing duplicates and retracted papers, and number of papers for bibliometric data analysis (2, 694 − 804), respectively

[a] Topic niches identified in the phase of preliminary search and initial screening of the research field presented in detail in Subsection 3.1 of the paper

[b] The search was updated and finalized, with the data being exported, on May 5, 2023

[c] Total number of records

[d] Selected Web of Science indexes, presented in Fig. 1

[e] Performing reading of the title, keywords, and abstract

[*] It is a wildcard character representing a sequence of literal characters or an empty string

We performed the search using a large number of keywords and 11 different search queries, with the query syntax adapted to the formatting rules of the WoS. The search used the operators OR, AND, and NOT. Wherever meaningful, we used the wildcard character "*" to control the retrieval of plurals and variant spellings. Quotation marks were used to search for exact phrases, such as "artificial intelligence" (Web of Science Core 2021). The selection of keywords related to AI aimed to cover as many different AI methods as possible. We avoided keywords that could yield papers based solely on statistical methods, that is, without an AI component.

The data search yielded a total of 4, 644 results, which underwent a screening procedure. This screening involved examining the title, keywords, and abstract of each paper. Unlike a systematic literature review, the bibliometric methodology only requires screening of the abstract and the full text when necessary (Guo et al. 2020). However, as a precaution, we read the abstracts of nearly all 4, 644 papers, except for those with titles that were overwhelmingly clear. The screening strategy was based on a broad understanding of entrepreneurial finance and its overlap with related disciplines such as corporate finance, management, business planning, accounting, and auditing. Thus, in addition to entrepreneurial finance literature, the corpus of data for analysis also included literature related to corporations and the financial sector, which contains implications for the financing of entrepreneurship and the financial management of new entrepreneurs and SMEs. We excluded scientific material that only had implications for financial institutions and financial markets.

The screening procedure for the 4, 644 records resulted in a set of 2, 694 relevant documents. This data set was then reduced by removing duplicates and retracted papers, creating a final corpus of 1,890 documents. The analysis was performed in Bibliometrix (4.1.2), a package within RStudio (2023.03.0 Build 386). Owing to its greater reliability in network analysis, as well as some additional features, we also used VOSviewer (1.6.19).

Research results

Preliminary data analyses

Table 4 presents descriptive statistics on the main information and keywords. The analysis covers documents starting from 1991, a year that marks the beginning of the widespread popularity and integration of computers among the public. The significant number of sources (637) provides authors with numerous options, indicating their relevance to the scientific community. A literature search shows that this relevance extends beyond finance and entrepreneurship, because many studies are published in computer science journals.

The analysis of a large number of documents (1, 890 in total) shows that the field has matured significantly, providing a strong motivation to determine its current state. This is further supported by the search for numerous authors (3, 879 in total; see Table 5), which suggests that there are many unresolved questions. The annual growth rate of

Table 4 Descriptive statistic on main information and keywords

Main information		Keywords	
Observed variable	**Variable value**	**Keywords plus**[a]	**Keywords**[b]
Time span	1991–2023	2, 015	4, 342
Sources	637		
Documents	1, 890		
Document Annual Growth Rate (%)	12.9		
Document Average Age (year)	5.6		
Average citation (per doc.)	23.21		
References	62, 567		

[a] Algorithmically generated by Web of Science

[b] Given by an author in the paper

Table 5 Descriptive statistics on authors and collaborations

Authors		Collaborations		
No.	**Single doc.**	**One author (per doc.)**	**Coauthors (per doc.)**	**International (%)**
3, 879	225	266	2.91	25.08

documents at 12.9% and an average document age of 5.6 years indicate that this is a popular area of research. Further data analysis will reveal that this field offers significant opportunities for both academia and industry. A key question remains: What will be the next major development? Will the integration of quantum computation and algorithmics lead the way, or will it develop alongside existing technologies? The future of quantum computation remains uncertain, though signs suggest it is likely to persist.

The average age of documents in this field (5.6 years) indicates that it is dynamic and generates a significant amount of new knowledge. This situation presents a steep learning curve for newcomers, necessitating continual self-improvement. However, working in such an evolving field is also fascinating and rewarding. This trend is likely to persist and may even accelerate, further reducing the average age of documents.

The average citation per document of 23.21 is high, owing to a smaller number of highly cited articles and possibly other characteristics of the field, such as the number of authors, the interdisciplinary nature of citations, and the number of research/industry projects in computing, particularly in AI. The total number of references is 62, 567, resulting in an average of 33 references per document, which is close to the minimum expected number for review papers. This situation likely stems from the factors influencing the citation count. Nevertheless, documents with a high number of references should be well grounded and, with a high number of citations, relevant to the field.

With a total of 4, 342 keywords, the expected number of keywords per document is two, which falls short of the typically recommended number of five. However, this does not necessarily imply that the papers are poorly supported by keywords; there may still be some outliers. A useful data point for future reference is the comparison of keywords and keywords plus (generated from references (Garfield and Sher 1993)), which is approximately 1 : 2. This ratio indicates that, using half of the original keywords, it is possible to describe the structure of the knowledge, but not the knowledge itself (Garfield and Sher 1993; Zhang 2015).

Table 5 shows data about authors and collaborations. The average number of authors per paper is approximately two, with 225 authors (5.8%) having published only one document. This suggests that most individuals in this field are committed to making a more lasting contribution over time. Regarding collaborations, 266 documents are authored by a single individual, a figure nearly equivalent to the number of authors who have published only one document. This similarity may indicate that authors of single documents are less likely to form collaboration groups. Additionally, the data reveal a high level of collaboration in the field, because the saturation of authors is not statistically significant, and about 14% of documents have one author only.

Confirmation of the above is the average number of authors per document, which is 2.91. This appears highly collaborative for computer science and economics, and is expected and a positive sign for a field at a crossroads. With 25.1% of co-authorships being international, this represents a substantial percentage on a global scale. It likely conceals other elements, such as networking, international collaborative groups, and international research projects.

Figure 2 presents the annual scientific production in the field, showing a slow start, with only two articles published in 1991, a trend that continued until about 2002. It took a considerable amount of time for AI technology to mature sufficiently. Given the added challenge of interdisciplinarity, such slow development was expected-the research was scarce, and contributions were limited. In 2003, a new era began with a steady influx of papers, year by year, following an approximately linear trend. As is the case in science, new technology is not always immediately recognized and applied. However, in the 2000 s, this trend began to change as researchers began to realize the potential of AI methods, techniques, and algorithms in the field. This realization had a secondary effect of attracting more scientists and practitioners, thus accelerating the advancement of knowledge in the field.

Around 2018, the number of publications in the field began to grow exponentially. This trend coincided with the publication of the first generative pretrained transformer (GPT, often called ChatGPT) by OpenAI in 2018 (OpenAI 2018), as well as the release of a deep learning transformer architecture by a team predominantly from Google Research and Google Brain in 2017 (Vaswani et al. 2017). These events have made AI significant, not only in finance and entrepreneurship, but also in many other areas. Such an extremely steep trend in the number of publications has increased the application

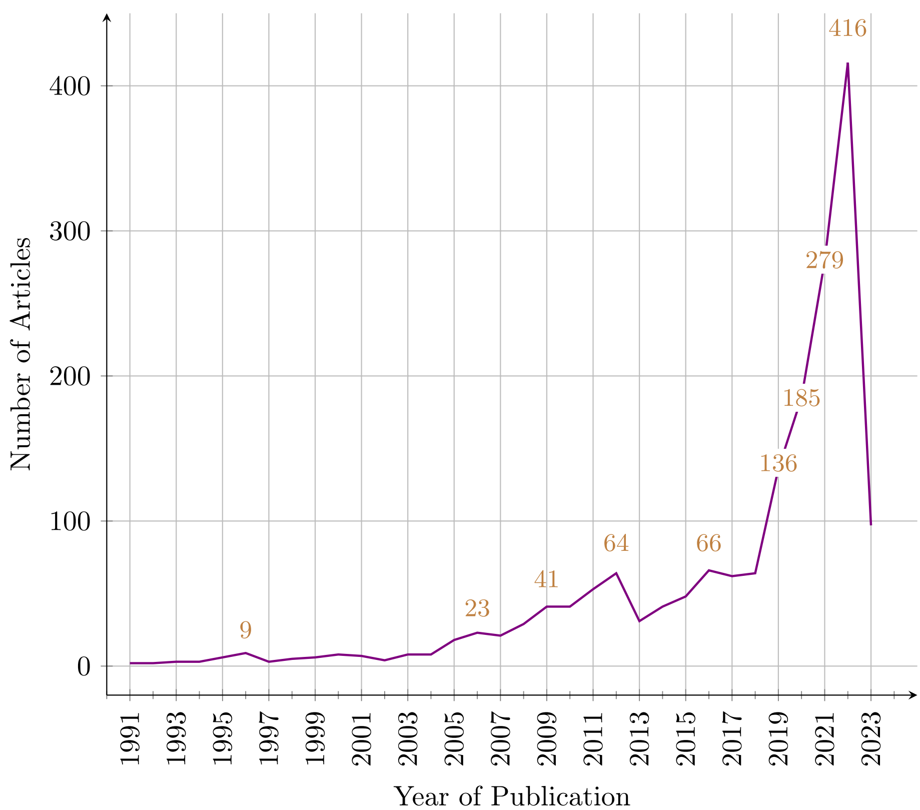

Fig. 2 Annual scientific production. Analyzed data for the year 2023 is incomplete

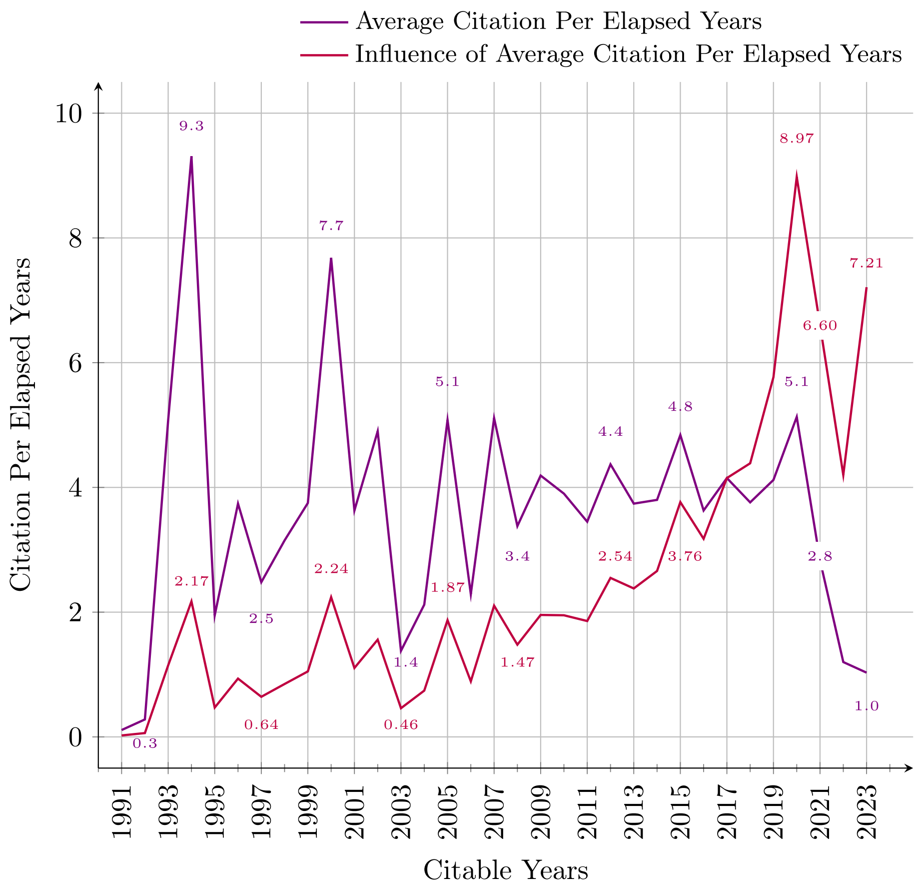

Fig. 3 Average citation per elapsed years. Until 2007 the situation was somewhat erratic. Afterward, it seemed a calm came, and the field had matured. However, this is deceptive as the influence of average citation reveals (as citations close to publication date are exceedingly more difficult to accumulate than those that will arrive later on—calculation was performed as per amortization described in Appendix A, with the result scaled by a factor of 7 to improve readability and reveal points of interest)

of AI tremendously, and innovation follows, whether through technology or optimization methods. From the information shown in this graph, this trend will continue for the foreseeable future.

By examining the influence of average citation per elapsed years, as shown in Fig. 3),[3] citations increased rapidly after the initial surge, peaking in 2020, which corresponds to the rapid development and growth of AI over the last decade. The year 2017 marked the first time AI citations grew to such an extent that their influence was more significant than average citations, with the influence of average citations scaled conservatively to the range between minimum and maximum values. According to the data, the most

[3] Fig. 3 indicates several turning points and periods relevant to the consideration of the development of the intellectual field. The first point of interest is in 1994. Since the number of documents was scarce during the preceding years, it is favorable to select the period until 1999 for inspection. The next period of interest is from 2000 until 2004, with the need to specifically determine the situation in 2000. Afterwards, there were two prominent peaks, in 2005 and 2007; therefore the period from 2005 to 2008 needs to be looked at. Then, it was a period of exponential explosion of both published documents and citations. During this time three relevant periods need to be looked at more closely, 2015–2018, 2019–2020, and the last speaking of things to come, 2021–2023. All of these have been analyzed with lesser or greater depth in the continuation of the paper. However, for the most definite conclusion, Figs. 8 and 9 should be consulted.

recent phase of rapid AI development began around 2015, following an earlier phase that ended in 2003–2004. Moreover, in 2019, the world faced the COVID-19 epidemic, which escalated to pandemic conditions in 2020, significantly affecting research in an increasingly online and digitally oriented world. The data from the past three years suggest that the field will continue to experience exponential growth in the future, at least in terms of the influence of average citations. This trend may indicate significant upcoming developments at the intersection of AI, entrepreneurship, and finance.

Average citation per elapsed year shows that, initially, a small number of papers accumulated a large number of citations over time, gaining substantial relevance. As time progresses, the average citation appears to stabilize into a "line," suggesting that these documents are less relevant in terms of citations. However, this perception is misleading, because the average calculation does not consider the greater significance of recent advancements in the field or the difficulty of accumulating citations in a short period. To address this, we suggest the influence of average citation per elapsed year, which posits that the relationship between average document citation and the number of elapsed years is exponentially inversely proportional. This approach not only accounts for the number of years that have passed, but also evaluates the strength of those years in terms of citation accumulation and relevance to the field. A detailed description of this calculation is available in Appendix A.

Comparing the influence of average citation with Fig. 2 and accompanying events, it is evident that such a curve more accurately represents the general situation. Therefore, it is advisable to consider both measures: average citation and the influence of average citation per elapsed years. By examining the influence of the average citation, we can identify three distinct periods and one emergence point. The first period ended around 2003, and the second around 2015, marked by the publication of the soft-search neural machine mechanism for translation in 2014 (Bahdanau et al. 2014), an important component of later GPT models. The last period began around 2015, with the two most recent periods separated by an emergence point during the 2016–2017 transition. Here, the influence of average citation has surpassed average citation, with documents becoming influential in terms of the mentioned fixed point and highly influential from that point onwards. We scaled the influence of average citation to the average citation range, considering the minimum and maximum values in a conservative manner.

Lastly, for this analysis, before the emergence point, two periods were influential: 1994–1995 and 2002–2007. Although these periods are separated by several years, they generally extend their influence to neighboring points, corresponding to the increased interest in AI, its coming of age, and subsequent applicatory and scientific breakthroughs. In the foreseeable future, documents are likely to remain in the influential to highly influential range as the field of AI continues to grow.

Sources data analyses

Figure 4 shows the sources and their respective outputs in terms of the number of documents. Expert Systems with Applications (ESA) is by far the most prolific source, followed by Computational Intelligence and Neuroscience, which lags significantly behind. Other sources follow in a decreasing sequence, with each source slightly trailing the previous one. ESA is particularly specialized in the field and serves as an excellent venue

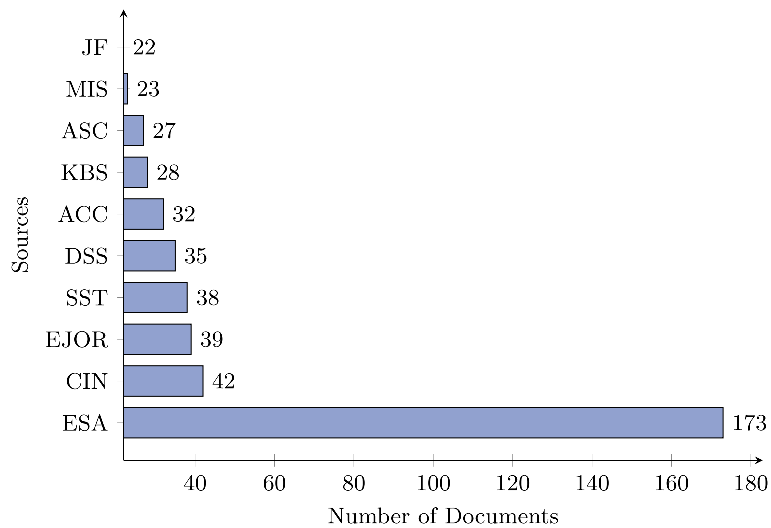

Fig. 4 Most relevant sources (in terms of number of documents published), ending in May 2023. Source titles are abbreviated, as follows: ESA—expert systems with applications; CIN—computational intelligence and neuroscience; EJOR—European journal of operational research; SST—sustainability; DSS—decision support systems; ACC—IEEE access; KBS—knowledge-based systems; ASC—applied soft computing; MIS—mobile information systems; JF—journal of forecasting

for authors to publish their work, although other sources also offer opportunities for research publication. These publications are valuable resources for staying informed about the subject. Of the sources, the Journal of Forecasting is unique in its focus on economic, social, and behavioral aspects, without a strong emphasis on computer science. In contrast, the remaining sources vary from having a minor to a very large emphasis on computer science, highlighting the role of computer science sources in encouraging application-based and interdisciplinary research. Economics journals, and likely most others, face challenges in evaluating research that incorporates significant elements of computer science, particularly AI.

Figure 4 shows that 629 (or 33.28%) papers were published in the top 20 most productive sources. In accordance with Bradford's Law (Bradford 1934), a high percentage of documents (33.28%) are published in a small number of sources (3.13%). This is a classic example of a center of power, which naturally leads authors to gravitate towards it.

Furthermore, Fig. 5 shows h-index proposed by Hirsch in 2005 (Hirsch 2005), defined as "the number of papers with citation number $\geq h$." ESA confirms its relevance, making a strong case for the top position. From EJOR onwards, other publications have gradually followed. By observing all sources and their corresponding indices, we see the Pareto distribution. When we examine not only citations, but also the spread of those citations, these sources are relevant in the field.

Words data analysis

Analyzing words is an important step in identifying prominent themes within a knowledge field. As shown in Table 6, the most relevant terms include "deep learning," "neural network," "support vector machine," "blockchain," and "decision tree" (computer orientation), as well as "bankruptcy prediction," "credit scoring," "firm performance," "business failure," and "fraud detection" (finance and/or entrepreneurship orientation). To achieve

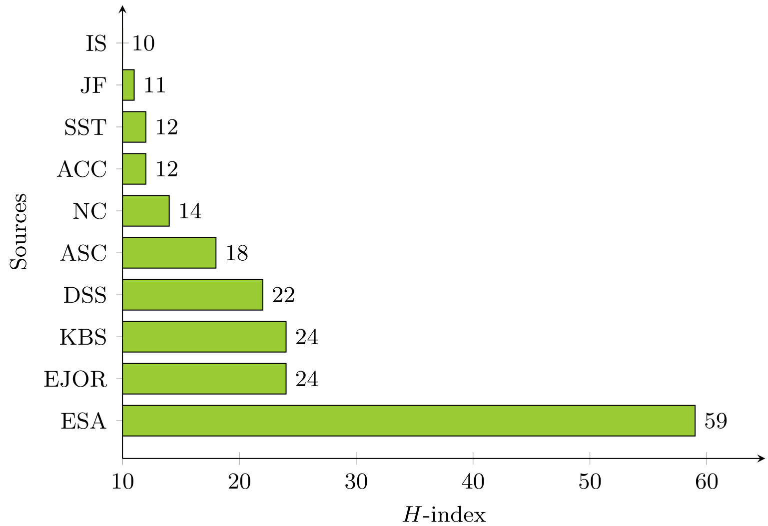

Fig. 5 Sources local impact measured by index *h* (Hirsch 2005), ending in May 2023. Source titles are abbreviated, as follows: ESA—expert systems with applications; EJOR—European Journal of operational research; KBS—knowledge-based systems; DSS—decision support systems; ASC—applied soft computing; NC—neurocomputing; ACC—IEEE access; SST—sustainability; JF—journal of forecasting; IS—information sciences

more detailed results, we performed a co-occurrence analysis (Fig. 6). From 1, 890 documents, we extracted 231 terms, carefully balancing quantity and quality. Considering 2, 490 links, totaling 4, 258 in strength, and with term occurrences reaching over 300, the analysis presents a compact occurrence network that describes the discipline in a relevant and thorough manner.

Machine learning, AI, and bankruptcy prediction have emerged as the main themes in the knowledge field. Within the machine learning cluster (colored blue), prominent terms include crowdfunding, NLP, firm performance, sentiment analysis, text analysis, and entrepreneurship. This cluster primarily covers themes related to predicting crowdfunding success using machine learning and NLP, particularly using text and sentiment analysis. A preliminary search also showed that NLP is used to predict the success of P2P financing. The AI cluster (colored red) focuses on applying modern computer technologies such as AI, digital technologies, big data, and FinTech (including blockchain, cryptocurrency, and P2P lending) in entrepreneurship to enhance performance. Important themes within this cluster are the application of AI and big data in entrepreneurship, digital transformation and its effects on firm performance, general FinTech themes, and the application of blockchain and big data in various areas, particularly in accounting and auditing. Additionally, this cluster addresses digitalization and AI application in achieving sustainability goals. Overall, the cluster represents a combination of new technologies and innovative business practices with traditional economic questions, signaling a changing economic environment and adaptation to new circumstances. Considering the number of publications in topic niches where the red and blue clusters overlap (niche 1a, 1b, and 2 from Table 7), and the temporal analysis from Figs. 7, 8, and 9, these clusters represent relatively new research areas.

Prominent terms related to bankruptcy prediction and business failure prediction, highlighted in pink and green clusters, include neural networks, SVMs, logistic

Table 6 Most frequent terms

Term	Frequency	Term	Frequency
Machine learning	306	*Artificial intelligence*	146
Bankruptcy prediction	144	*Neural networks*	93
Deep learning	91	*Data mining*	90
Credit scoring	80	Bankruptcy	77
Neural network	66	Learning	65
Prediction	59	Financial distress	58
Classification	54	Credit risk	52
Forecasting	52	Financial distress prediction	49
Support vector machine	47	Crowdfunding	45
Artificial neural networks	44	*Logistic regression*	43
Machine	43	Demand forecasting	41
Financial ratios	41	*Big data*	38
Feature selection	36	*Genetic algorithm*	35
Finance	33	Networks	31
Analysis	29	*Artificial neural network*	29
Blockchain	29	Accounting	27
Firm performance	27	Auditing	26
Natural language processing	25	Artificial	24
Fintech	24	*Support vector machines*	24
Decision trees	22	Financial	22
Model	22	Peer-to-peer lending	22
Business failure	21	Default prediction	21
Fraud detection	21	*Random forest*	21
Regression	21	Business	20
Decision tree	20	Smes	20

Sorted according to frequency; from left to right. Frequency is presented for 50 most occurring authors' keywords. Terms that are emphasized with bold letters represent data points of interest regarding the research objective. The aim was to extract algorithms, methods and techniques in AI found beneficial and applicable to entrepreneurial finance, with broadening the focus a bit for a more general overview

regression, decision trees, ensemble learning, boosting, and unbalanced data. These clusters focus on using state-of-the-art methods for business purposes while addressing data issues. Bankruptcy prediction is closely linked with credit scoring, represented by the brown cluster, where genetic programming, random forests, xboost, ensemble classifiers, and cluster analysis play an important role. The pink, green, and brown clusters, corresponding to topic niche 1c from Table 7, are the most productive areas in the field.

Finally, there are three additional highlighted clusters: (1) the yellow cluster, which focuses on using deep learning techniques for detecting financial statement fraud; (2) the purple cluster, which deals with time-series demand forecasting and the use of neural networks, big data, SVMs, and random forests; and (3) the orange cluster, which covers the prediction of financial risks, for example, in the context of developing early warning systems, where genetic algorithms and neural networks play a significant role. These three clusters correspond closely to topic niches 3a (yellow cluster) and 3b (purple and orange clusters) from Table 7. Given the number of papers in these niches, they are moderately saturated.

A diverse set of clusters has a strong neural net presence, with neural networks appearing in some form in seven out of 13 clusters. These clusters tend to focus more

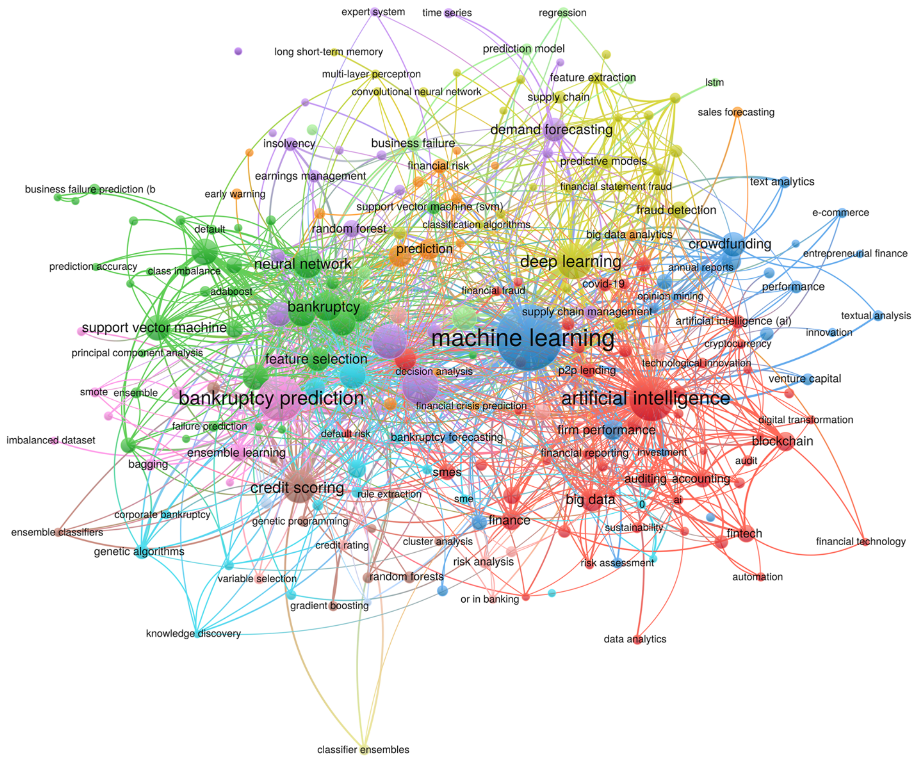

Fig. 6 Authors' keywords co-occurrence (determined according to documents in which items co-occur). The list of relevant terms was generated using authors' keywords, by VOSviewer (van Eck et al. 2006; Perianes-Rodriguez et al. 2016), for the entire data document lifespan

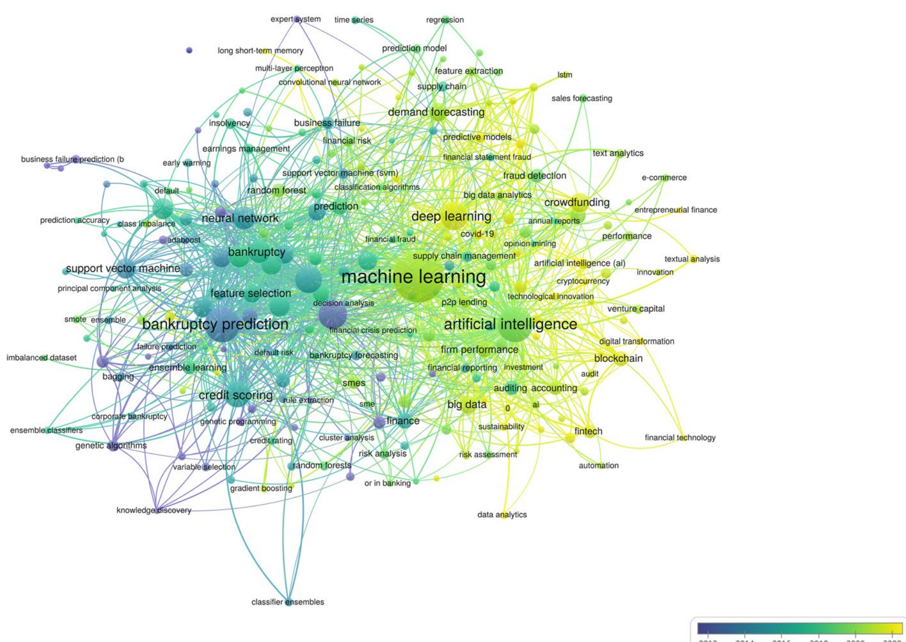

Fig. 7 Authors' keywords co-occurrence (determined according to number of documents in which items co-occur) overlay. The list of relevant terms was generated using authors' keywords, by VOSviewer (van Eck et al. 2006; Perianes-Rodriguez et al. 2016), for the entire data document lifespan, with the overlay focusing on the last decade. The overlay map represents a graph timeline, according to the legend on the lower right

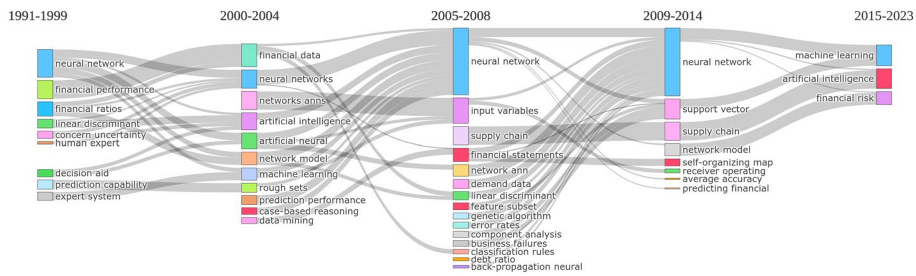

Fig. 8 Thematic evolution of concepts from authors' abstracts—1991–2014, with the last time slice 2015–2023, representing the future to come

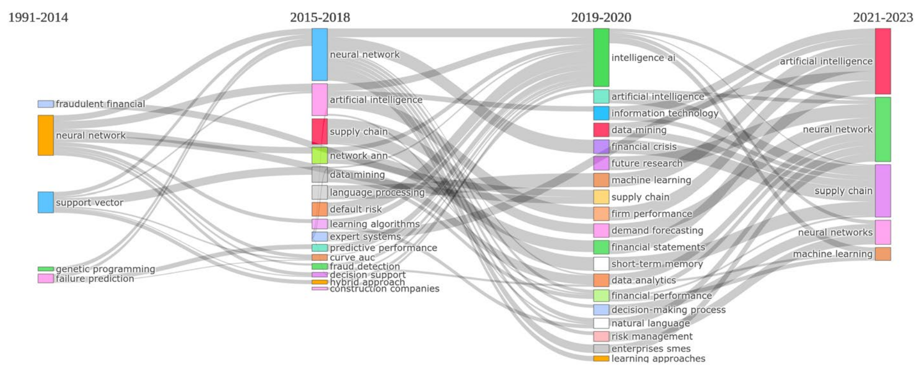

Fig. 9 Thematic evolution of concepts from authors' abstracts—2015–2023, with the last time slice 2021–2023, representing the future to come for which the data is incomplete

on computing or economics, depending on the scientific contributions and the authors' backgrounds. In general, the clusters are quite intertwined, both through co-occurrence and the appearance of certain themes across different clusters. These themes include neural networks, genetic algorithms, SVMs, bankruptcy prediction, business failure, and fraud detection.

Figure 7 shows the keyword co-occurrence overlay map, highlighting a shift in themes over the last decade. Initially, the focus was more contextual, but it shifted toward technology by the end of the decade. General terms such as machine learning and AI dominate, possibly indicating significant hype, with less emphasis on methods than expected. This trend aligns with the growing popularity of AI and related terms (digital transformation, big data, FinTech) among entrepreneurship researchers (Obschonka and Audretsch 2020). These researchers often explore the effects of technology on business practices, with less attention to the application of specific methods, techniques, and algorithms in research.

The network might appear misleading if not carefully analyzed. For example, while it seems that the presence of neural networks has decreased, deep learning remains highly influential as we approach the end of the decade. There is also a noticeable decline in the importance of expert systems, SVMs, and genetic programming, alongside the rise of NLP techniques. In terms of thematic focus, bankruptcy prediction has reached a point of saturation and has lost its appeal. However, topics related to firm performance and fraud detection continue to be relevant. Recent themes that occur frequently include

Table 7 Artificial intelligence method occurrence by topic niches

ON[a]	ND[b]	Topic Niches[c]	ANN	DNN	BPNN	DT	EL	GA	RNN	RF	GB	TM	SVM	CNN	SOM	CBR	PSO	GP	LSTM	FNN	FZNN	GHSOM	∑
1(a)	121	Investment success/business performance and entrepreneur's behavior and presentation	11	7																			18
1(b)	384	Sources of entrepreneurial finance	48	22	3	11	8	3		16	3	3	13										130
1(c)	950	Valuation of an entrepreneurial venture/Prediction of performance and/or bankruptcy	177	37	4	33	48	39		18	16		76	3	11	16	7	7	4	3	3		502
2	39	FinTech generally in the context of entrepreneurship		3																			3
3(a)	476	AI and accounting, auditing and detecting financial frauds	56	21		11		7	4	5	6		17	4	6				5			3	145
3(b)	573	Financial planning and other aspects of financial management	77	36	12	10	12	15	6	9	10		38	5		7	6		7	3			253
∑			369	126	19	65	68	64	10	48	35	3	144	12	17	23	13	7	16	6	3	3	

AI methods, techniques, and algorithms were extracted from documents, and categorized according to aforementioned niches, by VOSviewer (van Eck et al. 2006; Perianes-Rodriguez et al. 2016) via co-occurrence analysis for authors' keywords. Co-occurrence was determined according to the number of documents in which items co-occur. The authors' keywords were used to descriptively capture the content of the documents, because keywords plus are less comprehensive in terms of the actual content (Zhang 2015). The minimum number of keyword occurrences was set to 3, to leverage precision. Such analysis has produced clusters of term co-occurrences from which specific AI methods were manually extracted and occurrences obtained.

For the classification of AI methods, techniques and algorithms, e.g. (Dhall et al. 2019; Das and Rad 2020; Zhang and Lu 2021; Tapeh and Naser 2022) can be consulted

ANN, artificial neural network; DNN, deep neural network; BPNN, back propagation neural network; DT, decision tree; EL, ensemble learning; GA, genetic algorithm; RNN, recurrent neural network; RF, random forest; GB, gradient boost; TM, topic modeling; SVM, support vector machine; CNN, convolutional neural network; SOM, self-organizing map; CBR, case-based reasoning; PSO, particle swarm optimization; GP, genetic programming; LSTM, long short-term memory; FNN, feed-forward neural network; FZNN, fuzzy neural network; GHSOM, growing hierarchical self-organizing map

[a] Ordinal number identifying the particular niche

[b] Number of documents per specific niche—total sum is higher than 1, 890 (number of documents in bibliometric analysis) as papers can belong to different categories at the same time. Detected retracted papers are excluded. Documents analyzed span the entire period of the research.

[c] Topic niches identified during the preliminary literature search. Niches of type 1 are a part of the subject: AI as support for entrepreneurial financing decisions; niches of type 3 are a part of the subject: Management of entrepreneurial finance

crowdfunding, blockchain, FinTech, and big data. The blend of computing, economics, and statistics indicates the direction and development of the discipline in a changing environment. Overall, there is an excessive emphasis on computer science and statistics, possibly at the expense of adequate attention to problem domains. Some themes may require further development, or there might be a need for better collaboration between theory and practice and improved synergy among computing and economics experts.

Conceptual data analysis

The conceptual analysis, shown in Figs. 8 and 9, was conducted longitudinally using the selected abstracts. Because the analysis covers over 30 years, it is divided into two parts[4] (1) 1991–2014, (2) 2015–2023.

The first observation period, from 1991 to 1999, focuses on themes such as neural networks, performance, prediction, and expert systems, with a substantial prevalence of expert systems initially. However, neural networks and financial performance soon became the most dominant themes. The beginning of the 21st century saw a strong presence of financial data analysis in conjunction with AI, primarily machine learning and neural networks, while prediction continued to be a significant focus. After years of research, case-based reasoning also emerged as an important factor. From 2005 to 2008, neural networks significantly outpaced other themes, establishing a trend that continued in subsequent years. This period also saw a greater variety of themes, including input variables and financial statements analysis, supply chain relevance, some continuation of statistical themes, and the emergence of genetic algorithms. In the 2009–2014 period, there was a consolidation of themes, with neural networks continuing as a trend and SVMs becoming a dominant factor for the first time, alongside the noticeable presence of a self-organizing map. The period from 2015 to 2023 followed (Fig. 9), focusing on machine learning, AI, and financial risk, building on the previously mentioned themes.

Figure 9 begins with the period up until 2014, characterized by neural networks and financial predictions, where it appears that SVM emerged significantly. This highlights the importance of analyzing data at various levels of abstraction. From 2015 to 2018, previous themes were revitalized as research continued and improvements were made. Notably, two additions emerged: language processing and a hybrid approach. Given the new developments, hybridization naturally became a focal point. Thus, as a result of demand, language processing emerged as a sought-after innovation. Furthermore, the period from 2019 to 2020 is marked by a significant increase in themes, a logical consequence of the developments in AI. This period showed a general AI theme, which, while not particularly useful for identifying specifics, indicates a broad trend. Research continued, focusing on information technology, SMEs, and short-term memory, highlighting the roles of information, innovation, technology, and entrepreneurship during this period, and likely in the future. In the last analyzed period (2021–2023), AI, particularly neural networks, became the norm. This trend, which began in the late 20th century, continues to be strong. AI's maturation,

[4] Periods were selected for the reason of being one of the periods of interest from analysis in Fig. :3. A word of caution: analysis in, for example, Fig. 6 was conducted with authors' keywords, while the thematic evolution of concepts in Figs. 8 and 9 was performed with abstracts. Therefore, one should not compare terms in such a situation, but themes and ideas.

innovation, and environmental integration have made it a formidable force, likely to remain significant for some time. The supply chain was unusually robust, potentially owing to the COVID-19 pandemic that originated in Wuhan, China (Wu and McGoogan 2020). Machine learning remained influential, although the exclusivity of the term began to decrease.

Table 7 shows the occurrence of AI methods by topic niches. This analysis represents a minimum estimate of the methods used, because some applications might not be mentioned explicitly in the text. AI is referenced numerous times, but specific methods are mentioned much less frequently. This discrepancy may indicate that authors often associate their work with AI without engaging deeply with a particular method, resulting in research and applications that do not fully reflect the frequency of AI terms used. Additionally, it suggests a general interest in themes related to AI, particularly in examining the effects of technology on entrepreneurial practice.

Reading the bibliometric literature to determine which methods are being published is often only partially useful, because such analyses use very broad terms. These terms, such as AI and machine learning, describe either entire fields of AI or large subdivisions, without providing specific information. We take a different approach by avoiding overly broad and less useful terms. We focus on methods, techniques, and algorithms highly related to computing, because these items are most relevant today and will likely remain dominant for the foreseeable future. However, note that these methods also depend, to various degrees, on statistics. As such, we exclude keywords with fewer than three occurrences from the analysis.

The analyses conducted thus far confirm that the most prominent niche with the largest body of documents is 1(c), focusing primarily on bankruptcy prediction. Niche 3(b), which deals with financial planning, especially in terms of demand forecasting and financial risk prediction, is also notable. These niches see extensive use of AI methods, including ANN, deep neural networks, and SVM. Following these are niches 3(a) and 1(b), which also apply these methods. The absence of AI applications in niches 1(a) and 2 indicates that these topics are novel and not yet saturated, potentially highlighting the need for collaboration between experts in computer science and economics. Without such cooperation, it would be challenging to modernize economics and, specifically, entrepreneurship research.

In general, ANN and related items, including SVM, are extremely dominant, with ANN being significantly more prominent than any other method. This dominance is likely driven by their success in achieving results and possibly the surrounding hype as well. The analysis includes a substantial number of methods (20 different approaches), which shows an effort to address issues from various perspectives. These methods primarily consist of neural networks and statistical approaches, but also include heuristics, meta-heuristics, and programming paradigms. Some approaches, such as TM, FZNN, and GHSOM, have a smaller presence, but may represent initial attempts or suggest the potential for application in new areas. ANN and SVM are particularly prominent in niches 1(c) and 3(b), a natural pairing given the financial interests and the dynamic nature of these methods, which likely yield the best results. Additionally, ensemble learning and genetic algorithms play a role, combining multiple approaches to problem-solving and employing a metaheuristic for optimization and search.

Intellectual structure data analysis

To ascertain the authors' contributions and identify references that provide foundational knowledge in the field, we created a reference co-citation network. Because Bibliometrix is less effective than VOSviewer for visualizing large networks, we used both tools. The results from VOSviewer are displayed in Fig. 10 and Table 8. At first glance, the works of Altman (1968), Ohlson (1980), and Beaver (1966) appear highly relevant. However, note that, although these references are frequently cited, as shown through the analysis of reference co-citation, none of the research employs an artificial intelligence approach. Nevertheless, because these studies are pioneering in the field of bankruptcy prediction, subsequent authors frequently cite them in their papers (Shi and Li 2019).

The network comprises 353 nodes, which represent references, and a substantial number of edges, with the link strength indicating a dense network. This density primarily results from four of the five clusters focusing on a single topic niche (VP; (1(c) in Table 7)). The yellow cluster contains references from authors who have made significant contributions to the development of bankruptcy prediction models. The green and blue clusters include more recent references that apply AI within the VP domain. References in the red cluster are related to credit scoring, also predominantly associated with the VP niche. In contrast, the purple cluster is weakly connected to the rest of the network and within itself, with some links not visible, owing to VOSviewer's limit of displaying a maximum of 1,000 lines. This cluster includes references that address financial fraud detection and emerging topics at the intersection of AI, entrepreneurship, and finance, such as crowdfunding and the use of text analysis in finance and entrepreneurship.

A deeper insight into the sources and years of publication in Table 8 suggests a trend of switching from finance references to a stronger emphasis on computing.

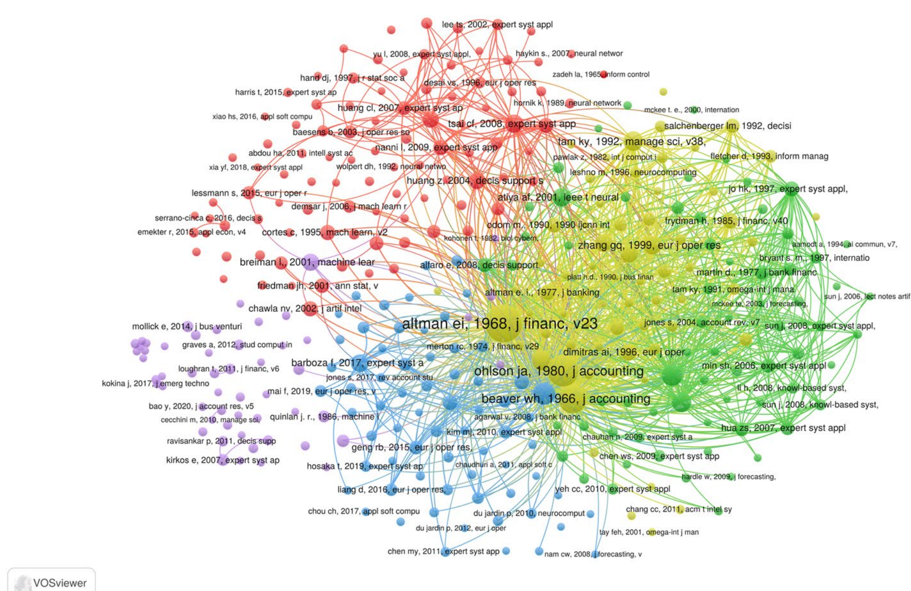

Fig. 10 References co-citation network (determined according to the number of times references have been co-cited, i.e., cited together in a third item). The figure was generated by VOSviewer (van Eck et al. 2006; Perianes-Rodriguez et al. 2016) with the citation data ending in July 2023. Compared to citations output by Bibliometrix (Aria and Cuccurullo 2017, 2023), and within the top 10 references, the results are almost identical

Table 8 Most relevant references in co-citation network from Fig. 10

Reference[a]	Cluster[b]	Niche[c]
Altman EI, 1968, J FINANC, V23	4	ref
Ohlson JA, 1980, J ACCOUNTING RES, V18	4	ref
Beaver WH, 1966, J ACCOUNTING RES, V4	4	ref
Kumar PR, 2007, EUR J OPER RES, V180	3	VP, FP
Min JH, 2005, EXPERT SYST APPL, V28	2	VP
Shin KS, 2005, EXPERT SYST APPL, V28	2	VP
Zmijewski ME, 1984, J ACCOUNTING RES, V22	4	ref
Zhang GQ, 1999, EUR J OPER RES, V116	4	VP
Tsai CF, 2008, EXPERT SYST APPL, V34	1	VP
Tam KY, 1992, MANAGE SCI, V38	4	ref

Sorted according to reference relevance in terms of Total Link Strength (full counting method used for links) calculated by VOSviewer, in decreasing order. Data from the table are retrieved from analysis in Fig. 10 with 353 references and 5 clusters.

VP Valuation of an entrepreneurial venture/Prediction of performance and/or bankruptcy

FP Financial planning and other aspects of financial management

[a] Reference label from Fig. 10

[b] Clusters from Fig. 10—5 (purple), 4 (yellow), 3 (blue), 2 (green), 1 (red)

[c] Subject niches as defined in Subsection 3.1—if stated as 'ref', the reference is not part of document corpus

This transformation is ongoing, and further results are anticipated. Although not the focus of this research, every transformation presents challenges, particularly when it involves digital technology. An evident lack of security and privacy content is visible, as indicated by the authors' keywords. Therefore, this theme is one of the warranted research areas in the context of individual, societal, social, and entrepreneurial aspects. Half of the references are not part of the research corpus, but are included in reference form only, highlighting the relevance of both old and new knowledge, as well as the importance of a broader understanding.

From bibliometrics to showing intelligent behavior

Could machines exhibit intelligent behavior? Turing postulated this thesis in the 1950 s, questioning not whether machines possess actual intelligence, real minds, or consciousness, but rather whether they can demonstrate intelligence through their inputs and outputs (Turing 1950). While questions of true intelligence and consciousness delve into the realms of philosophy and theology and are extremely difficult to determine and likely impossible to prove, focusing solely on the observable results of machine behavior simplifies the issue, though it remains challenging.

By examining AI and economics, we find a challenging situation, though not an unexpected one. It is difficult to establish an interdisciplinary connection between rapidly evolving technology and a field that is not used to such quick changes. The literature is replete with AI terminology and algorithms that implement various techniques and methods. However, there is a notable lack of empirical research to critically assess how well these financial technologies perform compared to expected outcomes (Biju et al. 2023). The most pressing issues include the pitfalls of machine learning and AI in prediction processes, primarily owing to biases in areas such as insurance, credit scoring, and mortgages (Biju et al. 2023). Consequently, there is a need to reconsider how to use these new technologies that are reshaping finance (Biju et al. 2023).

Technology has consistently advanced in innovation since the inception of digital computing in the 1940 s (Dyson 2012), and it appears that the pace of this innovation and knowledge discovery is accelerating. Computer experts are familiar with this rapid development, although it is rare for a research field to experience such conditions. It is sometimes argued that computing has not yet matured, because it continues to evolve at a remarkable speed. However, after approximately 80 years of progress in both software and hardware, this argument becomes more challenging to sustain. It seems that this characteristic of rapid advancement is not only driven by internal influences, but also significantly by external ones, with the most recent major advancement being quantum computing, which emerged from quantum mechanics (Dyson 2012; Brunette et al. 2009; Gyongyosi and Imre 2019).

The foundational paradigm of AI is randomization, characterized by its weights, probabilities, and outputs. Other ideas are grafted onto this foundation, advancing algorithms, techniques, and methods. Whether in evolutionary computation, machine learning, or another subfield of AI, randomization is difficult to avoid, because it introduces dynamic behavior and enables learning, pattern recognition, and greater adaptability. Beyond AI, randomization has facilitated two of the most widely known breakthroughs in quantum computing: Grover's search algorithm (Brickman 2005) and Shor's factorization algorithm (Monz 2016). These developments have placed randomized algorithms at the forefront more than ever. If quantum computers become a reality, randomized algorithms could become particularly significant.

Addressing the challenges of AI and finance offers advantages for the broader economic field, but also for all stakeholders, from computer experts to individuals from entirely different fields. To bridge the gap and advance the application of AI in entrepreneurship, this section reviews and establishes this fundamental paradigm. The most appropriate algorithm to focus on is a Monte Carlo randomized algorithm, because it aligns well with the uncertain nature of complex problems and provides the added benefit of securing confidence in the solution.

The Monte Carlo algorithm consists of a series of steps and, in a complete sense, is an algorithm that can find an optimal solution for a given problem in polynomial time and with arbitrary probability. The probability never reaches one, but as it approaches one, the confidence in having found the optimal solution increases (Kudelić et al. 2023).

By generalizing the algorithm, we arrive at a paradigm of thought and a method for creating the Monte Carlo algorithm. The implementation depends on the problem being solved. The steps are as follows:

1. An algorithm requires organized data to function effectively, so selecting an appropriate data structure to address the problem is crucial.
2. It is necessary to choose a distribution for generating random numbers, which are used to make decisions. The uniform distribution is typically selected, because it usually aligns well with the problem at hand.
3. Based on the chosen distribution, it is necessary to calculate the probability of achieving a non-optimal solution if the algorithm runs only once.

4. Based on the probability calculated for a single run, determine the confidence that the optimal solution was produced by the algorithm after n runs.

The question is how such a procedure can be implemented, and the best way to demonstrate this is by presenting an example of an existing algorithm. A "quintessential problem of algorithmics and, more generally, of computer science" is the minimum feedback arc set (MFAS) (Kudelić 2022). This problem finds applications in various fields, including hardware design, machine learning, deadlock prevention, and cell apoptosis, among others. The problem is classified as NP-complete, NP-hard, and APX-hard. The definition of the problem is as follows: "for a given directed graph $G = (V, A)$, find the smallest subset $A' \subset A$ such that $G' = (V, A \setminus A')$ is acyclic" citeKudelic2022.

The MFAS problem is shown in Fig. 11, which depicts three individuals: John, Ellen, and Tim. These friends meet one day, exchange cordial greetings, and engage in a conversation. After sharing sufficient information, they agree to continue their communication via landline once they return home. However, the communication follows a specific protocol: John agrees to send Ellen three messages, but only after receiving two from Tim. Ellen commits to sending Tim one message, but only after receiving three from John. Tim will send John two messages, but only after receiving one from Ellen. Satisfied with this arrangement, they bid each other farewell.

After returning home, the three individuals were ready to resume communication, but nothing occurred. They soon realized that there was a flaw in the design of the communication protocol. If the situation remained unchanged, communication would be impossible. To transmit their messages, each of them needed to first receive information, but this was unattainable, because they were stuck in a deadlock, waiting for each other. Because communication was not happening, they all left their homes and returned to their previous meeting place. Upon meeting, they greeted each other and pondered how to proceed. They brainstormed, discussed, and proposed new communication methods, but no viable ideas emerged. After some time, John suggested that the old protocol might not be entirely flawed and that the issue of initiating communication could be

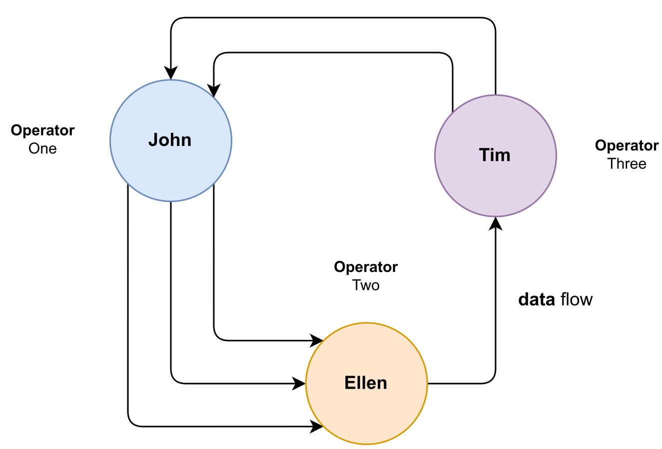

Fig. 11 Illustrative example of the Minimum Feedback Arc Set problem—communication between three parties. Each person prepares his information based on the information received. The question, however, is: How should communication start by causing a minimal upset in the data flow?

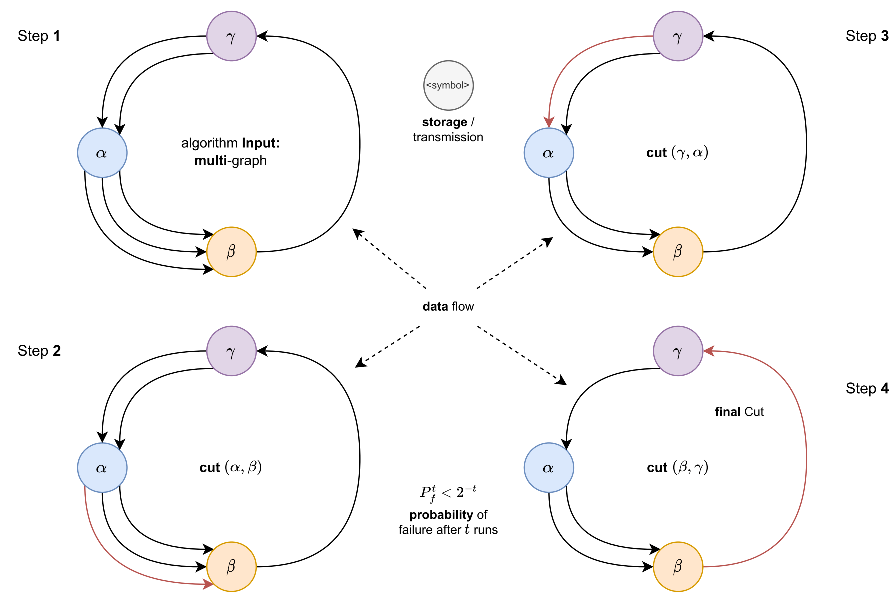

Fig. 12 Monte Carlo for the Minimum Feedback Arc Set—one algorithm run for illustrative example in Fig. 11. The input for the algorithm is the multi-graph. The algorithm chooses and breaks arcs in a uniform fashion until arcs have been broken and the graph is made acyclic

resolved. Ellen and Tim listened as John explained that all they needed was for Tim to start the communication, and everything else would fall into place. This approach would maintain their communication and minimally disrupt the protocol.

Examining Fig. 11 again, it is clear that John's solution to the problem is the correct approach to resolving the conundrum. Because only one message is missed in the data flow at the beginning of their communication, any alternative solution would result in a substantially greater loss of messages, and the communication channel would be more adversely affected. Therefore, this is the optimal solution to their problem, causing the least disruption to the network. This scenario is observable in many interconnected areas of science and the world.

When dealing with complex systems, manually examining the network to determine the best solution is usually not feasible, nor is aimlessly guessing an effective strategy. Fortunately, this problem can be addressed algorithmically (Kudelić 2023) and then implemented on a computing machine. The process is shown in Fig. 12.

For the Monte Carlo algorithm for MFAS to function effectively, the input must be a multi-graph.[5] On this multi-graph, the algorithm selects which arcs to break according to a uniform distribution. This means that the probability of selecting a set of arcs between any pair of nodes, $A'_{ij} \subseteq A' \subset A | i \neq j$, is inversely proportional to the probability that an arc from that set will be chosen. In step 2 of Fig. 12, the arc set $\{\alpha, \beta\}$ has the highest probability of being chosen. However, arcs are being chosen uniformly. Therefore, in the next iteration, step 3, an arc from the set $\{\gamma, \alpha\}$, will be chosen, after which an arc $a_{ij} \subseteq A'_{ij} | i \neq j$ will be chosen again, and this time it will be from the set $\{\beta, \gamma\}$.

[5] A graph that "allows multiple arcs between every pair of nodes, has no loops, and has no arc weights" is a multi-graph (Kudelić 2022).

What would happen if these arcs are not only chosen, but also broken or reversed? As shown in the figure, in step four, by cutting (β, γ), the arc was broken, leaving the graph acyclic, which was the desired outcome. This arc is in the minority compared to other sets, representing an idealized case. Nevertheless, arcs break uniformly, and each individual arc has the same probability of being broken. Therefore, the probability of breaking a cycle is highest in areas where the number of arcs is minimal, precisely at the right spot.

When the algorithm completes its final cut and has broken all cycles, it is highly useful to know the quality of its solution. This is one of the strengths of Monte Carlo algorithms, which calculate probabilities to determine solution quality. Specifically, for the MFAS Monte Carlo algorithm, the probability that the algorithm produces a suboptimal solution is $P_f^t < 2^{-t}$ (Kudelić and Ivković 2019), where t represents the number of times the algorithm has been run. Therefore, after running the algorithm t times, the probability that at least one of the solutions is optimal, classified as a success, is $P_s^t \geq 1 - 2^{-t}$. Figure 13 shows visually how the probability of success increases rapidly as the algorithm is run repeatedly.

In real-world scenarios, achieving convergence toward an optimal solution can be challenging, primarily owing to the quality of the random number generator and the dynamic nature of solution discovery. Nevertheless, finding an optimal or near-optimal

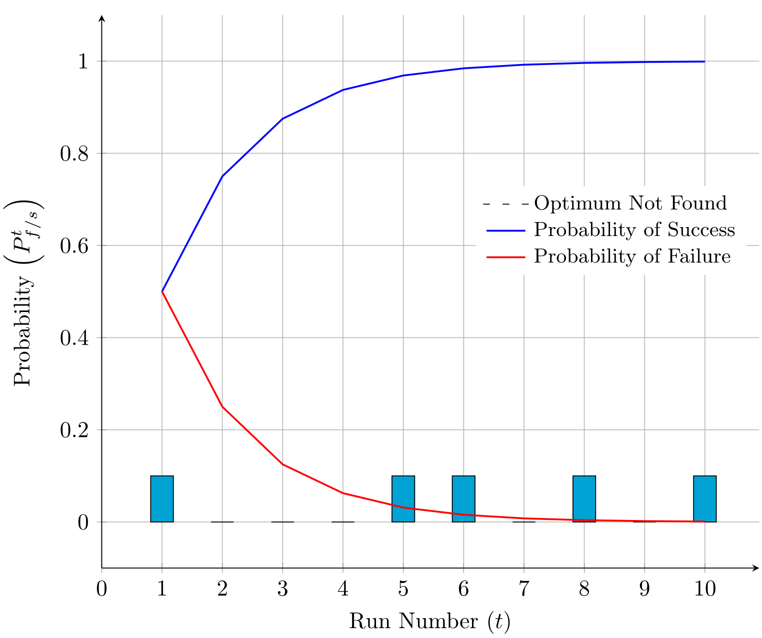

Fig. 13 Cumulative probability of failure/success after t runs. This figure succinctly depicts $P_{f/s}^t$ growth, and inverse proportionality thereof—Monte Carlo algorithm probability parabola. Cyan colored bar graph shows when the algorithm produced the optimal solution. As the probability on an individual run is $\frac{1}{2}$, expected number of optimal solutions cumulatively needs to be around that value, which is the case here. In this way, it is possible to verify whether the algorithm functions as designed, for inputs with known solutions. If the bar is raised, the optimum is found, no optimum otherwise

solution is a matter of probability, which is a fundamental aspect of the Monte Carlo method.[6] For pseudocode, refer to (Kudelić 2016) or, for a more accessible version, (Kudelić 2023).

The algorithm can be modified and even improved to converge towards an optimal solution. By adopting the concept from ant colony optimization (Dorigo et al. 2006) and incorporating a learning mechanism, it becomes possible to find a solution efficiently. Applying probability calculations vertically (on the first run in every series of runs) rather than horizontally (throughout the series of runs) allows us to maintain confidence in a solution measure (Kudelić and Ivković 2019). This leads to how to make algorithms navigate themselves. AI introduces an algorithm structure that mirrors nature and features far more dynamic computation, various kernels, and ever-changing paths toward the desired goal, essentially forming an approximation algorithm (Wang 2003; Asteris and Mokos 2019; Zhang et al. 2019; Bubeck et al. 2023).

Discussion and conclusion

The literature review presented offers valuable insights into the combined fields of AI, entrepreneurship, and finance. However, note that bibliometrics, being a quantitative method, does not necessarily provide insight into the quality of the publications analyzed. Keeping the limitations of bibliometric analysis in mind, this study achieves the objectives defined in Subsection 2.3 and provides comprehensive findings. The results indicate that the field has been experiencing exponential growth since 2018. There is a high level of cooperation, with a quarter of the co-authorships being international. Most papers are published in computer science journals, which suggests a significant contribution from informatics to the field. According to Bradford's Law, a large proportion of papers appear in a small number of sources, which highlights the natural tendency of researchers and authors to gravitate toward influential centers. Bankruptcy prediction, as the most represented theme, shows signs of saturation, while new themes such as crowdfunding, blockchain, FinTech, and big data in entrepreneurship are emerging. Recently, general AI themes, supply chain, and risk management have also gained popularity. In terms of applying AI methods across different topic niches, ANN, deep neural networks, and SVM are highly represented in almost all niches. In contrast, the use of topic modeling, fuzzy neural networks, and growing hierarchical self-organizing maps is quite rare. However, an examination of the evolution of concepts over time reveals the sustained importance of neural networks, the recent rise in popularity of deep learning and NLP, and the declining use of expert systems, genetic programming, and SVMs. Lastly, we also observe a gradual decrease in purely statistical approaches.

The data in Table 7 show most clearly the current state of research, identifying gaps and suggesting potential future research directions. This table shows the most prominent niches and the full range of computing methods used across these sub-divisions of entrepreneurial finance, making it evident where current successes lie and where future research could or should be directed. In addition to the research perspective, questions

[6] For a better understanding of various types of Monte Carlo, complexity classes, etc., further reading of (Kudelić et al. 2023) is recommended. For the problem of FAS, a monograph on the issue with the following three main chapters can be consulted: 1) dealing with everything important FAS (Kudelić 2022), 2) dealing with FAS algorithms (Kudelić 2022a), and 3) dealing with possible avenues for achieving results in different scenarios (Kudelić 2022b).

of application in entrepreneurship and investing also arise. The issues of application and entrepreneurship are clear, at least concerning the dominant niches and methods. However, potential avenues for those less prominent areas, as determined by other relevant methods and niches, are also beginning to emerge.

Answers to the questions investors might ask vary, depending on whether they are aiming for short-term or long-term investments, and are also influenced by the investment sector (whether it is a well-understood computing environment or one that ventures into less explored areas). According to Biju et al. (2023), there are three paths that offer medium to high gains. The first path emphasizes proper implementation within an economic context that includes a compelling product. The second path explores beyond current technologies to new sectors, laying the groundwork for future developments. The third path capitalizes on combining old and gradual innovations, either by merging innovation with major sectors or by introducing moderate innovation to less saturated sectors. The first and third paths are likely to be most attractive to investors, primarily owing to the shorter expected time span of these projects and their associated costs.

The research findings have the following implications for academic scholars and practitioners:

- Further development of entrepreneurship research in the FinTech sector, particularly the expansion of AI in alternative financing sources such as crowdfunding, peer-to-peer lending, and robo-advisors, is necessary. Although crowdfunding has recently become popular, other areas remain less explored. An intriguing research topic is the analysis of how robo-advisors can assist business angels in making investment decisions for financing entrepreneurial ventures and aid portfolio entrepreneurs in decisions about business expansion and new investment opportunities. The current study shows that there are fewer works in these emerging topic niches (1a, 1b, and 2 from Table 7).
- Using AI to prevent and detect financial fraud, which is becoming increasingly common in business-to-business financial transactions within the entrepreneurship sector, is recommended. By integrating AI, blockchain, and smart contracts, it is possible to address the shortcomings of auditing and financial reporting, thereby effectively preventing financial fraud related to auditing and anomalies in financial statements (Goodell et al. 2021; Kumar et al. 2022; Nazareth and Reddy 2023).
- The field of blockchain in entrepreneurship is emerging as a new area of research, particularly because the application of AI methods in this domain remains unexplored, such as using blockchain for business scaling and automation to enhance the performance of entrepreneurial ventures. Blockchain could become a crucial resource for entrepreneurs in the future, as it can contribute to the rationalization of business through savings in production, as well as in financial accounting, compliance requirements, and auditing (Giuggioli and Pellegrini 2022). However, this technology has also been associated with issues such as fraud, privacy concerns, security problems, and market volatility (Phan et al. 2019; Islam 2021; Feng et al. 2019; Liu and Serletis 2019; Bouri et al. 2019; Katsiampa 2019). Additionally, there is a need to ascertain the usefulness of machine learning techniques in cryptocurrency and blockchain (Nazareth and Reddy 2023). The more common application of ensem-

ble methods in finance and entrepreneurship is recommended. Despite the advantages of deep learning, classic machine learning approaches, such as decision trees, random forest, SVMs, k-NN, and Bayesian models, are still widely used. The use of ensemble approaches in finance and entrepreneurship is still in its early stages, but the early findings show evidence of good performance (Nazareth and Reddy 2023).

- Stronger development of predictive analytics, such as firm-level price forecasting, is necessary in business planning for entrepreneurs. Currently, few studies focus on this area, as most research concentrates on macroeconomic and microeconomic forecasting, including predicting oil or electricity prices and stock prices in the capital market. It is important to transfer knowledge about the performance of individual AI methods from the macroeconomic domain to business planning. LSTM models show outstanding performance in predicting financial time series on stock markets (Nazareth and Reddy 2023). However, the potential for implementing these models in entrepreneurial business planning remains unexplored.
- Further research is recommended on using NLP techniques in entrepreneurship studies, including less represented methods such as topic modeling. For example, future research could examine how the public narrative about a country's entrepreneurial ecosystem affects business investments in that area.
- Expanding AI applications to enhance communication strategies and impression management for securing financial resources in entrepreneurial ventures would be beneficial. Various NLP techniques are important in this context, and the combination of neuroscience and AI also shows promise. Research in this field includes developing interpretive models that explain the human brain's reactions during an entrepreneur's communication or presentation to potential investors and analyzing how these reactions affect the final financing decision. Investors can use this knowledge to rationalize their funding decisions, while entrepreneurs can adjust their behavior to ensure successful financing (Giuggioli and Pellegrini 2022). The research indicates a limited number of studies in this specific area (1(a) from Table 7) and a growing interest in the topic.
- Financial firms need to develop global authentication standards and improve the CIA triad (confidentiality, integrity, availability) for FinTech (Chaklader et al. 2023) along with a modern regulatory system (Li and Xu 2021). Additionally, it is necessary to introduce optimal security knowledge and training for professionals in the financial sector (Chaklader et al. 2023).
- Research in explainable AI and its applications in finance, entrepreneurship, and other areas is necessary. Reasoning from cause to effect is particularly important in situations characterized by potentially devastating consequences or high uncertainty. For example, an entrepreneur might attempt to optimize business processes to achieve greater financial gain. However, without understanding the method, they cannot be certain of the results, and the potential real consequences are challenging to predict.
- Research into constraints, risks, and implications of AI usage in entrepreneurial finance is needed (Obschonka and Audretsch 2020).

Many issues present both potential future challenges and topics for future research. One significant difficulty is the possible lack of cooperation between computer experts and economic scientists. Weak interdisciplinary connections lead to lower-quality research because economic scholars do not possess the computing expertise that is not easily acquired (Shi and Li 2019; Lévesque et al. 2020). Enhanced cooperation among authors from different disciplines could use state-of-the-art AI technologies and methods to test and build new entrepreneurship theories in a rigorous and relevant manner (Shi and Li 2019; Lévesque et al. 2020).

The evident lack of a policy framework for AI application poses a significant issue, particularly in determining how to use these technologies in morally acceptable ways within entrepreneurship and finance. Furthermore, the precise nature of what this framework should entail remains unclear, a logical outcome of such revolutionary technology (Chen 2023; Gupta et al. 2023; Lévesque et al. 2020). In addition to the necessary laws, education is essential, because people should become familiar with the new circumstances and adapt during the transition period (Chen 2023; Gupta et al. 2023; Lévesque et al. 2020). A particularly sensitive area, both in research and practice, involves the use of AI to identify facial expressions and emotions in entrepreneurial finance, where misconduct or manipulation using such technology could have extremely negative effects (Chen 2023; Gupta et al. 2023; Lévesque et al. 2020).

It is essential to adopt a constructive and critical approach when considering the constraints, risks, and implications of AI in entrepreneurial finance. Researchers and practitioners must be aware of and address biases, errors, and other issues associated with AI, ensuring transparency in the process. If not, users may blindly trust the algorithms, which could mislead them. It is crucial that the results produced by algorithms are verified, and the final decision should rest with a human.

The latest development in the study of trust involves "generating trustworthy counterfactual explanations," which enhances understanding in critical sectors (Del Ser 2024). This approach aligns with how humans typically familiarize themselves with new processes, by examining "the hypothetical input circumstances under which the output changes," thereby clearly benefiting the trust issue (Del Ser 2024). Beyond trust, fairness also plays a crucial role, particularly in AI-assisted decision-making (Angerschmid et al. 2022). Research shows that there is a relationship between fairness and trust, with low levels of fairness reducing user trust (Angerschmid et al. 2022). Not surprisingly, "application scenarios influenced trust and perceptions of fairness." However, introducing explanations can increase users' trust in AI-assisted decision-making (Angerschmid et al. 2022). The interplay among fairness, explanations, and trust presents a complex issue that necessitates further investigation (Angerschmid et al. 2022).

The research was conducted using a comprehensive, methodologically rigorous, and thorough approach. However, it has several limitations.

1. Bibliometrix has some bugs. When using a BibTeX file, some science categories are not recognized.
2. The study relies on data from the WoSCC, excluding other databases from the analysis. Including publications from additional databases would have expanded the

research sample and broadened the study's scope. However, using papers only from the WoSCC was a suitable approach given the iterative nature of scientific research.

3. The bibliometric analysis focused solely on English-language journal articles, excluding publications in conference proceedings and books. This approach prioritized the most comprehensive and relevant documents, because conference proceedings and books, despite their potential quality and relevance, do not primarily drive research and peer review, and are not typical avenues for bibliometric research.
4. In the analysis, data from the previous two to three years were incomplete, because some documents lacked the final publication date. This limitation affects the interpretation and projection of future events.
5. Because the study includes only publications from the WoSCC, generalizing the results is challenging. However, the study focused solely on the most impactful publications, which likely means that the findings do not significantly deviate from those that would include other databases, such as Scopus.

We propose a new bibliometric measure, the amortized h-index, discussed in Appendix A. This measure addresses the age deficiency of the h-index, yielding more realistic results about the item being measured. The amortized h-index offers insights into how an item performs over the years or decades compared to other items from different time spans, providing information on the successes or failures of the young, or the successes or failures of the old. Including such an index in the methodology of bibliometrics would provide additional insight into the knowledge structure for various instances.

The key contributions of the study are as follows:

- To the best of our knowledge, this study is the most comprehensive bibliometric research in the field. The review employs a multi-step, rigorous methodology. After a thorough screening of 4,644 articles, the bibliometric analysis was conducted on a very large final sample of documents (N = 1,890).
- The main themes within the knowledge field were identified, providing insights into their chronological development and enabling the identification of emerging research directions and significant research implications.
- Based on the literature we reviewed, this study offers the first insight into AI methods, techniques, and algorithms at the intersection of entrepreneurship and finance, highlighting underrepresented and promising methods in the field.
- To broaden the understanding and address the challenges of implementing AI in economic science, we present a discussion and demonstration of the Monte Carlo randomized algorithm. This approach establishes a solid foundation for the core principles of randomization, probability, and convergence.
- The amortized h-index developed in this study contributes to bibliometric methodology and citation metrics by addressing the issue of the age of data points in a more relevant and dynamic manner through the application of an appropriate weighting distribution.

Entrepreneurs are responsible for numerous and diverse tasks that demand extensive hours to complete. One of the most significant benefits of AI is its capacity to significantly reduce the time small business owners need to complete tasks, particularly those that are often burdensome. Since the Industrial Revolution, there has been concern that machines would replace human jobs, rendering humans redundant. However, many tasks performed by machines relieve humans from mundane duties, allowing them to concentrate on situations that require human intelligence and empathy. For example, humans can operate helplines, but many workers argue that such repetitive jobs do not leverage human skills and intelligence. AI systems can handle basic customer interactions, allowing humans to focus on those who need more personalized and interactive assistance. Entrepreneurial finance and the FinTech sector have experienced, and will continue to experience, significant advances in AI, particularly through the application of various approaches to a field traditionally resistant to change. This transformation is inevitable, and it is up to society to determine its outcome. Research and discussion play a crucial role in this process, areas in which academia excels and which should support this transformation.

Appendix A Amortized *h*-index

The calculation of the amortized *h*-index is a method used to measure influence over time when the relationship between variables is exponentially inversely proportional, considering a sequence of years up to the current year, such as 2010, 2011, 2012,..., 2023. An example of this calculation is shown in Table 9. In this example, the year 2000 serves as a fixed point, and the *h*-index remains unchanged, meaning the value for the amortized *h*-index is the same, while all other values are adjusted accordingly. For instance, the amortized *h*-index for 1991 is 5.1, compared to its original value of 51. This value is close to the fixed point of 5, which is considered in the adjusted value. The year 1999

Table 9 Amortized *h*-index example calculation

Year[a]	*h*-index	Citable Years[b]	Pondering Scalar[c] (PS)	Normalized[d] PS	Amortized *h*-index[e]
1991	51	10	1.0000	0.1000	5.1000
1992	44	9	1.1111	0.1111	4.8888
1993	42	8	1.2500	0.1250	5.2500
1994	36	7	1.4285	0.1428	5.1428
1995	34	6	1.6666	0.1666	5.6666
1996	27	5	2.0000	0.2000	5.4000
1997	21	4	2.5000	0.2500	5.2500
1998	14	3	3.3333	0.3333	4.6666
1999	11	2	5.0000	0.5000	5.5000
2000	5	1	10.0000	1.0000	5.0000

The data is sorted in ascending order by year, which is not a prerequisite for index calculation

[a] Year of an item, e.g. journal, author, etc., years can have any time span between them and they can be the same as well, e.g. 2010, 2014, 2015, 2015,..., 2023. The current year does not need to be an ongoing real-world year. It is up to the expert to choose the appropriate year for the instance analyzed, although an ongoing real-world year would be the typical case.

[b] Calculated as the difference of the last and current year, with the addition of one more year, so as to include the time passed in an incomplete year and make a conservative estimate.

[c] Calculated as a quotient of the highest citable years and current citable years, e.g. for 1993 calculation would be $\frac{10}{8} = 1.25$.

[d] As per maximum value of pondering scalar set—thus making the last observed year a fixed point for comparative analysis.

[e] Calculated as a product of normalized pondering scalar and *h*-index, e.g. for the year 1997 calculation would be $0.25 \times 21 = 5.25$

shows an amortized value half a point higher than the fixed point, and its proximity to the fixed point also indicates its closeness year by year. However, this instance is significantly younger than 1991, making it more influential. A similar logic applies to 1998, where the amortized value is slightly lower, owing to a lower original value and the passage of more time relative to the fixed point.

There is a possibility that some or all amortized h-indices may become equal, owing to original values, time spans, and distribution considerations. If prioritization is necessary, we can reduce each h-index by one point until all amortized h-indices are unique, thereby reflecting a potential recent state for ranking items. This adjustment can also be applied solely to equivalent items, making the ranking valid only among them, while positions of other items remain unchanged. Alternatively, preference can be given to more recent items by ranking them accordingly, without altering the positions of others. Additionally, calculating an average between the amortized measure and the unamortized one could also help resolve this issue.

If an extreme year is included in the data, it may be beneficial to analyze both with and without this extreme data point, particularly when the current year is variable, such as when attempting to understand historical conditions. This approach allows researchers to determine the effect of the extreme year and generate objective and relevant results regarding the relationship between items. Additionally, several constraints must be considered when performing and interpreting results with an amortized h-index.

1. The history of science can differ significantly from today in terms of the number of authors, journals, citation practices, institutional practices, and working environments. These factors, among others, can affect the validity of specific results.
2. Recent items are often given high importance, though time may reveal them to be less relevant.
3. Conversely, older items are considered less influential, which is disadvantageous in an environment experiencing substantial positive quantitative change.

Regarding the distribution used in this analysis, it is possible that a different distribution might be more suitable and should replace the one suggested in this paper. By using an amortized h-index, we can more accurately determine the relationship between various items where the observed metric should depend on time. Amortization can also be generalized by other characteristics.

Abbreviations

A&HCI	Arts and humanities citation index
ACC	IEEE access
AI	Artificial intelligence
ANN	Artificial neural network
ASC	Applied soft computing
BPNN	Back-propagation neural network
CBR	Case-based reasoning
CIA	Confidentiality, integrity, availability
CIN	Computational intelligence and neuroscience
CNN	Convolutional neural network
DNN	Deep neural network
DSS	Decision support system
DT	Decision tree
EJOR	European journal of operational research
EL	Ensemble learning

ES	Expert systems
ESA	Expert systems with applications
ESCI	Emerging sources citation index
FAS	Feedback arc set
FinTech	Financial technology
FNN	Feed-forward neural network
FP	Financial planning and other aspects of financial management
FZNN	Fuzzy neural network
GA	Genetic algorithm
GB	Gradient boost
GHSOM	Growing hierarchical self-organizing map
GP	Genetic programming
GPT	Generative pretrained transformer
HIS	Hybrid intelligent systems
IS	Information sciences
JF	Journal of forecasting
KBS	Knowledge-based systems
LSTM	Long short-term memory
MFAS	Minimum feedback arc set
MIS	Mobile information systems
NB	Naive Bayes
NC	Neurocomputing
NLP	Natural language processing
PS	Pondering scalar
PSO	Particle swarm optimization
RF	Random forest
RNN	Recurrent neural network
SCI	Science citation index
SME	Small and medium-sized enterprise
SOM	Self-organizing map
SSCI	Social sciences citation index
SST	Sustainability
SVM	Support vector machine
TM	Topic modeling
VP	Valuation of an entrepreneurial venture/Prediction of performance and/or bankruptcy
WoS	Web of science
WoSCC	Web of science core collection

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Author contributions
R.K. has contributed in: conceptualization, data curation, formal analysis, investigation, methodology, supervision, validation, visualization, writing—original draft, writing—review and editing. T.Š. has contributed in: conceptualization, data curation, formal analysis, investigation, methodology, validation, visualization, writing—original draft, writing—review and editing. S.R. has contributed in: validation, writing—original draft, writing—review and editing. All author(s) read and approved the final manuscript.

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