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Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review

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ABSTRACT

This bibliometric review examines the research state of artificial intelligence (AI) and machine learning (ML) applications in the Banking, Financial Services, and Insurance (BFSI) sector. The study focuses on Scopus-indexed articles to identify key research clusters. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, 39,498 articles were screened, resulting in 1045 articles meeting the inclusion criteria. N-gram analysis identified 177 unique terms in the article titles and abstracts. Co-occurrence analysis revealed nine distinct clusters covering fintech, risk management, anti-money laundering, and actuarial science, among others. These clusters offer a comprehensive overview of the multifaceted research landscape. The identified clusters can guide future research and inform study design. Policymakers, researchers, and practitioners in the BFSI sector can benefit from the study's findings, which identify research gaps and opportunities. This study contributes to the growing literature on bibliometrics, providing insights into AI and ML applications in the BFSI sector. The findings have practical implications, advancing our understanding of AI and ML's role in benefiting academia and industry.

1. Introduction

The use of AI and ML has rapidly increased in recent years, transforming the way businesses operate [1]. The BFSI sector is no exception, where AI and ML are being implemented to improve operational efficiency, enhance customer experience, and mitigate risks [2,3]. The use of AIML-based applications has increased significantly in the BFSI sector due to its potential to automate processes [4], enhance decision-making [5], improve customer experience [6], and detect fraud [7]. Using bibliometrics, this study aims to provide a comprehensive overview of the current state of research on AI and ML applications in the BFSI sector.

AI and ML have emerged as valuable tools in combating financial crimes, including money laundering and cybercrime [8,9]. Financial institutions prioritize anti-money laundering (AML) measures to comply with regulations and prevent illicit activities [10]. By automating the detection of suspicious transactions, AI and ML techniques enhance efficiency and minimize manual intervention [11]. Moreover, these technologies enable the identification of patterns in customer behaviour indicative of fraudulent activity, facilitating proactive measures [12].

Algorithmic trading, facilitated by computer algorithms, has gained considerable traction [13]. It is particularly prevalent in high-frequency trading [14]. AI and ML play a crucial role in developing sophisticated algorithms capable of analyzing large datasets

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and detecting patterns beyond human capacity. This advancement leads to enhanced trading performance and risk reduction [15].

AI and ML also find extensive applications in the insurance sector, specifically in claims reserving and risk assessment [16,17]. Through data analysis and predictive modelling, these technologies facilitate precise pricing and risk evaluations [18]. Furthermore, AI-powered chatbots and virtual assistants enhance customer experience by offering tailored recommendations and assistance [19].

Conversely, the BFSI sector is experiencing a growing adoption of blockchain technology [20]. Blockchain, as a decentralized ledger, facilitates secure and transparent transactions, eliminating intermediaries. Its application extends to areas like payments, trade finance, and supply chain management, promising revolutionary changes [21]. By analyzing the abundant data generated from blockchain transactions, AI and ML offer valuable insights for enhancing operational efficiency and risk mitigation [22].

Thus, AI and ML have brought about transformative changes in the BFSI sector, enhancing efficiency, customer experience, and risk management [6,11,23]. This progress has sparked substantial growth in the academic discourse on AI and ML applications within BFSI [24]. Research efforts have concentrated on algorithms, models, tools, and frameworks [3] while also delving into specific sub-sectors like banking, insurance, and asset management [21].

In the realm of AI and ML applications in BFSI, deep learning algorithms have emerged as a prominent research trend. These algorithms possess the capability to analyze extensive volumes of unstructured data, including text, images, and videos, extracting valuable insights [25]. Additionally, reinforcement learning has garnered attention as another research trend. This approach allows systems to learn from experience and make decisions based on rewards and penalties [26].

Research is also emerging on the use of AI and ML in insurance underwriting, where AI and ML algorithms can analyze large amounts of data to determine the level of risk associated with a policy [27]. Similarly, research has been conducted on the use of AI and ML in asset management, where AI and ML algorithms can analyze market trends and make investment decisions [28].

Given the diverse and evolving research landscape, a periodic comprehensive summary of the literature is essential for guiding future scholarly endeavours [28]. However, existing reviews such as Goodell et al. [3], Tepe et al. [21] and Pattnaik et al. [29] provide only fragmented insights. Goodell et al. [3] concentrated on the utilization of AI and ML applications in financial management. Their study examined 283 research articles, emphasizing the wide adoption of machine learning methods. They primarily narrowed down their suggested scope for future research to the areas of asset pricing, fintech, and financial fraud. Tepe et al. [21], on the other hand, examined financial services, financial access, and financial technology, with fintech at the centre. Pattnaik et al. [29] specifically reviewed the cryptocurrency and blockchain literature. Although these studies offer valuable insights into the fintech literature, they lack a comprehensive coverage of publications and are limited in suggesting the scope for future scholarship in BFSI.

To address this gap, our study fills the void by conducting a bibliometric review to assess the research landscape. We systematically analyze scholarly publications, citations, and themes, building upon the works of Goodell et al. [3], Pattnaik et al. [29] and Baker et al. [30]. Precisely, we answer the following research questions (RQs) to provide a comprehensive overview of the literature on AI and ML applications in the BFSI sector.

RQ1. What trends are evident in the research on AI and ML applications in the BFSI sector?

RQ2. What is the thematic structure of the research domain?

RQ3. What is the direction for future research?

In accordance with established bibliometric protocols, we screened and evaluated a total of 39,498 articles, resulting in the inclusion of 1045 articles that meet our specific selection criteria. Employing N-gram analysis, we identify 177 unique terms from the titles and abstracts of the selected articles. Furthermore, co-occurrence analysis on these terms yields nine distinct clusters representing various sub-domains within the study field. In contrast to previous reviews, we place specific emphasis on the average publication year

Table 1
Search criteria and article selection.

Filtering criteria	Accept	Reject
Search date: 25-07-2022		
Search engine: Scopus		
Search string: ("fintech" OR "financial technology" OR "AI" OR "artificial intelligence" OR "machine learning" OR "data mining" OR "data science" OR "algorithm" OR "analytics" OR "robot" OR "automation" OR "big data" OR "text mining" OR "natural language processing" OR "nlp" OR "soft computing") AND ("bank*" OR "insurance" OR "financial service*")	39,498	
Subject filters: Finance, Economics, Econometrics, Business Management, Accounting, Social Science, Arts and Humanities	6035	33,463
Document type: Articles and reviews only	4030	2005
Erroneous record screening: Valid author information	4013	17
Language filter: Only English	3816	197
Quality screening: Include documents in journals ranked "A*", "A", or "B" in the Australian Business Deans Council (ABDC)	1636	2180
Content screening: If title, abstract, and keywords indicate relevance to scope of study	1045	591

Note: This table presents the systematic process adopted to arrive at the final corpus of 1045 articles for review.

of each unique term contributing to the clusters. This focus helps us distinguish the most current topics from older ones, providing valuable insights that can guide future scholarly endeavours, particularly in the most emergent research areas.

Our study contributes to the expanding body of knowledge, providing invaluable insights into the research landscape. The findings hold practical implications for future research endeavours and advance our understanding of the pivotal role played by AI and ML technologies in shaping the BFSI sector, benefitting both academia and industry.

The remainder of the study has the following organization. Section 2 discusses the data and study methods. Section 3 presents the key findings, including the trends and thematic structure of the research domain. Section 4 enumerates the future research directions, and finally, in Section 5, we summarize the core content and conclude the paper.

2. Methodology

The review was conducted following the PRISMA protocol which provides a comprehensive guideline for conducting systematic reviews and meta-analyses in a transparent, reproducible, and comprehensive process [3,30–33]. Table 1 presents the systematic process adopted for article selection.

The search for articles on AI and ML applications in the BFSI sector was conducted in the Scopus database [30]. We limited the search to journals of at least B category as per the Australian Business Deans Council's (ABDC) Journal Quality List to ensure that the articles were of high quality [34,35]. The search was conducted using keywords such as "artificial intelligence," "machine learning," "bank*," "financial service," "insurance", and related terms and phrases to ensure that we capture all relevant articles following Goodell et al. [3]. The search strategy based on the inclusion and exclusion criteria mentioned in Table 1 yielded 1045 articles.

We analyzed the data using bibliometric techniques, including performance and network analyses as suggested by Pattnaik et al. [34] and Sreenivasan et al. [36], to identify the most influential articles, authors, and their affiliations. We employ various quantitative measures suggested in the paper to analyze BFSI publications and citations. Academic contributions are gauged using the total publications (TP), while the scientific impact is assessed through the total citations (TC). Additionally, we utilize other metrics, such as total cited publications (TCP), to identify impactful research and citations per cited publication (C/CP) to gauge the average impact.

Furthermore, we create a h-index and a g-index to evaluate influential and impactful research. We categorize the influence of articles into varying degrees, including low, mild, moderate, and highly impactful research, using the i-10, i-100, i-250, and i-500 indices. These indices consider the study articles cited at least 10, 100, 250, and 500 times, respectively.

To assess the activity and research productivity of BFSI authors, we analyze the number of active years (NAY) and the productivity per active year (PAY). The number of contributing authors is used to measure academic quality. We also investigate co-authorship and the evolution of author diversity at different stages in the development of AI and ML applications within the BFSI sector. Given the collaborative nature of contemporary research, the increased need for specialization, and methodological complexity, we delve into co-authorship analysis. This allows us to identify evolving collaborations among authors. We employ the average authors per co-authored article (AACA) as a metric to quantify the extent of collaborations. Mathematically, AACA is calculated as follows: AACA = (NCA - SA)/CA, where NCA represents the number of contributing authors, SA stands for sole-authored articles, and CA signifies co-authored articles. For instance, if NCA equals 40, SA is 5, and CA is 10, the AACA would be 3.50, indicating that more than three authors contribute to each co-authored article.

Table 2
Overview of AI and ML applications in BFSI sector.

	1971–2022	1971–1980	1981–1990	1991–2000	2001–2010	2011–2022
Panel A. Descriptive statistics						
Total publications (TP)	1045	8	14	59	110	854
Number of cited publications (NCP)	851	8	12	59	108	664
Total citations (TC)	16872	67	218	2577	3479	10531
Average citations (TC/TP)	16	8	16	44	32	12
h-index	59	3	7	25	33	46
g-index	98	8	12	50	56	76
i-10	367	1	5	35	68	258
i-100	25	0	0	5	8	12
i-250	5	0	0	1	1	3
i-500	2	0	0	1	0	1
Number of active years (NAY)	47	6	9	10	10	12
Productivity per active year (PAY)	22	1	2	6	11	71
Panel B. Co-authorship information						
Number of contributing authors (NCA)	2868	9	25	138	260	2436
Number of affiliated authors (excludes repetitions) (NAA)	2591	9	25	130	243	2210
Authors of single-authored documents (ASA)	160	7	6	16	22	111
Authors of co-authored documents (ACA)	2448	2	19	115	223	2112
Single-authored documents (SA)	165	7	6	16	22	114
Co-authored documents (CA)	880	1	8	43	88	740
Collaboration index (CI)	1.74	0.13	0.79	1.34	1.36	1.85
Collaboration coefficient (CC)	0.64	0.11	0.44	0.57	0.58	0.65
Average authors per co-authored article	3.07	2.00	2.38	2.84	2.70	3.14

Note: This table summarizes the research on AI and ML applications in BFSI sector published between 1971 and 2022.

Further, N-gram analysis of the articles' titles and abstracts revealed key themes related to AI and ML applications in the BFSI sector. Co-word analysis unveiled their thematic structure, while the average publication year (APY) of themes presented in the nodal network gave an idea about the degree of hotness and coldness of the topics. We analyzed the data using Excel, R, VOSviewer, and Gephi tools to visualize the networks.

3. Findings

Our analysis of the literature has yielded significant findings that provide valuable insights into the current state of the study field.

3.1. Performance analysis

Our first research question (RQ1) investigates the research trends in AI and ML applications in the BFSI sector. Table 2 provides an overview of the bibliometric analysis, presenting the publication trend, citation structure, influence, impact, activity, and productivity of the research domain. Subsequently, we discuss the top publications, authors, and their affiliations denoting research hotspots.

Panel A of Table 2 shows that the number of publications on AI and ML applications in the BFSI sector has seen an exponential jump in the past decade between 2011 and 2022, suggesting rapid growth of interest in this area of research. The h-index, g-index, i-10 index, and PAY all increased over time, indicating that the research output is becoming increasingly impactful.

Panel B of Table 2 provides co-authorship information, such as the number of contributing authors, affiliated authors, single-authored documents, co-authored documents, collaboration index, collaboration coefficient, and average authors per co-authored article. A total of 2868 contributing authors and 2591 affiliated authors contributed to the research. Out of these, 160 publications were single-authored and 2448 co-authored. Such a high number of co-authored publications suggests that collaboration is important in this field. This argument is further supported by the decreasing number of single-authored documents and the increasing collaboration index and collaboration coefficient. The average number of authors per co-authored article was found to be highest for the 2011–2022 period, with over three authors per article. However, the higher number of single-authored documents was in the most recent period, suggesting that there is a growing number of researchers who are making significant contributions independently.

Overall, Table 2 provides a comprehensive overview of the research trends, characteristics, and authorship patterns of AI and ML applications in the BFSI sector. Delving into the content of some notable works, the review highlights the need and the potential for further research, particularly in terms of investigating the impact of these technologies on the BFSI sector and identifying new areas for innovation and development.

Table 3 show the list of top articles based on the number of total citations (TC) and average yearly citations (ACY), respectively. The articles cover a wide range of topics, including finance, data mining, artificial intelligence, and management. The most cited article is

Table 3
Top articles (based on total citations).

TC	Author(s)	Title
722	Tam & Kiang (1992)	"Managerial applications of neural networks: The case of bank failure predictions"
578	Ngai et al. (2011)	"The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature"
346	Moro et al. (2014)	"A data-driven approach to predict the success of bank telemarketing"
317	Gomber et al. (2018)	"On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services"
310	Rubio-Ramírez et al. (2010)	"Structural vector autoregressions: theory of identification and algorithms for inference"
246	Manchanda et al. (1999)	"The "shopping basket": a model for multicategory purchase incidence decisions"
230	Chang et al. (2014)	"Understanding the paradigm shift to computational social science in the presence of big data"
227	Lempert & Groves (2010)	"Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west"
193	Alsajjan & Dennis (2010)	"Internet banking acceptance model: Cross-market examination"
190	Buchak et al. (2018)	"Fintech, regulatory arbitrage, and the rise of shadow banks"
186	Green et al. (2007)	"Coping with time-varying demand when setting staffing requirements for a service system"
151	Embrechts et al. (2013)	"Model uncertainty and VaR aggregation"
151	Varetto (1998)	"Genetic algorithms applications in the analysis of insolvency risk"
144	Angeletos et al. (2007)	"Dynamic global games of regime change: learning, multiplicity, and the timing of attacks"
142	Uğur & Akbıyık (2020)	"Impacts of COVID-19 on global tourism industry: a cross-regional comparison"
141	Lehrer et al. (2018)	"How big data analytics enables service innovation: materiality, affordance, and the individualization of service"
137	Stovel et al. (1996)	"Ascription into achievement: models of career systems at Lloyds bank, 1890–1970″
132	Thakor (2020)	"Fintech and banking: what do we know?"
130	Wang & Xu (2018)	"Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud"
128	Viaene et al. (2002)	"A comparison of state-of-the-art classification techniques for expert automobile insurance claim fraud detection"
113	Anagnostopoulos (2018)	"Fintech and regtech: Impact on regulators and banks"
109	Do & Faff (2010)	"Does simple pairs trading still work?"
104	Koutanaei et al. (2015)	"A hybrid data mining model of feature selection algorithms and ensemble learning classifiers for credit scoring"
102	Brockett et al. (1998)	"Using Kohonen's self-organizing feature map to uncover automobile bodily injury claims fraud"
101	Shapiro (2002)	"The merging of neural networks, fuzzy logic, and genetic algorithms"

Note: This table ranks the publications in AI and ML applications in the BFSI sector cited at least 200 times in Scopus on the search date.

“Managerial applications of neural networks: the case of bank failure predictions” by Tam and Kiang, with 722 citations on the search date. Following next is “The application of data mining techniques in financial fraud detection: a classification framework and an academic review of literature” by Ngai et al. with 578 citations. Conversely, as per ACY, “On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services”, published in 2018, leads the table with 53 average annual citations, followed by “Impacts of COVID-19 on global tourism industry: a cross-regional comparison” published in 2020 and “A data-driven approach to predict the success of bank telemarketing” published in 2014. Such evidence suggests that topics such as machine learning, big data analytics, and fintech applications in the area of BFSI are highly emerging.

Table 4 lists the top authors who have published on AI and ML applications in the BFSI sector based on various performance metrics. The data shows that X. Lin Sheldon and George Tzougas have the most publications (8 each). X. Lin Sheldon also has the most co-authored articles, with an average of 3.14 authors per article. The average number of authors per co-authored article ranges from 2 to 4.33, with the highest value belonging to Periklis Gogas and Theophilos Papadimitriou. The collaboration index ranges from 0.67 to 3.33, while the collaboration coefficient ranges from 0.4 to 0.77, indicating further scope for collaborative research in this evolving area of research.

Analysis of the leading authors’ affiliations reveals that the top researchers are spread across 37 institutions based out of 15 countries (see, Annexure 1). For example, Democritus University of Thrace (Greece), Heriot-Watt University (United Kingdom), Leuven Statistics Research Centre (Belgium), University of Toronto (Canada), Gordon S. Lang School of Business and Economics (Canada), and University of Connecticut (United States) affiliate two leading BFSI authors each while the other institutions associate

Table 4
Top authors.

Author	TP	SA	CA	NCA	AACA	CI	CC	TCP	TC	C/CP	*h*	*g*	*i-10*	NAY	PAY
X. Sheldon Lin	8	0	8	21	2.63	1.63	0.62	8	157	20	6	8	4	6	1
George Tzougas	8	1	7	18	2.43	1.25	0.56	7	30	4	4	5	0	4	2
Emiliano A. Valdez	7	0	7	21	3.00	2.00	0.67	7	88	13	4	7	1	4	2
Mario V. Wüthrich	7	2	5	15	2.60	1.14	0.53	7	90	13	5	7	4	4	2
Michel M. Denuit	6	1	5	17	3.20	1.83	0.65	3	16	5	3	3	1	5	1
Stéphane Loisel	6	0	6	21	3.50	2.50	0.71	4	24	6	3	4	1	6	1
Katrien Antonio	4	0	4	15	3.75	2.75	0.73	3	35	12	3	3	2	4	1
Andrei L. Badescu	4	0	4	13	3.25	2.25	0.69	4	33	8	3	4	1	2	2
Zhuo Jin	4	0	4	13	3.25	2.25	0.69	3	38	13	2	3	1	4	1
Tatjana Miljkovic	4	0	4	10	2.50	1.50	0.60	4	72	18	4	4	2	4	1
Jean Philippe Boucher	3	0	3	9	3.00	2.00	0.67	2	8	4	2	2	0	2	2
Mauro Castelli	3	0	3	8	2.67	1.67	0.63	2	4	2	1	2	0	2	2
Angelos Dassios	3	0	3	8	2.67	1.67	0.63	2	5	3	1	2	0	3	1
Ashraf M. Elazouni	3	0	3	6	2.00	1.00	0.50	3	142	47	3	3	0	3	1
Edward W. (Jed) Frees	3	1	2	5	2.00	0.67	0.40	2	19	10	2	2	1	3	1
Esther Frostig	3	0	3	7	2.33	1.33	0.57	3	9	3	3	3	0	3	1
Guojun Gan	3	0	3	9	3.00	2.00	0.67	3	16	5	2	3	0	3	1
Nadine Gatzert	3	0	3	6	2.00	1.00	0.50	2	27	14	2	2	1	3	1
Periklis Gogas	3	0	3	13	4.33	3.33	0.77	3	44	15	2	3	1	3	1
Pedro Guerra	3	0	3	8	2.67	1.67	0.63	2	4	2	1	2	0	2	2
Brian M. Hartman	3	0	3	6	2.00	1.00	0.50	1	2	2	1	1	0	1	3
Wookjae Heo	3	0	3	10	3.33	2.33	0.70	2	12	6	2	2	1	2	2
Yifan Huang	3	0	3	7	2.33	1.33	0.57	2	38	19	2	2	1	3	1
Himchan Jeong	3	0	3	8	2.67	1.67	0.63	3	14	5	2	3	0	2	2
Zhengjun Jiang	3	1	2	7	3.00	1.33	0.57	1	1	1	1	1	0	1	3
Dimitris Karlis	3	0	3	7	2.33	1.33	0.57	3	38	13	3	3	2	3	1
Robert J. Kauffman	3	0	3	11	3.67	2.67	0.73	3	558	186	3	3	3	3	1
Hong Li	3	0	3	7	2.33	1.33	0.57	3	13	4	2	3	1	2	2
Olivier Lopez	3	0	3	8	2.67	1.67	0.63	2	16	8	2	2	1	3	1
Elizabeth Manser Payne	3	0	3	9	3.00	2.00	0.67	3	94	31	3	3	3	2	2
Shengwang Meng	3	0	3	7	2.33	1.33	0.57	2	38	19	2	2	1	3	1
Xavier Milhaud	3	0	3	8	2.67	1.67	0.63	2	16	8	2	2	1	3	1
Victor Murinde	3	0	3	11	3.67	2.67	0.73	3	32	11	2	3	1	1	3
Theophilos Papadimitriou	3	0	3	13	4.33	3.33	0.77	3	44	15	2	3	1	3	1
James Jimmy Peltier	3	0	3	9	3.00	2.00	0.67	3	94	31	3	3	3	2	2
Gareth William Peters	3	0	3	9	3.00	2.00	0.67	3	21	7	2	3	1	3	1
Lysa Porth	3	0	3	12	4.00	3.00	0.75	3	10	3	1	3	0	3	1
Julien Trufin	3	0	3	12	4.00	3.00	0.75	0	0	0	0	0	0	2	2
Wim J. van der Linden	3	2	1	5	3.00	0.67	0.40	3	171	57	3	3	2	3	1
Roel Verbelen	3	0	3	12	4.00	3.00	0.75	3	35	12	3	3	2	3	1
Tim Verdonck	3	0	3	10	3.33	2.33	0.70	1	16	16	1	0	1	3	1
Howard R. Waters	3	0	3	6	2.00	1.00	0.50	3	36	12	3	3	2	2	2
Xueyuan Wu	3	0	3	10	3.33	2.33	0.70	3	10	3	2	3	0	3	1

Note: TP = total publications, SA = sole-authored articles, CA = co-authored articles, NCA = number of contributing authors, AACA = average authors per co-authored article, CI = collaboration index, CC = collaboration coefficient, TCP = total cited publications, TC = total citations, C/CP = citations per cited publication, *h* = *h*-index, *g* = *g*-index, *i-10* = *i-10* index, NAY = number of active years, and PAY = productivity per active year.

one, each. Interestingly, the majority of the leading BFSI authors work in the areas of actuarial sciences, contributing to risk modelling, claim settlement, chain ladder and mortality forecasting. Some of them also work on bankruptcy prediction, credit scoring, crop insurance, and oil price shocks, while some work on climate change and natural disasters like weather derivatives, heat waves, earthquakes, etc.

Conversely, the total citations range from 1 to 558, with Robert J. Kauffman having the most citations. The h, g and i-10 indices range from 0 to 6, 0 to 8 and 0 to 4, respectively. Interestingly, X. Lin Sheldon has the highest value in all these performance indicators. Similarly, the productivity per active year ranges from 1 to 3, with Brian M. Hartman, Zhengjun Jiang, and Victor Murinde having the highest productivity.

Furthermore, the information provided in Table 5 helps us to identify the research hotspots. The United States leads the pack with the highest number of total publications (TP), totalling 247. It also has a significant number of sole-authored articles (SA) and co-authored articles (CA). The United Kingdom follows closely with 133 total publications, showcasing a significant contribution to the field. The high collaboration index (CI) and collaboration coefficient (CC) for both these countries demonstrate a strong research culture and collaboration.

Other countries, such as China, Australia, Canada, Germany, Italy, India, France, and Belgium, also show notable research activity with substantial publication numbers and collaborative efforts. It highlights the growing global interest and engagement in exploring the intersection of AI, ML, and the BFSI industry.

3.2. Network analysis

Our second research question (RQ2) investigates the thematic structure of the research domain. Following the methodology of Pattnaik et al. [34], we conducted an N-gram analysis of the titles and abstracts of 1045 articles. This resulted in 327 terms after the removal of stop words and customized stop words. However, removing the duplications reduced the number of unique terms (also used as themes interchangeably) to 177. These themes were then backtracked to the 1045 articles. Co-occurrence analysis on the updated themes reveals nine clusters discussed subsequently.

Cluster 1—Transforming the banking sector: the fintech revolution and its implications for financial services—comprising 36 themes (see Fig. 1), suggests that the banking sector is a widely researched area. The rise of fintech has brought a new wave of research opportunities, as evidenced by academic studies that have focused on the impact of financial innovation on traditional banks [37,38]. These studies have examined the challenges of adverse selection, moral hazard, and default risk, as well as how fintech firms are providing

Table 5
Top authors' affiliated countries.

Country	TP	SA	CA	NCA	AACA	CI	CC	TCP	TC	C/CP	*h*	*g*	*i-10*	NAY	PAY
United States	247	48	199	668	3	1.70	0.63	207	6074	29	36	72	102	34	7
United Kingdom	133	19	114	364	3	1.74	0.63	114	2103	18	26	41	50	26	5
China	111	6	105	371	3	2.34	0.70	88	1676	19	18	38	37	13	9
Australia	87	5	82	272	3	2.13	0.68	76	1202	16	18	32	32	20	4
Canada	75	6	69	216	3	1.88	0.65	68	729	11	15	23	25	17	4
Germany	67	6	61	201	3	2.00	0.67	49	1312	27	20	35	28	15	4
Italy	54	3	51	174	3	2.22	0.69	39	876	22	14	29	16	17	3
India	49	5	44	148	3	2.02	0.67	41	584	14	15	23	18	13	4
France	44	4	40	135	3	2.07	0.67	30	476	16	13	21	19	14	3
Belgium	43	7	36	124	3	1.88	0.65	33	654	20	13	25	15	16	3
Spain	33	2	31	105	3	2.18	0.69	29	468	16	12	21	13	17	2
Netherlands	32	3	29	104	3	2.25	0.69	29	529	18	12	22	15	17	2
Switzerland	31	5	26	88	3	1.84	0.65	29	592	20	11	24	13	12	3
Taiwan	29	4	25	81	3	1.79	0.64	23	329	14	10	17	11	12	2
Greece	23	3	20	69	3	2.00	0.67	19	206	11	8	14	7	13	2
Turkey	21	2	19	58	3	1.76	0.64	18	475	26	11	18	11	11	2
Malaysia	20	0	20	76	4	2.80	0.74	17	100	6	5	9	3	5	4
Iran	16	1	15	47	3	1.94	0.66	14	206	15	5	14	5	7	2
Oman	16	2	14	50	3	2.13	0.68	13	193	15	7	13	7	10	2
Portugal	15	1	14	41	3	1.73	0.63	11	481	44	5	11	3	9	2
Austria	14	0	14	43	3	2.07	0.67	12	156	13	6	12	6	8	2
Korea	14	1	13	39	3	1.79	0.64	11	420	38	6	11	5	8	2
Georgia	12	1	11	31	3	1.58	0.61	10	159	16	6	10	5	9	1
Ireland	12	0	12	41	3	2.42	0.71	11	151	14	7	11	5	9	1
Singapore	12	1	11	36	3	2.00	0.67	12	591	49	4	12	3	6	2
South Africa	12	1	11	30	3	1.50	0.60	7	33	5	4	5	0	4	3
Viet Nam	12	0	12	42	4	2.50	0.71	9	96	11	4	9	4	3	4
Poland	10	3	7	20	2	1.00	0.50	5	27	5	3	5	1	5	2
Sweden	10	0	10	35	4	2.50	0.71	8	149	19	4	8	3	6	2

Note: TP = total publications, SA = sole-authored articles, CA = co-authored articles, NCA = number of contributing authors, NAA = number of affiliated authors, AACA = average authors per co-authored article, CI = collaboration index, CC = collaboration coefficient, TCP = total cited publications, TC = total citations, C/CP = citations per cited publication, *h* = *h*-index, *g* = *g*-index, *i-10* = *i-10* index, NAY = number of active years, and PAY = productivity per active year.

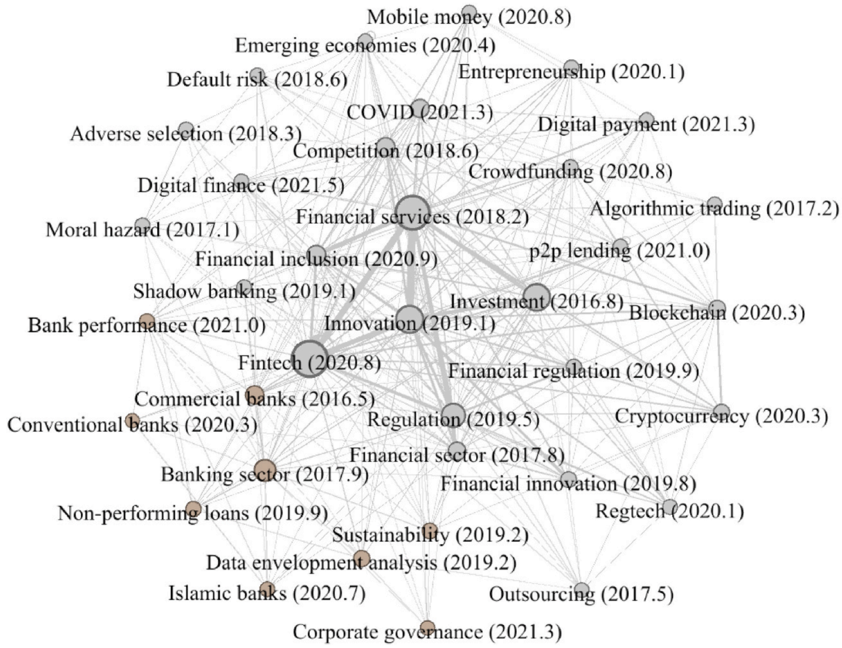

Fig. 1. Cluster 1. **Note:** This figure shows the themes constituting cluster 1. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

solutions to these challenges through their innovative products and services [39,40].

Researchers such as Azzutti [13], Manahov [14], and Prix et al. [15] have extensively studied algorithmic trading to explore its impact on investment efficiency and potential risks. Digital payments [41–43], mobile money [44,45], and peer-to-peer lending [46, 47] have also garnered interest, with studies analyzing their effects on financial inclusion in emerging economies.

Scholars such as Anagnostopoulos [48] and Micheler and Whaley [49] have also investigated the impact of outsourcing on commercial banks and their performance, as well as the impact of corporate governance practices on the sustainability of the banking sector along with the use of regulatory technology (regtech) in improving financial regulation and the governance of financial

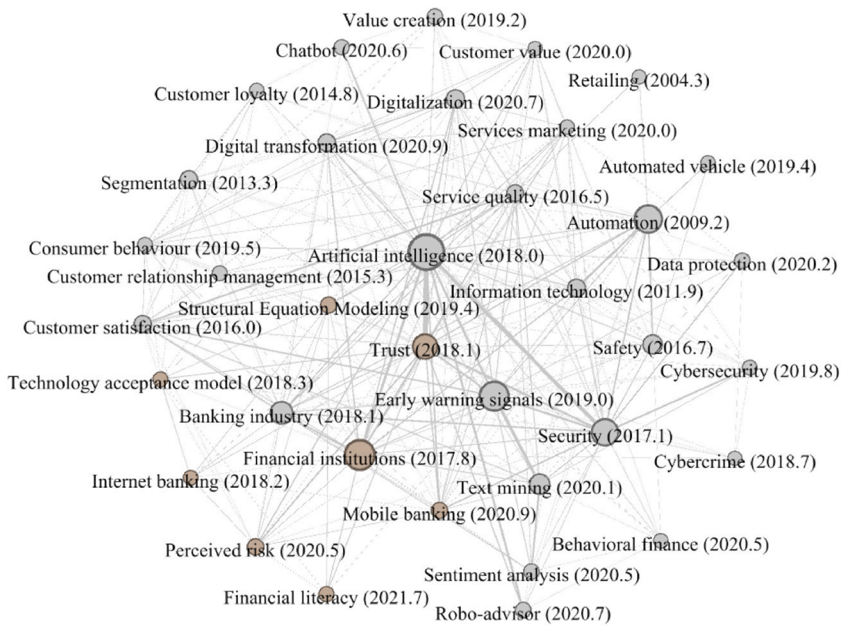

Fig. 2. Cluster 2. **Note:** This figure shows the themes constituting cluster 2. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

institutions.

Expanding the dimensions of the cluster further, the COVID-19 pandemic has brought new research opportunities, with studies examining the acceleration of the adoption of digital finance and its impact on financial services [50]. Additionally, scholars have analyzed the potential risks associated with the shadow banking sector and the cybersecurity implications of digital finance [51]. Thus, the extensive research in Cluster 1 highlights the wide interest in the banking sector, particularly the transformative impact of the fintech revolution.

Cluster 2—Exploring the role of AI and ML in the banking industry: enhancing service quality, customer satisfaction, and mitigating risk—comprising 36 themes (see Fig. 2) suggests that academic research in the banking industry has focused extensively on the role of digital transformation, artificial intelligence, and automation in enhancing customer satisfaction, loyalty, and value creation.

Researchers, including Gatzert and Schubert [52] and Northey et al. [53], have conducted studies investigating the use of chatbots and robo-advisors to enhance customer relationship management, as well as the potential of sentiment analysis and text mining to gain insights into customer behaviour and segmentation. Moreover, scholars such as Anand and Mishra [54] and Heo et al. [55] have examined the impact of digitalization and internet banking on financial literacy. They have also explored the factors influencing customer perceptions of new technologies using the technology acceptance model.

Furthermore, researchers have devoted attention to the challenges of cybersecurity and data protection in the banking industry, as well as the risk mitigation measures implemented by financial institutions [56,57]. The perceived risks associated with these issues have been analyzed, and the role of early warning systems (EWS) in risk monitoring and mitigation have been explored [58]. In addition, studies have investigated the impact of automation on retailing and the potential of behavioural finance to enhance customer decision-making [59,60].

Thus, the extensive research in Cluster 2 on the role of AI and ML in the banking industry indicates a strong focus on digital transformation, AI, and automation for enhancing customer satisfaction, loyalty, and value creation, as well as addressing cybersecurity and risk mitigation concerns.

Cluster 3—Machine learning applications in banking and finance: a review of techniques and challenges—comprising 28 themes (see Fig. 3) suggests that the application of artificial neural networks and ML techniques in the banking and finance sector has gained significant attention in recent years. Researchers such as Ekinci and Erdal [61], Jing and Fang [62] and Petropoulos et al. [63] have focused on using these technologies to predict bank failures, assess risks accurately, and develop innovative financial products.

Classification and clustering techniques have been widely used in identifying patterns in financial data. Credit ratings and credit scoring models have been developed using ML techniques to predict creditworthiness accurately [64,65]. Several machine learning algorithms, such as random forest, gradient boosting, and support vector machines, have been used for risk assessment and failure prediction, offering promising results [3]. Researchers have also explored the use of telematics and vehicle telematics to develop innovative usage-based insurance products along with the use of alternative techniques like SMOTE [66–68] to address class imbalance in credit scoring models, and sentiment analysis and text mining [24,69] to extract useful information from unstructured data.

Cluster 4—Advancements in AI and ML applications for financial stability and risk management in the BFSI sector—visualized in Fig. 4,

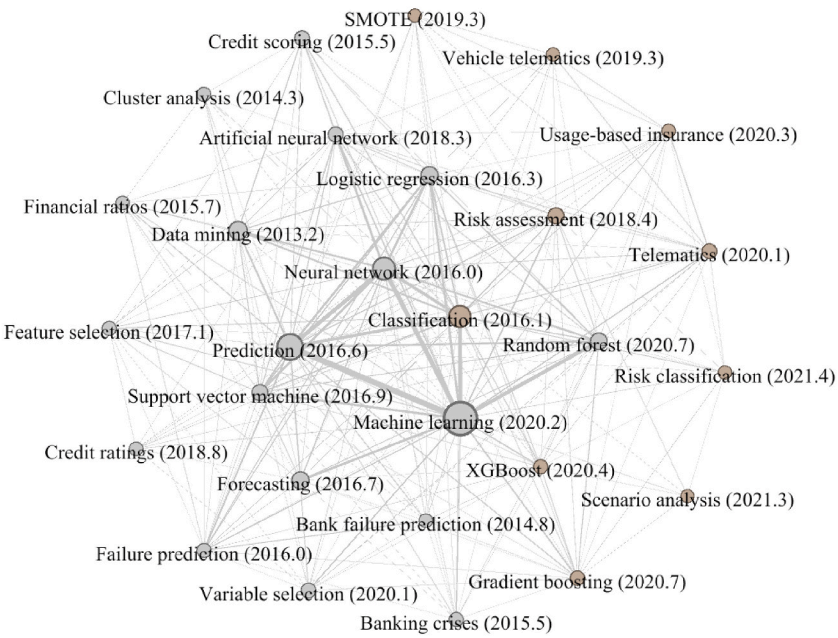

Fig. 3. Cluster 3. **Note:** This figure shows the themes constituting cluster 3. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

suggests a significant increase in the applications of AI and ML techniques for financial management, monetary policy, and financial stability, among others.

One area that has seen a significant amount of research is financial networks. Researchers have used network analysis to identify the key players in the interbank market and the structure of the financial system, allowing for the assessment of systemic risk. Deep neural networks and deep learning techniques have been used to model the dynamics of financial networks and predict the spread of financial shocks.

Another area of research has been the application of optimization techniques in financial management, including scheduling and reinsurance. Researchers have used dynamic programming and genetic algorithms to optimize reinsurance policies, allowing for efficient risk management [70,71]. Furthermore, fuzzy logic has been used to model the behaviour of financial systems, allowing for the prediction of exchange rate dynamics and inflation [72,73].

Markov Chain approximation [74] and regime-switching models [75,76] have also been used to analyze the effect of monetary policy on the financial system. Researchers have shown that these models can help in better understanding the relationship between interest rates and financial stability.

Finally, researchers have explored the use of Lasso techniques [66,77] in effectively identifying the most important factors that can improve the accuracy of financial stability models.

So, the application of AI and ML techniques in the BFSI sector has led to significant advancements in various areas, including financial stability [40,78] financial management, and monetary policy [79,80].

Cluster 5—Advances in AI and ML applications for risk assessment and management in the BFSI sector—has been growing at a rapid pace in recent years. Among the most promising applications are those related to risk assessment and management, which require sophisticated algorithms and numerical techniques. Fig. 5 reveals the related themes constituting this cluster.

One approach that has gained significant attention in the field of risk management is copula modelling. Copulas are mathematical functions that allow for the modelling of the dependence structure between different risk factors, such as credit risk and market risk [81], as they help to improve the accuracy of risk measures, especially in the tail of the distribution [82,83].

Another popular approach is Monte Carlo simulation, which involves generating random scenarios to estimate the probability of different outcomes [84,85]. This technique can be used to model complex financial instruments, such as variable annuities and CPPI strategies, and to estimate their potential risks and returns.

In the area of credit risk management, quantile regression [23,86] has emerged as a powerful tool for modelling the relationship between credit scores and default rates, which can help banks and financial institutions to assess the creditworthiness of borrowers better and to optimize their lending strategies.

Stochastic simulation [87,88] and Markov chain Monte Carlo algorithms [89,90] are also commonly used in risk management to model the dynamic evolution of financial markets and to estimate the potential impact of different events on financial systems. These techniques can be used to identify systemic risks and to evaluate the impact of changes in monetary policy or financial regulations.

Other important applications of AI and ML in risk management include operational risk assessment, risk aggregation, and Solvency II compliance [91,92]. These applications rely on sophisticated numerical algorithms and simulation techniques to estimate the

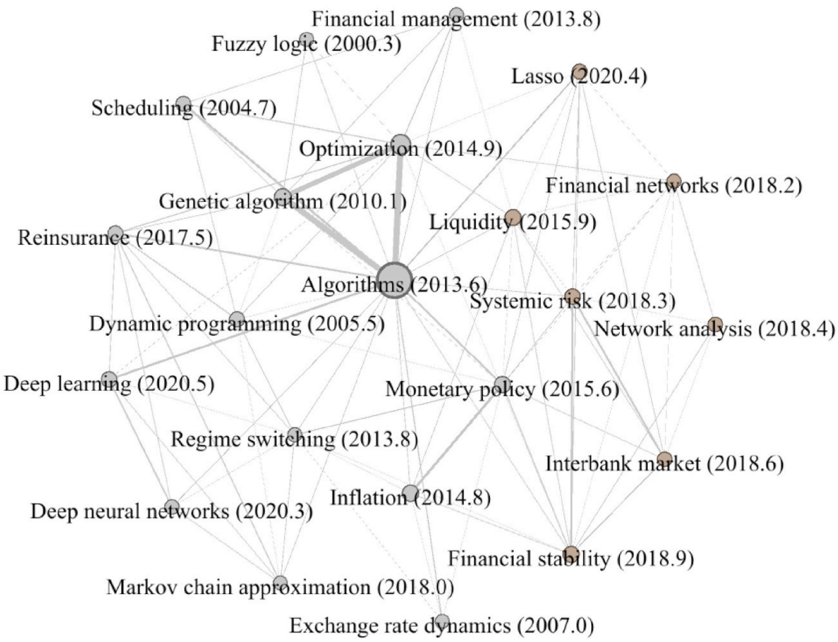

Fig. 4. Cluster 4. **Note:** This figure shows the themes constituting cluster 4. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

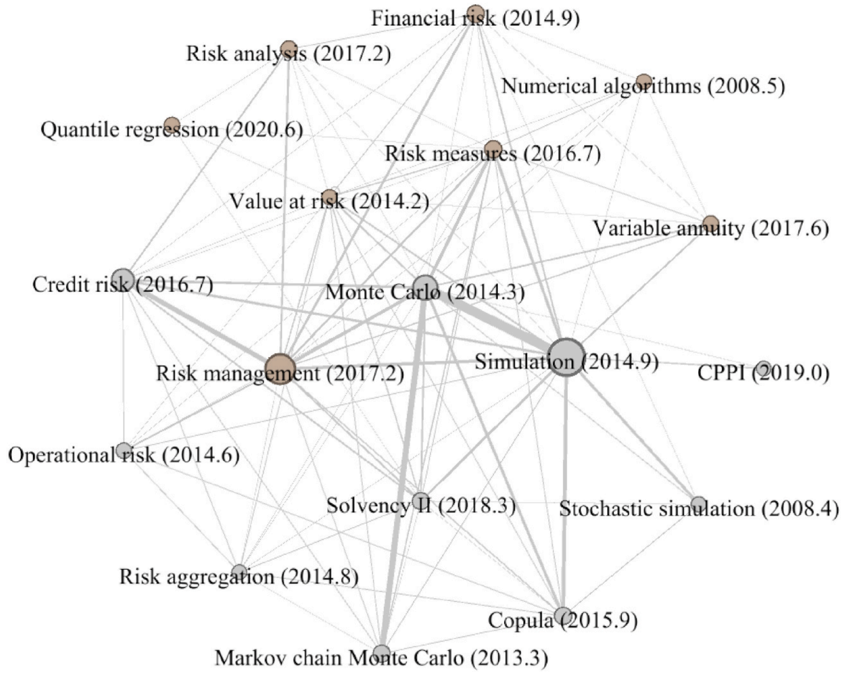

Fig. 5. Cluster 5. **Note:** This figure shows the themes constituting cluster 5. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

potential losses associated with different risks and to ensure that financial institutions have adequate capital reserves to absorb them.

Cluster 6—The intersection of AI and ML and big data in BFSI: opportunities and challenges—highlighted in Fig. 6 refer to AI and ML themes related to data analytics and business intelligence, which has allowed financial institutions to gain insights into their customer's behaviour, preferences, and needs.

It also suggests that another area where AI and ML have been applied in the BFSI sector is in predictive modelling. Predictive models use algorithms and statistical techniques to analyze data and make predictions about future outcomes. They help in detecting

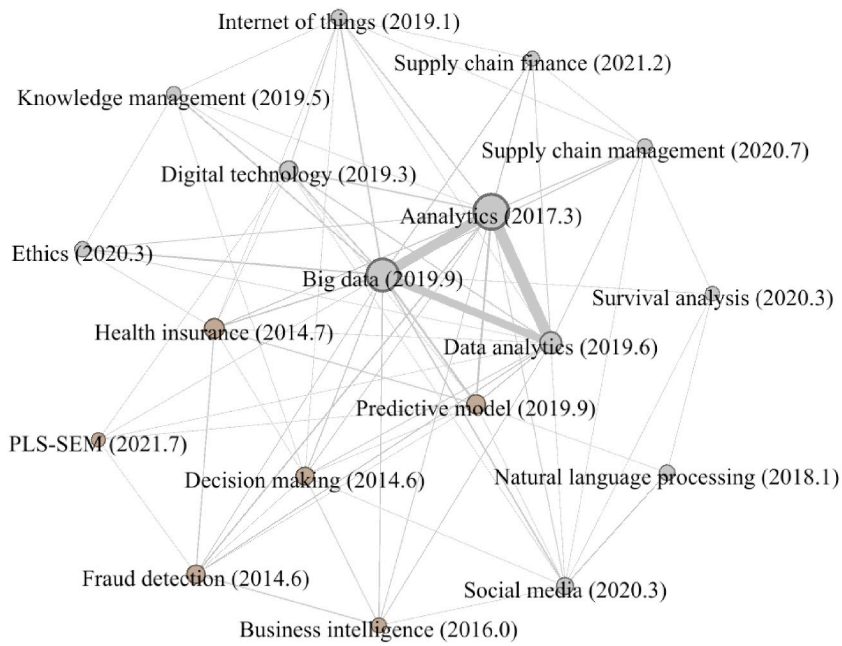

Fig. 6. Cluster 6. **Note:** This figure shows the themes constituting cluster 6. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

patterns and anomalies in large data sets that are indicative of fraudulent activity [12,93].

Moreover, the advent of the Internet of Things (IoT) has opened new doors for financial institutions to collect and analyze data [94,95]. IoT devices, such as health monitors, sensors, and GPS trackers, generate massive amounts of data that can be used to develop predictive models and improve decision-making.

Natural Language Processing (NLP) is another area where AI and ML have been applied. NLP techniques enable financial institutions to analyze and understand unstructured data, such as social media posts and customer reviews, to gain insights into customer preferences and sentiments [96,97].

Supply chain finance and management is another area where AI and ML have been applied. AI and ML algorithms are being used to analyze data from suppliers' financial statements and credit reports to assess their creditworthiness, determine the risk of default, and help them access finances based on their invoices [98,99].

Lastly, ethical considerations in the use of AI and ML in the BFSI sector cannot be overemphasized. To this end, researchers have developed frameworks and models such as Partial Least Squares Structural Equation Modelling (PLS-SEM) [100,101] and survival analysis [102,103] to assess the impact of AI and ML on various stakeholders, such as customers, employees, and society at large.

Cluster 7—Advances in AI and ML applications for actuarial science in the BFSI sector—related to the applications of AI and ML in the insurance industry have gained significant attention in recent years, as portrayed among the constituent themes in Fig. 7. These technologies offer a variety of benefits, including more accurate pricing, improved risk assessment, and enhanced customer experiences. In particular, actuarial science, which involves the use of mathematical and statistical methods to assess risk in insurance and finance, has been transformed by the application of AI and ML techniques [18,93].

AI and ML techniques such as the EM algorithm [104,105] and other advanced statistical models have improved the accuracy of claims reserving, especially in cases of individual claims reserving and non-life insurance. Conversely, censoring and survival analysis are also important techniques which are helping insurance companies to estimate the cost of future claims [102].

Ratemaking is another important area where AI and ML are being applied. This involves the development of pricing models that accurately reflect the risks associated with various types of insurance policies [105,106]. ML algorithms analyze large amounts of data and identify factors that are important in determining risk. This has allowed insurers to develop more accurate and competitive pricing models [107].

In addition, AI and ML techniques are being used to improve fraud detection and prevention in the insurance industry. By analyzing data from a variety of sources, such as social media and internet of things (IoT) devices, insurers can detect patterns of fraudulent activity and take appropriate measures to prevent it [108]. Simultaneously, NLP is also used to analyze unstructured data from claims and other sources [109]. It is quite apparent that AI and ML are becoming increasingly important in the insurance industry, both from the operational as well as regulatory aspects.

Cluster 8— Exploring the role of AI and ML in anti-money laundering: applications of clustering, item response theory, and pattern recognition—suggests rapid expansion of AI and ML applications in risk assessment and management, customer service, fraud detection, and compliance as highlighted in Fig. 8. Among the most promising applications are those related to anti-money laundering (AML), which aims to prevent financial crimes by identifying suspicious transactions and activities [8,10,110]. The use of advanced analytics and machine learning algorithms in AML has greatly enhanced the effectiveness and efficiency of AML programs, allowing financial institutions to detect and prevent money laundering activities.

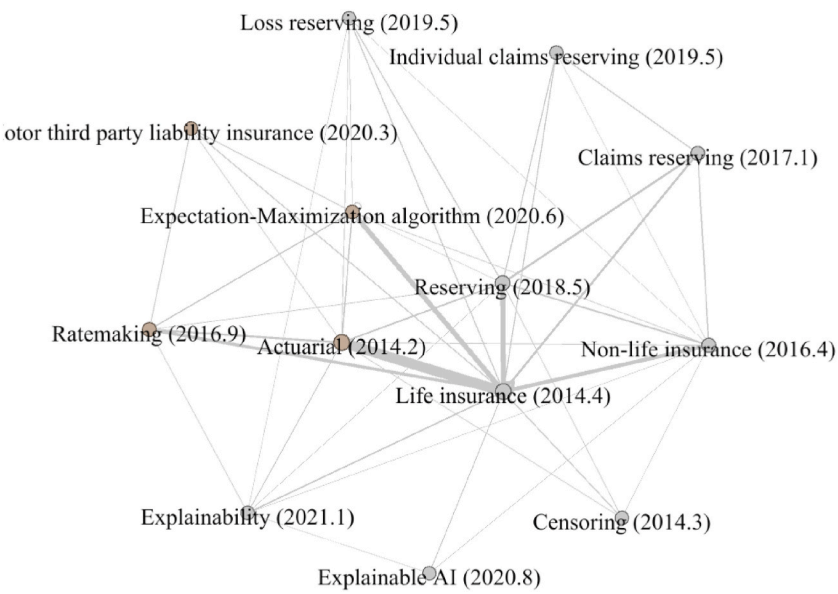

Fig. 7. Cluster 7. **Note:** This figure shows the themes constituting cluster 7. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

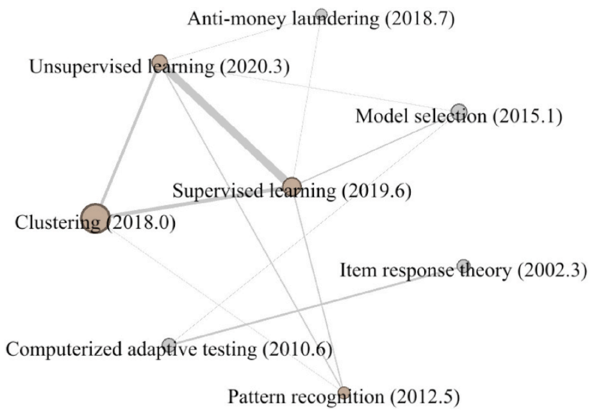

Fig. 8. Cluster 8. **Note:** This figure shows the themes constituting cluster 8. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

One area of research in AML that has gained significant attention is clustering, which enables financial institutions to group customers based on their attributes and patterns and thereby detect unusual or abnormal activities that might indicate potential money laundering or terrorist financing [93,111,112]. Clustering techniques include both supervised and unsupervised learning methods, such as k-means, hierarchical clustering, and density-based clustering.

Another area of research in the BFSI sector is computerized adaptive testing (CAT), which uses machine learning algorithms to adapt the difficulty level of questions based on the user's response [113,114]. This approach has been applied in the insurance industry to improve the accuracy and efficiency of risk assessment and underwriting. Item response theory (IRT) is a related approach that uses statistical models to estimate the user's latent ability or trait based on their responses to a set of questions [115,116]. Similarly, pattern recognition techniques, such as support vector machines (SVM) and random forests, are commonly used for model selection in finance and insurance applications [54,117].

Finally, explainable AI is an emerging area of research in the BFSI sector that focuses on developing machine learning models that are transparent and interpretable. This is particularly important in regulated industries such as finance and insurance, where the decision-making process must be explained and justified to stakeholders. Techniques such as LIME and SHAP can be used to generate explanations for machine learning models, allowing users to understand and trust the predictions made by the model [106].

Cluster 9—Exploring the application of Banach contraction principle, q-scale function, and ruin probability in the BFSI Sector—discuss concepts in the field of actuarial science and risk management that have received significant attention from researchers in the BFSI sector, as shown in Fig. 9.

The Banach contraction principle is a powerful mathematical tool used to prove the existence and uniqueness of solutions to many different types of problems, including those related to risk management. It has been used to develop new algorithms and models for estimating risk measures, such as value-at-risk and expected shortfall. The Banach contraction principle ensures that these models are well-defined and reliable, providing a strong foundation for risk management strategies [118,119].

The Q-scale function is another important concept in the field of actuarial science, which is used to model the distribution of losses in insurance portfolios. It provides a flexible and robust framework for estimating the probability of extreme losses, which is critical for assessing the solvency of insurance companies and ensuring that they have adequate capital reserves to absorb potential losses [119].

Ruin probability is a measure of the likelihood that an insurance company will become insolvent or fail to meet its financial obligations. It is a key parameter in many different models and algorithms used in risk management, including those based on the Banach contraction principle and the Q-scale function. By accurately estimating the ruin probability, financial institutions can better understand and manage the risks associated with their portfolios, improving their overall financial stability and resilience [120–122].

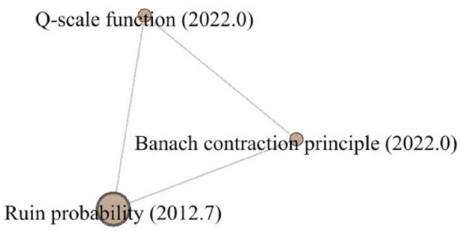

Fig. 9. Cluster 9. **Note:** This figure shows the themes constituting cluster 9. Each node represents a theme along with its average publication year (APY). The size of nodes represents the degree of occurrence whereas the intensity of link between nodes represents the degree of co-occurrence.

4. Summary and future research directions

The clusters uncovered through co-occurrence analysis provide valuable insights into the multifaceted nature of research in this field, spanning fintech, risk management, anti-money laundering, and more. Our examination of the current literature through our third research question (RQ3) aims to identify themes for future research. Based on the average publication year of topics and the intensity of their co-occurrence within a cluster, we have the following recommendations.

1. Cluster 1 focuses on the fintech revolution and its implications for financial services, highlighting the transformative impact of AI and ML applications in the banking sector. The most recent topics in this cluster are related to Covid (APY: 2021.3) and its impact on digital payments (APY: 2021.3) and p2p lending (APY: 2021.0). As the world emerges from the pandemic, there is a need to re-look at the innovation and sustainability aspects. Therefore, future research is likely to focus on governance, regulation, and performance evaluation of services such as crowdfunding, blockchain, cryptocurrency and many other innovative services which are likely to emerge in the coming days.
2. Cluster 2 explores the role of AI and ML applications in the banking industry, with a specific emphasis on enhancing service quality, customer satisfaction, and mitigating risk. As a summation, academic research progressing in this cluster has highlighted the potential benefits of AI and ML applications in the banking industry, emphasizing the importance of ensuring trust, security, and privacy. Financial literacy (APY: 2021.7) is the most recent topic in this cluster. Digital transformation (APY: 2020.9), use of Robo-advisors (APY: 2020.7) and data protection (APY: 2020.2) mechanisms are likely to continue in the coming days, resulting in the need for more studies on financial and digital literacy. These transitions will also result in new research possibilities related to behavioural finance (APY: 2020.5)
3. Cluster 3 provides a comprehensive review of ML techniques in the banking and finance sector that have shown promising results in various areas, such as risk assessment, failure prediction, and product innovation. The most recent topics in this cluster are risk classification (APY: 2021.4) and scenario analysis (APY: 2021.3). As the use of AI and ML has changed the operating landscape of financial institutions and the sector, there is a need to evaluate and access the risk involved. Therefore, future studies in this cluster can be around risk assessment by conducting sensitivity and scenario analysis, which can help in tackling bank failure and crisis.
4. Cluster 4 delves into advancements in AI and ML applications for financial stability and risk management in the BFSI sector, and the most recent topics are deep learning (APY: 2020.5) and deep neural networks (APY: 2020.3). Future research in this area should therefore focus on developing more robust and accurate models along with the development of more advanced and sophisticated algorithms for risk assessment and management, as well as addressing the ethical concerns associated with the use of AI and ML in finance.
5. Cluster 5 highlights the advances in AI and ML applications for risk assessment and management in BFSI. Research assessing the uses of sophisticated algorithms and numerical techniques, such as copula modelling (APY: 2015.9), Monte Carlo simulation (APY: 2014.3), and Markov chain Monte Carlo algorithms (APY: 2013.3) in understanding and managing complex risks, improving the overall financial stability and resilience is highly recommended. However, the APY counts of the above topics suggest that they are not in much use in recent times. This provides an enormous scope for future research as it will help in the development of simulation algorithms for accessing both the operational and financial risk of fintech and other traditional financial institutions.
6. Cluster 6 examines the intersection of AI, ML, and big data in BFSI, presenting opportunities and challenges in this area. Supply chain financing (APY: 2020.7), social media (APY: 2020.3) along with research techniques such as PLS-SEM (APY: 2021.7) and survival analysis (APY: 2020.3) are some of the most recent topics in this cluster. The growing usage of AI and ML will also increase the importance of fraud detection and ethical issues. Therefore, future research needs to focus on both improvisations of new techniques as well as policy prospective.
7. Cluster 7 suggests that the use of AI and ML in the insurance industry is transforming traditional actuarial practices, allowing insurers to understand better and be able to make more informed decisions about pricing, reserving, and fraud prevention, resulting in a more efficient and effective industry, particularly in the context of severe pandemics. Explainability (APY: 2021.1) and explainable AI (APY: 2020.8) are the most recent topics in this cluster. Future research can extend the existing learnings to develop new insurance products that are affordable and easily accessible. Further, future studies can also focus on using AI and ML to improve the penetration of insurance among people from rural and poorer communities. Research in these areas provides ample opportunities for further exploration.
8. Cluster 8 explores the role of AI and ML in anti-money laundering, with specific applications of clustering, item response theory, and pattern recognition. The recent topics are Unsupervised learning (APY: 2020.3), which is strongly connected with supervised learning (APY: 2019.6), and clustering (APY: 2018.0). The scope of similar studies is likely to increase further in the new digitalized interconnected world. Future research is likely to advance the usage of unsupervised learning in understanding and managing various aspects of financial institutions, such as risk assessment, detection and prevention of financial crimes, and means of providing better services to their customers.
9. Cluster 9 explores the application of Banach contraction principle (APY: 2022.0), Q-scale function (APY: 2022.0), and ruin probability (APY: 2012.7) in managing risk of financial service providers. As the BFSI sector continues to evolve and become more complex, these concepts and techniques will likely play an increasingly important role in ensuring the stability and resilience of financial institutions. Therefore, future research can investigate the usage of the techniques mentioned above in various other operational aspects of fintech and financial institutions.

5. Conclusions

Through a comprehensive bibliometric analysis, this study provides a panoramic view of the research landscape surrounding the applications of AI and ML in the BFSI sector. Our findings highlight the significant emphasis placed by academia on exploring this area, underscoring the extensive research interest it has garnered. Understanding the dynamic trends and patterns within the literature becomes imperative for gaining valuable insights into the advancements, challenges, and prospects of this rapidly evolving domain.

RQ1 delves into the publication trends, revealing a remarkable surge in the number of publications focused on AI and ML applications in the BFSI sector over the past decade. RQ2 meticulously examines the thematic structure, enabling the categorization of the vast body of literature into nine distinct clusters. Furthermore, RQ3 identifies crucial research gaps that offer valuable opportunities for future scholarly pursuits.

Extensive scholarly endeavours have brought to light a multitude of benefits and challenges in areas such as digital finance, cybersecurity, behavioural finance, and the application of ML techniques in risk management and forecasting. These advancements have empowered financial institutions to gain better insights into and effectively mitigate risks. However, ethical concerns and data privacy issues persist, emphasizing the need for further research to inform best practices within the industry.

The insurance industry has witnessed significant transformations through the utilization of AIML techniques, revolutionizing actuarial science and claims reserving. The effectiveness of anti-money laundering programs has also experienced notable enhancements with the adoption of clustering, CAT, IRT, and explainable AI. As technology continues to evolve, we can anticipate further innovations in AIML applications that will drive continued advancements in the BFSI sector.

Moreover, our findings highlight the profound impact of AI and ML techniques in enhancing the efficiency and effectiveness of anti-money laundering programs within the banking, financial services, and insurance (BFSI) sector. With the increasing digitization of the financial industry and the rise of online transactions, the importance of robust AML programs becomes increasingly critical.

Conversely, while AI and automation offer significant benefits, they also pose substantial challenges. Policymakers, businesses, and individuals must collectively address these challenges and ensure that the advantages of AI and automation are harnessed while minimizing potential negative consequences. A thoughtful and nuanced approach is essential, considering the complex and evolving nature of AI and automation and their impact on society. Ultimately, the goal is to utilize these technologies in a manner that maximizes their potential to improve lives while mitigating potential harm.

Although our study provides valuable insights and contributions, it is important to acknowledge its limitations. One of these is our reliance on data obtained solely from Scopus. By expanding the databases used for data collection, the analysis could be further enhanced in the future.

Data availability statement

Data will be made available on reasonable request to the communicating author.

Annexure 1
Affiliation and research area of leading BFSI authors

Author	Affiliation	Research Area
X. Sheldon Lin	University of Toronto, Toronto, Canada	claim; chain ladder; bonus-malus systems; variable annuities; life insurance; costs and cost analysis; fire insurance; composite model; pareto distribution
George Tzougas	Heriot-Watt University, Edinburgh, United Kingdom	claim; chain ladder; bonus-malus systems; count data; Poisson regression; regression model; expert opinions; decision making; G-idea protocol
Emiliano A. Valdez	University of Connecticut, Storrs, United States	variable annuities; life insurance; costs and cost analysis; claim; chain ladder; bonus-malus systems; copula; bivariate; vines
Mario V. Wüthrich	ETH Zürich, Zurich ZH, Switzerland	claim; chain ladder; bonus-malus systems; longevity risk; mortality forecasting; life expectancy; classifier ensemble; adaboost; transfer of learning
Michel M. Denuit	Université Catholique de Louvain, Louvain-la-Neuve, Belgium	optimal reinsurance; value at risk; expected shortfall; claim; chain ladder; bonus-malus systems; longevity risk; mortality forecasting; life expectancy
Stéphane Loisel	Laboratoire de Sciences Actuarielle et Financière, Lyon, France	longevity risk; mortality forecasting; life expectancy; variable annuities; life insurance; costs and cost analysis; copula; bivariate; vines
Katrien Antonio	Leuven Statistics Research Centre, Heverlee, Belgium	claim; chain ladder; bonus-malus systems; longevity risk; mortality forecasting; life expectancy; product-service systems; service economy; value co-creation document
Andrei L. Badescu	University of Toronto, Toronto, Canada	claim; chain ladder; bonus-malus systems; fire insurance; composite model; pareto distribution; risk model; ruin probability; classical risk model
Zhuo Jin	Macquarie University, Sydney, Australia	mean-variance; surplus process; defined contribution pension plan; risk model; ruin probability; classical risk model; Hawkes processes; stochastic intensity; maximum likelihood method
Tatjana Miljkovic	Miami University, Oxford, United States	fire insurance; composite model; pareto distribution; model-based clustering; cluster analysis; EM algorithm; heat wave; climate change; distributed lag
Jean Philippe Boucher	Université du Québec à Montréal, Montreal, Canada	claim; chain ladder; bonus-malus systems; imbalanced data; cost-sensitive learning; data classification; annuities; health insurance; adverse selection
Mauro Castelli	NOVA Information Management School, Universidade Nova de Lisboa, Lisbon, Portugal	grammatical evolution; symbolic regression; genetic programming; object detection; deep learning; IOU; bankruptcy prediction; credit scoring; prediction

(*continued on next page*)

Annexure 1 (*continued*)

Author	Affiliation	Research Area
Angelos Dassios	London School of Economics and Political Science, London, United Kingdom	option pricing; jump-diffusion model; levy; Hawkes processes; stochastic intensity; maximum likelihood method; Laplace transform; occupation time; jump-diffusion process
Ashraf M. Elazouni	Sultan Qaboos University, Muscat, Oman	cash flow; construction project; contractors; decomposition; evolutionary multi objective optimization; pareto front; construction safety; occupational accidents; accident
Edward W. (Jed) Frees	ANU College of Business & Economics, Canberra, Australia	copula; bivariate; vines; customer churn; sales; customer relationship management; medical malpractice; tort reform; jurisprudence
Esther Frostig	Holon Institute of Technology, Holon, Israel	risk model; ruin probability; classical risk model
Guojun Gan	University of Connecticut, Storrs, United States	variable annuities; life insurance; costs and cost analysis; claim; chain ladder; bonus-malus systems; object detection; deep learning; IOU
Nadine Gatzert	Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany	corporate reputation; brand management; branding; cause-related marketing; corporate social responsibility; corporate philanthropy; exchange rate exposure; enterprise risk management; firm
Periklis Gogas	Democritus University of Thrace, Komotini, Greece	bankruptcy prediction; credit scoring; prediction; mixed frequency data; factor; macroeconomic forecasting; oil price shocks; oil markets; petroleum
Pedro Guerra	NOVA Information Management School, Universidade Nova de Lisboa, Lisbon, Portugal	bankruptcy prediction; credit scoring; prediction
Brian M. Hartman	Milliman Inc., Seattle, United States	claim; chain ladder; bonus-malus systems; palivizumab; bronchiolitis; human respiratory syncytial virus; outages; resilience; cyclonic storms
Wookjae Heo	Purdue University, West Lafayette, United States	debt; personal finance; credit cards; investors; individual investors; financial adviser; China; dependency ratio; financial development
Yifan Huang	University of International Business and Economics, Beijing, China	claim; chain ladder; bonus-malus systems; Bayesian nonparametric; Dirichlet process; cluster analysis
Himchan Jeong	Simon Fraser University, Burnaby, Canada	claim; chain ladder; bonus-malus systems; copula; bivariate; vines; varying coefficient model; quantile regression; high-dimensional
Zhengjun Jiang	United International College, Zhuhai, China	risk model; ruin probability; classical risk model
Dimitris Karlis	Athens University of Economics and Business, Athens, Greece	claim; chain ladder; bonus-malus systems; count data; Poisson regression; regression model; galectin; biomarkers; heart failure
Robert J. Kauffman	Singapore Management University, Singapore City, Singapore	crowdfunding; lending; fintech; social media; online reviews; brand community; resource allocation; spot market; virtual machine
Hong Li	Gordon S. Lang School of Business and Economics, Guelph, Canada	longevity risk; mortality forecasting; life expectancy; price discovery; stock index futures; China; crops; CERES (experiment); climate change impact
Olivier Lopez	Sorbonne Université, Paris, France	copula; bivariate; vines; epidemic model; SIR; moment closure; claim; chain ladder; bonus-malus systems
Elizabeth Manser Payne	Beacom School of Business, Vermillion, United States	product-service systems; service economy; value co-creation; technology acceptance model; mobile payment; e-learning; Machiavellianism; psychopathy; triad
Shengwang Meng	Renmin University of China, Beijing, China	claim; chain ladder; bonus-malus systems; aftershock; earthquake; seismicity; Bayesian nonparametrics; Dirichlet process; cluster analysis
Xavier Milhaud	Institut de Mathématiques de Marseille, Marseille, France	claim; chain ladder; bonus-malus systems; multiple testing; microarray data; false; discovery rate; variable annuities; life insurance; costs and cost analysis
Victor Murinde	SOAS University of London, London, United Kingdom	bank efficiency; banking industry; banking; credit; microcredit; financial inclusion; financial development; economic growth; trade openness
Theophilos Papadimitriou	Democritus University of Thrace, Komotini, Greece	bankruptcy prediction; credit scoring; prediction; mixed frequency data; factor; macroeconomic forecasting; oil price shocks; oil markets; petroleum
James Jimmy Peltier	University of Wisconsin-Whitewater, Whitewater, United States	product-service systems; service economy; value co-creation; marketing education; salespeople; marketing; channel integration; electronic commerce; multichannel marketing
Gareth William Peters	University of California, Santa Barbara, Santa Barbara, United States	longevity risk; mortality forecasting; life expectancy; stochastic geometry; mobile communication systems; coverage probability; covariance function; Spatio-temporal; variogram
Lysa Porth	Gordon S. Lang School of Business and Economics, Guelph, Canada	crop insurance; weather derivatives; agriculture; crops; CERES (experiment); climate change impact; optimal reinsurance; value at risk; expected shortfall
Julien Trufin	Université Libre de Bruxelles, Brussels, Belgium	claim; chain ladder; bonus-malus systems; copula; bivariate; vines; risk model; ruin probability; classical risk model
Wim J. van der Linden	Universiteit Twente, Enschede, Netherlands	adaptive testing; item response theory; latent trait; Rasch analysis; Rasch model; differential item functioning; large-scale; post-stratification; college admission test
Roel Verbelen	Leuven Statistics Research Centre, Heverlee, Belgium	claim; chain ladder; bonus-malus systems; varying coefficient model; quantile regression; high- dimensional
Tim Verdonck	KU Leuven, 3000 Leuven, Belgium	imbalanced data; cost-sensitive learning; data classification, multivariate outliers; statistic; breakdown point; credit card fraud; fraud detection; crime
Howard R. Waters	Heriot-Watt University, Edinburgh, United Kingdom	actuarial mathematics; modelling critical illness
Xueyuan Wu	University of Melbourne, Melbourne, Australia	risk model; ruin probability; classical risk model; claim; chain ladder; bonus-malus systems; count data; Poisson regression; regression model

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CRediT authorship contribution statement

Debidutta Pattnaik: Conceptualization, Data curation, Methodology, Visualization, Writing - original draft, Writing - review & editing. **Sougata Ray:** Data curation, Visualization, Writing - original draft, Writing - review & editing. **Raghu Raman:** Visualization, Methodology, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] H. Herrmann, What's next for responsible artificial intelligence: a way forward through responsible innovation, Heliyon 9 (2023), https://doi.org/10.1016/j.heliyon.2023.e14379.
[2] F. Mi Alnaser, S. Rahi, M. Alghizzawi, A.H. Ngah, Does artificial intelligence (AI) boost digital banking user satisfaction? Integration of expectation confirmation model and antecedents of artificial intelligence enabled digital banking, Heliyon 9 (2023).
[3] J.W. Goodell, S. Kumar, W.M. Lim, D. Pattnaik, Artificial intelligence and machine learning in finance: identifying foundations, themes, and research clusters from bibliometric analysis, J. Behav. Exp. Financ. 32 (2021), 100577, https://doi.org/10.1016/j.jbef.2021.100577.
[4] L. Moutinho, A. Smith, Modelling bank customer satisfaction through mediation of attitudes towards human and automated banking, Int. J. Bank Market. 18 (2000) 124–134, https://doi.org/10.1108/02652320010339699.
[5] P.V. Polychroniou, I. Giannikos, A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank, Career Dev. Int. 14 (2009) 372–387, https://doi.org/10.1108/13620430910979853.
[6] N. Zeinalizadeh, A.A. Shojaie, M. Shariatmadari, Modeling and analysis of bank customer satisfaction using neural networks approach, Int. J. Bank Market. 33 (2015) 717–732, https://doi.org/10.1108/IJBM-06-2014-0070.
[7] I. Vorobyev, A. Krivitskaya, Reducing false positives in bank anti-fraud systems based on rule induction in distributed tree-based models, Comput. Secur. 120 (2022), 102786, https://doi.org/10.1016/j.cose.2022.102786.
[8] A.I. Canhoto, Leveraging machine learning in the global fight against money laundering and terrorism financing: an affordances perspective, J. Bus. Res. 131 (2021) 441–452, https://doi.org/10.1016/j.jbusres.2020.10.012.
[9] A. Nagurney, A multiproduct network economic model of cybercrime in financial services, Science 7 (2015) 70–81.
[10] K. Singh, P. Best, Anti-Money Laundering: using data visualization to identify suspicious activity, Int. J. Account. Inf. Syst. 34 (2019), 100418, https://doi.org/10.1016/j.accinf.2019.06.001.
[11] T. Cao, W.D. Cook, M.M. Kristal, Has the technological investment been worth it? Assessing the aggregate efficiency of non-homogeneous bank holding companies in the digital age, Technol. Forecast. Soc. Change 178 (2022), 121576, https://doi.org/10.1016/j.techfore.2022.121576.
[12] H. Farbmacher, L. Löw, M. Spindler, An explainable attention network for fraud detection in claims management, J. Econom. 228 (2022) 244–258, https://doi.org/10.1016/j.jeconom.2020.05.021.
[13] A. Azzutti, AI trading and the limits of EU law enforcement in deterring market manipulation, Comput. Law Secur. Rep. 45 (2022), 105690, https://doi.org/10.1016/j.clsr.2022.105690.
[14] V. Manahov, Can high-frequency trading strategies constantly beat the market? Int. J. Financ. Econ. 21 (2015) 167–191.
[15] J. Prix, O. Loistl, M. Huetl, Algorithmic trading patterns in Xetra orders, Eur. Int. J. Financ. Econ. 13 (2007) 717–739, https://doi.org/10.1080/13518470701705538.
[16] N. Chukhrova, A. Johannssen, Stochastic claims reserving methods with state space representations: a review, Risks 9 (2021) 198, https://doi.org/10.3390/risks9110198.
[17] A. Pnevmatikakis, S. Kanavos, G. Matikas, K. Kostopoulou, A. Cesario, S. Kyriazakos, Risk assessment for personalized health insurance based on real-world data, Risks 9 (2021) 46, https://doi.org/10.3390/risks9030046.
[18] S. Meng, Y. Gao, Y. Huang, Actuarial intelligence in auto insurance: claim frequency modeling with driving behavior features and improved boosted trees, Insur. Math. Econ. 106 (2022) 115–127, https://doi.org/10.1016/j.insmatheco.2022.06.001.
[19] M. Bouhia, L. Rajaobelina, S. PromTep, M. Arcand, L. Ricard, Drivers of privacy concerns when interacting with a chatbot in a customer service encounter, Int. J. Bank Market. 40 (2022) 1159–1181, https://doi.org/10.1108/IJBM-09-2021-0442.
[20] M. Ghaemi Asl, M.M. Rashidi, S.A. Hosseini Ebrahim Abad, Emerging digital economy companies and leading cryptocurrencies: insights from blockchain-based technology companies, J. Enterprise Inf. Manag. 34 (2021) 1506–1550, https://doi.org/10.1108/JEIM-08-2020-0348.
[21] G. Tepe, U.B. Geyikci, F.M. Sancak, Fintech companies: a bibliometric analysis, Int. J. Financ. Stud. 10 (2022) 2, https://doi.org/10.3390/ijfs10010002.
[22] P. Gomber, R.J. Kauffman, C. Parker, B.W. Weber, On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services, J. Manag. Inf. Syst. 35 (2018) 220–265, https://doi.org/10.1080/07421222.2018.1440766.
[23] Q. Li, Z. Xu, X. Shen, J. Zhong, Predicting business risks of commercial banks based on bp-ga optimized model, Comput. Econ. 59 (2021) 1423–1441, https://doi.org/10.1007/s10614-020-10088-0.
[24] D. Mittal, S.R. Agrawal, Determining banking service attributes from online reviews: text mining and sentiment analysis, Int. J. Bank Market. 40 (2022) 558–577, https://doi.org/10.1108/IJBM-08-2021-0380.
[25] T. Kristóf, M. Virág, EU-27 bank failure prediction with C5.0 decision trees and deep learning neural networks, Res. Int. Bus. Finance 61 (2022), 101644, https://doi.org/10.1016/j.ribaf.2022.101644.
[26] T. Lux, Emergence of a core-periphery structure in a simple dynamic model of the interbank market, J. Econ. Dynam. Control 52 (2015) A11–A23, https://doi.org/10.1016/j.jedc.2014.09.038.
[27] R.M. Akakpo, M. Xia, A.M. Polansky, Frequentist inference in insurance ratemaking models adjusting for misrepresentation, ASTIN Bull 49 (2019) 117–146, https://doi.org/10.1017/asb.2018.41.
[28] A. Khan, A. Ahmad, S. Shireen, Ownership and performance of microfinance institutions: empirical evidences from India, Cogent Econ. Finance. 9 (2021), 1930653, https://doi.org/10.1080/23322039.2021.1930653.
[29] D. Pattnaik, M.K. Hassan, A. Dsouza, A. Ashraf, Investment in gold: a bibliometric review and agenda for future research, Res. Int. Bus. Finance 64 (2023), 101854, https://doi.org/10.1016/j.ribaf.2022.101854.
[30] H.K. Baker, S. Kumar, D. Pattnaik, N. Pandey, The journal of accounting and public policy at 40: a bibliometric analysis, J. Account. Publ. Pol. (2022), 107003, https://doi.org/10.1016/j.jaccpubpol.2022.107003.

[31] M.J. Page, J.E. McKenzie, P.M. Bossuyt, I. Boutron, T.C. Hoffmann, C.D. Mulrow, L. Shamseer, J.M. Tetzlaff, E.A. Akl, S.E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M.M. Lalu, T. Li, E.W. Loder, E. Mayo-Wilson, S. McDonald, L.A. McGuinness, L.A. Stewart, J. Thomas, A.C. Tricco, V.A. Welch, P. Whiting, D. Moher, The PRISMA 2020 statement: an updated guideline for reporting systematic reviews, Int. J. Surg. 88 (2021), 105906, https://doi.org/10.1016/j.ijsu.2021.105906.
[32] R. Raman, V.K. Nair, V. Prakash, A. Patwardhan, P. Nedungadi, Green-hydrogen research: what have we achieved, and where are we going? Bibliometrics analysis, Energy Reports 8 (2022) 9242–9260, https://doi.org/10.1016/j.egyr.2022.07.058.
[33] R. Raman, V.K. Nair, A. Shivdas, R. Bhukya, P.K. Viswanathan, N. Subramaniam, P. Nedungadi, Mapping sustainability reporting research with the UN's sustainable development goal, Heliyon 9 (2023), e18510, https://doi.org/10.1016/j.heliyon.2023.e18510.
[34] D. Pattnaik, S. Kumar, B. Burton, Thirty years of the australian accounting review: a bibliometric analysis, Aust. Account. Rev. 31 (2021) 150–164, https://doi.org/10.1111/auar.12332.
[35] R. Raman, H. Lathabhai, S. Mandal, C. Kumar, P. Nedungadi, Contribution of business research to sustainable development goals: bibliometrics and science mapping analysis, Sustainability 15 (2023), 12982, https://doi.org/10.3390/su151712982.
[36] A. Sreenivasan, M. Suresh, P. Nedungadi, R.R. R, Mapping analytical hierarchy process research to sustainable development goals: bibliometric and social network analysis, Heliyon 9 (2023), e19077, https://doi.org/10.1016/j.heliyon.2023.e19077.
[37] A. Boot, P. Hoffmann, L. Laeven, L. Ratnovski, Fintech: what's old, what's new? J. Financ. Stabil. 53 (2021) https://doi.org/10.1016/j.jfs.2020.100836.
[38] V. Murinde, E. Rizopoulos, M. Zachariadis, The impact of the fintech revolution on the future of banking: opportunities and risks, Int. Rev. Financ. Anal. 81 (2022), 102103, https://doi.org/10.1016/j.irfa.2022.102103.
[39] E.A. Akartuna, S.D. Johnson, A. Thornton, Preventing the money laundering and terrorist financing risks of emerging technologies: an international policy Delphi study, Technol. Forecast. Soc. Change 179 (2022), 121632, https://doi.org/10.1016/j.techfore.2022.121632.
[40] S.N.M. Daud, A.H. Ahmad, A. Khalid, W.N.W. Azman-Saini, Fintech and financial stability: threat or opportunity? Finance Res. Lett. 47 (2022), 102667 https://doi.org/10.1016/j.frl.2021.102667.
[41] MdM. Alam, A.E. Awawdeh, A.I.B. Muhamad, Using e-wallet for business process development: challenges and prospects in Malaysia, Bus. Process Manag. J. 27 (2021) 1142–1162, https://doi.org/10.1108/BPMJ-11-2020-0528.
[42] R.J. Nathan, B. Setiawan, M.N. Quynh, Fintech and financial health in Vietnam during the COVID-19 Pandemic: in-depth descriptive analysis, J. Risk Financ. Manag. 15 (2022), https://doi.org/10.3390/jrfm15030125.
[43] J.M. Visconti-Caparrós, J.R. Campos-Blázquez, The development of alternate payment methods and their impact on customer behavior: the Bizum case in Spain, Technol. Forecast. Soc. Change 175 (2022), 121330, https://doi.org/10.1016/j.techfore.2021.121330.
[44] I. Koomson, E. Martey, P.M. Etwire, Mobile money and entrepreneurship in East Africa: the mediating roles of digital savings and access to digital credit, Inf. Technol. People 36 (2022) 996–1019, https://doi.org/10.1108/ITP-11-2021-0906.
[45] G. Okello Candiya Bongomin, J. Ntayi, Trust: mediator between mobile money adoption and usage and financial inclusion, SRJ 16 (2019) 1215–1237, https://doi.org/10.1108/SRJ-01-2019-0011.
[46] K. Anil, A. Misra, Artificial intelligence in peer-to-peer lending in India: a cross-case analysis, Int. J. Emerg. Mark. 17 (2022) 1085–1106, https://doi.org/10.1108/IJOEM-05-2021-0822.
[47] D. Xiang, Y. Zhang, A.C. Worthington, Determinants of the use of fintech finance among Chinese small and medium-sized enterprises, in: 2018 IEEE International Symposium on Innovation and Entrepreneurship, TEMS-ISIE, 2018, pp. 1–10, https://doi.org/10.1109/TEMS-ISIE.2018.8478470.
[48] I. Anagnostopoulos, Fintech and regtech: impact on regulators and banks, J. Econ. Bus. 100 (2018) 7–25, https://doi.org/10.1016/j.jeconbus.2018.07.003.
[49] E. Micheler, A. Whaley, Regulatory technology: replacing law with computer code, Eur. Bus. Organ Law Rev. 21 (2020) 349–377, https://doi.org/10.1007/s40804-019-00151-1.
[50] J. Fu, M. Mishra, Fintech in the time of COVID−19: technological adoption during crises, J. Financ. Intermediation 50 (2022), 100945, https://doi.org/10.1016/j.jfi.2021.100945.
[51] Z. Bao, D. Huang, Shadow banking in a crisis: evidence from fintech during COVID-19, J. Financ. Quant. Anal. 56 (2021) 2320–2355, https://doi.org/10.1017/S0022109021000430.
[52] N. Gatzert, M. Schubert, Cyber risk management in the US banking and insurance industry: a textual and empirical analysis of determinants and value, J. Risk Insur. 89 (2022) 725–763, https://doi.org/10.1111/jori.12381.
[53] G. Northey, V. Hunter, R. Mulcahy, K. Choong, M. Mehmet, Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice, Int. J. Bank Market. 40 (2022) 1182–1199, https://doi.org/10.1108/IJBM-09-2021-0439.
[54] S. Anand, K. Mishra, Identifying potential millennial customers for financial institutions using SVM, J. Financ. Serv. Market. 27 (2022) 335–345, https://doi.org/10.1057/s41264-021-00128-7.
[55] W. Heo, J.M. Lee, A.G. Rabbani, Mediation effect of financial education between financial stress and use of financial technology, J. Fam. Econ. Issues 42 (2021) 413–428, https://doi.org/10.1007/s10834-020-09720-w.
[56] L. Găbudeanu, I. Brici, C. Mare, I.C. Mihai, M.C. Şcheau, Privacy intrusiveness in financial-banking fraud detection, Risks 9 (2021) 104, https://doi.org/10.3390/risks9060104.
[57] I. Hazan, O. Margalit, L. Rokach, Supporting unknown number of users in keystroke dynamics models, Knowl. Base Syst. 221 (2021), 106982, https://doi.org/10.1016/j.knosys.2021.106982.
[58] T. Wang, S. Zhao, G. Zhu, H. Zheng, A machine learning-based early warning system for systemic banking crises, Appl. Econ. 53 (2021) 2974–2992, https://doi.org/10.1080/00036846.2020.1870657.
[59] Y. Xu, C.-H. Shieh, P. van Esch, I.-L. Ling, AI customer service: task complexity, problem-solving ability, and usage intention, Australas. Mark. J. 28 (2020) 189–199, https://doi.org/10.1016/j.ausmj.2020.03.005.
[60] E.H. Manser Payne, J. Peltier, V.A. Barger, Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms, J. Res. Interact. Mark. 15 (2021) 68–85, https://doi.org/10.1108/JRIM-10-2020-0214.
[61] A. Ekinci, H.İ. Erdal, Forecasting bank failure: base learners, ensembles and hybrid ensembles, Comput. Econ. 49 (2017) 677–686, https://doi.org/10.1007/s10614-016-9623-y.
[62] Z. Jing, Y. Fang, Predicting US bank failures: a comparison of logit and data mining models, J. Forecast. 37 (2018) 235–256, https://doi.org/10.1002/for.2487.
[63] A. Petropoulos, V. Siakoulis, E. Stavroulakis, N.E. Vlachogiannakis, Predicting bank insolvencies using machine learning techniques, Int. J. Forecast. 36 (2020) 1092–1113, https://doi.org/10.1016/j.ijforecast.2019.11.005.
[64] H. Ince, B. Aktan, A comparison of data mining techniques for credit scoring in banking: a managerial perspective, J. Bus. Econ. Manag. 10 (2009) 233–240, https://doi.org/10.3846/1611-1699.2009.10.233-240.
[65] V. Plakandaras, P. Gogas, T. Papadimitriou, E. Doumpa, M. Stefanidou, Forecasting credit ratings of EU banks, Int. J. Financ. Stud. 8 (2020) 49, https://doi.org/10.3390/ijfs8030049.
[66] S. Shrivastava, P.M. Jeyanthi, S. Singh, Failure prediction of Indian Banks using SMOTE, Lasso regression, bagging and boosting, Cogent Econ. Finance. 8 (2020), 1729569, https://doi.org/10.1080/23322039.2020.1729569.
[67] B. So, J.-P. Boucher, E.A. Valdez, Synthetic dataset generation of driver telematics, Risks 9 (2021) 58, https://doi.org/10.3390/risks9040058.
[68] B. So, J.-P. Boucher, E.A. Valdez, Cost-sensitive multi-class Adaboost for understanding driving behavior based on telematics, ASTIN Bulletin: J. of IAA. 51 (2021) 719–751, https://doi.org/10.1017/asb.2021.22.
[69] B.-H. Leem, S.-W. Eum, Using text mining to measure mobile banking service quality, Ind. Manag. Data Syst. 121 (2021) 993–1007, https://doi.org/10.1108/IMDS-09-2020-0545.
[70] Z. Jin, H. Yang, G. Yin, A hybrid deep learning method for optimal insurance strategies: algorithms and convergence analysis, Insur. Math. Econ. 96 (2021) 262–275, https://doi.org/10.1016/j.insmatheco.2020.11.012.

[71] I.C. Sabban, O. Lopez, Y. Mercuzot, Automatic analysis of insurance reports through deep neural networks to identify severe claims, Ann. Actuar. Sci. 16 (2022) 42–67, https://doi.org/10.1017/S174849952100004X.
[72] J. Pathak, N. Vidyarthi, S.L. Summers, A fuzzy-based algorithm for auditors to detect elements of fraud in settled insurance claims, Manag. Audit J. 20 (2005) 632–644, https://doi.org/10.1108/02686900510606119.
[73] A.F. Shapiro, The merging of neural networks, fuzzy logic, and genetic algorithms, Insur. Math. Econ. 31 (2002) 115–131, https://doi.org/10.1016/S0167-6687(02)00124-5.
[74] M.-Y. Cheng, N.-D. Hoang, Evaluating contractor financial status using a hybrid fuzzy instance based classifier: case study in the construction industry, IEEE Trans. Eng. Manag. 62 (2015) 184–192, https://doi.org/10.1109/TEM.2014.2384513.
[75] F. Zampolli, Optimal monetary policy in a regime-switching economy: the response to abrupt shifts in exchange rate dynamics, J. Econ. Dynam. Control 30 (2006) 1527–1567, https://doi.org/10.1016/j.jedc.2005.10.013.
[76] M. Gross, W. Semmler, Inflation targeting, credit flows, and financial stability in a regime change model, Macroecon. Dyn. 23 (2019) 59–89, https://doi.org/10.1017/S136510051700102X.
[77] F.X. Diebold, M. Shin, Machine learning for regularized survey forecast combination: partially-egalitarian LASSO and its derivatives, Int. J. Forecast. 35 (2019) 1679–1691, https://doi.org/10.1016/j.ijforecast.2018.09.006.
[78] S. Afrin, I. Skamnelos, W. Sarder, Drivers of intermediation costs, financial repression and stability, J. Econ. Finance 46 (2022) 283–307, https://doi.org/10.1007/s12197-022-09569-9.
[79] O. Joaqui-Barandica, D.F. Manotas-Duque, J.M. Uribe, Commonality, macroeconomic factors and banking profitability, N. Am. J. Econ. Finance 62 (2022), 101714, https://doi.org/10.1016/j.najef.2022.101714.
[80] S.S. Poloz, Technological progress and monetary policy: managing the fourth industrial revolution, J. Int. Money Finance 114 (2021), 102373, https://doi.org/10.1016/j.jimonfin.2021.102373.
[81] G.B. Masala, M. Micocci, Loss-Alae modeling through a copula dependence structure, Invest. Manag. Financ. Innovat. 6 (2009) 67–80.
[82] C. Neves, C. Fernandes, E. Melo, Forecasting surrender rates using elliptical copulas and financial variables, North Am. Actuar. J. 18 (2014) 343–362, https://doi.org/10.1080/10920277.2014.888315.
[83] Y. Zhang, V. Dukic, Predicting multivariate insurance loss payments under the bayesian copula framework, J. Risk Insur. 80 (2013) 891–919, https://doi.org/10.1111/j.1539-6975.2012.01480.x.
[84] P. Kritzer, G. Leobacher, M. Szölgyenyi, S. Thonhauser, Approximation methods for piecewise deterministic markov processes and their costs, Scand. Actuar. J. 2019 (2019) 308–335, https://doi.org/10.1080/03461238.2018.1560357.
[85] G.W. Peters, R.S. Targino, M.V. Wüthrich, Bayesian modelling, Monte Carlo sampling and capital allocation of insurance risks, Risks 5 (2017) 53, https://doi.org/10.3390/risks5040053.
[86] M. Guillen, L. Bermúdez, A. Pitarque, Joint generalized quantile and conditional tail expectation regression for insurance risk analysis, Insur. Math. Econ. 99 (2021) 1–8, https://doi.org/10.1016/j.insmatheco.2021.03.006.
[87] G. Castellani, U. Fiore, Z. Marino, L. Passalacqua, F. Perla, S. Scognamiglio, P. Zanetti, Machine learning techniques in nested stochastic simulations for life insurance, Appl. Stoch Model Bus. Ind. 37 (2021) 159–181, https://doi.org/10.1002/asmb.2607.
[88] A. Udhayakumar, V. Charles, M. Kumar, Stochastic simulation based genetic algorithm for chance constrained data envelopment analysis problems, Omega 39 (2011) 387–397, https://doi.org/10.1016/j.omega.2010.09.002.
[89] B. Avanzi, G. Taylor, B. Wong, X. Yang, On the modelling of multivariate counts with Cox processes and dependent shot noise intensities, Insur. Math. Econ. 99 (2021) 9–24, https://doi.org/10.1016/j.insmatheco.2021.01.002.
[90] J. Hirz, U. Schmock, P.V. Shevchenko, Actuarial applications and estimation of extended creditrisk+, Risks 5 (2017) 23, https://doi.org/10.3390/risks5020023.
[91] M. Drenovak, V. Ranković, B. Urošević, R. Jelic, Bond portfolio management under solvency ii regulation, Eur. Int. J. Financ. Econ. 27 (2020) 857–879.
[92] N. Gatzert, D. Heidinger, An empirical analysis of market reactions to the first solvency and financial condition reports in the European insurance industry, J. Risk Insur. 87 (2020) 407–436, https://doi.org/10.1111/jori.12287.
[93] G. Gan, E.A. Valdez, Data clustering with actuarial applications, North Am. Actuar. J. 24 (2020) 168–186, https://doi.org/10.1080/10920277.2019.1575242.
[94] D. Mehta, S. Tanwar, U. Bodkhe, A. Shukla, N. Kumar, Blockchain-based royalty contract transactions scheme for Industry 4.0 supply-chain management, Inf. Process. Manag. 58 (2021), 102586, https://doi.org/10.1016/j.ipm.2021.102586.
[95] M. Pitera, T. Schmidt, Estimating and backtesting risk under heavy tails, Insur. Math. Econ. 104 (2022) 1–14, https://doi.org/10.1016/j.insmatheco.2022.01.006.
[96] Z. Alzamil, D. Appelbaum, R. Nehmer, An ontological artifact for classifying social media: text mining analysis for financial data, Int. J. Account. Inf. Syst. 38 (2020), 100469, https://doi.org/10.1016/j.accinf.2020.100469.
[97] E.D. Liddy, C.L. Jorgensen, E.E. Sibert, E.S. Yu, A sublanguage approach to natural language processing for an expert system, Inf. Process. Manag. 29 (1993) 633–645, https://doi.org/10.1016/0306-4573(93)90084-Q.
[98] S. Chen, J. Du, W. He, M. Siponen, Supply chain finance platform evaluation based on acceptability analysis, Int. J. Prod. Econ. 243 (2022), 108350, https://doi.org/10.1016/j.ijpe.2021.108350.
[99] F. Olan, E.O. Arakpogun, U. Jayawickrama, J. Suklan, S. Liu, Sustainable supply chain finance and supply networks: the role of artificial intelligence, IEEE Trans. Eng. Manag. (2022) 1–16, https://doi.org/10.1109/TEM.2021.3133104.
[100] K.A. Özdemir, Understanding latent drivers of firm behaviour: a new methodological approach applied to agents' company visit scores, Econ, Model 94 (2021) 455–472, https://doi.org/10.1016/j.econmod.2020.11.001.
[101] M. Rahman, T.H. Ming, T.A. Baigh, M. Sarker, Adoption of artificial intelligence in banking services: an empirical analysis, Int. J. Emerg. Mark. ahead-of-print (2021), https://doi.org/10.1108/IJOEM-06-2020-0724.
[102] M. Aleandri, A. Eletti, Modelling dynamic lapse with survival analysis and machine learning in CPI, Decis. Econ. Finance 44 (2021) 37–56, https://doi.org/10.1007/s10203-020-00285-9.
[103] C. Liao, P. Du, Y. Yang, Z. Huang, Carrots or sticks in debt collection services? A voice metrics and text analysis of debt collection calls, JSTP 31 (2021) 950–973, https://doi.org/10.1108/JSTP-12-2020-0290.
[104] E. Calderín-Ojeda, K. Fergusson, X. Wu, An em algorithm for double-pareto-lognormal generalized linear model applied to heavy-tailed insurance claims, Risks 5 (2017) 60, https://doi.org/10.3390/risks5040060.
[105] G. Tzougas, EM Estimation for the Poisson-inverse gamma regression model with varying dispersion: an application to insurance ratemaking, Risks 8 (2020) 97, https://doi.org/10.3390/risks8030097.
[106] S. Matthews, B. Hartman, mSHAP: SHAP values for two-part models, Risks 10 (2022) 3, https://doi.org/10.3390/risks10010003.
[107] C. Blier-Wong, H. Cossette, L. Lamontagne, E. Marceau, Machine Learning in P&C Insurance: a review for pricing and reserving, Risks 9 (2020) 4, https://doi.org/10.3390/risks9010004.
[108] A.M. Hormozi, S. Giles, Data mining: a competitive weapon for banking and retail industries, Inf. Syst. Manag. 21 (2004) 62–71, https://doi.org/10.1201/1078/44118.21.2.20040301/80423.9.
[109] T. Warin, W. Sanger, The speeches of the European central bank's presidents: an nlp study, Global Econ. J. 20 (2020), 2050009.
[110] A. Amicelle, E.K. Jacobsen, The cross-colonization of finance and security through lists: banking policing in the UK and India, Environ. Plann. D 34 (2016) 89–106, https://doi.org/10.1177/0263775815623276.
[111] T. Miljkovic, D. Fernández, On two mixture-based clustering approaches used in modeling an insurance portfolio, Risks 6 (2018) 57, https://doi.org/10.3390/risks6020057.
[112] S. Yin, G. Gan, E.A. Valdez, J. Vadiveloo, Applications of clustering with mixed type data in life insurance, Risks 9 (2021) 47, https://doi.org/10.3390/risks9030047.

[113] W.J. van der Linden, Computerized adaptive testing with equated number-correct scoring, Appl. Psychol. Meas. 25 (2001) 343–355, https://doi.org/10.1177/01466210122032208.
[114] M.A. Sorrel, F.J. Abad, P. Nájera, Improving accuracy and usage by correctly selecting: the effects of model selection in cognitive diagnosis computerized adaptive testing, Appl. Psychol. Meas. 45 (2021) 112–129, https://doi.org/10.1177/0146621620977682.
[115] R.D. Armstrong, D.H. Jones, C.S. Kunce, IRT test assembly using network-flow programming, Appl. Psychol. Meas. 22 (1998) 237–247, https://doi.org/10.1177/01466216980223004.
[116] C.-L. Hsu, W.-C. Wang, Multidimensional computerized adaptive testing using non-compensatory item response theory models, Appl. Psychol. Meas. 43 (2019) 464–480, https://doi.org/10.1177/0146621618800280.
[117] A. Bansal, R.J. Kauffman, R.M. Mark, E. Peters, Financial risk and financial risk management technology (RMT): issues and advances, Inf. Manag. 24 (1993) 267–281, https://doi.org/10.1016/0378-7206(93)90004-D.
[118] Z. Jiang, Banach contraction principle, q -scale function and ultimate ruin probability under a Markov-modulated classical risk model, Scand. Actuar. J. 2022 (2022) 234–243, https://doi.org/10.1080/03461238.2021.1958917.
[119] Y. Liu, Z. Jiang, Y. Zhang, q-scale function, Banach contraction principle, and ultimate ruin probability in a Markov-modulated jump–diffusion risk model, Scand. Actuar. J. 2023 (2023) 38–50, https://doi.org/10.1080/03461238.2022.2078221.
[120] R.M.R. Cardoso, H.R. Waters, Recursive calculation of finite time ruin probabilities under interest force, Insur. Math. Econ. 33 (2003) 659–676, https://doi.org/10.1016/j.insmatheco.2003.09.008.
[121] E. Frostig, M. Denuit, Ruin probabilities and optimal capital allocation for heterogeneous life annuity portfolios, 2009, Scand. Actuar. J. (2009) 295–305, https://doi.org/10.1080/03461230902753507.
[122] Y. Liu, Z. Jiang, Y. Qu, Gambler's ruin problem in a markov-modulated jump-diffusion risk model, Scand. Actuar. J. 2022 (2022) 682–694, https://doi.org/10.1080/03461238.2021.2025145.