

Artificial intelligence and digital trust: a comparative bibliometric analysis of e-reputation research in scopus and web of science (2015-2025)

SABIR Nouhaila

*Doctorante, Ecole Nationale de Commerce et de Gestion, Université Sultan Moulay Slimane
Béni-Mellal-Maroc.*

ELACHHAB Nouhaila

*Doctorante, Ecole Nationale de Commerce et de Gestion, Université Sultan Moulay Slimane
Béni-Mellal-Maroc.*

ELBAZI Ismail

*Professeur d'enseignement supérieur, Ecole Nationale de Commerce et de Gestion,
Université Sultan Moulay Slimane Béni-Mellal-Maroc.*

CHARRASS Abdelmajid

*Professeur d'enseignement supérieur, Ecole Nationale de Commerce et de Gestion,
Université Sultan Moulay Slimane Béni-Mellal-Maroc.*

ABYRE Asmaa

*Professeur d'enseignement supérieur, Ecole Nationale de Commerce et de Gestion,
Université Sultan Moulay Slimane Béni-Mellal-Maroc.*

Correspondence address

ENCG, Université Sultan Moulay Sliman
Béni-mellal- Maroc

Cite this article

SABIR, N, and al. (2026). Artificial intelligence and digital trust: a comparative bibliometric analysis of e-reputation research in scopus and web of science (2015-2025).
International Journal of Economics and Management Sciences,
Volume 5, Issue 4 (2026), pp. 233-254

Submitted: 18/09/2026

Accepted: 14/10/2026

Abstract

In the Digital Age, artificial intelligence, consumer trust and e-reputation are the focus of the factors determining an organization's competitiveness and brand equity. However, there is still no synthesis on a large number of major indexing tools that relates technological infrastructure, perceptions and consumer behavior. This paper analyzes the evolution of studies on AI, e-reputation and consumer trust from 2015 to 2025 with comparative bibliometric design on Scopus (n = 541) and Web of Science (n = 293).

This analysis tracks publication volume by year, measuring prolific authors, publication sources, international co-authorship and keyword co-occurrence clusters. Results show that Scopus is a technological radar focusing on applied algorithms, blockchain verification and machine learning. Web of Science is a filter consolidating theory-driven economic concept, consumer behavior, brand management and relational trust. Consumer trust is the one common bridge that links technological reliability with behavioral commitment. In the end, this study offers a unified multi-theoretical lens (Signaling Theory, the Technology Acceptance Model and Multi-Dimensional Trust Theory) to reconcile algorithmic control and relational trust management.

Keywords: Artificial intelligence, online reputation management, consumer trust, bibliometric analysis, digital trust.

Introduction

The domain of e-reputation, trust and artificial intelligence is gaining a critical importance, forming the foundations to understand the mechanisms that make sense of the digital exchanges, of the functioning of the organization and of the competitiveness of the organization in its environment (Davenport et al., 2020; Verhoef et al., 2021). The foundations of reputation and trust studies go back to between the 1970's and 1990's and mostly focused on the cognitive and psychological bases of credibility, relational processes and cooperation. These previous studies focused on the effects of trust on interpersonal and organizational relationships, such as the effects of trust on dependability, commitment, and reduction of risk (Deutsch, 1973; Lewicki & Bunker, 1996; Zucker, 1986), as well as the development of concepts related to credibility and relational processes.

These concepts which transferred to online channels owing to the growth of digital technologies include brand evaluation, information asymmetry and e-WOM (Chevalier & Mayzlin, 2006; Filieri et al., 2018; Morgan & Hunt, 1994). Between 2015-2025, recent researches argue that AI had a vital effect on moderating reputation as to two main frames, which could be summarized as offering decision support systems through predictive analytics, sentiment analysis and automated tracking of consumer responses, having continuously monitored customers' trust signals and consequently minimizes the risk and enhances credibility (Dwivedi et al., 2021; Kaplan & Haenlein, 2019; Rai, 2020). Furthermore, the scope of e-reputation is now enriched by various dimensions, including cybersecurity, blockchain, customer behavior and social media (Castelo et al., 2019; Zhang et al., 2024). Despite complementary coverage profiles, the documentation indexation in core bases exposes bias: Scopus mainly documents applied technological infrastructure and computer algorithms while Web of Science concentrates on consumers' worldview, organizational structures and brand equity (Donthu et al., 2021). Our conception of the two databases as complementary perspectives, with Scopus providing an early technological radar and Web of Science as a theoretical consolidation filter, requires a comparative mapping to hedge against bias due to single-database retrieval.

From this perspective both history and now also the contemporary views lead to analyze e-reputation studies progression with the combination of AI and how has consumer trust been presented as a key element of the transformation. This is where the problem of systematically and analytically mapping the entire area comes in-both from the perspective of technological development and from the point of view of consumer trust in an AI-powered e-reputation study (Aria & Cuccurullo, 2017; Zupic & Čater, 2015):

How has the scientific field of e-reputation evolved with the integration of artificial intelligence (AI) between 2015 and 2025 and to what extent has consumer trust been addressed as a central component of this evolution?

In order to guide the development of this research the following research questions have been defined that provide a focus for the comparative bibliometric analysis and highlight the convergence and interaction between e-reputation, AI and consumer trust:

- What are the core publication trajectories, prolific authors, primary sources and geographic distribution hubs driving research across both databases?
- Which distinct thematic clusters emerge from keyword co-occurrence analysis in Scopus and Web of Science?
- What structural features characterize international collaboration and co-authorship networks within the field?
- How does the integration of AI reconfigure the theoretical and practical relationship between e-reputation and consumer trust?

1. Theoretical background

The academic research on AI driven e-reputation is grounded on three main complimentary theorizations: signaling, technology acceptance and trust. The theoretical streams that influence today's Online Reputation Management (ORM) work in an intrinsically interlinked and cohesive manner. Reputation traditionally refers to the social assessment on the identity of an actor carried out by third party stakeholders without relating to the projected identity that an actor communicates of itself (Chun & Davies, 2001). Although not the cause for the distinction between the projected identity and the perceived reputation, the digitally accelerated, global and instantly transparent nature of this gap that arises in today's online world is solely attributable to the Digital Revolution. The e-reputation of a firm is the aggregation of the information available on the internet, via the web sites, on social media platforms and in review sites which results in a number of new characteristics, such as its irrevocability and the authority of User Generated Content (UGC).

In order to bring together all these major changes, Table 1 contrasts the traditional with the digital approach to the management of reputation.

Table 1: Paradigmatic comparison of reputation management (from the past to AI)

Dimensions	Traditional reputation	Online reputation in the AI era
Media channels	Print/broadcast (TV, radio, newspaper), online (web pages, ads) in episodic fashion (media campaign).	Facebook, X (Twitter), LinkedIn, blogs, review websites and platforms (Google, Amazon), search engine results, in an always-on fashion.
Communications flow (or modality)	Unidirectional (brand messaging to masses); brand-dominated.	Bidirectional and participation-based; user-generated word of mouth as a key communication mode (or mode of interaction and information diffusion).
Reputation creation (or sources)	Traditional media organizations and brand communications; creation through brand and mediated interaction.	Driven by UGC (customers and end-users) and spread across the social graph, as well as with an AI algorithmic diffusion spread and is decentralized.
Reputation monitoring & measurement	Monitoring of conventional media, customer surveys, market research techniques; results comeback days, weeks or months later (late signal).	Real-time AI-based listening (using sophisticated tools like Brand watch, Hootsuite and custom ML models) on social media, forums, websites and apps to track keywords and hashtags (continuous process; instant notification and signal); also tracking how messages travel across networks.
Reputation management	Crisis management using public relations (PR) firms; damage control after an event.	Predictive analytics; identifying anomalies and emerging signals of crisis using AI algorithms before negative consequences arise.
Sources of trust	Traditional reputation built on institutional credibility, media's perceived reliability, media coverage; authority-based.	Two layers of trust: reliance on the reliability of underlying algorithms that guide digital engagement and the relationality of brand interaction with digital communities plus the organization's ability to build rapport through interactive engagement.
Range (or scale)	Primarily local or country-based; episodic with a focus on significant business and corporate events (quarterly reporting, new product launches ...etc).	Global reach and platform-agnostic; always optimizing brand interactions to maximize impact on real-time consumer sentiment and engagement levels.

Source: Authors' synthesis based on Chun & Davies (2001); Kapferer (2011); Coombs (2007); Kaplan & Haenlein (2019) ; Dwivedi et al. (2021); Morgan & Hunt (1994); Rai, (2020); Zucker (1986).

Using Signaling Theory (Spence, 1973) helps to understand this calculated status and specifically explains how AIs minimize information asymmetry by weighting and aggregating reputational signals-such as review scores and sentiment indices-over millions of data points. The perceived credibility of signals and AI is rooted in signal cost and observability, and AI operates as an infrastructure for the calibration of this weighting on an aggregate level. TAM (Davis, 1989) makes the point that AIs and signals can only do this by perceived usefulness and ease of use; in the absence of explainability, it is user disbelief-that is, a form of the algorithm aversion dynamic-that can trump technical correctness. Thus, technological efficiency is neither a sufficient nor a necessary condition for digital trust. Trust exists along two dimensions: institutional trust, a belief in the dependability of structural mechanisms (like the blockchain) and relational trust, built up over time through numerous positive exchanges (Morgan & Hunt, 1994; Zucker, 1986).

Table 2 below provides a consolidation of how these different theoretical concepts can be integrated.

Table 2: Theoretical frameworks for the e-reputation research

Theory	Main idea	Application to e-reputation in the AI era
Signaling theory (Spence, 1973)	Asymmetry between buyer and seller decreases by sending an information signal deemed to be reliable.	AI may be seen as the receiver of online information (a badge or a rating), processing and weighing information and even magnifying certain aspects of it in order to create the image of a trustworthy entity.
Technology acceptance (Davis, 1989)	The uptake or lack of acceptance of any technology depends on the perceptions that technology would be useful and that it would be easy to use.	Acknowledges that users will more than likely avoid AI inputs if the technology does not seem transparent or accountable, a phenomenon known as Algorithm Aversion.
Institutional trust (Zucker, 1986)	Perceived legitimacy and reliability of any social organization or mechanism.	Can be provided through technological systems of authentication, block-chaining and verification from recognized review sites.
Relational trust (Morgan & Hunt, 1994)	The dependent construct based on past relationship experience, history and commitment.	It is sustained through human-centric interaction with the brand; acts as a necessary supplement to AI.

(Authors' own work)

This merging of frameworks is arguably most obvious in the contemporary ORM cycle, whereby AI becomes the functional engine that enables monitoring, influencing and improving the perception of brands and their digital presence. During monitoring, automated surveillance is enabled through machine learning and natural language processing tools that allow reputational data to be transformed from a leading to lagging indicator. Influencing becomes more feasible through scalable resolution of service issues through AI chatbots and story-telling technology, yet algorithmic engagement continues to face a trade-off where it could potentially fail to convince and therefore reduce utility of technology. Predictive analytics represents the most tactically important boundary in which this integration is manifest-instead of acting on accumulated signals, it endeavors to predict reputational trends based on early behavioral patterns.

Instead of viewing these theoretical angles as separate paradigms, the paper builds these perspectives into a continuous, integrated sequence through Signaling Theory, the Technology Acceptance Model and Multi-Dimensional Trust Theory. System trust and transparent review (TAM) build structure verification (Institutional Trust), which generates an authentication of

signals (Signaling Theory) to create potential long-term customer loyalty (Relational Trust). This paper makes use of these three additional complementary theoretical prisms to analyze keyword clusters and bibliometric structures in Web of Science and Scopus, respectively.

2. Methodology

The methodology design of this research takes a three-stage comparative bibliometric approach in aligned with business, management and information systems research (Donthu et al., 2021; Zupic & Čater, 2015). The first stage defines the retrieval strategy and builds the corpus in Web of Science and Scopus with an identical Boolean search. The second stage implements the multi-stage screening process based on PRISMA guidelines, noting the number of documents retained and technical ingest changes reflected in the analysis software. The third stage merges the comparative framework with the computational environment, outlining the specific network mapping parameters run in VOSviewer and Bibliometrix/Biblioshiny.

2.1. Construction of bibliometric corpus and research strategy

The bibliographic data set was obtained from two complementary international indexing services, Web of Science (Core Collection) and Scopus, by employing a matching protocol of identical search criteria and search string fields. The scopes of each index were chosen in accordance with their acknowledged complementarity for science mapping (Zupic & Čater, 2015). Although identical inclusion criteria were applied, greater numbers of applied interdisciplinary journals and conference proceedings emerge in Scopus, whereas Web of Science lists more traditional business and management periodicals.

Firstly, to enable comparison and to overcome retrieval asymmetry caused by vocabulary differences, a symmetrical three-pillar Boolean search was run simultaneously on both platforms. The first pillar covers the technological infrastructure of the mechanism by using the core computational terms "artificial intelligence", "machine learning", "deep learning" and "AI". The second pillar comprised the reputational construct and screened for electronic reputation management, review systems and electronic word-of-mouth by using the terms "reputation", "online reputation", "e-reputation", "ewom" and "online reviews". The third pillar introduced the relational element of trust by using the terms "trust" and "consumer trust".

Field equivalence was tested using the Topic (TS) field in Web of Science (searches titles, abstracts, author keywords and Keywords Plus) and the TITLE-ABS-KEY (searches titles, abstracts, author keywords and Keywords Plus) field in Scopus. Both searches were combined using the following query: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "AI") AND ("reputation" OR "online reputation" OR "e-reputation" OR "ewom" OR "online reviews") AND ("trust" OR "consumer trust")

2.2. Eligibility criteria and PRISMA screening process

The final corpus was defined by four successive screening stages of the retrieved publications. Firstly, the temporal horizon was defined by excluding the years prior to 2015 and after 2025, by constraining the number of publication years to 11, thus avoiding partial indexing years. Secondly, publication typology was constrained by excluding documents that are not subject to rigorous reviews by the scientific community, with only peer-reviewed documents (articles, proceedings and conference papers, review articles, and book chapters) kept and editorial items, letters and book reviews being systematically excluded. Third, language was constrained to English publications. Fourth, content was constrained by excluding management, business, decision sciences, applied computer science and social sciences (SC); non-managerial physical hardware engineering (radio transmission systems, antennas, etc.); as well as clinical medical fields of practice (radiology, surgery, ophthalmology, etc.).

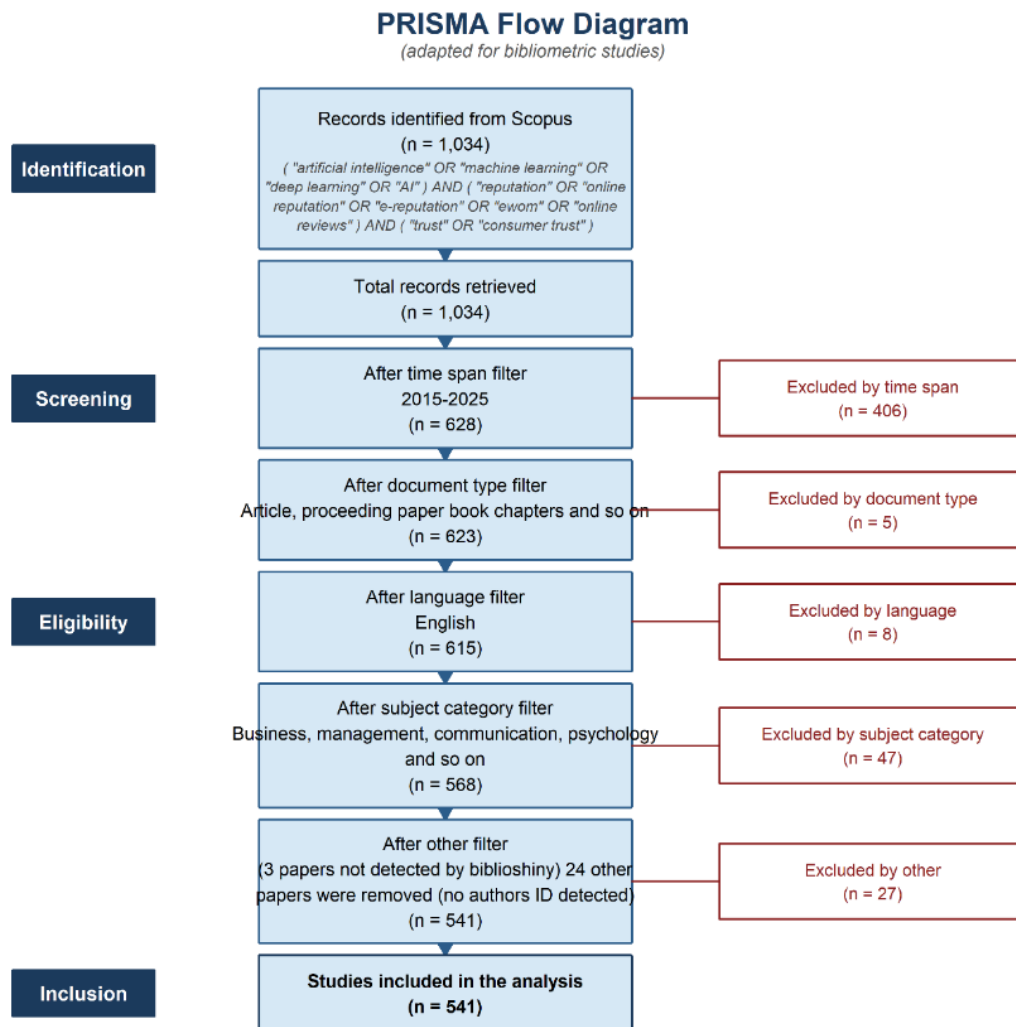
The quantitative progression of this screening procedure is reported in Table 3.

Table 3: Multi-stage corpus screening and refinement (PRISMA flow)

Screening Stage	Web of Science (WoS Topic)	Scopus (TITLE-ABS-KEY)
Initial search records	553	1,034
Stage 1: Time span (2015-2025)	408	628
Stage 2: Document Types (Articles, Proceedings, Reviews, Chapters)	395	623
Stage 3: Language (English)	391	615
Stage 4: Disciplinary Screening (Management, IS & Applied Social Sciences)	311	568
Exported Records (100%)	311	568
Biblioshiny processing adjustments	293 (18 early-access records cataloged for 2026 excluded)	541 (3 undetected files; 24 excluded due to missing author metadata)

(Authors)

Figure 1: PRISMA flow diagram for scopus selection



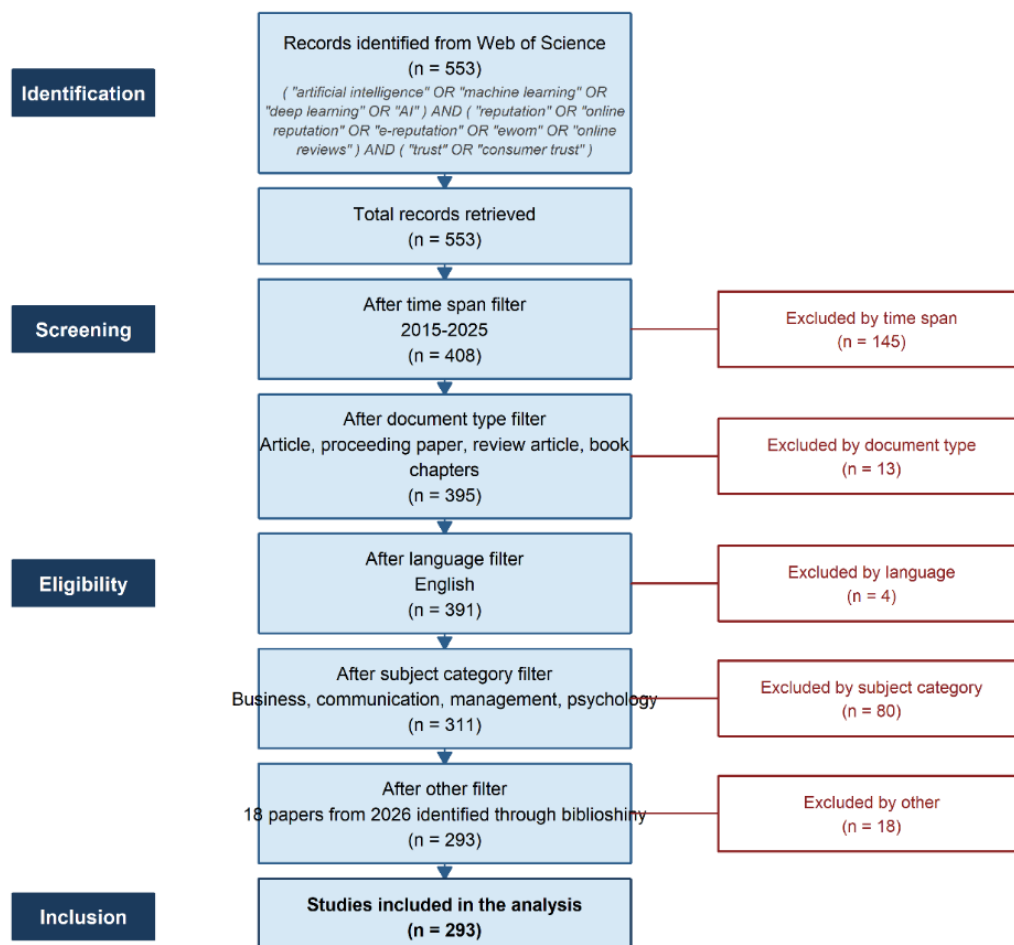
(Biblioshiny)

Figure 2: PRISMA flow diagram for WoS selection
(Biblioshiny)

All 311 eligible Web of Science records and all 568 eligible Scopus records were exported fully in BibTeX format including citing references. When ingesting these files in Biblioshiny, statistical descriptions required some slight package dependent adjustments; 18 Web of Science

PRISMA Flow Diagram

(adapted for bibliometric studies)



records with early-access dates for the publication year of 2026 were disregarded by the package date parser and the Web of Science dataset finalised at n=293 complete records valid within the 2015-2025 time span. For Scopus, 3 records were missed by the import routine, and 24 records with missing valid author identification metadata were ignored when checking data structures, accounting for the final Scopus count of n=541 records for authorship and n=565 for keyword analysis.

2.3. Comparative approach and analytical tools

The data were analyzed within a unified comparative framework that examines publication growth, influential sources, country distributions and conceptual networks side by side rather than in isolation (Donthu et al., 2021). Metrics of description, annual production and publication source were generated based on the R package bibliometrix with its web-interface biblioshiny (V.5.0) (Aria et al., 2026; Aria & Cuccurullo, 2017) in RStudio (V. 2026.09.0 Build 174) following the SAAS (Science Mapping Analysis Software) workflow.

Visualizations of the spatial network were performed by VOSviewer (v.1.6.21, CWTS Leiden) (Van Eck & Waltman, 2010) from reference manager file formats (BibTeX and RIS). Networks

of terms co-occurrences were built on full counting method, based on all keywords, involving the combination of author keywords with database index vocabularies.

The 568 records on the Scopus dataset combined had 3,978 unique keywords. Keywords that appeared less than 4 times were below the minimum threshold of 4, giving 320 keywords included in the network visualisation. The primary nodes identified by total link strength comprise machine learning (125 occurrences; link strength: 979), learning systems (99 occurrences; link strength: 960), artificial intelligence (141 occurrences; link strength: 777), blockchain (83 occurrences; link strength: 696) and trust (79 occurrences; link strength: 492). For the Web of Science dataset, the 311 records generated 1,549 distinct keywords. Applying the same minimum threshold of 4 occurrences yielded 117 keywords that met the criterion, all of which were selected for network construction. The central nodes by total link strength consist of trust (126 occurrences; link strength: 527), reputation (84 occurrences; link strength: 341), machine learning (60 occurrences; link strength: 193), blockchain (43 occurrences; link strength: 166) and online reviews (27 occurrences; link strength: 140). Table 4 synthesizes the software environment and parameter settings used across the analyses

Table 4: Software environment and parameter settings

Parameter	Specification	Notes
Software packages	RStudio (v.2026.09.0 Build 174)	Combined descriptive metrics and network visualization following the SAAS workflow (Aria et al., 2026).
	R package bibliometrix / biblioshiny (v.5.0)	
	VOSviewer (v.1.6.21, CWTS Leiden)	
Input data format	Reference manager exports (BibTeX / RIS)	Full records including abstracts, keywords and cited references.
Analysis type	Co-occurrence mapping	Evaluates thematic links among keywords across publications.
Unit of analysis	Keywords (All Keywords)	Integrates author keywords and database index terms.
Counting method	Full Counting	Assigns an equal weight of 1 to each co-occurrence tie.
Threshold criteria	Minimum 4 occurrences per keyword	Retains 320 nodes out of 3,978 in Scopus and 117 nodes out of 1,549 in WoS.

(Authors)

The thematic groups derived from both datasets are explained by means of the following theories: Signaling Theory (Spence, 1973), The Technology Acceptance Model (Davis, 1989) and Multi-Dimensional Trust Theory (Morgan & Hunt, 1994; Zucker, 1986). These three theories bring the computational processes of machine learning algorithms together with the perceptions of organizational and consumer trust and reputation.

3. Results

3.1. Annual scientific production

The evolution of indexed literature by year in Scopus and WoS, from 2015 to 2025, reveals the sustained growth in the volume of annual scientific output related to the convergence of artificial intelligence, e-reputation, and consumer trust. Throughout the eleven-year monitoring period, there were 541 documents published in total in the two indices (Table 3), scoring the highest number of records in Scopus (541 items) and WoS (293 items). As can be seen in figure

1 and table 3, the comparative annual publication growth trend in terms of three sequential temporal stages in both open access sources.

Between 2015 and 2018, the production was low and similar in scope on each platform, with between 10 and 15 publications each year for Scopus and between 6 and 9 for the Web of Science. Between 2019 and 2022, the annual output has increased at a similar rate, with between 23 and 36 each year for Scopus and between 19 and 29 each year on the Web of Science. A divergence in total publication volume is recorded in the last period (2023-2025), with the rise in science production being very steep on Scopus, where it increased from 61 on 2023 to 207 publications in 2025, whereas the number of publications on Web of Science changed steadily, with 32 documents in 2023 and 78 in 2025.

Table 5: Annual production

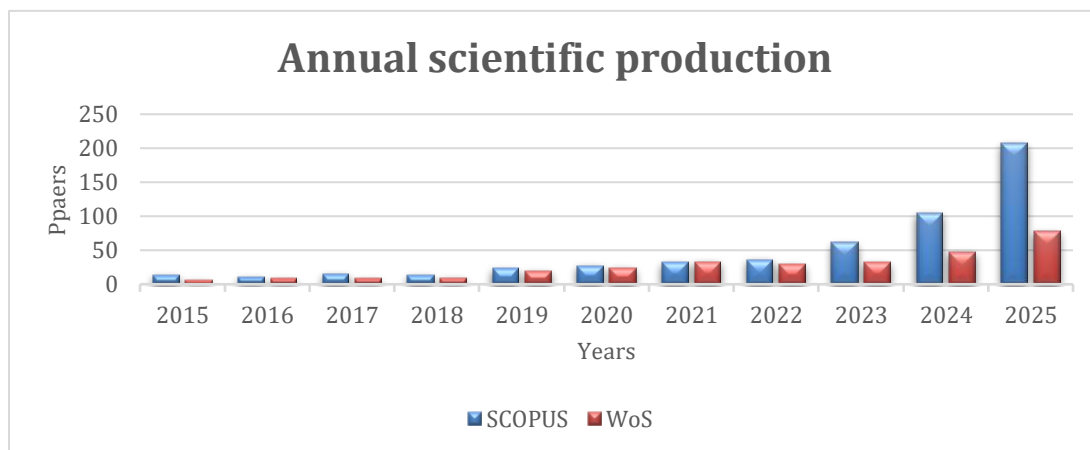
Year	SCOPUS	WoS
2015	13	6
2016	10	8
2017	15	8
2018	13	9
2019	23	19
2020	27	24
2021	32	33
2022	36	29
2023	61	32
2024	104	47
2025	207	78

(Excel)

Figure 3 : Annual scientific production

(Excel)

By comparing the trajectory in Table 5 and in Figure 3, both coverage profiles follow consistent long-term growth trends, however, quantitative differences exist in term of volume and



accumulation rate. As it can be seen in the yearly level, the ratio of publication of Scopus over Web of Science remained nearly balanced from 2016 to 2022 (from 0.97 to 1.88) and then increased dramatically from 2023 to 2025 up to reach a peak of 2.65 in 2025. Such numerical

inconsistencies are merely a result of database indexing scales, journal coverage scales and document type inclusion strategies between two indexing services, and do not represent separate research fields.

3.2. Geographical scientific production

The geographic distribution of scientific production shows wide participation from the entire world in both indexes, with scientific work emanating from countries in all categories of development, including emerging ones. As can be seen in Table 6, Figure 4 and Figure 5, the number of publications per country indicates shared global leadership, as well as regional differences, between Scopus and WoS.

The distribution of the scientific output shows India on the lead position in Scopus with 74 publications. China follows in second position with 54 publications. Then comes the USA with 41 publications. The UK with 13 publications. Italy and Malaysia followed with 11 publications each. Australia and Korea with 10 publications each, then the group of Morocco, Romania, Saudi Arabia and Spain with 8 publications each. Then several contributions across the continents from North America, Europe, Asia and MENA region, including Canada, Ireland and Pakistan (7 publications each), Indonesia (6 publications), followed by Bangladesh, Germany and Greece (5 publications each).

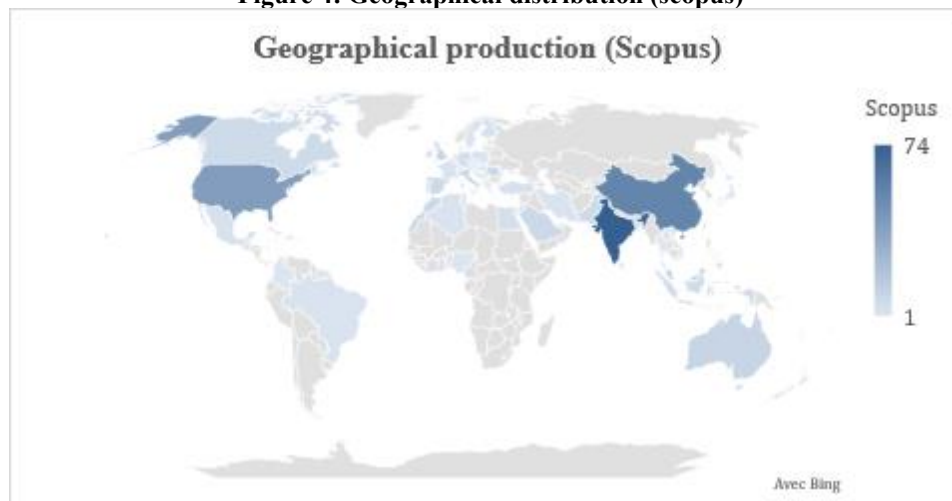
In Web of Science search, China leads in scientific production with 57 publications; the United States is second with 40 publications; and India third with 29 publications. Out of the leading positions on the Web of Science; the United Kingdom is fourth with 20 publications; Spain, 12 publications; Korea, 11 publications; Australia and Saudi Arabia (10 publications each); lower volume of papers is scattered among Ireland and Italy (7 publications); Canada, Greece, Malaysia, Singapore and Turkey (5 publications each); and Iran and Morocco (4 publications each).

Table 6: Geographical production

Country	Scopus	Country	Wos
India	74	China	57
China	54	USA	40
USA	41	India	29
United Kingdom	13	United Kingdom	20
Italy And Malaysia	11	Spain	12
Australia and Korea	10	Korea	11
Morocco, Romania, Saudi Arabia, Spain	8	Australia And Saudi Arabia	10
Canada, Ireland, Pakistan	7	Ireland And Italy	7
Indonesia	6	Canada, Greece, Malaysia, Singapore, Turkey	5
Bangladesh, Germany, Greece	5	Iran And Morocco	4
Egypt	4	Egypt, Finland, Germany, Netherlands, Pakistan, Romania, UAE	3
Finland, Jordan, Mexico, Portugal, Turkey	3	Algeria, France, Hungary, Indonesia, Japan, Portugal, Qatar, Russia, Vietnam	2
Algeria, Brazil, France, Ghana, Iran, Poland, Singapore, United Arab Emirates	2	Austria, Belgium, Brazil, Chile, Colombia, Denmark, Jordan, Lebanon, Mexico, New Zealand, Philippines, Polan, Slovenia, Thailand, Tunisia	1
Austria, Bahrain, Colombia, Cyprus, Czech Republic, Denmark, Hong Kong, Hungary, Japan, Lebanon, Netherlands, New Zealand, Nigeria, Serbia, Slovakia, Slovenia, Sri Lanka, Sweden, Switzerland, Thailand, Tunisia, Vietnam	1		

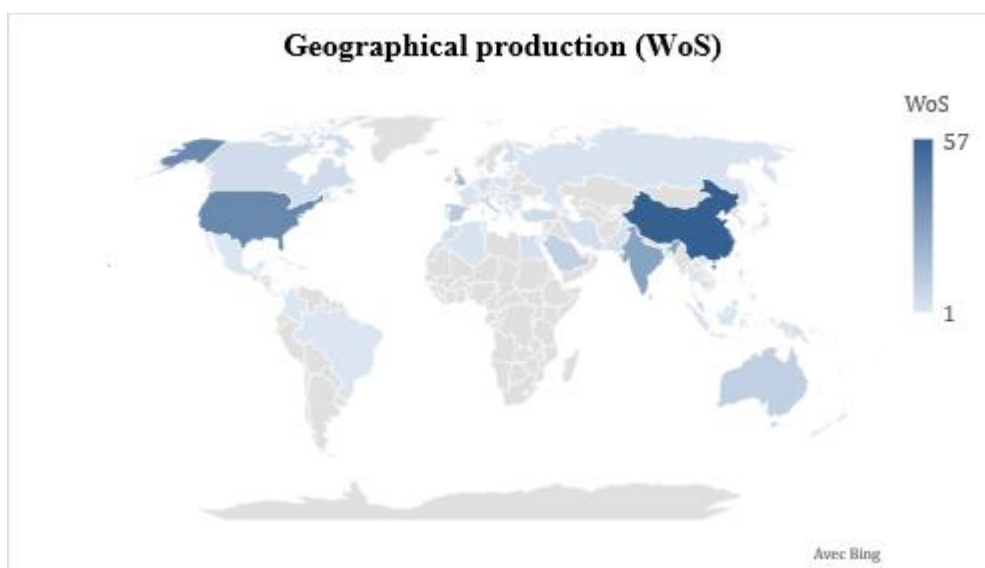
(Excel)

Figure 4: Geographical distribution (scopus)



(Excel)

Figure 5: Geographical distribution (WoS)



(Excel)

A comparative analysis of Table 6, Figure 4 and Figure 5 reveals that four countries (China, India, the US and the UK) represent the largest geographic core of production in both datasets; however, there are interesting variations in the positions of countries and their absolute number of publications. While India represented the highest absolute number in the Scopus dataset (74 publications), the country with the most entries in Web of Science (57 publications) was China. Both datasets also included some geographic variations in being able to encompass other regions of active research (from Europe, Asia, Latin America or the MENA region) such as Morocco, Romania, Egypt or Indonesia. These shifts demonstrate variations in international coverage and the regional institution indexing in the two databases.

3.3. Most relevant authors

The authorship patterns of articles in these two datasets show a highly skewed distribution of contribution with most authors being short-term contributors, and a small core of authors producing at a reasonable level. As shown in Figure 6 (Scopus) and Figure 7 (Web of Science), the number of articles published per individual ranges from 1 to 4.

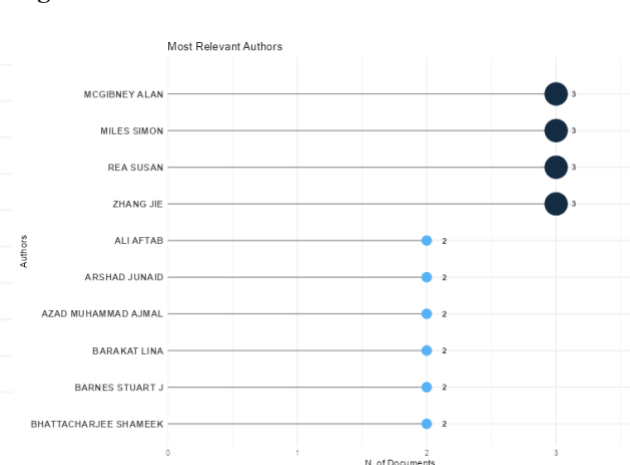
Within the Scopus corpus, the overall author productivity reaches a max of 4 publications, for 1 author, shameek bhattacharjee (see figure 6). 13 authors published a grand total of 3 articles: Aftab Ali, Sajal k. das, Prabhat Kumar, Ankita Kumari, Madhusanka Liyanage, Alan McGibney, Luc moreau, Liam Murphy, Yi Qian, Rashmi Ratnayake, Susan Rea, Domenico rosaci and Mudita Uppal. An even larger secondary group of authors all produced 2 publications, the rest of the authors in the corpus produced 1 publication.

In the WoS corpus, author productivity is limited to 3 items per author. As can be seen in Figure 7, there were a set of 4 core authors (Alan McGibney, Simon Miles, Susan Rea and Jie Zhang), who wrote 3 articles each. These are then followed by a second band of authors who each wrote 2 articles (Aftab Ali, Junaid Arshad, Muhammad Ajmal Azad, Lina Barakat, Stuart J. Barnes and Shameek Bhattacharjee). The remaining WoS authors wrote a single article.

Figure 6: Most relevant authors in scopus database



Figure 7: Most relevant authors in WoS database



(Biblioshiny)

Overall similarities can be found by the comparison of the distributions represented in Figure 6 and Figure 7. It is clear that single-authors are the majority of output for each database and that the most prolific researchers exist within the parameters of both index outputs (Alan McGibney, Susan Rea and Shameek Bhattacharjee to name a few). Total numbers of authors between Web of Science and Scopus reflects the variation in the size of each database as well as differences in the number of documents included within the corpus.

3.4. Co-authorship and collaboration networks

The social topology of scientific production in the two databases is characterized by a collaboration system that has a high degree of fragmentation, made up of isolated research groups and dense pairs of co-authors. As can be seen in Figure 8 (Scopus) and Figure 9 (Web of Science), research collaboration in this field takes place solely within closed research groups, with no global network.

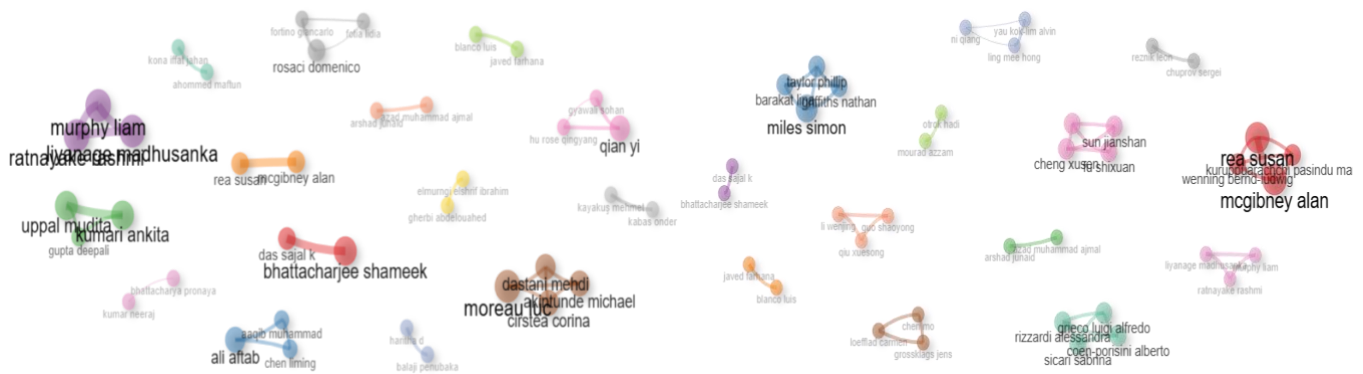
In the co-authorship network within Scopus (Figure 8), co-authorship breaks down into 15 isolated research groups. Collaborative research pairs and several clusters include Luc Moreau and colleagues, Mehdi Dastani and colleagues, Corina Cirstea and colleagues, as well as Michael Akintunde and colleagues, and the triadic group of researchers consisting of Yi Qian, Sohan Gyawali, and Rose Qingyang Hu. Other collaborative pairs and small teams are

consisting of Shameek Bhattacharjee and Sajal K. Das, Alan McGibney and Susan Rea, Aftab Ali, Muhammad Aaqib and Liming Chen, as well as Domenico Rosaci, Giancarlo Fortino and Lidia Fotia.

In the Web of Science authorship network (Figure 9) we observe again a similar network topology on 13 disconnected sub-graphs. Our major authorship collaborations are with teams of Alan McGibney, Susan Rea, Pasindu Manisha Kuruppuarachchi and Bernd-Ludwig Wenning, and members of the research group of Simon Miles, Phillip Taylor, Lina Barakat and Nathan Griffiths. Other clusters include teams composed of Jianshan Sun, Xusen Cheng, Shixuan Fu and Xiangsong Meng, Luigi Alfredo Grieco, Alessandra Rizzardi, Alberto Coen-Porisini and Sabrina Sicari, while other authorship dyads are visible (Junaid Arshad with Muhammad Ajmal Azad, or Azzam Mourad with Hadi Otkot).

Figure 8: Co-authorship from scopus database

Figure 9: Co-authorship from wos database



(Biblioshiny)

By comparing Figure 8 and Figure 9, one can verify the pattern of collaboration remains the same in both indexing platforms. No, group of authors provide a central point of connectivity for the rest of the field; scientific production takes place within the confines of individual institutional or project-centered teams. The key collaborative duo (Susan Rea and Alan McGibney), the Junaid Arshad/Muhammad Ajmal Azad team or the link between Sajal K. Das and Shameek Bhattacharjee all consistently appear across the two networks. Although overall levels of publication volume differ substantially, this indicates the basic social organization of scientific publication between the two indexes is very similar.

3.5. Most relevant sources

The distribution of documents across publication sources reveals the main outlets of publication at this intersection of artificial intelligence, e-reputation and consumer trust. As seen in Figure 10 (Scopus) and Figure 11 (Web of Science), the 10 most common publication sources have very different outlet profiles in each of the two indexes.

The publication venues in the Scopus corpus are widely led by IEEE Journal and computer science conference proceedings volumes series. As seen in figure 10, the leading publication venues are, in order of decrease, "IEEE Access", (16 publications), followed by "Lecture Notes in Computer Science" (13 publications), and "Lecture Notes in Networks and Systems" (11 publications). All other venues had 5 and 6 publications, namely, "ACM International Conference Proceeding Series" (6 publications), "Communications in Computer and Information Science" (6 publications), "IEEE Internet of Things Journal" (6 publications), "Advances in Intelligent Systems and Computing" (5 publications), "Journal of Theoretical and Applied Information Technology" (5 publications), "Lecture Notes on Data Engineering and

Communications Technologies" (5 publications) and "Procedia Computer Science" (5 publications).

Publication sources in the Web of Science corpus provide a slightly different distribution, blending engineering, information systems, and domain-specific management journals. As shown in Figure 11, the IEEE Access journal is still by far the most prominent with 19 publications, followed by the IEEE Internet of Things Journal with six, and the International Journal of Hospitality Management with five. The remaining top source publications contain three or four publications: CMC-Computers, Materials & Continua (4), Decision Support Systems (3), Electronic Commerce Research and Applications (3), Electronics (3), Engineering Applications of Artificial Intelligence (3), Information (3), and Journal of Hospitality and Tourism Insights (3).

Figure 10: Most relevant sources Scopus

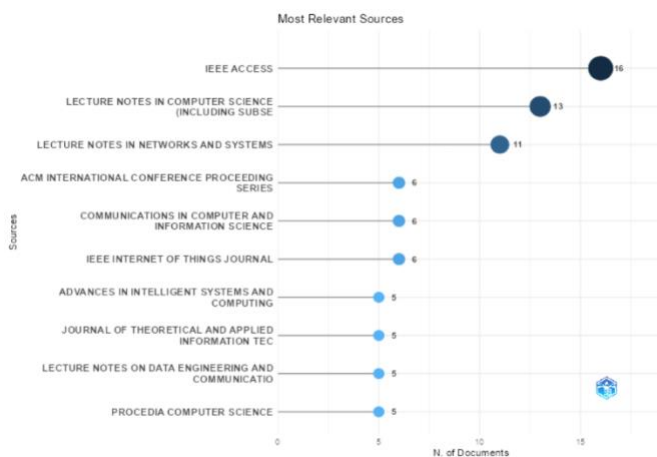
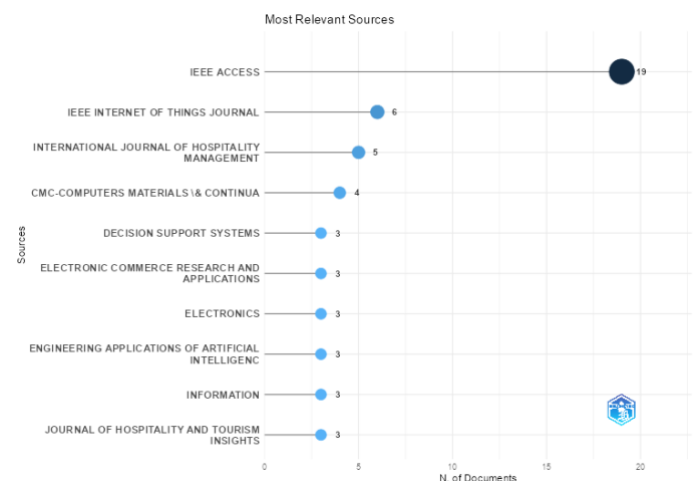


Figure 11: Most relevant sources WoS



(Biblioshiny)

The plots of the outlet distributions in Figure 10 and Figure 11 show the existence of similar journals together with some differences between the two search engines. Outlets such as the IEEE Access or the IEEE Internet of Things Journal belong to the major common outlet in both data bases, while Scopus counts more book series and conference proceedings related to computer science and network engineering (Lecture Notes in Computer Science, Procedia Computer Science) and Web of Science more particular business, information systems and sectoral management related journals (Decision Support Systems, Electronic Commerce Research and Applications, International Journal of Hospitality Management).

3.6. International collaboration

The structure of the global research networks by countries reveal different shapes of international collaboration in both databases. As seen in Figure 12 (Scopus) and Figure 13 (Web of Science), bilateral country collaborations vary in the strength of collaboration, from the most frequent links to sprawling peripheries.

Figure 12 depicts the international collaboration network for Scopus data, with bilateral collaborations among 1–2 as well as more than 2 countries all displayed. Four grades of strength of bilateral collaboration are expressed: high degree, 6 country pairs with 5 or more collaborations each; medium degree, 12 country pairs with 3–4 collaborations each; moderate degree, 33 pairs with 2 collaborations each; and low degree, the remaining 108 unique bilateral pairings. High degree collaborations consist of: India with the USA, 8 collaborations; China with Pakistan, 7; Pakistan with Saudi Arabia, 6; and China with Canada, Hong Kong and the USA, 5 each; and India with Malaysia, 5. Medium degree collaborations include: China with Australia; Saudi Arabia with Jordan; and the United Kingdom with Malaysia, 4 each. Moderate

degree collaborations include: Ghana with South Africa; Romania with Turkey; and Iraq with Uzbekistan, 2 each.

According to the Web of Science international collaboration network (Figure 13) of global partnerships, the global collaborations have a more intensive structure. The top high-intensity level comprises six pairs of countries with at least five collaborations each, led by China- USA (9 collaborations) and followed by Saudi Arabia -Pakistan (6), China- Australia (5), China- Canada (5), China- Singapore (5) and United Kingdom (UK)- Malaysia (5). The next medium-intensity level has 9 pairs of countries with 3 to 4 collaborations each, led by China-Korea and China- UK, the UK- Saudi Arabia and the USA- Australia and India. And the low-intensity level has 90 pairs of countries with at least 2 collaborations, among which we find Pakistan-France, Spain- France- Portugal and the UAE- Lebanon.

Figure 12: International collaboration Scopus

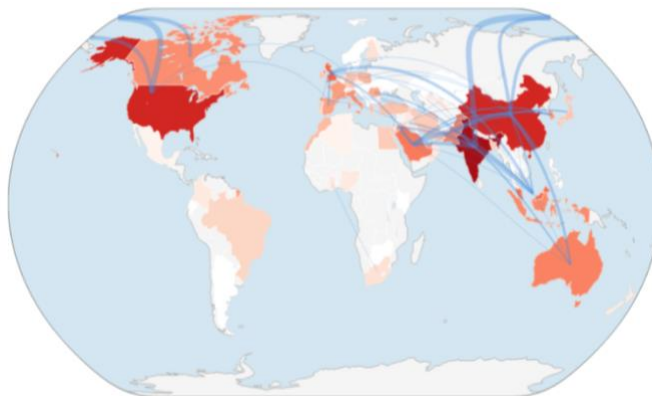
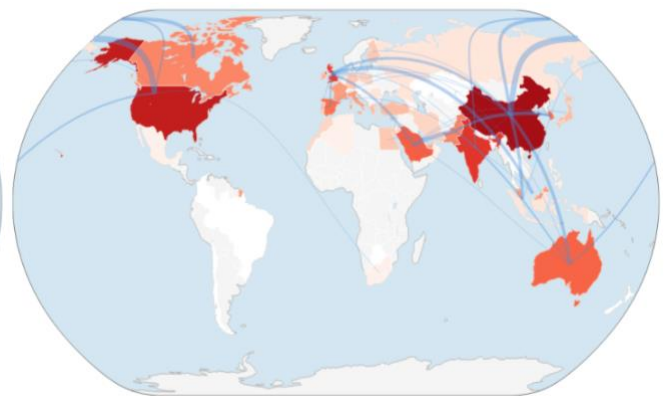


Figure 13: International collaboration WoS



(Biblioshiny)

As observed through the comparison of Figure 12 to Figure 13, consistent global collaborative centers are complemented by database-specific differences in network density. As primary international axes between major publishing and indexing countries such as China and the US, China and Canada, Saudi Arabia and Pakistan and the UK and Malaysia consistently serve as collaborative sharing bridges across both indexing tools. As a whole, however, Scopus exhibits a greater quantity of total international collaboration connections with 159 total collaboration pairs across the intensity levels and 125 total collaboration pairs in Web of Science. This discrepancy harks towards variations in overall sample size, inclusion of journals and/or geographic distribution of indexed countries.

3.7. Keyword frequency analysis: comparative insights

The frequency of the top keywords illustrates the subject distribution covered by the different indexing platforms. Figure 14 (Scopus) and Figure 15 (Web of Science) below, clearly demonstrate significant differences between the two indexing platforms for keyword distributions and term ranking.

Within the Scopus corpus, we note the bulk of keyword appearances focus on technical algorithms and system infrastructure ideas. As we can see in figure 14, the keywords artificial intelligence (140 occurrences), machine learning (125) and learning systems (99) dominate the most prevalent keywords. Other keywords ranked highly include those associated with system security and architectural functionality such as blockchain (83 occurrences), machine-learning (occurrence 76), network security (76), deep learning (75), block-chain (59), and federated learning (47). Among the top ten keywords in Scopus, the relational element trust is fifth with 80 appearances.

In the Web of Science corpus, the keyword frequency distribution reveals a clear hierarchy, with a predominance of relational and perceptual keywords. As shown in Figure 15, trust is the top keyword, which occurs 124 times, and the second is reputation which occurs 83 times. In second position are methodological and technological keywords, led by machine learning (50 occurrences), blockchain (41 occurrences), artificial intelligence (26 occurrences), and security (26 occurrences). Completing the top ten in Web of Science are internet (23 occurrences), federated learning (22 occurrences), online reviews (22 occurrences) and trust management (21 occurrences).

Figure 14: Most relevant words Scopus

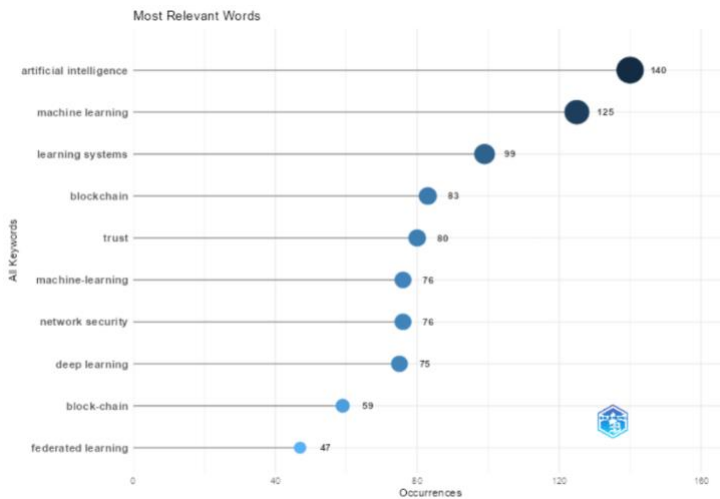
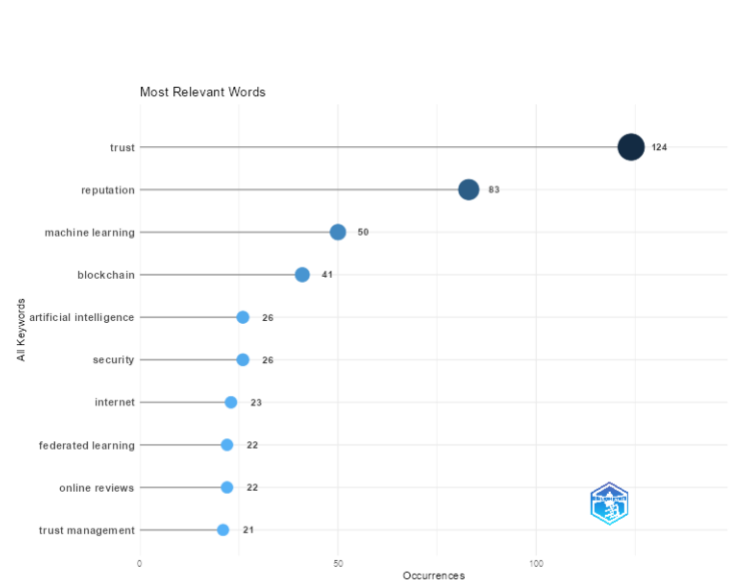


Figure 15: Most relevant words WoS



(Biblioshiny)

Figure 14 and Figure 15 establish a very real shift in the state of keywords for these two separate indexing tools. Even though both databases contain keywords of fundamental importance (trust, machine learning, blockchain, artificial intelligence, and federated learning), counts of these terms are wildly different. In contrast to Web of Science, which favors relational attributes, while regard is gained to structural attributes (represented by the variations in counts above), in Scopus, well regarded keywords are technological and computational, such as the leader artificial intelligence (140 counts) and machine learning (125 counts).

3.8. Keyword co-occurrence analysis

Exploring conceptual structures To reveal the underlying conceptualization of the domain, both full-counting keyword co-occurrence networks were created in VOSviewer (v.1.6.21) with a minimum occurrence threshold of $n = 4$. Based on structural mappings, which show what links thematic groups together and how these connections shape the entire co-occurrence network, both databases illustrate different conceptual themes.

Figure 16: Scopus keyword co-occurrence

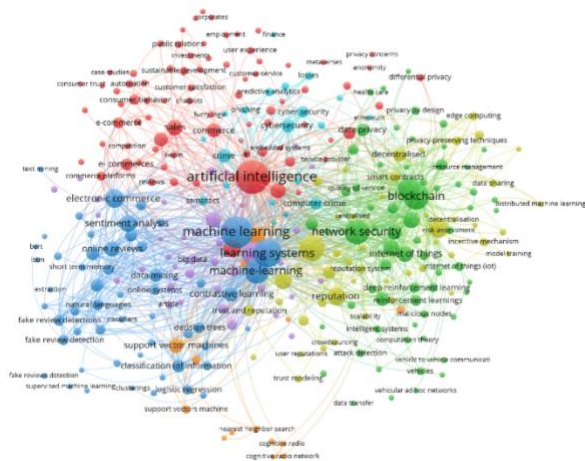
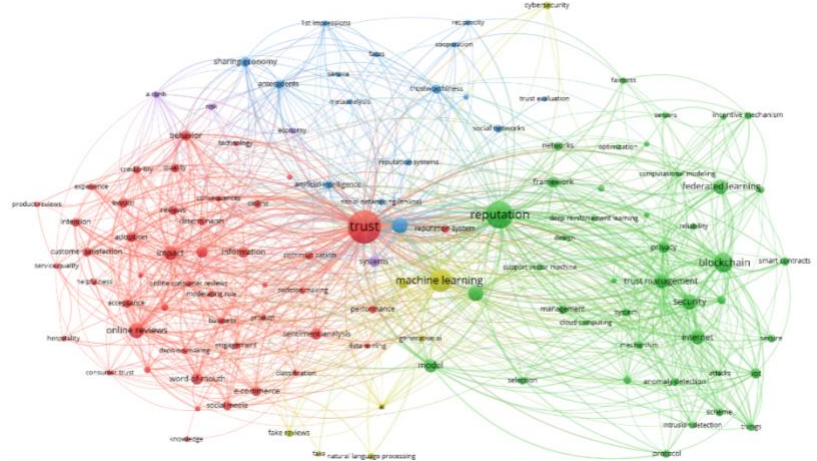


Figure 17: WoS keyword co-occurrence



(Vosviewer)

In the Scopus list, use of $n \geq 4$ as a threshold of keywords we will keep 320 keywords from 3,978 keywords and map them into seven cores as shown in figure 16: The first core (Red, 65 keywords) relates to the AI, E-Commerce and Customer behavior core area having the following focal points as central hubs: artificial intelligence (140 keywords), behavioral research (30 keywords), commerce (24 keywords), and consumer behavior (14 keywords). Corresponding to the traditional TAM model (Davis, 1989), this core section mainly explores research using the relationship between artificially intelligent automation decision engines to influence customer adoption and customer satisfaction. The second cluster (Green, 62 items) is labeled Blockchain, Security and Decentralized Infrastructure, with nodes such as blockchain (83), network security (76), security (31) and trust management (30). Drawing on Multi-Dimensional Trust Theory (Zucker, 1986), it replaces interpersonal reliance with computational agreements based on institutions. The third cluster (Blue, 55 items) is labeled Machine Learning, Deep Learning and Text Analytics, with nodes such as deep learning (75), sentiment analysis (36), online reviews (30) and fake detection (23). Adopting Signaling Theory (Spence, 1973), these machine learning models serve as a signaling verification device that eliminates noise and protects the market signal authenticity. The fourth cluster (Yellow, 46 items) relates to Federated Learning, Decentralized Privacy and System Architecture has: federated learning (47), trust (80), reputation (42). The fifth cluster (Purple, 39 items) relates to Neural Networks, Data Mining and Analytical Modeling with: convolutional neural network (13), data mining (21). The two remaining smaller clusters define specialized technical domains: the sixth cluster (Cyan, 38 items) is related to Cybersecurity, Crime and Predictive Analytics while the seventh (Orange, 15 items) captures Cognitive Radio and Wireless Communication.

Similarly, using the threshold of $n \geq 4$ for Web of Science produces 117 keywords of 1,549 total keywords, of grouping into five clusters (figure 17). The red group of 43 items represents the Trust, eWOM, Consumer Behavior and Satisfaction area anchored by the most popular node in the whole network, trust (124), and online reviews (22), satisfaction (16), word-of-mouth (16), and behavior (12). Based on Multi-dimensional Trust Theory (Morgan & Hunt, 1994) and Signaling Theory (Spence, 1973), this cluster focuses on the relational trust and review metrics as informational signals for reducing market uncertainty. The second cluster (Green, 38 items) discusses Blockchain, Security, IoT and Trust Governance, based on reputation (83 articles), blockchain (41 articles), security (26 articles), trust management (21 articles). The third cluster (Blue, 18 articles) represents Social media, Service Quality and Relational Dynamics, comprising artificial intelligence (26 articles) and sharing economy (11 articles). The fourth cluster (Yellow, 12 items) includes Machine Learning, Deep Learning and Generative AI

focused on machine learning (50 documents), deep learning (26 documents) and generative ai (6 documents) using the technology acceptance model (TAM) (Davis, 1989) to measure algorithmic acceptance. The fifth cluster (Purple, 6 items) stands alone as a sub-domain of Sharing Economy Risks and Organizational Systems connecting the terms Airbnb (5 documents), risk (5 documents), and systems (14 documents).

A comparative synthesis of Figure 16 and Figure 17 exposes the structural alignments and sharply defined differences in keyword importance across the two indexing services. Both graphs incorporate the same core groups of thematic building blocks, which present the literature in terms of algorithmic application, cryptographic security and consumer trust relationships. The two visualizations are not identical, though, because their different topological centers are based on different overall indexing scopes. Scopus employs a computational theme-centric network of ideas (using artificial intelligence and machine learning as the top axes), while the Web of Science tends to an idea network of perception and relationships (trust and reputation as the empiric axes).

4. Discussion

The results of this comparative bibliometric study reveal differences in research regarding the use of AI, e-reputation and consumer trust captured by both platforms from a structural perspective. These differences in finding are not between two clearly separated paradigms, but are related to the types of documentation, the editorial time-lags and complementary indexing scopes of both indexes. For example, Scopus serves as an advanced technological radar. Powered by extensive inclusion of conference proceedings, IEEE engineering literature and applied decision science outlets, Scopus also detects ongoing breakthroughs like new deep learning architectures, federated learning protocols and blockchain-enabled review verification mechanisms. By contrast, Web of Science functions more as a theoretical aggregation sieve. With a focus on highly selective inclusion of key Social Sciences Citation Index (SSCI) journals in the disciplines of management, business and information systems, Web of Science emphasizes the organizational and relational implications of deploying the technology. Acknowledgment of the complementarity of these two databases is critical to bibliometric research design. To only use one of the two databases would risk only being shown a portion of the field: Scopus only is too heavily skewed towards technical infrastructure to catch a glimpse of the social shaping and human factors theories, while a Web of Science only search ignores the newly introduced algorithmic capabilities. Including these sources together is a holistic picture of the technology of artificial intelligence, which documents from original system design until its eventual place in institutional architecture and public confidence.

Thematic clusters between the two databases will not be presented in the form of conceptual diagrams but rather in context of core assumptions of the conceptual models of Signaling Theory, TAM and Multi-Dimensional Trust Theory. In the user interface and adoption context, information quality and quantity offered by an algorithm and correlation between algorithm's performance and users' interdependence on algorithm may be explained by the Technology Acceptance Model. Recommendations engine with automated sentiment summaries are likely to appeal to consumer's perceived usefulness and perceived ease of use while artificial intelligence assumes an autonomous function of rating aggregation and instant replies. Related to the level of structure and infrastructure, the theory behind Multi-Dimensional Trust, especially the institutional-based trust explains how technical integrity is formed in digital markets. The strong blockchain and cybersecurity clusters we observe across both databases indicate that system-based certainty has substituted for interpersonal certainty in cryptographic

ledgers and federated machine learning as the base of trust. The integrity of e-reputation is thus formed on the technical level when trusted data becomes safeguarded from faking and tampering. When seen through the lens of market communication, Signaling Theory, processed reputational information serves as proof to consumers that there is less information discrepancy between the two parties. ML algorithms can act as signal-cleaners for fake reviews and noise, hence converting processing-based trust into enduring relationship-based trust and brand equity as per the commitment-trust view.

These quantitative results provide practical implications for managers working in environments of connected AI: platform architects, brand managers and digital marketers. First, in signal authentication, platform operators need to deploy natural language processing and deep learning classifiers to authenticate fake reviews and detect sentiment manipulation systems in real time. Authenticating the signals is a critical first step to preserve brand equity and prevent consumer skepticism against online reviews. Second, in algorithmic automation and transparency, automated response agents and conversational artificial intelligence help reduce human resource costs, but too much transparency and lack of explanation for algorithmic decisions will introduce the risk of algorithmic aversion. Managers should provide appropriate transparency and escalation options for sensitive service failures. Third, in cryptographic systems, with regard to e-commerce platforms and peer-to-peer systems, employing blockchain or distributed ledger verification technology to create the audit trail for consumer feedback builds institutional trust in high-asymmetry environments.

There are a few methodological limitations in the study that should be kept in mind when analyzing the data. This includes the use of the same search strings across the two field-matched databases whereas the difference in their indexing policies and keyword assignment procedures does affect the frequency of occurrence of the terms. Furthermore, science mapping relies on co-occurrence algorithms and, therefore, term links are merged but the context of citing is not revealed (such as positive, neutral, or negative). Finally, while all eligible records within the 2015-2025 decade are studied, additional domain-specific databases or full-text mining may contribute to larger coverage in future research.

Conclusion

A comprehensive bibliometric analysis of research on e-reputation combined with artificial intelligence that emerged from 2015 to 2025 was led in this article, with trust at the centre of the study. The bibliographic study of Scopus (n = 541) and Web of Science (n = 293) showed two image complementary of the field of study, with a larger role for the technological aspect focused on the predictive process and their algorithms, which is dominant in Scopus compared to Web of Science, for consumers' behaviour, brand management and trusting hypothesis. These images show the transition of AI from a passive tool in terms of analysis to one of a leading actor in the strategic management of digital identities and credibility. In addition, the study shows the emergence of a decentralization of the domain of knowledge, with the dominant active participation of new research centers in Asia, Europe and the MENA zone (including Morocco).

Several limitations should be taken into account when interpreting our results. First, although we used the same search strings in each field-equivalent database and exported all the relevant records (100%) according to PRISMA methodology, the different indexing policies and keyword assignment procedures of the two databases (Scopus, and Web of Science) meant that the frequency of terms co-occurring was not the same. Second, science mapping is based on co-occurrences algorithms that group together ties in metadata, which reveals structural ties and thematic directions but does not reflect the qualitative context or empirical depth of each

individual publication. As such, our findings refer to structural mapping of scientific borders rather than to a comprehensive qualitative synthesis of the literature.

Moving forward, there are three broader research agendas in this field. First, combining quantitative bibliometric science mapping with qualitative systematic review and empirical field studies can help test the design of AI trust dynamics in different cultures and industry contexts; second, field studies (such as longitudinal research) can test the impact of dynamic AI transparency communication on brand legitimacy and customer algorithmic aversion; third, deepening studies can be conducted to explore the mediating effect between computational verification and relationship trust. This study reaffirms that consumer trust is the main link to connect technology innovation and consumer behavior, and maintaining an optimum level between algorithmic automation and relationship development should be a future research agenda for academia and practitioners.

References

- Aria, M., & Cuccurullo, C. (2017). bibliometrix : An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959-975. <https://doi.org/10.1016/j.joi.2017.08.007>
- Aria, M., Cuccurullo, C., D'Aniello, L., & Spano, M. (2026). Biblioshiny and the SAAS Workflow : An integrated framework for transparent and reproducible science mapping. A demonstration through the replication of a study. *Journal of Informetrics*, 20(3), 101837. <https://doi.org/10.1016/j.joi.2026.101837>
- Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, 56(5), 809-825. <https://doi.org/10.1177/0022243719851788>
- Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales : Online Book Reviews. *Journal of Marketing Research*, 43(3), 345-354. <https://doi.org/10.1509/jmkr.43.3.345>
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42. <https://doi.org/10.1007/s11747-019-00696-0>
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319. <https://doi.org/10.2307/249008>
- Deutsch, M. (1973). The Resolution of Conflict : Constructive and Destructive Processes. *American Behavioral Scientist*, 17(2), 248-248. <https://doi.org/10.1177/000276427301700206>
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis : An overview and guidelines. *Journal of Business Research*, 133, 285-296. <https://doi.org/10.1016/j.jbusres.2021.04.070>
- Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research : Perspectives and research propositions. *International Journal of Information Management*, 59. <https://eprints.whiterose.ac.uk/id/eprint/163654/>
- Filieri, R., McLeay, F., Tsui, B., & Lin, Z. (2018). Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. *Information & Management*, 55(8), 956-970. <https://doi.org/10.1016/j.im.2018.04.010>

- Kaplan, A., & Haenlein, M. (2019). Rulers of the world, unite ! The challenges and opportunities of artificial intelligence. *Business Horizons*, 63. <https://doi.org/10.1016/j.bushor.2019.09.003>
- Lewicki, R., & Bunker, B. (1996). Developing and Maintaining Trust in Working Relations. In *Trust in organizations : Frontiers of theory and research* (p. 114-139). <https://doi.org/10.4135/9781452243610.n7>
- Morgan & Hunt. (1994). (PDF) *The Commitment-Trust Theory of Relationship Marketing*. https://www.researchgate.net/publication/233894851_The_Commitment-Trust_Theory_of_Relationship_Marketing
- Morgan, R. M., & Hunt, S. D. (s. d.). *The Commitment-Trust Theory of Relationship Marketing*.
- Rai, A. (2020). Explainable AI : From black box to glass box. *Journal of the Academy of Marketing Science*, 48(1), 137-141. <https://doi.org/10.1007/s11747-019-00710-5>
- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation : A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Zhang, X., Chen, A. L., Piao, X., Yu, M., Zhang, Y., & Zhang, L. (2024). Is AI chatbot recommendation convincing customer? An analytical response based on the elaboration likelihood model. *Acta Psychologica*, 250, 104501. <https://doi.org/10.1016/j.actpsy.2024.104501>
- Zucker, L. G. (1986). Production of trust : Institutional sources of economic structure, 1840–1920. *Research in Organizational Behavior*, 8, 53-111.
- Zupic, I., & Čater, T. (2015). Bibliometric Methods in Management and Organization. *Organizational Research Methods*, 18(3), 429-472. <https://doi.org/10.1177/1094428114562629>