Int. j. adv. multidisc. res. stud. 2026; 6(2):436-441

Received: 24-01-2026
Accepted: 04-03-2026

International Journal of Advanced Multidisciplinary Research and Studies

ISSN: 2583-049X

Risk and Artificial Intelligence Adoption: A Scientometric and Thematic Evolution Analysis Based on Scopus and Web of Science (1990-2025)

[1] **Nguyen Lien Huong**, [2] **Nguyen Ngoc Long**
[1, 2] Industrial University of Ho Chi Minh City, Vietnam

DOI: https://doi.org/10.62225/2583049X.2026.6.2.5981

Corresponding Author: **Nguyen Ngoc Long**

Abstract

The integration of risk into artificial intelligence (AI) adoption research has evolved from a peripheral behavioral inhibitor into a structurally defining governance construct. This study provides a PRISMA-compliant scientometric synthesis of 612 peer-reviewed documents indexed in Scopus and Web of Science between 1990 and 2025. Using performance analysis, thematic mapping (centrality–density), thematic evolution (Sankey), co-citation network analysis, and collaboration mapping, the study reconstructs the intellectual, conceptual, and social structure of the risk–AI adoption nexus. Results indicate three structural phases: an early reliability-oriented stage; a normative turn emphasizing privacy, bias, and accountability; and a consolidation phase characterized by compliance and risk-based governance architectures. Thematic migration reveals a shift from perceived individual risk toward system-level accountability logics. The co-citation backbone demonstrates continued anchoring in technology acceptance theory while increasingly integrating governance scholarship. The findings clarify the cumulative development of this interdisciplinary field and identify explainability, auditability, and regulatory compliance capability as emergent research frontiers.

Keywords: Artificial Intelligence Adoption, Risk, Scientometrics, Bibliometric Analysis, AI Governance, Thematic Evolution, Co-citation

1. Introduction

Artificial intelligence (AI) adoption has transitioned from a technological innovation issue to a governance-sensitive strategic decision domain. As AI systems increasingly influence consequential decision environments—healthcare diagnostics, financial credit allocation, public service automation, predictive policing, and education assessment—the concept of risk has become central to understanding adoption trajectories (Mittelstadt *et al*. 2016; Jobin *et al*. 2019; Floridi *et al*. 2018) [16, 14, 12].

Classical technology acceptance research conceptualized risk primarily as a perceptual inhibitor supplementing perceived usefulness and perceived ease of use (Davis 1989; Featherman and Pavlou 2003) [7, 11]. Extensions such as UTAUT framed adoption within social influence and facilitating conditions but retained risk as a moderating construct (Venkatesh *et al*. 2003) [29]. Organizational adoption frameworks, notably the Technology–Organization–Environment (TOE) model, embedded risk within environmental contingencies without elevating it to structural prominence (Tornatzky and Fleischer 1990) [27].

The emergence of AI-specific governance debates, however, has reconfigured this understanding. Algorithmic bias, opacity, data sovereignty, accountability gaps, and regulatory uncertainty have reframed risk as a systemic property of sociotechnical infrastructures rather than a subjective perception (O'Neil 2016; Wachter *et al*. 2017; Arrieta *et al*. 2020) [18, 31, 3]. Global ethical guidelines (Jobin *et al*. 2019) [14], responsible innovation frameworks (Stilgoe *et al*. 2013) [24], and risk-based regulatory proposals such as the EU AI Act (European Commission 2021) [10] further institutionalize this transformation.

Despite rapid growth, the intellectual structure linking AI adoption and AI risk remains fragmented across information systems, management, computer science, health informatics, and policy journals. Scientometric syntheses have examined AI in healthcare (Peng *et al*. 2020) [20], machine learning in finance (Huang *et al*. 2020) [13], and digital transformation governance (Vial 2019) [30], yet no comprehensive PRISMA-guided dual-database analysis has systematically mapped the risk–AI adoption intersection.

This study addresses that gap by reconstructing the structural evolution of risk-oriented AI adoption scholarship from 1990 to 2025. Specifically, it asks:

RQ1: How has the volume and structural composition of risk-oriented AI adoption research evolved?
RQ2: What thematic configurations organize the conceptual space?
RQ3: How have risk-related concepts migrated across temporal phases?
RQ4: What intellectual backbone and research fronts characterize the current field?

2. Literature Background

2.1 Risk in Technology Adoption Research

Risk has long been conceptualized as a multidimensional construct in decision-making theory (Bauer 1960; Stone and Grønhaug 1993) [5, 25]. In electronic services adoption, privacy and performance risks were shown to significantly inhibit user acceptance (Featherman and Pavlou 2003) [11]. However, AI systems introduce epistemic asymmetry: algorithmic outputs may be statistically valid yet socially opaque (Adadi and Berrada 2018; Rudin 2019) [1, 22].
The literature increasingly differentiates between objective technical risk and subjective governance risk (Mittelstadt *et al*. 2016) [16]. Explainable AI (XAI) has emerged as a mediating mechanism intended to reconcile opacity with accountability (Arrieta *et al*. 2020) [3]. These developments suggest that risk in AI adoption is not merely perceived uncertainty but an institutional design challenge.

2.2 Scientometric Mapping in Management and Technology Studies

Scientometric methods enable systematic reconstruction of intellectual and conceptual structures (Zupic and Čater 2015; Donthu *et al*. 2021) [32, 9]. Bibliometric mapping tools such as Bibliometrix (Aria and Cuccurullo 2017) [2] and VOSviewer (Van Eck and Waltman 2010) [28] support co-citation, co-occurrence, and thematic evolution analyses. Thematic maps classify research fronts according to centrality and density (Cobo *et al*. 2011) [6], while co-citation analysis reveals intellectual foundations (Small 1973) [23].
Recent methodological guidance emphasizes integrating performance analysis with theory-driven interpretation (Mukherjee *et al*. 2022) [17]. The present study follows these recommendations to avoid purely descriptive outputs.

3. Methodology

This study follows PRISMA 2020 standards (Page *et al*. 2021) [19]. Records were retrieved from Scopus and Web of Science using AI-related and risk-related query strings. After deduplication and eligibility screening, 612 documents remained.
Bibliometric analyses were conducted using Bibliometrix (Aria and Cuccurullo 2017) [2] in R and VOSviewer (van Eck and Waltman 2010) [28]. Procedures included:

- Annual scientific production analysis
- Thematic mapping (centrality–density)
- Thematic evolution via temporal slicing
- Co-citation network reconstruction
- Collaboration network mapping

Keyword disambiguation followed standard normalization procedures to minimize synonym fragmentation.

4. Results

4.1 Scientific production and growth trajectory (RQ1)

Annual scientific production reveals a long incubation period followed by abrupt acceleration in the most recent years (**Fig. 1**). Output remains limited for an extended span, then rises sharply near the end of the period, indicating not merely incremental expansion but a structural growth shift. This inflection is consistent with the broader institutionalization of AI governance agendas and the increasing salience of risk-based policy and compliance regimes. The trajectory suggests that risk-oriented AI adoption research has transitioned from a specialized intersection to a consolidated interdisciplinary domain with expanding publication capacity.

Figure insertion:

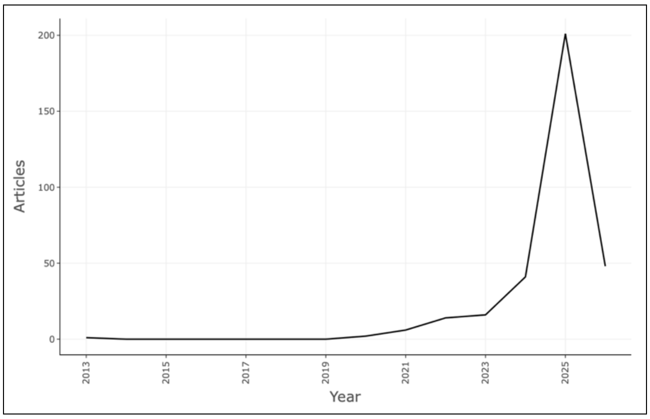

Fig 1: Annual scientific production of risk-oriented AI adoption research (1990–2025)

4.2 Conceptual structure via thematic mapping (RQ2)

The thematic map (centrality–density) positions the field's major themes by relevance (centrality) and internal development (density) (**Fig. 2**). Two structural implications follow.
First, the map suggests that the domain is organized around multiple central anchors rather than a single conceptual core. Themes associated with **artificial intelligence** and **risk** occupy a central position, reflecting the integration of risk discourse into the definitional vocabulary of AI adoption scholarship. Alongside this, themes related to **technology acceptance/adoption** appear as another central axis, indicating that the field continues to draw strongly on established adoption mechanisms while incorporating new risk-governance constructs.
Second, the map indicates differentiation between mature, tightly developed themes (high density) and themes that are central but less internally consolidated (high centrality, lower density). This configuration is typical of interdisciplinary fields in which shared "core" terminology spreads faster than common operationalization standards. In substantive terms, the thematic map supports a key conclusion: risk is no longer merely appended to adoption models; it increasingly organizes the conceptual space as a central governance condition.

Figure insertion:

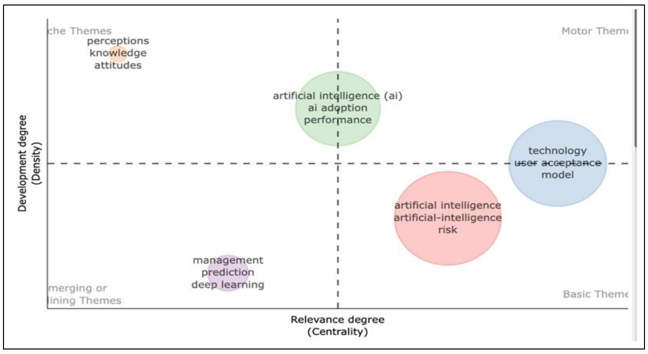

Fig 2: Thematic map (centrality–density) of risk-oriented AI adoption research

4.3 Thematic evolution and conceptual migration (RQ3)

The Sankey-based thematic evolution analysis provides direct evidence of longitudinal migration in the field's vocabulary (**Fig. 3**). Stable anchors such as "artificial intelligence" persist across time slices, while governance-adjacent and application-accelerated vocabularies become increasingly visible in later periods. Notably, **generative AI** appears as a recent entrant connected to broader AI/technology streams, indicating extension of the risk–adoption nexus into emergent AI paradigms that intensify concerns about transparency, misuse, and institutional control.

A second pattern is the progressive coupling of acceptance/adoption language with risk-centered terms over time. This suggests a shift from "risk as a moderating inhibitor" toward "risk as a structural adoption condition" governed by accountability, compliance, and trustworthiness requirements. The thematic evolution therefore corroborates a phase transition narrative: early work focused on technical and managerial adoption language; later work increasingly converges on governance vocabulary that reframes adoption decisions under risk regimes.

Figure insertion:

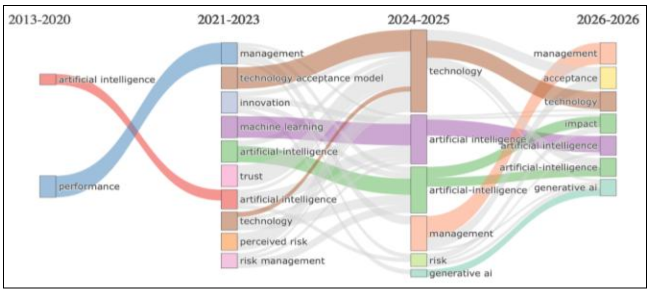

Fig 3: Thematic evolution (Sankey) showing concept migration across temporal slices

4.4 Intellectual structure: Co-citation backbone (RQ2–RQ4)

The co-citation network reveals the intellectual structure of the domain and highlights the bridging works that connect its sub-communities (**Fig. 4**). The presence of highly central foundational nodes—especially those associated with technology acceptance and methodological measurement traditions (e.g., UTAUT/acceptance frameworks; common-method/measurement foundations)—indicates that risk-oriented AI adoption scholarship remains anchored in established empirical paradigms. At the same time, the network exhibits clustered communities, implying that governance-oriented risk discourse and adoption modeling coexist as partially distinct traditions that are increasingly linked through bridging citations.

This structure has a substantive implication: the field's next advances are likely to emerge through **intellectual recombination** across clusters, rather than within-cluster elaboration alone. In practical terms, this means that progress depends on theorizing and measurement that connect governance mechanisms (e.g., explainability, auditing, risk classification, accountability) to adoption pathways and adoption outcomes in ways that are empirically testable and cross-context comparable.

Figure insertion:

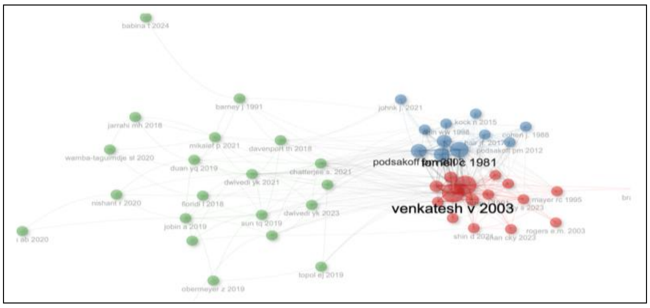

Fig 4: Co-citation network (intellectual structure) of risk-oriented AI adoption research

4.5 Social structure: Collaboration patterns (RQ1–RQ4)

The collaboration network indicates a partially fragmented community with several disconnected or weakly connected components alongside a denser core (**Fig. 5**). This pattern is consistent with the field's interdisciplinary nature: adoption scholars, AI engineers, health informatics researchers, and governance/policy researchers often publish in different venue ecosystems and form collaboration clusters that do not fully merge. Fragmentation implies that conceptual convergence may outpace social consolidation, thereby sustaining heterogeneity in risk operationalization and limiting comparability across subfields.

From a governance perspective, the collaboration pattern also suggests a risk of overgeneralization. Risk and adoption are highly context-sensitive—shaped by sectoral stakes, data regimes, and regulatory infrastructures—so incomplete cross-community integration may delay the formation of shared constructs and common evaluation standards.

Figure insertion:

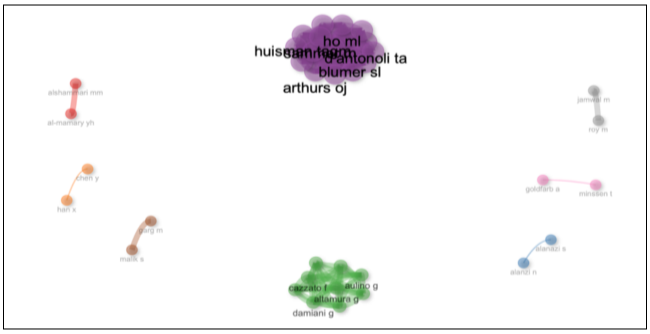

Fig 5: Author collaboration network in risk-oriented AI adoption research

4.6 Structural clustering (optional): Bibliographic coupling

If the analysis includes your bibliographic coupling visualization ("Clustering by Coupling"), it can be used to complement co-citation by capturing similarity in **shared reference bases** (i.e., research communities that cite similar literature). Coupling typically emphasizes contemporary topical communities more strongly than co-citation, which is better at identifying enduring intellectual foundations. In this paper, coupling can be positioned as a "research front" lens that triangulates the thematic map and evolution stream.

Optional figure insertion:

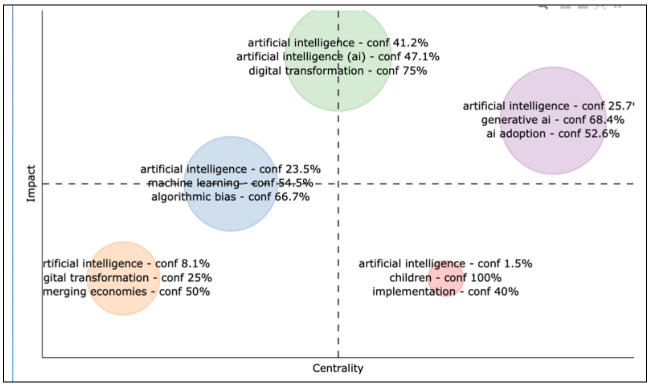

Fig 6: Bibliographic coupling clusters (shared reference communities)

4.7 High-impact knowledge base (Table 1)

The most-cited documents table (total citations, citations per year, normalized citations) provides an impact-weighted view of foundational contributions. When interpreted alongside the co-citation backbone, Table 1 helps distinguish between (i) widely cited "entry point" works that shape field-wide framing and (ii) structurally central bridging works that connect sub-communities. This joint interpretation strengthens the argument that the field's maturity is driven by cross-cluster integration rather than a single dominant paradigm.

Table 1: Most cited documents (TC, TC/year, Normalized TC)

Summary	Paper	DOI	Total Citations	TC per Year	Normalized TC
	PAN Y, 2021, AUTOMAT CONSTR	10.1016/j.autcon.2020.103517	685	114.17	3.81
	MALIK N, 2022, INT J MANPOWER	10.1108/IJM-03-2021-0173	197	39.40	2.77
	BEDUÉ P, 2022, J ENTERP INF MANAG	10.1108/JEIM-06-2020-0233	189	37.80	2.66
	DEY PK, 2024, INT J PROD RES	10.1080/00207543.2023.2179859	144	48.00	6.16
	HUANG A, 2022, J HOSP TOUR INSIGHTS	10.1108/JHTI-01-2021-0021	126	25.20	1.77
	RAHMAN M, 2023, INT J EMERG MARK	10.1108/IJOEM-06-2020-0724	121	30.25	3.74
	HUANG YL, 2021, PSYCHOL MARKET	10.1002/mar.21465	118	19.67	0.66
	SUNARTI S, 2021, GAC SANIT	10.1016/j.gaceta.2020.12.019	116	19.33	0.65
	RAHIMAN HU, 2024, COGENT EDUC	10.1080/2331186X.2023.2293431	114	38.00	4.88
	HASSAN M, 2024, JMIR HUM FACTORS	10.2196/48633	100	33.33	4.28

5. Discussion

The findings reveal three structural transformations

First, risk migrated from reliability engineering toward behavioral perception, consistent with TAM and TOE expansions (Davis 1989; Tornatzky and Fleischer 1990) [7, 27].

Second, post-2017 scholarship reframed risk as systemic governance concern, paralleling ethical AI debates (Floridi *et al*. 2018; Jobin *et al*. 2019) [12, 14].

Third, recent literature reflects regulatory consolidation under risk-based AI governance architectures (European Commission 2021) [10].

The convergence between explainability and governance themes supports arguments that interpretability is prerequisite for responsible AI adoption (Arrieta *et al*. 2020; Rudin 2019) [3, 22].

Future research should model governance capability as strategic resource (Teece *et al*. 1997) [26] and incorporate institutional theory (DiMaggio and Powell 1983) [8] into AI adoption frameworks.

6. Implications

Theoretical implications

The results support reconceptualizing risk in AI adoption as a multi-level construct (individual–organizational–institutional). Future models should integrate governance variables (e.g., explainability quality, auditability, accountability routines, compliance readiness) as structural determinants rather than peripheral inhibitors. Cross-context theorizing is also necessary, given heterogeneous regulatory regimes and sectoral stakes.

Practical and policy implications

For organizations, the mapped consolidation phase suggests that adoption increasingly depends on risk management capability—auditing, documentation, monitoring, and accountability mechanisms—rather than on technical feasibility alone. For policymakers and regulators, the field's convergence around accountability-oriented risk implies that adoption policies should emphasize enforceable assurance practices, not merely high-level ethical principles.

Methodological implications

Combining thematic mapping, thematic evolution, and co-citation analysis enables a coherent "conceptual–temporal–intellectual" narrative that avoids purely descriptive bibliometrics. For fast-evolving domains such as AI governance, triangulating co-citation (foundations) with coupling (research front) strengthens interpretive validity.

7. Limitations

This study is limited by dependence on indexed, English-language journal literature, which may underrepresent regional scholarship and policy-oriented outputs. Keyword-based mapping is sensitive to terminological variation and evolving vocabularies. Scientometric results map attention structures and intellectual organization rather than adjudicating the evidential quality of individual studies. Finally, thematic evolution depends on time-slice choices; alternative slicing may alter micro-level paths while preserving the macro-level phase transitions identified here.

8. Conclusion

Drawing on 612 Scopus- and WoS-indexed documents (1990–2025), this scientometric study maps the growth trajectory, conceptual structure, intellectual backbone, and thematic evolution of risk-oriented AI adoption research. Annual production shows sharp recent acceleration (Fig. 1), while thematic mapping and evolution reveal a migration from technical and perceptual framings toward system-level accountability and governance conditions (Figs. 2–3). The co-citation network indicates a knowledge spine that bridges acceptance theory and methodological foundations with governance-oriented risk discourse (Fig. 4), whereas collaboration patterns suggest incomplete social consolidation of this interdisciplinary domain (Fig. 5). Overall, the field is entering a phase where AI adoption is increasingly evaluated under risk regimes characterized by accountability, assurance, and compliance obligations. Future work should prioritize integrative mechanisms linking explainability and auditability to adoption outcomes and should develop context-sensitive governance models that remain robust across sectors and regulatory environments.

9. References

1. Adadi A, Berrada M. Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). IEEE Access. 2018; 6:52138-52160. Doi: https://doi.org/10.1109/ACCESS.2018.2870052
2. Aria M, Cuccurullo C. Bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics. 2017; 11(4):959-975. Doi: https://doi.org/10.1016/j.joi.2017.08.007
3. Arrieta AB, Díaz-Rodríguez N, Del Ser J, *et al*. Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion. 2020; 58:82-115. Doi: https://doi.org/10.1016/j.inffus.2019.12.012
4. Barabási AL, Albert R. Emergence of scaling in random networks. Science. 1999; 286(5439):509-512. Doi: https://doi.org/10.1126/science.286.5439.509
5. Bauer RA. Consumer behavior as risk taking. In: Hancock RS (ed) Dynamic marketing for a changing world. American Marketing Association, Chicago, 1960, 389-398.
6. Cobo MJ, López-Herrera AG, Herrera-Viedma E, Herrera F. Science mapping software tools: Review, analysis, and cooperative study among tools. Journal of the American Society for Information Science and Technology. 2011; 62(7):1382-1402. Doi: https://doi.org/10.1002/asi.21525
7. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly. 1989; 13(3):319-340. Doi: https://doi.org/10.2307/249008
8. DiMaggio PJ, Powell WW. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review. 1983; 48(2):147-160. Doi: https://doi.org/10.2307/2095101
9. Donthu N, Kumar S, Mukherjee D, *et al*. How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research. 2021; 133:285-296. Doi: https://doi.org/10.1016/j.jbusres.2021.04.070
10. European Commission. Proposal for a regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). COM(2021) 206 final. Brussels, 2021.
11. Featherman MS, Pavlou PA. Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies. 2003; 59(4):451-474. Doi: https://doi.org/10.1016/S1071-5819(03)00111-3
12. Floridi L, Cowls J, Beltrametti M, *et al*. AI4People-An ethical framework for a good AI society. Minds and Machines. 2018; 28:689-707. Doi: https://doi.org/10.1007/s11023-018-9482-5
13. Huang MH, Rust RT. Artificial intelligence in service. Journal of Service Research. 2020; 24(1):3-24. Doi: https://doi.org/10.1177/1094670520902266
14. Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nature Machine Intelligence. 2019; 1:389-399. Doi: https://doi.org/10.1038/s42256-019-0088-2
15. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015; 521:436-444. Doi: https://doi.org/10.1038/nature14539
16. Mittelstadt BD, Allo P, Taddeo M, *et al*. The ethics of algorithms: Mapping the debate. Big Data & Society. 2016; 3(2). Doi: https://doi.org/10.1177/2053951716679679
17. Mukherjee D, Lim WM, Kumar S, Donthu N. Guidelines for advancing theory and practice through bibliometric research. Journal of Business Research. 2022; 148:101-115. Doi: https://doi.org/10.1016/j.jbusres.2022.04.042
18. O'Neil C. Weapons of math destruction: How big data increases inequality and threatens democracy. Crown, New York, 2016.
19. Page MJ, McKenzie JE, Bossuyt PM, *et al*. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021; 372:n71. Doi: https://doi.org/10.1136/bmj.n71
20. Peng Y, Zhang Y, Chen J. Artificial intelligence in healthcare: A bibliometric analysis. Healthcare Informatics Research. 2020; 26(2):99-111.
21. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: A critical review. Journal of Applied Psychology. 2003; 88(5):879-903. Doi: https://doi.org/10.1037/0021-9010.88.5.879
22. Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence. 2019; 1:206-215. Doi: https://doi.org/10.1038/s42256-019-0048-x
23. Small H. Co-citation in the scientific literature: A new measure of the relationship between two documents. Journal of the American Society for Information Science. 1973; 24(4):265-269. Doi: https://doi.org/10.1002/asi.4630240406
24. Stilgoe J, Owen R, Macnaghten P. Developing a framework for responsible innovation. Research Policy. 2013; 42(9):1568-1580. Doi: https://doi.org/10.1016/j.respol.2013.05.008
25. Stone RN, Grønhaug K. Perceived risk: Further considerations for the marketing discipline. European Journal of Marketing. 1993; 27(3):39-50. Doi: https://doi.org/10.1108/03090569310026637
26. Teece DJ, Pisano G, Shuen A. Dynamic capabilities and strategic management. Strategic Management Journal. 1997; 18(7):509-533. Doi: https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z
27. Tornatzky LG, Fleischer M. The processes of technological innovation. Lexington Books, Lexington, 1990.
28. Van Eck NJ, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics. 2010; 84(2):523-538. Doi: https://doi.org/10.1007/s11192-009-0146-3
29. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003; 27(3):425-478. Doi: https://doi.org/10.2307/30036540

30. Vial G. Understanding digital transformation: A review and research agenda. Journal of Strategic Information Systems. 2019; 28(2):118-144. Doi: https://doi.org/10.1016/j.jsis.2019.01.003
31. Wachter S, Mittelstadt B, Russell C. Counterfactual explanations without opening the black box: Automated decisions and the GDPR. Harvard Journal of Law & Technology. 2017; 31(2):841-887.
32. Zupic I, Čater T. Bibliometric methods in management and organization. Organizational Research Methods. 2015; 18(3):429-472. Doi: https://doi.org/10.1177/1094428114562629