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Review

Uncovering Research Trends on Artificial Intelligence Risk Assessment in Businesses: A State-of-the-Art Perspective Using Bibliometric Analysis

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Abstract: This paper presents a quantitative vision of the study of artificial intelligence risk assessment in business based on a bibliometric analysis of the most relevant publications. The main goal is to determine whether the risk assessment of artificial intelligence systems used in businesses is really a subject of increasing interest and to identify the most influential and productive sources of scientific research in this area. Data were collected from the Web of Science Core Collection, one of the most complete and prestigious databases. Regarding the temporal evolution of publications and citations this study evidences, this research subject shows rapid growth in the number of publications (at a compound annual rate of 31.20% from 2018 to 2024 inclusive), showing its high attraction for researchers, responding to the need to implement systematic risk assessment processes in the organizations using AI to mitigate potential harms, ensure compliance with regulations, and enhance artificial intelligence systems' trust and adoption. Especially after the surge of large language models like ChatGPT or Gemini, AI is revolutionizing the dynamics of human–computer interaction using natural language, video, and audio. However, as the scientific community initiates rigorous studies on AI risk assessment within organizational contexts, it is imperative to consider critical issues such as data privacy, ethics, bias, and hallucinations to ensure the successful integration and interaction of AI systems with human operators. Furthermore, this paper constitutes a starting point, including for any researcher who wants to be introduced to this topic, indicating new challenges that should be dealt by researchers interested in AI and hot topics, in addition to the most relevant literature, authors, and journals about this research subject.

Keywords: artificial intelligence; bibliometrics; risk assessment; risk; impact assessment; AI

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1. Introduction

Artificial intelligence (AI) is a highly used concept in business nowadays, and is sometimes even used as a synonym for digital transformation. In many cases, managers and other decision-makers do not understand the pros and cons of AI initiatives inside their organizations.

The confidentiality and privacy of the corporate or personal data provided to the AI systems is sometimes assumed and not guaranteed in many cases [1].

Also, there are concerns about the ethical aspects of AI implementation [2,3], especially in some fields like healthcare [4]. That is the reason we can find recent and interesting works on explainable (or interpretable) AI [5,6].

On the other hand, AI is a promising technology, and businesses should see how this technology allows them to compete in a better way, in terms of quality improvement or cost reduction.

This paper aims to identify and study the state-of-the-art research on the assessment of these risks introduced by artificial intelligence systems on businesses because this could be an emerging theme with interesting development opportunities.

For this, we will use these research hypotheses:

1. The state-of-the-art developments in this research subject are characterized by a concentration of highly cited publications, predominantly authored by leading researchers from top-tier institutions and published in high-impact journals.
2. The number of publications on AI risk assessment in businesses has significantly increased over the last seven years, reflecting a growing global emphasis on cybersecurity and explainable AI.
3. Collaborative research involving multiple institutions is undertaken frequently and generates a scientific impact on the research subject of AI risk assessment in businesses.

Just to clarify what we are talking about, risk assessment is defined in the ISO 31000:2018 standard [7] as "the overall process of risk identification, risk analysis, and risk evaluation", so it is a more general concept than risk analysis or risk evaluation. Actually, these concepts are part of the assessment process.

This risk assessment should be done systematically, iteratively, and collaboratively, according to ISO, and so it should also be done in the AI context.

Besides that, official references from the government about risk assessment are present in the European AI Regulation, which was recently published [8], or in the NIST AI risk management framework [9].

This allows businesses to apply a risk–benefit analysis in their decisions concerning AI investments, in case they are both acquiring or developing an AI system.

Our study demonstrates that this is a very novel concept in research, although it has increased its relevance in synchrony with the explosion of research production in artificial intelligence.

This paper aims to assess the relevance of the research subject of risk assessment of artificial intelligence initiatives in businesses, to be useful as a guide for other researchers interested in this topic, indicating the most relevant references, listing the most relevant researchers and institutions, identifying the journals with a specific interest in this topic, and finally, signaling the ability of this research subject to attract funds for research.

This paper is distributed in the following way: The first section presents an introduction to the research subject and to the bibliometric analysis, explaining why and how we have decided to use these methods and indicating relevant works on bibliometric analysis in AI and the differences between them.

The next section presents the methodology we have decided to use for the study, including the search strategy, the methods of analysis, and the tools used.

The following section analyzes the results of our research, highlighting the most important findings in the most productive and influential journals, the most influential articles, the most prolific and influential authors, institutions, and countries, and the collaboration between countries. Then, we identify the landscapes and evolution of our research subject and the emerging related topics.

Finally, this paper presents the conclusions of this research and the bibliography used.

2. Literature Review

According to Noyons et al. [10], Gil-Gomez et al. [11], and Ninkov et al. [12], bibliometrics represents a statistically standard way to analyze scientific performance and dynamics in a specific research subject, based on a quantitative analysis of bibliographic data of academic publishing.

Bibliometrics is, according to them, a useful way to determine if the interest of the subject is expanding or reducing in a specific period of time and to identify the most relevant authors, publications, and institutions generating knowledge on the topic.

Nevertheless, bibliometrics has been used in this way in an important number of research subjects. Just looking at management research areas, we can find relevant works such as green supply management [13], operations research [14], sustainable manufacturing [15], entrepreneurship [16], or crowdfunding [11].

Besides that, according to Passas [17], while a meta-analysis is focused on quantitative analysis and a systematic literature review is focused on qualitative analysis, a bibliometric analysis can cover both sides, and that is the approach we used when defining this research. Additionally, given the size and the heterogeneity of our dataset, a systematic literature review was not realistic if we wanted to cover all the different approaches, and a meta-analysis was not feasible without excessively restricting the number of studies analyzed, given the mentioned heterogeneity and scarcity of quality studies.

By looking at new technologies (such as artificial intelligence), we can also find relevant bibliometrics works in Big Data Analytics [18,19], artificial intelligence in e-commerce [20], blockchain in logistics and supply chain [21], digital transformation [22], artificial intelligence in society [23], or even cybersecurity in healthcare [24].

In our preliminary search to verify that this paper would be relevant enough, we did not find previous bibliometric research on the business risk assessment of artificial intelligence. There are some works, such as the aforementioned Fosso Wamba et al. [23], and Zhang et al. [25] and Albahri and AlAmoodi [26], about the impact of artificial intelligence on society. The first two were focused on ethics in society, and the last one performed a bibliometric analysis on cybersecurity aspects of artificial intelligence, but none were specifically on the risk assessment of artificial intelligence in businesses.

Finally, and complementarily to our bibliometric analysis, we conducted additional manual searches using alternative platforms such as arXiv and ResearchGate.

ArXiv: Our search on arXiv yielded eight references, primarily communications to international conferences and preprints. Our reading of these references identified no leading journal or relevant paper to be included in our research.

ResearchGate: On ResearchGate, we discovered several journals with noteworthy publications, although they were not considered influential in our initial bibliometric analysis. For example, Novelli et al. published works in "*AI & Society*", a Q3 journal with an impact factor of 2.9, and in "*Digital Society*", which is not indexed in the Web of Science catalog with a high number of citations. These works [27,28] are coincident in proposing an alternative model for AI risk assessment based on real-world risk scenarios and frameworks developed previously for climate change, offering a different approach from the existing European AI regulation. Both works are highly cited according to ResearchGate. Additionally, the "*AGI—Artificial General Intelligence, Robotics, Safety & Alignment*" journal includes impactful articles such as "The AI Risk Repository: A Comprehensive Meta-Review, Database, and Taxonomy of Risks From Artificial Intelligence" by Slattery et al. [29], which proposes a living database with 777 risk entries based on various taxonomies, hosted at MIT "https://airisk.mit.edu (accessed on 10 January 2025)", one of the most comprehensive and dynamic repositories of potential AI risks for businesses, classified by both causes and by domains.

These findings suggest that some researchers publish their work on AI risk assessment in journals that may not be highly visible in mainstream repositories but offer valuable and innovative real-world approaches; so, we should take these into account, although it does not replace a bibliometric analysis at all.

Future research could explore the reasons behind this publication trend and the potential benefits of considering these alternative sources.

3. Materials and Methods

The bibliometric analysis in this paper is developed to identify the most active and influential research clusters, both in terms of authors and themes on the subject of artificial intelligence risk assessment in business.

Applying a bibliometric analysis can avoid the subjectivity of a literature review and comprehensively and objectively reflect the status of a research subject.

The analysis is based on data collected from the Web of Science Core Collection (WoSCC) database, a database with a specially high reputation as a scientific repository [30,31]. These data made it possible to analyze the number of publications and number of citations, in terms of affiliation, authors, or countries, and elaborate the h-Index, co-occurrence network, and thematic or strategic map, among other techniques, to set a high-resolution picture of the current situation of this research area.

For this research, we excluded Google Scholar due to its inclusion of non-peer-reviewed publications and the lack of a mechanism to export the entire dataset for further analysis. This limitation forces the manual selection of each publication before exporting, which is impractical for a comprehensive bibliometric analysis.

Additionally, the differences between Scopus' subject areas and the Web of Science Core Collection (WoSCC) research areas' classification posed challenges for direct comparison. For instance, equating Scopus' "Business, Management and Accounting" with WoSCC's "Business Economics" is highly subjective and debatable. Ultimately, WoSCC provided a slightly larger dataset than Scopus, and WoSCC's inclusion of high-quality, peer-reviewed journals ensures reliable and representative data, consequently enhancing the validity of the results presented.

To develop a bibliometric study, this paper follows the steps indicated in Figure 1:

1. The choice of the subject ("artificial intelligence risk assessment on business"), the time span (we chose two periods; the first one includes all production before 2018, and the second one includes the period between 2018 and 2024, both inclusive), and keywords ("risk assessment" AND "business" AND ("artificial intelligence" OR "machine learning")).
2. The choice of Web of Science Core Collection as the database to use responds to productivity criteria (92 million records since the year 1900 with more than 22,000 peer-reviewed journals) and influence criteria (2.2 billion cited references) [32]
3. In order to reduce the noise generated by the results, this paper excluded retracted publications and 2025 production (to ensure a fair comparison of annual production); and it included only articles and review articles of the following research areas: Computer Science, Engineering, Business Economics, Operations Research Management Science, Mathematics, Science Technology Other Topics, Telecommunications, Government Law, Public Administration, Social Sciences Other Topics, Information Science Library Science, Sociology, Mathematical Methods In Social Sciences, Instruments Instrumentation, Remote Sensing, and Medical Informatics.
4. Our research obtained 244 publications that met the chosen criteria (227 of them between 2018 and 2024). Of these, 18 publications (7.4%) were reviews and 226 (92.6%) were articles.

5. According to the methodology described, this paper classifies the results according to the performance analysis and the science mapping.
6. Finally, this paper discusses and presents the conclusions, identifying the most productive and influential authors, sources, articles, and countries and the most relevant relationships between them.

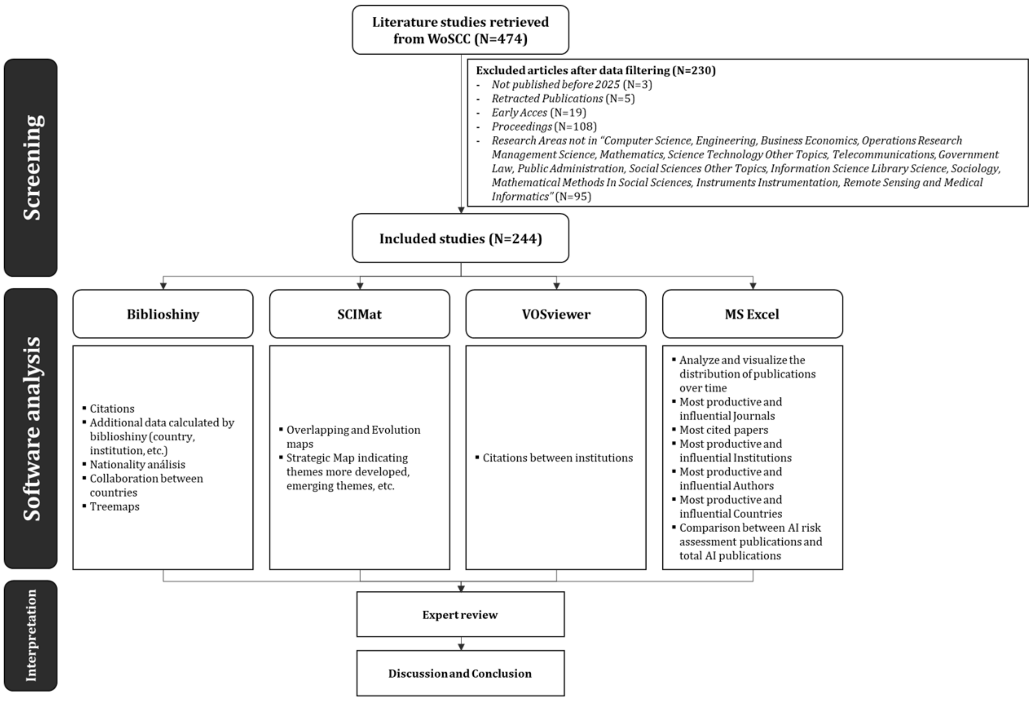

Figure 1. Flowchart of the bibliometric research strategy.

Method of Analysis

According to Noyons et al. [10], there are two main procedures in bibliometric analysis: performance analysis and science mapping.

While the former aims to evaluate the impact of the activity of authors, institutions, countries, etc., the second is focused on displaying the structure and dynamics of the research on one specific area, according to Cobo et al. [33].

A performance analysis is usually composed of the number of publications, the number of citations, and an index based on both numbers, the h-Index [34]. Although many authors have reviewed the h-Index and proposed alternatives ([35–38], among others), this index offers a high value and is easy to obtain, so it is used very frequently in bibliometric performance analysis.

We discarded the use of the g-Index in our bibliographic analysis for several reasons: we saw few differences in using this index compared with the use of the h-Index (no new entrants nor items exiting from the tables). This can be due to the generally low number of citations [39], as this topic is very new, and the g-Index is not an official number given by WoS. Thus, the process of calculations could introduce undesired errors in our analysis due to authors using different names, the absence of ORCID ID in some cases, etc.

Based on the previous considerations, this paper shows the journals ordered according to the h-Index computed based on the author's number of existing publications and citations in the WoSCC dataset (h); second, by the number of citations (TC); and third, by total scientific production in AI (TPAI).

In the case of the most productive and influential journals, this paper combines these indexes with the impact factor (IF) for 2023 (the last year published at the time we wrote this paper), and the last 5-year impact factor (5-IF) to provide a complete picture of each included source.

Regarding the science mapping techniques, these are aimed at monitoring a research field to define its cognitive structure, that is, the structure of relationships between keywords, authors, etc., and its evolution in specific periods [10].

For the selected period, we analyzed all results from the Web of Science Core Collection (WoSCC) spanning from 1997 to 2024, the time at which this analysis was conducted. Upon examining the evolution of published material, we observed a significant increase starting in 2018. Furthermore, we chose to specifically analyze the period between the substantial rise of large language model-based chatbots (2021) and the last year analyzed. Consequently, we divided the dataset into two distinct periods (pre-2018 and post-2018) and conducted a detailed examination of the years 2021–2024 for a specific inquiry.

This research used a suite of software tools for comprehensive quantitative analysis and visualization of the collected literature. These tools included R-version 4.4.1 combined with Bibliometrix and Biblioshiny [40], VOSviewer 1.6.20, SCIMat 1.1.06 [33], and Microsoft Excel for Microsoft 365 Version 2410 Build 16.0.18129.20158.

This paper presents and discusses different charts within this science mapping, like the coupling maps chart, the co-occurrence networks chart, and the thematic evolution chart.

4. Results

The results are presented in the following order: the most productive and influential journals are shown and discussed first; then we analyze the evolution of published articles on the research subject we selected; and after that, this paper discusses the most prolific and influential authors, and the most productive and influential institutions. Then a country analysis is performed, and finally, after presenting the landscape and evolution, and the current emerging issues of our research subject, we discuss the general results.

4.1. Publishing Journals

After analyzing the 244 journals returned by the previously described query to the Web of Science Core Collection, Table 1 was prepared to show the publication trends of each of the top 25 journals:

In Table 2, if we look just at the last four years of our dataset (2021–2024), a period chosen for the appearance of relevant outcomes on large language models (LLMs) from OpenAI (GPT-3), Google (BERT), Facebook (preparing OPT), and Microsoft (Azure OpenAI service) that have enabled easier access to AI systems for the general public and social and economic actors, then we see how, except for the top 5, all the other positions change, showing differences in which journals are becoming more active on this topic (like *RISKS*, *RISK ANALYSIS* or *SENSORS*), and which ones are losing positions (like *ARTIFICIAL INTELLIGENCE REVIEW*, *STOCHASTIC ENVIRONMENTAL RESEARCH AND RISK ASSESSMENT*, and *SCIENTIFIC REPORTS*).

Finally, if we zoom out and look at publishers, we identify the top 5 in Table 3.

We can see in Table 3 that MDPI is the most productive publisher between these years, with four journals having an h-Index greater than 1. Looking at the journals of this publisher, *SENSORS* is the most cited journal, and also contains MDPI's most cited article of the dataset with 40 citations.

Note that, due to the novelty of the research subject, the dataset is relatively small, and given the multidisciplinary nature of AI, encompassing aspects of computer science, business, ethics, and more, the combination of that results in a very heterogeneous set of journals.

Table 1. Publication trends by journal (top 25).

	1997–2017	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	*2024*	*TOTALS*
EXPERT SYSTEMS WITH APPLICATIONS	5	0	0	1	0	4	2	1	13
ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	0	0	1	0	0	0	3	3	7
SUSTAINABILITY	0	0	1	0	0	0	4	2	7
IEEE ACCESS	0	1	0	0	2	2	0	2	7
APPLIED SOFT COMPUTING	0	1	0	0	2	0	2	1	6
ARTIFICIAL INTELLIGENCE REVIEW	1	0	1	0	0	0	3	1	6
STOCHASTIC ENVIRONMENTAL RESEARCH & RISK ASSESSMENT	0	0	1	0	1	1	1	1	5
SCIENTIFIC REPORTS	0	0	1	0	0	0	1	3	5
RISKS	0	0	0	0	2	1	1	1	5
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	1	0	0	2	0	0	1	0	4
SAFETY SCIENCE	0	0	1	2	1	0	0	0	4
SENSORS	0	0	0	1	0	2	0	1	4
RISK ANALYSIS	0	0	0	0	0	1	1	2	4
REMOTE SENSING	0	0	0	1	1	0	1	0	3
INDUSTRIAL MANAGEMENT & DATA SYSTEMS	0	0	0	1	1	0	1	0	3
NANOTOXICOLOGY	0	0	1	1	0	0	0	0	2
JOURNAL OF CLEANER PRODUCTION	0	0	0	0	1	0	1	0	2
SOCIETY	0	0	0	0	2	0	0	0	2
RELIABILITY ENGINEERING & SYSTEM SAFETY	0	0	0	0	1	0	0	1	2
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	0	0	0	1	0	0	1	0	2
COMPLEX & INTELLIGENT SYSTEMS	0	1	0	0	0	0	1	0	2
NEURAL COMPUTING & APPLICATIONS	0	0	0	0	1	1	0	0	2
PATTERNS	0	0	0	0	2	0	0	0	2
DECISION SUPPORT SYSTEMS	0	0	0	1	0	0	1	0	2
RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE	1	0	0	0	0	0	1	0	2
TOTAL PUBLICATIONS IN TOP 25 JOURNALS	8	3	7	11	17	12	26	19	103
TOTAL PUBLICATIONS IN DATASET	13	10	10	26	40	38	52	55	244

5	4	3	2	1	0	Publications

In Table 4, ordered first by h-Index, second by the total number of citations, and third by the total number of publications on this research subject, we can see clearly that the Journal "*EXPERT SYSTEMS WITH APPLICATIONS*" is the most influential one, according to its h-Index (11), owning the highest number of papers about the research subject (13) and the highest number of citations (661), and being second in terms of the ratio between citations and publications, with a value of 50.85. This journal is also one of the two unique members of the list with a paper having more than 100 citations, i.e., "Risk assessment in social lending via random forests". R denotes the rank, while Name refers to the journal or source title. The h-Index is represented by h, and TC signifies the total number of citations. TP stands for the total number of papers published. The ratio of total citations to total published papers is expressed as TC/TP. The number of papers with more than 100, 50, 25, and 10 citations is indicated as >100, >50, >25, and >10, respectively. IF represents the 2023 impact factor, and 5-IF denotes the five-year impact factor.

Table 2. Publication trends by journal (top 25 between 2021 and 2024).

	2021	*2022*	*2023*	*2024*	*TOTALS*	*VAR (+/−)*
EXPERT SYSTEMS WITH APPLICATIONS	0	4	2	1	7	
ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE	0	0	3	3	6	
SUSTAINABILITY	0	0	4	2	6	
IEEE ACCESS	2	2	0	2	6	
APPLIED SOFT COMPUTING	2	0	2	1	5	
RISKS	2	1	1	1	5	+3
ARTIFICIAL INTELLIGENCE REVIEW	0	0	3	1	4	−1
STOCHASTIC ENVIRONMENTAL RESEARCH & RISK ASSESSMENT	1	1	1	1	4	−1
SCIENTIFIC REPORTS	0	0	1	3	4	−1
RISK ANALYSIS	0	1	1	2	4	+3
SENSORS	0	2	0	1	3	+1
JOURNAL OF CLEANER PRODUCTION	1	0	1	0	2	+5
SOCIETY	2	0	0	0	2	+5
RELIABILITY ENGINEERING & SYSTEM SAFETY	1	0	0	1	2	+5
NEURAL COMPUTING & APPLICATIONS	1	1	0	0	2	+7
REMOTE SENSING	1	0	1	0	2	−2
PATTERNS	2	0	0	0	2	+6
INDUSTRIAL MANAGEMENT & DATA SYSTEMS	1	0	1	0	2	−3
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	0	0	1	0	1	−9
SAFETY SCIENCE	1	0	0	0	1	−9
TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE	0	0	1	0	1	−1
COMPLEX & INTELLIGENT SYSTEMS	0	0	1	0	1	−1
DECISION SUPPORT SYSTEMS	0	0	1	0	1	+1
RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE	0	0	1	0	1	+1
NANOTOXICOLOGY	0	0	0	0	0	−9
TOTAL PUBLICATIONS IN TOP 25 JOURNALS	17	12	26	19	74	
TOTAL PUBLICATIONS IN DATASET	40	38	52	55	185	

6	5	4	3	2	1	0	Publications

Table 3. Publication trends by publisher (top 5 between 2021 and 2024).

	2021	2022	2023	2024	TOTALS	Journal's h-Index > 1
MDPI	6	5	8	12	31	4
ELSEVIER	8	2	6	10	26	1
SPRINGER	3	4	6	7	20	4
PERGAMON-ELSEVIER SCIENCE LTD	0	4	5	4	13	2
WILEY	1	3	3	2	9	1

The rest of the journals have five or fewer publications on this research subject.

If we look at the number of citations, the top five Journals are "*EXPERT SYSTEMS WITH APPLICATIONS*", "*APPLIED SOFT COMPUTING*", "*ARTIFICIAL INTELLIGENCE REVIEW*" (containing another paper with more than 100 citations, "Financial credit risk assessment: a recent review"), "*EUROPEAN JOURNAL OF OPERATIONAL RESEARCH*", and "*SAFETY SCIENCE*", all with more than 100 citations.

Table 4. The 25 most productive and influential journals on artificial intelligence risk assessment in businesses.

R	Row Labels	h	TC	TP	TC/TP	>100	>50	>25	>10	IF (2023)	5-IF
1	*EXPERT SYSTEMS WITH APPLICATIONS*	11	661	13	50.85	1	4	1	5	7.5	7.6
2	*APPLIED SOFT COMPUTING*	5	156	4	39.00	0	1	1	0	7.2	7
3	*ARTIFICIAL INTELLIGENCE REVIEW*	4	198	4	49.50	1	0	2	1	10.7	11.7
4	*EUROPEAN JOURNAL OF OPERATIONAL RESEARCH*	4	130	3	43.33	0	1	1	2	6	5.9
5	*SAFETY SCIENCE*	4	129	3	43.00	0	0	3	0	4.7	5.3
6	*STOCHASTIC ENVIRONMENTAL RESEARCH AND RISK ASSESSMENT*	4	78	5	15.60	0	1	0	0	3.9	3.6
7	*ENGINEERING APPLICATIONS OF ARTIFICIAL INTELLIGENCE*	4	43	5	8.60	0	0	0	1	7.5	7.4
8	*SENSORS*	3	81	3	27.00	0	0	2	0	3.4	3.7
9	*SUSTAINABILITY*	3	39	5	7.80	0	0	0	2	3.3	3.6
10	*IEEE ACCESS*	3	29	5	5.80	0	0	0	1	3.4	3.7
11	*NANOTOXICOLOGY*	2	77	2	38.50	0	0	2	0	3.6	4.6
12	*SCIENTIFIC REPORTS*	2	68	5	13.60	0	1	0	0	3.8	4.3
13	*JOURNAL OF CLEANER PRODUCTION*	2	63	1	63.00	0	0	1	1	9.7	10.2
14	*SOCIETY*	2	52	2	26.00	0	0	1	1	1.4	0.9
15	*RELIABILITY ENGINEERING & SYSTEM SAFETY*	2	52	2	26.00	0	0	1	0	9.4	8.1
16	*TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*	2	50	1	50.00	0	0	1	0	12.9	13
17	*COMPLEX & INTELLIGENT SYSTEMS*	2	49	1	49.00	0	0	1	1	5	5.2
18	*NEURAL COMPUTING & APPLICATIONS*	2	48	2	24.00	0	0	1	1	4.5	4.7
19	*REMOTE SENSING*	2	46	3	15.33	0	0	1	1	4.2	4.9
20	*PATTERNS*	2	37	2	18.50	0	0	0	1	6.7	6.6
21	*INDUSTRIAL MANAGEMENT & DATA SYSTEMS*	2	34	3	11.33	0	0	0	2	4.2	5.4
22	*DECISION SUPPORT SYSTEMS*	2	32	2	16.00	0	0	1	0	6.7	7.5
23	*RESEARCH IN INTERNATIONAL BUSINESS AND FINANCE*	2	28	2	14.00	0	0	0	1	6.3	5.8
24	*RISKS*	2	20	4	5.00	0	0	0	0	2	1.7
25	*RISK ANALYSIS*	2	19	3	6.33	0	0	0	1	3	3.5

"*ARTIFICIAL INTELLIGENCE REVIEW*", with 198 citations, is the one with the second highest impact factor in the list (both in 2023, 10.7, and in the 5 last years, 11.7) of this top five, and "*SAFETY SCIENCE*", the one with a lower impact factor (4.7 and 5.3 for 2023 and for the 5 last years, respectively).

Based on these data, we can consider these top five journals to be the most productive and influential ones.

A special mention should be made regarding "*TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*", in 16th position, "*JOURNAL OF CLEANER PRODUCTION*", ranked in 13th position, and "*ARTIFICIAL INTELLIGENCE REVIEW*", ranked third, as the three journals with the highest impact factor in the list. Note that this impact factor is not focused on the subject of our research, but it is general.

4.2. Evolution of Published Articles

As we could expect after the previous analysis, the number of published articles and citations is low compared to the bibliometric analysis conducted for other topics, showing that this topic has not been a main topic in scientific research until recent years.

A chart was elaborated to identify whether the research on this area was stable or increasing (or decreasing).

In Figure 2, we can see that the annual number of publications has been increasing since 2018, with a Compound Annual Growth Rate (CAGR) of 31.20% calculated from 2018 to 2024 inclusive.

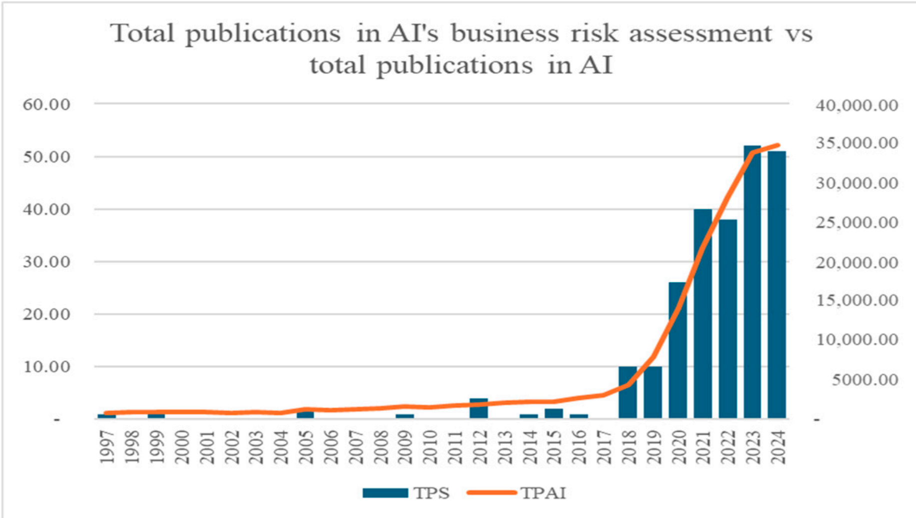

Figure 2. Number of annual publications according to WoS Core Collection query on artificial intelligence's business risk assessment (TPS) vs. annual publications in AI (TPAI).

We can benchmark this CAGR with the one from the results of a more general query "ARTIFICIAL INTELLIGENCE" in WoS Core Collection between 2018 and 2024 and with the other restrictions applied to make it comparable, i.e., 41.15%. So, a part of our research subject CAGR could be explained by the CAGR of research in the artificial intelligence subject, although we can take account of two additional considerations:

- While the CAGR of publications in the period between 1997 and 2017 of the search term "artificial intelligence" was 5.14%, the CAGR of publications in the same period of our search terms was 0%.
- On the other hand, analyzing the correlation between publications on "artificial intelligence" and publications analyzed in this paper, we can find a correlation of 0.99 with a p-value < 0.001, so we can consider it is very correlated.

In Figure 2 we can see the compared data:

In any case, we can consider that the interest in this topic has increased, especially since 2018. The first paper on this research subject was published in 1997 (42 years after the first mention of artificial intelligence, in 1955 [41]).

Note that the youth of this research topic, while justifying the importance of this paper's research, is why, in most of the tables, we can see lower productivity and influence measurements compared to other research topics with a longer life in scholar terms. That is the reason we built Table 5, allowing readers to compare the period between 2018 and 2024 with the whole dataset results.

Table 5 shows that 94.67% of the papers on this research topic were published in the period between 2018 and 2024, and 83.5% of the papers with more than 20 citations were published in 2018–2024 period as well.

This is the reason why, in specific parts of this paper, when appropriate, we made a distinction between these two periods.

Table 5. General citation structure on artificial intelligence risk assessment in businesses in WOS database.

Citations	All Time		2018–2024	
	Number of Papers	% Papers	Number of Papers	% Papers
>200 citations	3	1.230	1	0.433
>100 citations	2	0.820	1	0.433
>50 citations	13	5.328	10	4.329
>20 citations	41	16.803	37	16.017
≤20 citations	185	75.820	182	78.788
Total	244	100.000	231	100.000

4.3. The Most Influential Articles

The next step in the performance analysis is to identify the most influential articles on this subject so far. With this aim, Table 6 was built, ranking the 30 articles with the biggest number of citations, also calculating the citations per year in the whole period to include a relative indicator that allows for comparison of the influence of each article independently from the year it was published.

The most cited paper in the dataset we are analyzing was published by Wang, Yongqiao et al. [42], followed closely by papers by Malekipirbazari and Aksakalli [43] and Liao et al. [44].

These should, therefore, be considered the most influential studies in the business risk assessment of artificial intelligence.

On the other hand, if we look at the number of citations per year, the most important paper was published very recently, in 2022, and appears in fourth position in our list [45], another symptom of the youth of the research topic our paper is analyzing. The second paper in the top 30 was the aforementioned paper by Liao et al., and the third was by Malekipirbazari and Aksakalli [43], with 25.89 citations per year.

So, in relative terms of citations per year, the paper by Sun et al. should be considered the most influential paper, while in absolute terms of the total number of citations, the Wang, Yongqiao, et al. 2005 paper should be the most influential paper.

Additionally, Table 6 shows that five of the most cited papers correspond with the most influential journal in Table 4, "*EXPERT SYSTEMS WITH APPLICATIONS*".

The five journals that concentrate the majority of citations in Table 6 are, in this order, "*EXPERT SYSTEMS WITH APPLICATIONS*", "*IEEE TRANSACTIONS ON FUZZY SYSTEMS*", "*INTERNATIONAL JOURNAL OF FUZZY SYSTEMS*", "*ARTIFICIAL INTELLIGENCE REVIEW*", and "*APPLIED SOFT COMPUTING*". These thirty papers gather 2180 citations, 59.94% of the total citations in the dataset.

The three journals that concentrate the highest number of papers in Table 6 are, in this order, "*EXPERT SYSTEMS WITH APPLICATIONS*", "*SAFETY SCIENCE*", and "*APPLIED SOFT COMPUTING*", but the fact is that, actually, the thirty most influential papers of Table 6 are very scattered in up to twenty-four different journals.

Finally, if we look at the WoS h-Index of both corresponding authors, Sun has an h-Index of seven and Wang has an h-Index of one, again a symptom of the freshness of this research field (Malekipirbazari, the corresponding author of the second paper in the list, has an h-Index of ten). The exception is Liao, the corresponding author of the paper in third position, who has an h-Index of seventy-two.

Table 6. The 30 most cited papers on artificial intelligence risk assessment in businesses.

R	Journal	TC	Title	Author/s	Year	C/Y
1	*IEEE TRANSACTIONS ON FUZZY SYSTEMS*	247	A new fuzzy support vector machine to evaluate credit risk [42]	WANG YQ; WANG SY; LAI KK	2005	13.00
2	*EXPERT SYSTEMS WITH APPLICATIONS*	233	Risk assessment in social lending via random forests [43]	MALEKIPIRBAZARI M; AKSAKALLI V	2015	25.89
3	*INTERNATIONAL JOURNAL OF FUZZY SYSTEMS*	216	Hesitant fuzzy linguistic term set and its application in decision making: a state-of-the-art survey [44]	LIAO HC; XU ZS; HERRERA-VIEDMA E; HERRERA F	2018	36.00
4	*IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING*	122	Predicting citywide crowd flows in irregular regions using multi-view graph convolutional networks [45]	SUN JK; ZHANG JB; LI QF; YI XW; LIANG YX; ZHENG Y	2022	61.00
5	*ARTIFICIAL INTELLIGENCE REVIEW*	106	Financial credit risk assessment: a recent review [46]	CHEN N; RIBEIRO B; CHEN A	2016	13.25
6	*EXPERT SYSTEMS WITH APPLICATIONS*	87	Improving returns on stock investment through neural network selection [47]	QUAH TS; SRINIVASAN B	1999	3.48
7	*EXPERT SYSTEMS WITH APPLICATIONS*	85	Exploring the behaviour of base classifiers in credit scoring ensembles [48]	MARQUÉS AI; GARCÍA V; SÁNCHEZ JS	2012	7.08
8	*APPLIED SOFT COMPUTING*	78	Dynamic ensemble classification for credit scoring using soft probability [49]	FENG XD; XIAO Z; ZHONG B; QIU J; DONG YX	2018	13.00
9	*EXPERT SYSTEMS WITH APPLICATIONS*	74	Two-level classifier ensembles for credit risk assessment [50]	MARQUÉS AI; GARCÍA V; SÁNCHEZ JS	2012	6.17
10	*COGNITIVE SYSTEMS RESEARCH*	72	Enterprise credit risk evaluation based on neural network algorithm [51]	HUANG XB; LIU XL; REN YQ	2018	12.00
11	*NANOMATERIALS*	63	Practices and trends of machine learning application in nanotoxicology [52]	FURXHI I; MURPHY F; MULLINS M; ARVANITIS A; POLAND CA	2020	15.75
12	*EUROPEAN JOURNAL OF OPERATIONAL RESEARCH*	63	Unsupervised quadratic surface support vector machine with application to credit risk assessment [53]	LUO J; YAN X; TIAN Y	2020	15.75
13	*EXPERT SYSTEMS WITH APPLICATIONS*	62	A novel tree-based dynamic heterogeneous ensemble method for credit scoring [54]	XIA YF; ZHAO JH; HE LY; LI YG; NIU MY	2020	15.50
14	*INTERNATIONAL JOURNAL OF MANAGING PROJECTS IN BUSINESS*	61	A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies cost overrun in construction projects [55]	AFZAL F; SHAO YF; NAZIR M; BHATTI SM	2021	20.33
15	*STOCHASTIC ENVIRONMENTAL RESEARCH AND RISK ASSESSMENT*	58	Short term rainfall-runoff modelling using several machine learning methods and a conceptual event-based model [56]	ADNAN RM; PETROSELLI A; HEDDAM S; SANTOS CAG; KISI O	2021	19.33

Table 6. *Cont.*

R	Journal	TC	Title	Author/s	Year	C/Y
16	*SCIENTIFIC REPORTS*	57	Objective risk stratification of prostate cancer using machine learning and radiomics applied to multiparametric magnetic resonance images [57]	VARGHESE B; CHEN F; HWANG D; PALMER SL; ABREU ALD; UKIMURA O; ARON M; ARON M; GILL I; DUDDALWAR V; PANDEY G	2019	11.40
17	*INTERNATIONAL JOURNAL OF MACHINE LEARNING AND CYBERNETICS*	57	Improved TODIM method for intuitionistic fuzzy MAGDM based on cumulative prospect theory and its application on stock investment selection [58]	ZHAO MW; WEI GW; WEI C; WU J	2021	19.00
18	*PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA*	57	The hemispheric contrast in cloud microphysical properties constrains aerosol forcing [59]	MCCOY IL; MCCOY DT; WOOD R; REGAYRE L; WATSON-PARRIS D; GROSVENOR DP; MULCAHY AP; HU YX; BENDER FAM; FIELD PR; CARSLAW KS; GORDON H	2020	14.25
19	*APPLIED SOFT COMPUTING*	50	A machine learning approach combining expert knowledge with genetic algorithms in feature selection for credit risk assessment [60]	LAPPAS PZ; YANNACOPOULOS AN	2021	16.67
20	*BUSINESS HORIZONS*	50	Cybersecurity: risk management framework and investment cost analysis [61]	LEE I	2021	16.67
21	*JOURNAL OF FORECASTING*	49	Application of machine learning methods to risk assessment of financial statement fraud: evidence from China [62]	SONG XP; HU ZH; DU JG; SHENG ZH	2014	4.90
22	*SAFETY SCIENCE*	49	Machine learning in occupational accident analysis: a review using science mapping approach with citation network analysis [63]	SARKAR S; MAITI J	2020	12.25
23	*NANOTOXICOLOGY*	49	Nanotoxicology data for *in silico* tools: a literature review [64]	FURXHI I; MURPHY F; MULLINS M; ARVANITIS A; POLAND CA	2020	12.25
24	*TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*	46	Machine learning and credit ratings prediction in the age of fourth industrial revolution [65]	LI JP; MIRZA N; RAHAT B; XIONG DP	2020	11.50
25	*COMPUTER LAW & SECURITY REVIEW*	45	Principles and business processes for responsible AI [66]	CLARKE R	2019	9.00
26	*SAFETY SCIENCE*	43	A machine learning approach for monitoring ship safety in extreme weather events [67]	RAWSON A; BRITO M; SABEUR Z; TRAN-THANH L	2021	14.33
27	*RELIABILITY ENGINEERING & SYSTEM SAFETY*	43	The value of meteorological data in marine risk assessment [68]	ADLAND R; JIA HY; LODE T; SKONTORP J	2021	14.33
28	*NORTH AMERICAN JOURNAL OF ECONOMICS AND FINANCE*	41	A comparative study of forecasting corporate credit ratings using neural networks, support vector machines, and decision trees [69]	GOLBAYANI P; FLORESCU I; CHATTERJEE R	2020	10.25

Table 6. *Cont.*

R	Journal	TC	Title	Author/s	Year	C/Y
29	*SENSORS*	40	Secure smart wearable computing through artificial intelligence-enabled internet of things and cyber-physical systems for health monitoring [70]	RAMASAMY LK; KHAN F; SHAH MHM; PRASAD BVVS; IWENDI C; BIAMBA C	2022	20.00
30	*JOURNAL OF CLEANER PRODUCTION*	40	Development of flood hazard map and emergency relief operation system using hydrodynamic modeling and machine learning algorithm [71]	RAHMAN M; CHEN NS; ISLAM MM; MAHMUD GI; POURGHASEMI HR; ALAM M; RAHIM MA; BAIG MA; BHATTACHARJEE A; DEWAN A	2021	13.33

4.4. The Most Prolific and Influential Authors

The next ranking shows the most prolific and influential authors. It was elaborated based on the number of publications of the authors on the risk assessment of artificial intelligence in business.

Table 7 details these authors and their production, along with the number of citations, the local h-Index (elaborated with the data collected), and the global h-Index (taken directly from the WoS database).

Table 7. The 20 most productive and influential authors on artificial intelligence risk assessment in businesses.

R	Author's Name	Institution	Country	Local h-Index	Global h-Index	TC	TP	TC/TP	≥ 50	≥ 20	≥ 10
1	MULLINS, M	Univ Limerick	Ireland	4	21	155	4	38.75	1	2	1
2	GARCIA, V.	Univ Jaume 1	Spain	3	23	180	3	60.00	2	1	0
3	MARQUES, A. I.	Univ Jaume 1	Spain	3	34	180	3	60.00	2	1	0
4	SANCHEZ, J. S.	Univ Jaume 1	Spain	3	31	180	3	60.00	2	1	0
5	FURXHI, I	Univ Limerick	Ireland	3	12	140	3	46.67	1	2	0
6	MURPHY, F	Univ Limerick	Ireland	3	23	140	3	46.67	1	2	0
7	POLAND, CA	ELEGI/Colt Laboratory	Scotland	3	27	140	3	46.67	1	2	0
8	GOH, M	Natl Univ Singapore	Singapore	3	49	78	3	26.00	0	2	1
9	RAO, CJ	Wuhan Univ Technol	Peoples' R China	3	20	78	3	26.00	0	2	1
10	HERRERA-VIEDMA, E	Univ Granada	Spain	2	101	283	3	94.33	1	2	0
11	XU, ZS	Sichuan University	Peoples' R China	2	125	256	3	85.33	1	1	0
12	LIAO, HC	Sichuan University	Peoples' R China	2	72	225	2	112.50	1	0	0
13	CHEN, A	Chinese Acad Sci	Peoples' R China	2	10	144	2	72.00	1	1	0
14	CHEN, N	Beijing City Univ	Peoples' R China	2	21	144	2	72.00	1	1	0
15	ARVANITIS, A	Aristotle University of Thessaloniki	Greece	2	11	112	2	56.00	1	1	0
16	PETROSELLI, A	Univ Tuscia	Italy	2	31	66	2	33.00	1	0	0
17	BRITO, M	Univ Southampton	England	2	16	61	3	20.33	0	1	1
18	XIAO, XP	Wuhan Univ Technol	Peoples' R China	2	26	61	2	30.50	0	2	0
19	ARON, M	University of Southern California	USA	2	26	57	1	57.00	1	0	0
20	RAWSON, A	Univ Southampton	England	2	9	56	2	28.00	0	1	1

Abbreviations are the same as in Tables 1 and 3. h-Index is calculated from the dataset (local) and as indicated by WoS (global).

To complete the data, this table includes the authors' affiliation to an institution and the country indicated in the WoS database.

Data are ordered first by local h-Index, second by total number of citations, and third by the total number of publications.

Global h-Index is not used in the order because it is not based on the dataset obtained and does not depend on it, although it is considered an additional value that should be considered for our analysis.

A share of 53.33% of the citations in Table 7 is concentrated on the seven authors with more citations, "HERRERA-VIEDMA, E", "XU, ZS", "LIAO, HC", "GARCIA, V", "MARQUES, A. I", "SANCHEZ, J. S", and "MULLINS, M".

None of the authors with the highest local h-Index are from the U.S.A., with China being first in the ranking, with six authors, followed by Spain with four authors and Ireland with three authors, in the first 20. These last three countries have 13 of 20 authors with the highest local h-Index. By looking at the whole dataset, we find the first U.S.A. author in position 19th, "ARON, M", with a local h-Index of 2, as for others in the table, and with 57 citations for two publications and a global h-Index of 26.

Despite that, note that there is an important overlap between some of the authors: MARQUEZ, SANCHEZ, and GARCIA published together all their papers in the dataset, and the same happened with POLAND, MURPHY, and FURXHI (and partially MULLINS and ARVANITIS).

This could be understood as a consequence of being a very specialized research subject, with few people highly cited. Note anyway that, while the publications of the second group ranged from 2019 to 2020, the three publications of the first group are from 2012.

The publications of the other Spanish author, HERRERA-VIEDMA, are more stable in time, with the first in 2018 and the last in 2023, and were made in collaboration with people from China, the country with most of the authors in the list.

4.5. The Most Productive and Influential Institutions

This paper provides another interesting ranking comparing the production and influence of institutions. Note that different authors in the same paper could be linked to different entities.

We can see the results in Table 8, ordered first by the h-Index, representing the influence of each institution, second by the total number of citations (TC), and third by the total number of publications, satisfying the criteria indicated in Section 3.

In this case, Table 5 includes the position of the institution in two well-known rankings, ARWU (Shanghai Academic Ranking of World Universities) and QS (Quacquarelli Symonds World University Rankings). In cases where the institution is not in any of these rankings, we put two hyphens "--" representing this situation.

Finally, the table includes a ratio ($\times$1000) between the total number of publications that meet the requirements of this paper (TPS) and the total number of publications of each institution, to put it in relative terms (some institutions can produce more papers in risk assessment of artificial intelligence in business, but they can produce more papers in general due to their type or size, for example).

The third institution in terms of influence (h-Index and citations) and production (number of publications included in our research) in the table is "KING ABDULAZIZ UNIVERSITY" from Saudi Arabia, followed by "NATIONAL UNIVERSITY OF SINGAPORE", and "UNIVERSITY OF EDINBURGH" from the United Kingdom.

These top five institutions represent 43.02% of the total citations and 34.34% of the publications in Table 8.

In these data, as well, the youth (and the specialization) of the research subject is evident; the former because of small values of publications and citations compared to more extended topics, and the latter because the papers of these institutions published in the research subject only represent 0.019‰ of the papers these institutions have published in the same period.

Table 8. The 25 most productive and influential institutions on artificial intelligence risk assessment in businesses.

R	Institution	Country	h	TC	TPS	TC/ TPS	≥ 50	≥ 20	≥ 10	ARWU	QS	TP	TPS/TP ×1000
1	SICHUAN UNIVERSITY	People's R China	7	330	9	36.67	1	2	2	98	336	160,468	0.06
2	CHINESE ACADEMY OF SCIENCES (1)	People's R China	6	458	8	57.25	2	2	2	--	--	1,112,433	0.01
3	KING ABDULAZIZ UNIVERSITY	Saudi Arabia	4	301	7	43.00	1	2	1	201–300	149	73,484	0.10
4	NATIONAL UNIVERSITY OF SINGAPORE	Singapore	4	200	5	40.00	1	2	1	68	8	218,642	0.02
5	UNIVERSITY OF EDINBURGH	United Kingdom	4	193	5	38.60	1	3	0	40	27	224,252	0.02
6	UNIVERSITY OF LIMERICK	Ireland	4	155	4	38.75	1	2	1	801–900	421	25,434	0.16
7	HOHAI UNIVERSITY	People's R China	4	117	4	29.25	1	2	0	401–500	1001–1200	42,736	0.09
8	UNIVERSITY OF CHINESE ACADEMY OF SCIENCES, CAS (1)	People's R China	4	105	5	21.00	0	2	2	--	--	303,004	0.02
9	UNIVERSITY OF NEW SOUTH WALES SYDNEY	Australia	4	85	6	14.17	0	1	3	77	19	210,937	0.03
10	SOLENT UNIVERSITY	United Kingdom	4	78	4	19.50	0	1	2	--	--	2476	1.62
11	UNIVERSITY OF SOUTHAMPTON	United Kingdom	4	78	4	19.50	0	1	2	151–200	80	152,444	0.03
12	UNIVERSITY OF GRANADA	Spain	3	286	4	71.50	1	2	0	301–400	431	84,885	0.05
13	UNIVERSITAT JAUME I	Spain	3	180	3	60.00	2	1	0	601–700	--	2020	1.49
14	STOCKHOLM UNIVERSITY	Sweden	3	81	3	27.00	1	0	2	101–150	153	86,128	0.03
15	WUHAN UNIVERSITY OF TECHNOLOGY	People's R China	3	78	3	26.00	0	2	1	201–300	801–850	56,434	0.05
16	HENAN POLYTECHNIC UNIVERSITY	People's R China	2	144	2	72.00	1	1	0	901–1000	--	18,054	0.28
17	SOUTHWESTERN UNIVERSITY OF FINANCE AND ECONOMICS—CHINA	People's R China	2	122	5	24.40	2	0	0	701–800	--	8196	0.61
18	INSTITUTO POLITECNICO DO PORTO	Portugal	2	116	2	58.00	1	0	1	--	--	12,706	0.16
19	DONGBEI UNIVERSITY OF FINANCE AND ECONOMICS	People's R China	2	96	3	32.00	1	1	0	--	--	3096	0.97
20	TUSCIA UNIVERSITY	Italy	2	66	2	33.00	1	0	0	901–1000	901–950	11,017	0.18
21	UNIVERSITY OF GLASGOW	United Kingdom	2	39	2	19.50	0	1	1	101–150	78	170,885	0.01
22	KAUNAS UNIVERSITY OF TECHNOLOGY	Lithuania	2	38	2	19.00	0	1	1	--	751–760	13,873	0.14
23	RUTGERS UNIVERSITY NEW BRUNSWICK	USA	2	35	3	11.67	0	1	0	101–150	328	245,099	0.01
24	KHALIFA UNIVERSITY OF SCIENCE AND TECHNOLOGY	United Arab Emirates	2	35	2	17.50	0	1	0	601–700	202	18,613	0.11
25	WUHAN INSTITUTE OF TECHNOLOGY	People's R China	2	29	2	14.50	0	1	0	901–1000	--	11,710	0.17

A total of 15 entities from the list of 25 are positioned in all the university rankings included, and 14 entities from the list of 20 are ranked in the top 500 in some of the university rankings included.

In Figure 3, we can see clearly the novelty of this field, with papers cited between the top 22 institutions ranging from 2018 to 2024. The first of the four clusters identified by VOSviewer comprises Chinese Academy of Sciences, Dalian University of Technology, Dongbei University of Finance and Economics, and Universitat Jaume I; the second cluster is formed by Sichuan University, Rutgers University-New Brunswick, and King Abdulaziz University; the third one is composed of the University of Edinburgh, the University of Limerick, and Sejong University; and finally the fourth one holds the National University of Singapore, the Southwestern University of Finance, and Wuhan Technology School.

Again, we see that institutions from China are the most prolific and influential, with 7 Chinese institutions included, accounting for a total of 1479 citations and 41 papers, led by "SICHUAN UNIVERSITY" in first place, followed by "CHINESE ACADEMY OF SCIENCES" in second place and "UNIVERSITY OF CHINESE ACADEMY OF SCIENCES, CAS" in third place. Although the names are similar and they have strong links, we preferred to keep separate the Chinese Academy of Sciences and the University of Academy of Sciences, run by the former [72], just as WoS does. That allows the research to respect the exact affiliation indicated by each author.

At Figure 3, the size of the nodes represents the number of citations, while the connection thickness represents the strength of citation relationships; thicker, stronger, and lighter-color lines represent newer activity, and the darker color represents older activity.

So, we can see that Sichuan University is pivotal in this citation network, with its research widely recognized. Other institutions, like Sejong University at the right, could be considered new research leaders, and the Chinese Academy of Sciences and Sichuan University could be especially suitable for collaboration, as they bridge multiple organizations.

4.6. Country Analysis

The following elaborated ranking in Table 9 allows us to compare productivity and influence between countries and see if it is aligned with the previous rankings.

Table 9. The 15 most productive and influential countries in research on artificial intelligence risk assessment in businesses.

R	Country	h	TC	TPS	Pop	TC/Pop	TPS/Pop	≥100	≥50	≥20
1	CHINA	23	1909	96	1422.58	1.342	0.067	4	6	16
2	USA	10	371	23	343.48	1.080	0.067	0	3	5
3	UNITED KINGDOM	8	217	11	68.68	3.159	0.160	0	0	4
4	AUSTRALIA	5	101	8	26.45	3.818	0.302	0	0	1
5	INDIA	5	85	9	1438.07	0.059	0.006	0	0	2
6	IRELAND	4	155	4	5.20	29.827	0.770	0	1	2
7	MALAYSIA	4	63	4	35.13	1.794	0.114	0	0	1
8	ITALY	4	57	5	59.50	0.958	0.084	0	0	1
9	SPAIN	3	186	7	47.91	3.882	0.146	0	2	1
10	SWEDEN	3	67	3	10.55	6.350	0.284	0	0	1
11	PORTUGAL	3	46	3	10.53	4.368	0.285	0	0	1
12	SAUDI ARABIA	3	24	6	33.26	0.721	0.180	0	0	0
13	TURKEY	2	235	2	87.27	2.693	0.023	1	0	0
14	GREECE	2	90	4	10.24	8.787	0.391	0	1	1
15	NORWAY	2	54	3	5.52	9.783	0.543	0	0	1

The abbreviations are the same as in Tables 1 and 3, except for Pop—population (in millions), TPS/Pop—studies per millions of population, and TC/Pop—citations per millions of population.

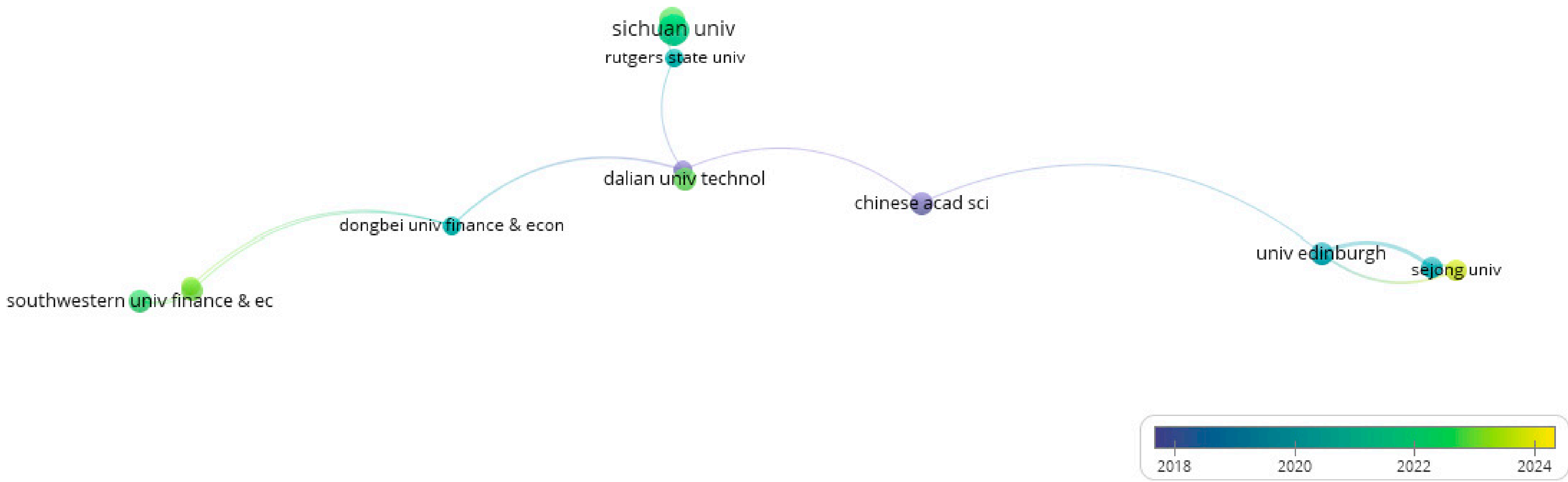

Figure 3. Citations between institutions. Overlay visualization via VOSviewer.

As for the previous ones, it is ordered first by the country's local h-Index, second by the number of citations received, and third by the number of papers published on the research subject, according to the WoS database.

We can see in Table 9 some countries that were identified before, such as China, the U.S.A., the United Kingdom, Australia, Ireland, Italy, Spain, Sweden, Portugal, and Saudi Arabia.

In contrast, there are countries appearing in Table 8 that do not appear in Table 9, such as Singapore, Lithuania, and UAE. This is because other countries have a higher number of active and influential institutions, allowing them to overcome the former in terms of the combination of the h-Index, the number of publications, and the number of citations.

On the other hand, countries appearing in Table 9 for the first time, namely, India, Malaysia, Turkey, Greece, and Norway, have a high number of publications but are highly distributed among different institutions; India, for example, has nine publications from nine different institutions.

These are the reasons why Table 9 has been included in this paper, that is, in order to provide a precise view of the most productive and influential countries.

Countries with larger populations can have some advantages regarding scientific production. To take this into account, the total populations in millions in 2023 according to Our World In Data, a website curated by the University of Oxford [73], have been included, accompanied by the ratios of citations and publications per million inhabitants. Population data for 2024 were not available at the time we wrote this paper.

According to these data, the country with the most publications and citations per inhabitant was Ireland, followed by Norway, Greece, and Australia (all above average).

Additionally, only two countries (China and Turkey) have papers with 100 or more citations, five have papers with 50 or more citations (China, U.S.A., Ireland, Spain, and Greece), and thirteen have papers with 20 or more citations.

Another aspect that this paper evaluates is the diversity of nationalities of the teams that collaborate in each paper. In Figure 4 we can see in green the number of papers that Bibliometrix considers an intra-country collaboration, and in red the number of papers that Bibliometrix considers an inter-country collaboration.

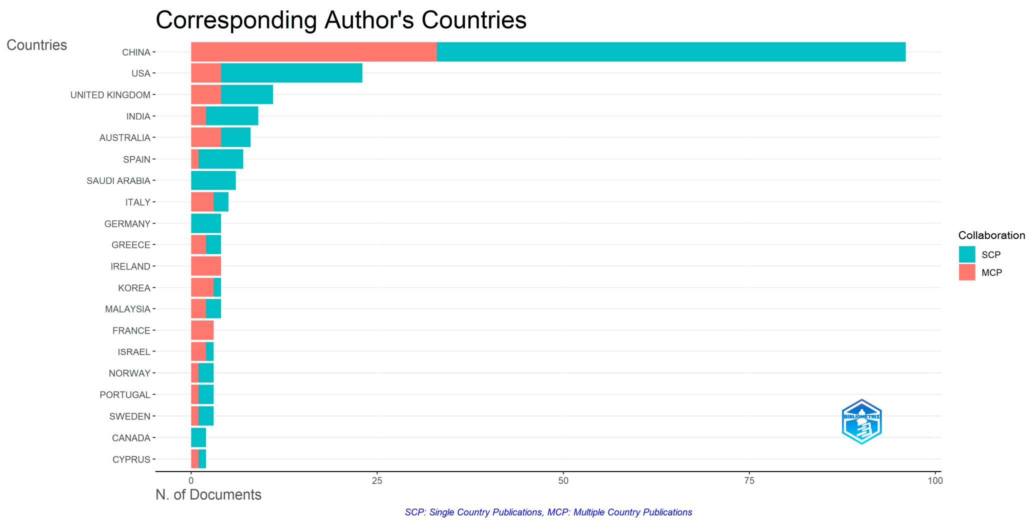

Figure 4. Corresponding author's countries and diversity of nationalities.

The data analyzed show that the total production of French and Irish corresponding authors is in collaboration with other countries, and that when the corresponding author is from Saudi Arabia, Germany, or Canada, all the production is intra-country. This could contribute to the fact that countries with an important AI industry and influence, like Germany or France, are not in Table 9.

The average percentage of inter-country collaboration in the top 20 is 41.32% and 41.75% if we omit the outliers (0% and 100%).

Please note that Bibliometrix uses the corresponding author's country to assign the publication's country. We should be aware of this because, for instance, articles in which Herrera-Viedma, a Spanish author, has collaborated, are assigned to China, as the corresponding author has this nationality. So, we can have articles that contribute to the production or influence of some authors but are assigned to a different country (in the MCP bar).

Figure 5, generated with the Bibliometrix tool, shows graphically the collaboration links between different countries. The thickness of red lines is related to the production of each country, and the lines between different countries show the strength of collaboration between them.

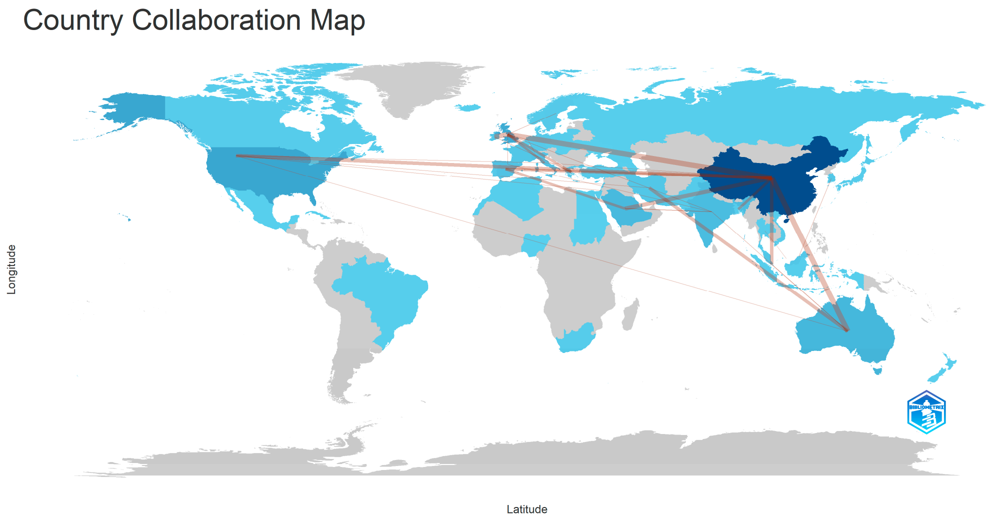

Figure 5. Collaboration between countries.

4.7. Landscapes and Evolution of Artificial Intelligence's Risk Assessment in Business

As we have seen in the previous sections of this paper, the selected subject is very young, scholarly speaking; although this bibliometric analysis has enough data to reach some important conclusions, numbers are very low compared to older subjects.

The landscape in Figure 6, based on the most used words through Keywords Plus, that is, on the frequency that these words appear in the titles of the papers referenced by each publication [74], throws no surprises: "risk-assessment", "model", "classification", "prediction", and "feature-selection" or "performance" constitute the basis of the challenges any AI tool has to deal with, so we can consider the basis is shared with many AI research topics.

If, alternatively, we look at the Bibliometrix treemap using author's keywords in Figure 7, we can see the landscape is slightly different: although we have "machine learning" and "risk assessment" as two of the main keywords, together with "artificial intelligence" and "deep learning", we can see that terms like "credit risk", "credit scoring", and "risk management" now have more importance.

Additionally, if we look in detail at the Bibliometrix list of the 25 most used author's keywords, we can see a new word at the "tail" of the list more related to risk assessment, namely, "cybersecurity".

Figure 6. Bibliometrix 25-word treemap (Keywords Plus).

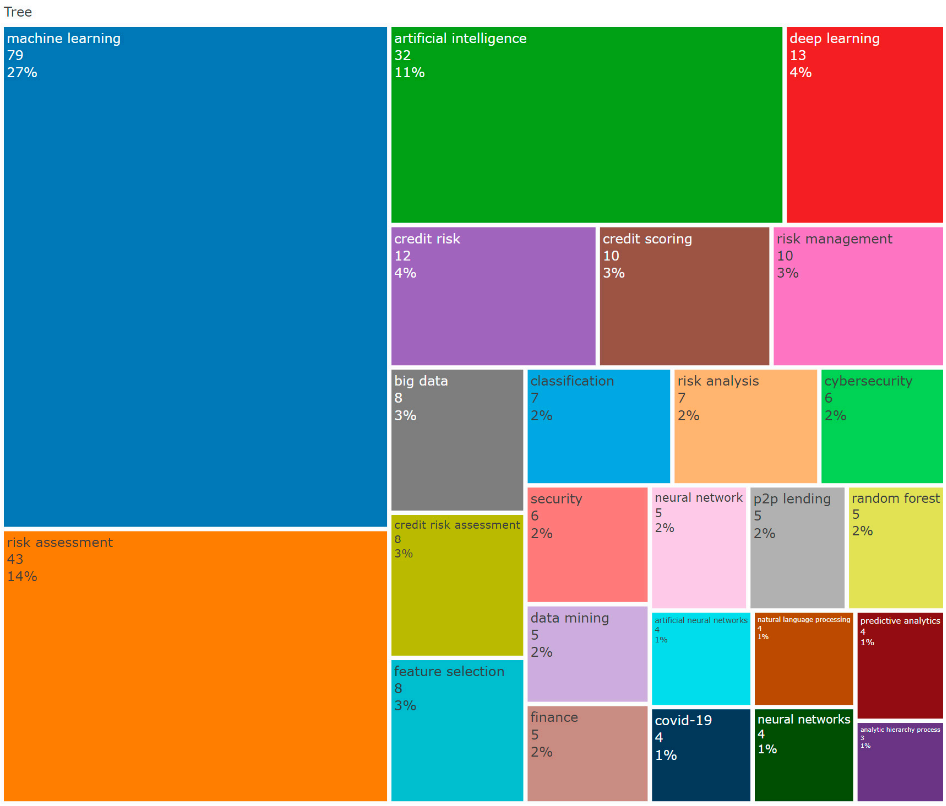

Figure 7. Bibliometrix 25-word treemap (author's keywords).

If we look in Figure 8 at these author's keywords in a chronological way, we can easily see the recent emergence of interest in risk assessment in AI, noting that the peak year was 2023, with 43 occurrences, and is still echoing today. Of course, there are more general terms, such as "machine learning" with a larger size of the bubble (more occurrences), and others, such as "neural network", more present over time, but if we focus on the risk topics, the risk assessment is the most important subject of research.

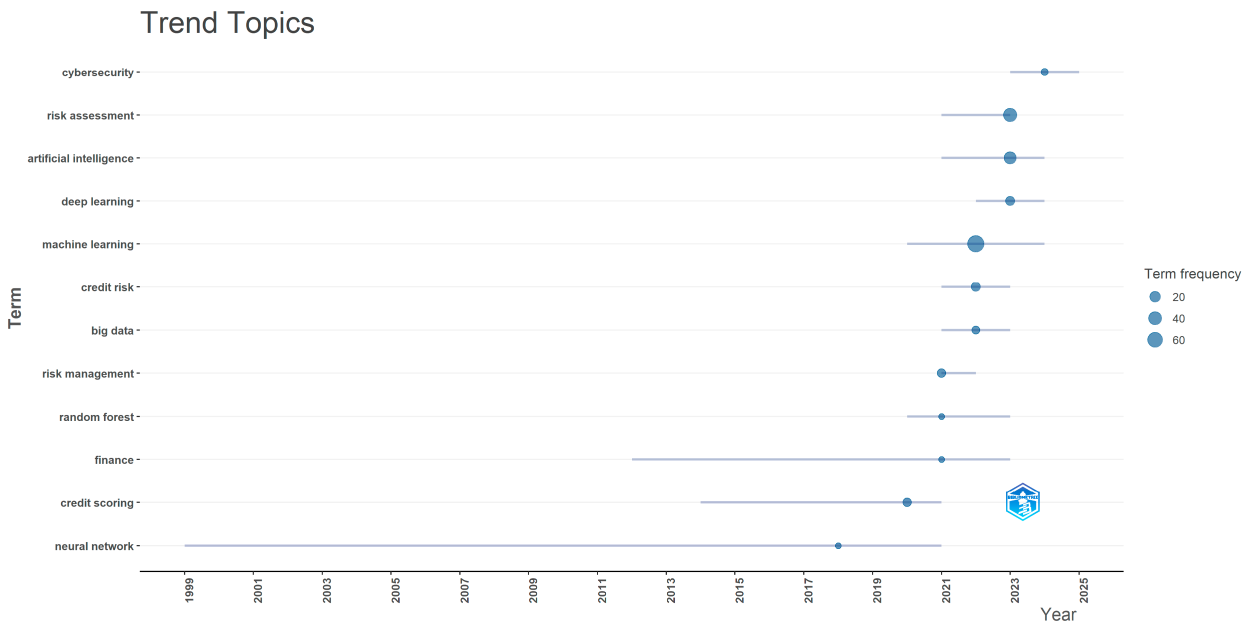

Figure 8. Trends in the co-occurrence of author's keywords over time.

4.8. Current Emerging Issues in Artificial Intelligence's Risk Assessment in Business

This paper uses SciMat to elaborate on the strategic map and identify emerging issues in artificial intelligence risk assessment in business.

The periods are annual between 2018 and 2024, including all the publications returned by the search strategy explained in Section 3. A unique period was allocated comprising years between 1997 and 2017, both inclusive, given that it was an interval with very few publications, i.e., only 13 in total (0.62 publications per year on average, considerably less than in any year from 2018 until 2023).

Taking this into account, Figures 9–11. were elaborated, using the SciMat tool with the following parameters [33]: We chose words as the unit of analysis, including author's words, source words, and added words; we also used a frequency reduction for all the periods of 2; a co-occurrence matrix; network reduction of 2; normalization by an equivalence index; a simple center algorithm as the clustering algorithm, with network size between 3 and 12; a union mapper as document mapper; h-Index and sum of citations as quality measures; an evolution map based on an inclusion index; and Jaccard's index for an overlapping map.

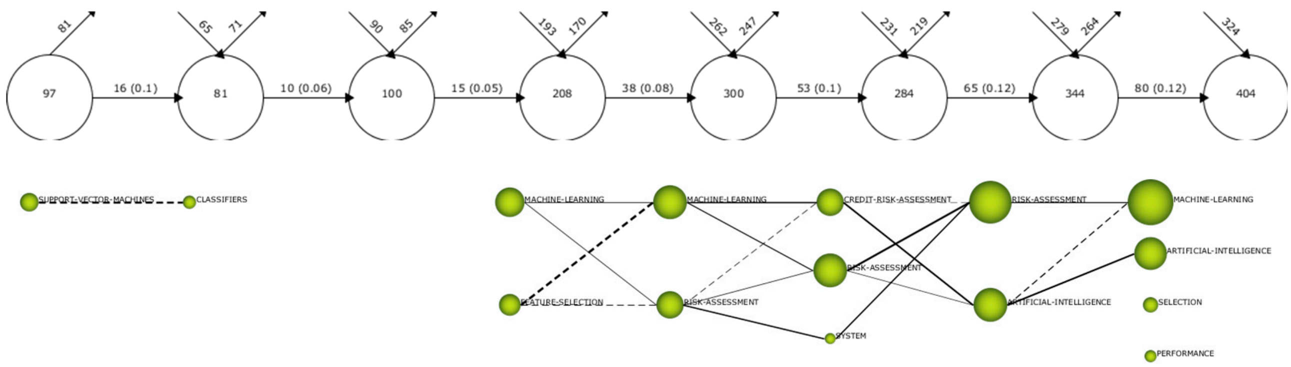

Figure 9. SciMat overlapping map and document count evolution map.

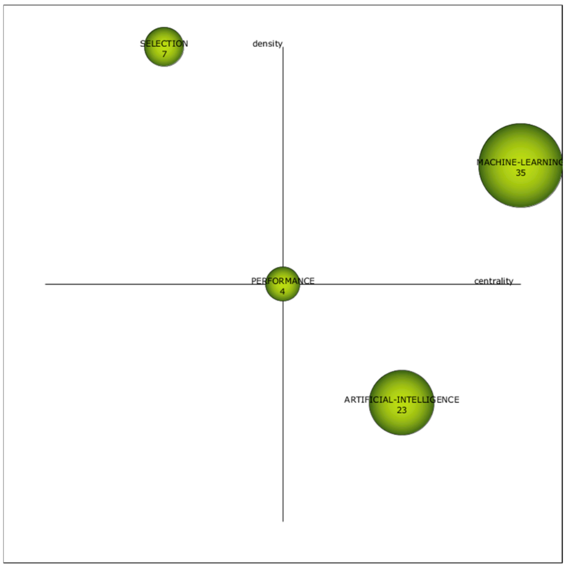

Figure 10. SciMat document count strategic map.

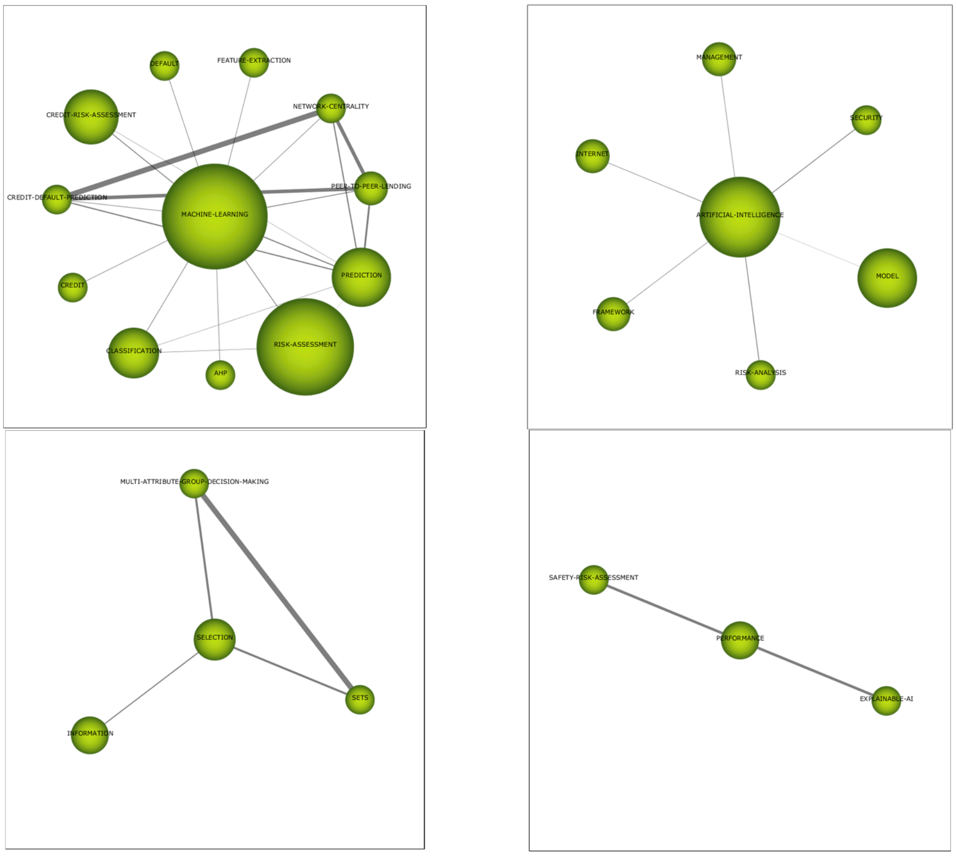

Figure 11. SciMat cluster networks.

We can see in the thematic overlapping map that for each period selected, the number of words entering and exiting is relevant, with similar numbers of words entering and exiting around the research subject; this shows a very dynamic research subject, although a total of 53, 65, and 80 keywords were maintained for periods 2022, 2023, and 2024, respectively. By looking at this progression, we can appreciate a potential progressive stabilization of the research subject.

We can see by looking at the evolution map that in the period between 2021 and 2024, the term "risk assessment" was used frequently in most of the dataset papers, although in

2024 the term does not appear unless looking at the cluster networks of artificial intelligence, machine learning, and performance.

Figure 10 shows the strategic map for the last period analyzed (2024). As Cobo et al. explain [33], this map is divided into quadrants regarding Callon's centrality and density factors. The upper-left quadrant shows the niche of very developed themes (such as selection), the upper-right quadrant shows the motor themes (such as machine learning in this case), and at the lower-right quadrant, corresponding to basic or transversal themes, we can find artificial intelligence, which does not show unexpected results.

Despite this, if we delve into detail in these terms' cluster networks in Figure 11, we can see some interesting findings around the importance of risk assessment and risk analysis, safety, and explainability of artificial intelligence systems.

5. Discussion

This paper identifies the top 25 most productive and influential journals for risk assessment of AI in businesses. The top 13 journals in the list (52%) concentrate 78.95% of the citations, with the top 4 having 51.59% of the citations; so, a certain concentration can be identified, although it is not considered relevant.

Applying the Herfindhal–Hirschman concentration index to evaluate the concentration of the market in specific journals [75] shows that it is not a highly concentrated market (0.12 in citations, 0.06 in papers published).

This paper has also identified an important increase in the number of papers published since 2018 on the research subject of risk assessment of artificial intelligence in business. Note that 2018 is the first year with 10 publications, compared to 9 in the 10 previous years and 13 in total in the 20 previous years.

This increase in the topic "risk assessment in artificial intelligence on business" is consistent with the increase in publications about "artificial intelligence", as we have seen in the results.

This paper also confirms that this subject is a very novel one, with a relevant number of data to enable a bibliometric analysis. However, the number of citations and publications is still far from that of other more mature topics, and is also significantly lower in relation to the total number of publications of the institutions where corresponding authors are affiliated.

The novelty of this research subject signals it as an emerging theme with great potential development opportunities.

This is also evident when we look at the publishing dates of the three most influential articles: 2005, 2015, and 2018, while the term artificial intelligence was coined in 1955. We could say that only in recent years, once the significant progress of artificial intelligence has been recognized, has society started analyzing its risks.

As could be expected in a novel research subject, the local h-Index (calculated within the given dataset) of the 20 most productive and influential authors is very low, ranging in the top 20 between 4 and 2. One interesting finding is that only in the cases of China and Spain can we find very influential authors (by looking at the global h-Index) contributing to the risk assessment of artificial intelligence in business.

We have also identified the most productive and influential institutions, with the ones from China, Spain, and the United Kingdom having the highest number of citations.

When we look at the ranking of the top 15 countries, data are not exactly the same because other countries are more influential and have, in some cases, more publications. However, we see China and the United Kingdom as the leaders, with the U.S.A. also included.

We should note that, with the European Union AI regulation becoming effective on 1 August 2024 [8], other regions are leading the research on AI risk assessment in business instead, although in most cases, these non-EU countries' researchers are collaborating with EU researchers on an inter-country basis.

This is aligned with Bradford's law, claiming that "there are a few very productive periodicals, a larger number of more moderate producers, and a still larger number of constantly diminishing productivity" [76].

Another positive finding in this paper is that explainable AI and cyber security are both part of the emerging concepts related to the research on risk assessment of AI in business, so transparency and security of the AI systems are identified as a clear trend by the results obtained.

According to our research results, a scientist could probably consider China, Spain, and the United Kingdom as the best places to look for research institutions to work with. However, relying solely on quantitative data can be misleading, as AI risk assessment challenges are global, and advances are intertwined across countries and institutions. As the data show, it is not just about which country is leading, but about fostering collaboration and openness to diverse perspectives. While China, Spain, and the UK are leading because of their research throughput, other countries like the US, France, and Germany also contribute significantly to high-quality AI research, particularly due to their strong AI industries. However, the fact that the corresponding author is not of these countries or that the collaboration between these and other countries is rare is penalizing these countries in the overall ranking.

An analogous situation happens when looking solely at journals from MDPI and Elsevier as the most influential for an author to submit his or her work. It is crucial for science to prioritize those journals with strong peer review standards, rigorous editorial policies, and a proven track record of publishing impactful, high-quality work. Therefore, any journal from other publishers meeting these criteria could be a perfectly suitable candidate for submitting research.

At this point, we found several gaps in the research about risk assessment in organizations. For instance, a search for explainable AI in our dataset shows only 11 papers, all between 2021 (1) and 2024 (4), mostly centered on AI in financial (6), medicine (2), and insurance (2) sectors. In a search for standardized AI risk assessment tools, we found NIST AI risk management framework and MIT AI risk database references (2), but none indexed at the WoSCC dataset. Only one of the papers (from 2021) in our dataset [77] deals with corporate digital responsibility (that is, managing opportunities while addressing the related risks of digital transformation, a key to AI adoption), and was cited 38 times according to our dataset. When we searched for "agents", given that agentic AI seems one of the recent fields to be explored, only one result was found. Furthermore, when looking for challenges related to intellectual property, consumer protection, democracy, or multimodal AI risks, zero results were found. In the specific case of explainable AI, we can find works included in the analyzed dataset such as Bharodia and Chen [78], Chen et al. [79], Cho and Shin [80], Pnevmatikakis et al. [81], and Yang et al. [82].

The fact that risk assessment is found inside 2024 SCIMat clusters and not in the evolution map nor in the strategic map could be a symptom of this research subject being strongly associated with artificial intelligence and machine learning, as is the case of "explainable-AI" as well.

We can also identify that the performance of artificial intelligence systems is, in 2024, a focus word and that explainability, safety, and risk assessment are strongly linked to performance research as well (note that these could be antagonistic targets in many cases).

Additionally, we found the relative novelty of this subject, showing only in recent years, once the significant progress of artificial intelligence had been recognized, that society started to analyze its risks in a scientific way. Policy-related facts mentioned in the introduction, such as the emergence of the European AI regulation or the NIST AI Risk Management Framework, could probably be other factors facilitating this surge of studies in the last few years. An additional factor related to the increasing focus on AI has been the appearance of LLM-based conversational generative AI, which has enabled easier access to AI systems for the general public, just as the IBM PC did with computers.

6. Conclusions

The findings of this paper determine which are the most productive and influential references in the research subject of risk assessment of artificial intelligence in business. We have identified the following:

- The evolution of production on the research subject through the years;
- The most cited papers;
- The most productive and most influential journals, authors, institutions, and countries;
- The existing collaboration links between countries;
- The landscape and evolution of the selected research subject;
- The emerging concepts that specialized scholars are now dealing with.

Based on the results and the discussion above, we recommend the following actionable insights for scientists, businesses, and policymakers:

1. Focus on explainable AI: Researchers should prioritize developing and implementing explainable AI (XAI) techniques. This will enhance transparency and trust in AI systems, making it easier for stakeholders to understand and manage AI-driven decisions.
2. Enhance cybersecurity measures: Given the increasing integration of AI in business operations, it is crucial to incorporate robust cybersecurity measures. This includes developing AI systems resilient to cyber threats and maintaining data privacy and security.
3. Interdisciplinary collaboration: Encourage collaboration between AI researchers and experts in cognitive biases, behavioral economics, and organizational psychology. This interdisciplinary approach can provide deeper insights into AI's human and organizational impacts, leading to more comprehensive risk assessments.
4. Policy development: Policymakers should consider the implications of AI risk assessment in their regulatory frameworks. This includes creating guidelines that promote the ethical use of AI and addressing potential risks associated with AI deployment in various sectors. Initiatives like the EU AI Regulation could be a reference for them.
5. Continuous monitoring and adaptation: Businesses should establish mechanisms for continuous monitoring of AI systems to identify and mitigate risks promptly. This involves regular audits, updates to AI models, and adapting to new threats and challenges as they arise. Databases such as that at https://airisk.mit.edu (accessed on 10 January 2025) could be helpful for them.

This research offers interesting findings related to the emerging technologies of human–computer Interaction because although AI is revolutionizing the dynamics of human–computer interaction, this advancement presents a dual-edged sword: as the scientific community initiates rigorous studies on AI risk assessment within organizational contexts, it is imperative to consider critical issues such as data privacy, consumer protection, intellectual property, AI corporate digital responsibility, ethics, multimodal AI risks, bias, and explainable AI. Addressing these factors is essential to ensure the successful integration and interaction of AI systems with human operators.

These challenges, together with the promising line of research in how the social and governmental initiatives, such as regulations and guidelines could have accelerated the scientific progress of AI risk assessment, are signaled as future research directions for our community.

Regarding limitations, it is necessary to state that this study is limited to the WoS Core Collection database. Although this repository is well recognized in all areas, we could expect differences in results and conclusions if another database is used, as discussed in Section 3.

Another issue we have identified is that the results include both the risk assessment of AI in businesses and AI-based risk assessment in businesses. Although that does not reduce the importance of this paper, future research separating both concepts should be interesting for specialized research.

Other interesting future research would be to evaluate the content and significance of key papers or authors as a qualitative analysis or to combine metrics with societal or political impact.

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