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Bibliometric perceptions into AI and cloud computing applications for innovative product development

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C H R O N I C L E

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This paper provides a bibliometric analysis of AI and cloud computing in product revolution and development. It attempts to make sense of its evolution and styles of research to date. A systematic analysis based on the PRISMA protocol was regulated over journals rescued from Web of Science Core Current Contents Connect (CCC) and Web of Science Core Collection (WoSCC) related to 118 articles published between 2009 and 2025. Python-based Bibliometric performance through analytical tools and visualization using VOSviewer statistics and science mapping. The findings reveal an authoritative yearly growth trend and rising academic attraction in the subject, and especially since 2018. The big players were universal in co-occurrence analysis of keywords. AI-focused Product Design, Cloud-based Collaborative engineering, digital twin, data analytics, generative AI and open innovation ecosystems. Furthermore, temporal overlay analysis shows a progressive transition from the pioneer articles of digital infrastructures to intelligent innovation systems. The results increase existing research on innovation management literature by aiming at how AI technologies, cloud programs and digital innovation ecosystems converge, revealing rich avenues for further cross-disciplinary research.

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1. Introduction

During the last few years, emerging digital technologies have been prospering at an unprecedented rate. revolutionizing product innovation and NPD quarters. Most markedly, AI and CC have become vital technology enablers for which benefits guided product design, which include prototyping, testing and lifecycle management (Qudah & Alqudah, 2026). Traditionally, product innovation relied profoundly on the expertise of individuals, a series of stages in its development, and constrained data utilization. Computational capabilities and digital infrastructures have, and organizations have relied on AI-driven analytics and cloud-based process of accelerated frameworks in innovation, detection as a result, digital technologies are transforming the way firms source ideas, assess product concepts, and manage difficult innovation ecosystems (Brem et al., 2021; Verganti et al., 2020).

AI technologies are progressively included into product development procedures to develop data-driven decision-making, ideas generation and solutions optimization. For instance, machine learning algorithms and natural language processing tools accept organizations to analyze massive amounts of customer feedback, market trends, and technological data to discover potentially promising innovation opportunities (Christensen et al., 2017; Hoornaert et al., 2017). Also, systems based on AI help innovative groups to create ideas, discover alternatives for designs, and provide knowledge management (Botega & Da Silva 2020). Subsequently, AI is being increasingly viewed as a co-creator that can enhance human creativity and provide additional horsepower to innovation groups (Bouschery et al., 2023; Garbuio & Lin, 2021).

In parallel, CC has emerged as a fundamental infrastructure for the digital transformation of product innovation. Cloud programs accept organizations to store, procedure and share vast amounts of data among distributed groups and partners to collaborate on product development and make decisions in real time. Cloud-based computing frameworks enable firms to

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deploy AI applications at scale and integrate advanced analytics into innovation workflows (Robertson et al., 2021). The advent of interconnected digital programs and digital twins, meanwhile, has further elevated product lifecycle management by accepting constant monitoring, simulation, and optimization of products as they move through the development period and into their operational phases (Van Dyck et al., 2023). As a result, the application of AI and cloud technologies has fostered the development of data-driven and cloud-permitted Innovation ecosystems through which organizations can collaborate, evaluate ideas, and create value faster than ever before.

Besides, the increasing accessibility of big data and online collaboration software solutions has expedited the evolution of innovation management approaches. Innovative procedures based on data accept companies to apply perceptions from social media, customer interactions, and digital programs to identify emerging market needs and technological opportunities (Esfahani et al., 2019; Salimi et al., 2019). Meanwhile, AI managed analytics can harness predictive modeling and decision confirm in diverse fields of product design, machineering optimization, and market prediction (Ghorbani & Ghousi, 2019). As a result, organizations are progressively adopting AI-powered analytics, generative design tools, and collaborative cloud programs to develop the speed and quality of their innovation endeavours (Jiang et al., 2023; Cooper & Brem, 2024).

While AI and CC have increasingly developed critical for product innovation, the literature is dispersed across several academic fields. AI-permitted innovation papers are diffused in the literature of machineering management, innovation management, computer science, and information systems. For example, several papers address the effects of advanced AI models in design and product development workflows (Plantec et al., 2023), while others investigate the roles of digital technologies for organizations' innovation capabilities and contribution to sustainability (Lin et al., 2024; Ogbeibu et al., 2024). Research on NPD also sustains the interest of researchers in managerial challenges surrounding innovation procedures such as organizational barriers, collaboration dynamics, or decision-making uncertainties (Markham et al., 2010; Rodríguez-Escudero et al., 2010). Nonetheless, these papers are in diverse research streams, the general intellectual structure and thematic evolution of AI-permitted product innovation research are still poorly understood.

Likewise, the most recent research indicates that embedding AI technologies into innovative procedures necessitates considerable adjustment and strategic alignment within organizations. This firm will require novel capabilities around data management, algorithmic decision-making, and cross-functional collaboration to fully realize AI-driven innovation systems (Cooper, 2025; Schwaeke et al., 2025). Concurrently, the implementation of Industry 4.0 technologies is permitting circular economy practices and the sustainable development of products to take place, which further drives the strategic role played by digital technologies in innovation management (Pinheiro et al., 2022; Jian et al., 2024). Thus, the increasing significance for scholars and practitioners alike of understanding the growth and character of research in this field has grown.

Thus, this paper seeks to conduct a bibliometric analysis of works related to the combination of AI and CC in terms of innovative product development from 2003-2025. That is, the study aims at variety of analyses such as trends in publication output and citation impact; most recorded journals, documents, and scholars are presented in the field; concept (co-citation) and thematic structures associated with the papers. Additionally, the study examines trends in technological technology, method and research themes over time while also mapping new research gaps and future directions for AI-permitted product innovation effort. Lastly, the paper proceeds as follows: Section 2 presents literature and theoretical perspectives; Section 3 presents an overview of the methodology guiding the bibliometric analysis. The empirical results are then presented in the results section, followed by a discussion of theoretical implications and opportunities for future research before concluding the study.

2. Literature Review

AI and CC assimilation into product modernization revolutionizes the ways corporations create, develop, and deliver new products. Put in a nutshell, AI acts as an intellectual machine late product ideation, design optimization and predictive development that chains organizations in their endeavors to progress data-driven insights in the market for illegal strategic decisions (Brem et al., 2021; Botega & Da Silva, 2020). In addition, CC offers essential ascendable infrastructure talented at handling high volumes of product data, validating collaboration in distributed design environments and facilitating sophisticated PLM (product lifecycle management) systems (Robertson et al., 2021). Together these two technologies fabricate a series of digital programs that when embedded together through the introduction of such organizational means help firms achieve phases agile originalities while remaining responsive (Van Dyck et al., 2023; Verganti et al., 2020).

Thus, a chronological overview of product release evolution of AI and CC is a linear trajectory of rising operational maturity. Single-point PDF-based advance the first stage of digital transformation (2003-2010), organizations focused on cloud migration to store consolidated data and basic computer-aided design (CAD) systems. Early PLM organizations were planned to help sort out product data and ease up on development processes; However, these technologies were opened where Innovation was not endorsed first-hand in a strategic innovation context Enactment into Process was indorsed primarily (Carbonell et al., 2009; Markham et al., 2010). The early years laid down the infrastructure necessary for more Integration of advanced AI and cloud in latter stages. Here, the tone was immediate data-driven innovation and collaborative cloud between

2011 and 2018. Moreover, organizations mutually leveraged big data analytics for insights reviews, social media activity and trends to allow Evidence-Based Decision Making in Product Design (Esfahani et al., 2019; Salimi et al., 2019). A the idea of cloud-ready design where the design is done on a accommodating platform that enabled the Which allows reliable iterative design and collaborative for geographically distributed engineering teams In precise, concurrent machine ring approaches (Christensen, et al. 2017; Hoornaert, et al. 2017) This period marked a critical shift from technology as either a back-office enabler or as its individuality of: a strategic enabler of innovation, where firms could distill perceptions from multiple stakeholders and optimize product portfolios in real-time (Plantec et al., 2023; Jian et al., 2024).

The study has been for AI driven intelligent ecosystems crossing from 2019 up to as far as the year 2025 product development, which is the border at this moment in time. They are being utilized for Generative AI methods to build automated concept generation, design exploration, and optimization of prototypes; digital twins and simulation tools subsequently permit virtual testing and performance prediction (Bouschery et al., 2023; Van Dyck et al., 2023). AI-assisted prototyping and AI-driven programs have. Diminished the iteration cycles resulting in rapid time-to-market and better product quality (Jiang et al., 2023; Cooper & Brem, 2024).At the same time, CC remains an essential component of these advancements as it offers necessary computational and collaboration frameworks (Robertson et al., 2021; Hutchinson, 2021) for incorporating AI tooling on organizational and ecosystem dimensions.

On the other hand, additionally to technology, understanding AI and cloud adoption can only happen through an organization and ecosystem perspective in product innovation. Open innovation structures and platform-based ecosystems except for knowledge sharing, collaborative design, and co-creation between internal and external stakeholders (Garbuio & Lin, 2021; Pinheiro et al., 2022). Cloud-based innovation network and AI-permitted knowledge management facilitate distributed research-and-development (R&D) across firms and develop organizational learning and decision-making capabilities (Brem et al 2021; Ogbeibu et al., 2024). Extensive changes in innovation practices, including those that digital technologies have facilitated, highlight the vectoral and integrative roles of such technologies as contingency factors in determining firms' innovation performance and competitive advantage.

Nonetheless, there were still some gaps in the literature regarding AI and CC in product innovation. Currently existing bibliometric and systematic review are confined to narrow context, for example specific technology or industrial context rather than the broad set of stakeholders involved in included ecosystem (Ghorbani & Ghousi, 2019; Esfahani et al., 2019). Likewise, while the study witness a burgeoning dialogue surrounding AI's role in NPD, this nascent research stream has yet to adequately explore the constant interplay between complementary resources and procedures such as CC (Cook & Meyer, 2024) or thematic evolution among NPD entities across multiple disciplines at once (Lin et al., 2024; Schwaeke et al., 2025; Witkowski & Wodecki, 2025). The second point is important as addressing these gaps will offer a fuller picture of the intellectual structure and future paths of AI- and cloud-permitted product innovation research.

This review Thus lays the conceptual groundwork, identifies technological evolution, explicates organizational ramifications, and pinpoints significant research gaps, which together serves as a basis for both the bibliometric analysis and thematic synthesis that is subsequently presented as part of this study.

3. Methodology

3.1 Research Method: Bibliometric and Science-Mapping Approach

Adopting quantitative bibliometric and science-mapping research design, this study systematically explores the academic evolution of artificial intelligence (AI) and CC applications to confirm innovative product development. Bibliometric analysis is acknowledged as a practical way for quantitatively exploring research productivity, citation structures, and knowledge diffusion across various scientific domains. It accepts researchers to spot influential publications, new themes, and collaborative research within a specified domain (Donthu et al., 2021; Öztürk et al., 2024). Besides, science mapping techniques include an integral dimension of bibliometric performance analysis as it visualizes the architecture and thematic linkages amongst publications. A substantial number of papers have implemented bibliometric approaches to study technological innovation (Alqudah et al., 2025), sustainability research (Abdo et al., 2025), financial technologies, and digital transformation papers, over recent years. Similarly, several articles have occupied bibliometric methods to investigate the progression of newborn fields like green economy research and creative accounting enhancements (Alqudah et al., 2024; ALShanti et al., 2024). Based on this methodological Building on network visualization and performance analysis methods, the study in the different aspects of the addressed area of interest, but there are no cumulative reviews at least until October 2023. AI and cloud-permitted product innovation.

3.2 Data Source and Search Strategy

The Web of Science (WoS) Core Collection was chosen as the core database for this research due to high-quality indexing standards and full coverage of peer-reviewed academic journals. WoS has such a harsh citation indexing and structured metadata that Provided WoS being the larger database for strong bibliometric analysis mostly used by bibliometric papers

(AlQudah & Bariviera, 2026).We manufactured a search query wide enough to capture as many different angles on product innovation as specific enough that relevant publications can still be filtered (as illustrated in Table 4) while enduring as broad as possible. Specifically, the search string included combinations of words like “artificial intelligence,” “AI,” “machine learning,” “deep learning” and “neural networks” with terms such as CC, cloud technology, cloud-based systems and distributed computing. These technology words were mixed up with innovation-related keywords such as “innovative product development,” “product innovation,” “new product development,” “NPD,” “product design innovation” and “technology-driven product development.”

Likewise, only English-language journal articles listed in category Management of Web of Science were created for conductive results. Madonna used several years to publish materials specifically 2001, 2004, 2007 and 2026 were excluded, to maintain an even analytical period. As a result, those datasets primarily cover publications from 2009 to 2025, the time when AI and CC technologies started being used in product innovation procedures. Data was obtained on 2026.01.07, accepting the retrieval procedure to be verifiable and reproducible (Arnaud et al., 2021).

3.3 Screening and Selection Procedure

Following a search and extraction of data, an initial screening and selection procedure is completed in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which is a widely used framework that guides systematic literature identification, filtration, and selection for bibliometric evaluation. The initial search query yielded 151 records (Fig. 1) from the Web of Science database.

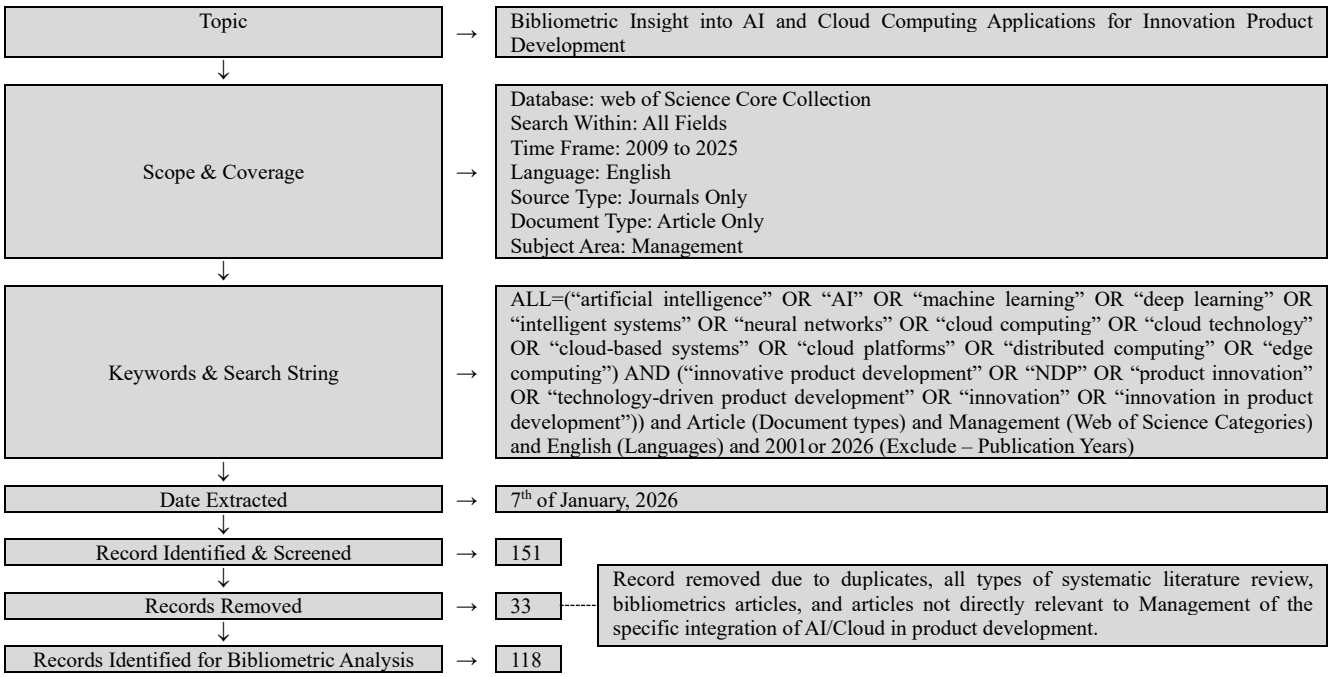

Fig. 1. Flowchart of the Literature Search and Screening Strategy

Then, the records that did not meet the inclusion criteria were filtered out. 33 records were removed since they had duplicates or other types of documents such as bibliometric reviews, systematic reviews, and articles that did not specifically deal with the application of AI or cloud technologies to product development or innovation management contexts. As a result of this extensive filtering procedure, the final dataset comprised 118 publications that were included in further bibliometric analysis.

3.4 Data Cleaning and Harmonization

To the best of my knowledge, bibliometric data obtained from conventional publication databases is not uncommon, but controlled, and so the study took several cleaning/harmonizing steps to arrive at the final dataset used for analysis. Harmonizing author names, normalizing keywords and declining this took my last invoked step. duplicate or incomplete records. The ingrained prerendering capabilities are a foundation for expanding the reliability of the bibliometric metrics and networks. Open-source Python libraries (like pandas, were used (NumPy, and bibliometric). These tools are used to reoperation of bibliographic datasets and accelerate reproducible data workflows. The strengthening ubiquitousness of Python-centric bibliometric pipelines demonstrates their dexterity and efficiency when managing bulky datasets in a transparent and reproducible manner (Rose & Kitchin 2019; Toaza & Esztergár-Kiss 2024). Restoring exclusive software

with open-source scripts can supply methodological transparency for this study and aid replication of the data preparation procedure.

3.5 Analytical Tools and Techniques

This study combines some complementary analytical methods through bibliometric analysis. For performance analysis: matplotlib, seaborn and SciPy. These were used to analyze important bibliometric statistics such as publication trends, citation impact, and authorship productivity.

Second, science-mapping techniques were performed using the well-known software VOSviewer which can visualize bibliometric networks and identify conceptual structures of scientific literature (Van Eck & Waltman, 2010). Using co-occurrence and co-citation analyses, VOSviewer accepts them to achieve thematic clusters and intellectual connections between papers. Likewise, clustering techniques based on citation data accept the identification of knowledge networks and research collaborations in the field (Van Eck & Waltman, 2017). Previous papers have also utilized similar bibliometric visualization techniques to study emerging research areas and thematic trends (Srisusilawati et al., 2021).

Besides, thematic evolution and life-cycle modeling were performed using python packages including scikit-learn and stats models. Researchers utilize these analysis methods to detect upcoming research trends and examine the evolution of research fields over time.

3.6 Methodological Rigor and Reproducibility

Methodological rigor and reproducibility were convinced by a transparent, systematic research workflow. All the bibliometric pipelines: from mechanisms for data retrieval, screening, cleaning, analysis and visualization, are documented and executed with reproducible python-based scripts. Such an approach train's trustworthiness of results and allows imitation by other researchers in the future. Also, the use of open-source tools and precise methodological procedures grows research transparency. Thus, via its mechanism of bringing the homogeneous bibliometric frameworks and reproducible analytical pipelines, this study allows a robust methodological foundation for examining the gradually relevant research areas of AI- and cloud-based smart services in new product development.

4. Results

4.1 Document Profiles and Citation Metrics

In particular, the first character of bibliometrics dataset overview grants an informative lens for both the composition of structure and influence in product development and in the field of AI and cloud-enabled innovation - literature. procurement system. In particular, and as described in Table 1, the data contains a collection of 118 scholarly Paper trails of a 17-year period from 2009-2025 that chronicles the advance of the domain from being in its infancy with the advent of digital infrastructure (e.g., blogs), to more recent phenomenon like generative AI technologies. On the academic side, there are 48 sources that cover these publications, indicating that research in the field is instead distributed across different disciplinary outlets of being in one scholarly venue.

Table 1
Bibliometric Analysis Dataset (2009–2025)

Category	Description	Results
Main Information	Timespan	2042:45:00
	Sources (Journals, Books, etc)	48
	Documents	118
	Annual Growth Rate %	21.48%
	Document Average Age	3.64 years
	Average citations per doc	26.5
	References	8377
Document Contents	Keywords Plus (ID)	369
	Author's Keywords (DE)	519
Authors	Authors	329
	Authors of single-authored docs	8
Collaboration	Single-authored docs	17
	Co-Authors per Doc	3.06
	International co-authorships %	0.85%
Document Types	Article	105
	Article; early access	11
	Article: proceedings paper	1
	Article; retracted publication	1

Moreover, the dataset consists of works from 329 authors, showing the growing size of an expanding research field. On average, publications have 3.06 co-authors, and which is a sign of how collaborative research in techno-complex domains is so established today. (Ing). Still, the fact that 17 of the documents are single-authored and eight dramatists generated

autonomous papers recommends that although the study sees collaboration as one of the primary styles of knowledge production, separate scholarly contribution relics noteworthy in shaping theoretical perspectives. Citation metrics add more evidence of authorship patterns by academic influence by the field. This means that naturally each article gets an average of 26.5 citations per paper. The publications included have been highly cited by other researchers. Concurrently, the data includes 8,377 cited references indicating that existing research depends on big and heterogeneous knowledge bases. The average document age of 3.64 years further supports the novel acreages of literature as would be anticipated from a descriptive stroke at a rapid growth technology study domain.

No less important are citation-based performance statistics like h-index and g-index which precise productivity in terms of scholarly influence. These indices steadily grow over time as depicted in Fig. 2. More specifically, the strong parallelism in trajectories of h-index and g-index indicate that the growth under publication output has been paralleled with similar growth in citation impact. As such, field increase can be thus viewed as a product of academic interaction and the focus should be on knowledge diffusion, rather than growing volume of publications. Similarly, the 21.48% year-over-year growth is an exceptionally strong measure of academic momentum! High growth rates are common in technology-driven research domains and digitally innovative. Indeed, similar growth patterns were found among bibliometric papers and the ecosystem of digital marketing with a focus on big data analytics (Esfahani et al., 2019; Salimi et al., 2019). The current dataset shows that, globally, innovative practices are being transformed by digital technologies across industries.

Yet within these promising omens, one viewpoint of the dataset stood out for a downside. The international co-authorship rate is simply 0.85%, which is rather low (Table 1). Even as authorship runs rampant Intra-institutional collaboration is common, cross-border collaboration is rare. This pattern indicates that research attempts may continue to be included in networks connected on a more regional or institutional basis, as opposed to being integrated into networks of global-scaled knowledge production. PKD: Prior research shows (international collaborations improve citation visibility and quality of research (specific to multidisciplinary papers). Hence, expansion of global research partnerships indicates a potential point of further academic development.

Lastly and built on the overall report, file profile assessment, notwithstanding that in quality of top journals similarities to other fields finds its source in the rapid growth. co-authorship levels although the citation output seems bright; reviewing Outcomes patterns also allows us to identify areas in which international research assistance might be fruitfully extended.

4.2 Trends on Publication and Evolution Over Time

Now that the structural characteristics of the dataset are showed by the study, it wants to explore how the field modified and developed in terms of time. Annual overview of (See Fig. 2) solid and clear upward route of scientific production from 2009 to 2023. At first, the number of publications was rather low. But as digital technologies cultivated and artificial intelligence (AI) applications grew, research activity started to pierce greatly.

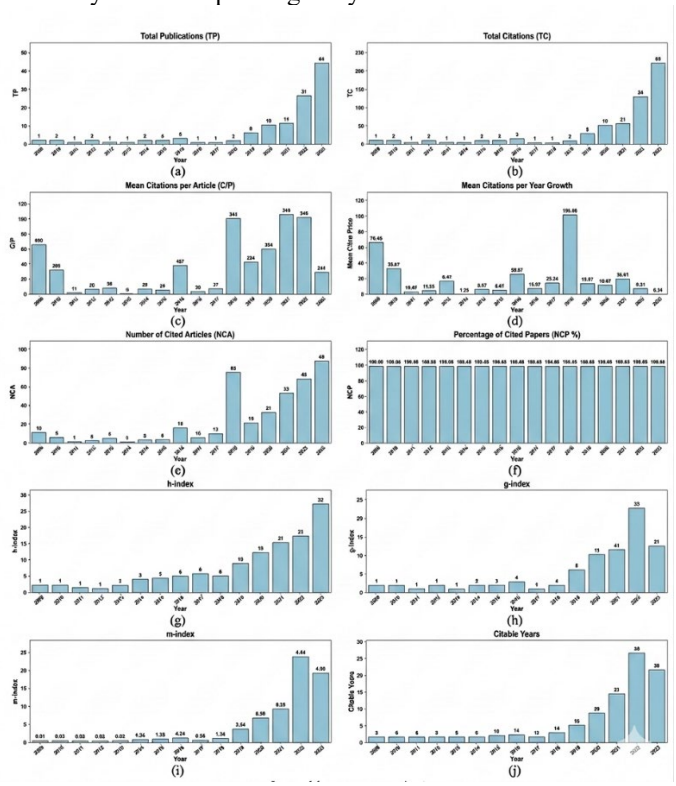

Fig. 2. Trends in Bibliometric Performance Statistics (2009–2023).

More specifically, the progression of the research domain is likely to present a three-fold publicizing phases: emergence, acceleration, and consolidation as involved by publication trends. These phases each highlight remarkable changes, both technological and conceptual, that have altered the surroundings of literature.

Emergence Phase

Emergence Phase: 2009-2015 The Emergence phase is like a nascent stage of academic interest. In that period the IM (innovation management) and NPD. An identify wave of papers, for example, examined how organizations can combine their view of product innovation to incorporate customer feedback and collaborative procedures (Carbonell et al., 2009). Similarly [context on the previous sentence] also triggered investigations around innovation management that addressed organizational features of bringing new products in uncertain technological contexts (Markham et al., 2010). Back then, AI technologies were still in their infancy and had never acquired significant academic study coverage, while some words postered the possibilities of computational methods for confirming modernization procedures. More precisely, the researchers investigated how deep learning or using text mining is to obtain potential product ideas from online communities (Christensen et al., 2017). Similarly, other researchers looked at whether crowdsourcing programs could originate creative product ideas far better than concept generation methods (Hoornaert et al., 2017). These first inquiries laid the groundwork for future research on AI-permitted product innovation.

Acceleration Phase

For the first discovery period, the field started to ramp up between 2016 and 2020. It was also a period when AI technical reinforcements blossomed with advances in CC, big AI was not itself as wide consumers OL and to Digital Programs they would finance a platform linear in e data analytics and digital programs which facilitated. At first CC infrastructure allowed organizations to secure high-performance processing on demand. Without the need for expensive hardware purchases. Subsequently, researchers started to Consider What Cloud Environments Would Enable Collaborative Product Development Procedures and distributed innovation systems. For instance, Robertson et al. Cloud-based computing They have their huge-scale AI applications and cross-domain data incorporation frameworks possible (2021). Digital technologies enhanced along with changes in industrial systems. Introduction of Industry 4.0 technologies (cyber-physical systems, smart manufacturing), supported chances to develop products for the digitally included. Accordingly, researchers gradually investigated how new digital technologies might help stimulate product innovation and enhance organizational performance. For example, Pinheiro et al. (2022) INDUSTRY 4.0 TECHNOLOGIES IN THE CIRCULAR ECONOMY | Industrial Management & Data Systems The analysis of Industry 4.0 technologies as a prime driver of circular economic initiatives and sustainable product modernization strategies shows the importance of these candidates to be explored further in this dimension. In addition, this period was also categorized by increasing interest in the strategic side of AI when it comes to insurrection management. Brem et al. (2021) presented the hypothesis of AI technologies as operational and foundational components of digital modernization ecosystems.

Besides, this period also was marked with the deepening interest in the tactical aspect of AI in advanced management. Brem et al. (2021) argued that AI technologies are both operational tools and introductory elements of digital innovation ecosystems. In this frame, companies started investigating how AI could assist in decision-making procedures, develop product design, and optimize knowledge management systems.

Consolidation Phase

The research field then entered a consolidation phase, starting around 2021 and continuing through the latest years of dataset. This period saw an explosion of literature documenting how AI technologies developed deeply embedded into the product development procedure.

This phase witnesses a remarkable development in applying AI technologies in confirming the iterative procedures of innovative ideation within manufacturing organizations. For example, Jiang et al. (2023) explored how companies manage their own AI systems to iteratively improve product designs and speed up innovation cycles.

Likewise, a growing area of research has been highlighting the interaction between human creativity and AI systems. Bouschery et al. (2023) also investigated the potential of transformer-based language models for enhancing human innovation groups through idea generation and concept development. And sustainability aspects have gained importance within literature as a result. Recent research highlights how AI technologies can bolster environmental performance and contribute to green innovation efforts (Lin et al., 2024). Analogously, firms are investigating included role of smart technologies and Algorithmic Decision Confirm systems on sustainable Human Resource Management (HRM) and ecological responsible business strategies (Ogbeibu et al., 2024).

So, the temporal evolution visualization clearly shows that the research domain has moved from a foundational conceptual science to technologically advanced innovation systems.

4.3 Scientific Production Life Cycle

To give a better insight into the future movement of research domain, logistic growth model analysis was used to investigate about life cycle of scientific production. This model is particularly well-suited for studying the dynamics of emerging areas of research, as it describes the familiar S-shaped growth trajectory observed in many fields of science.

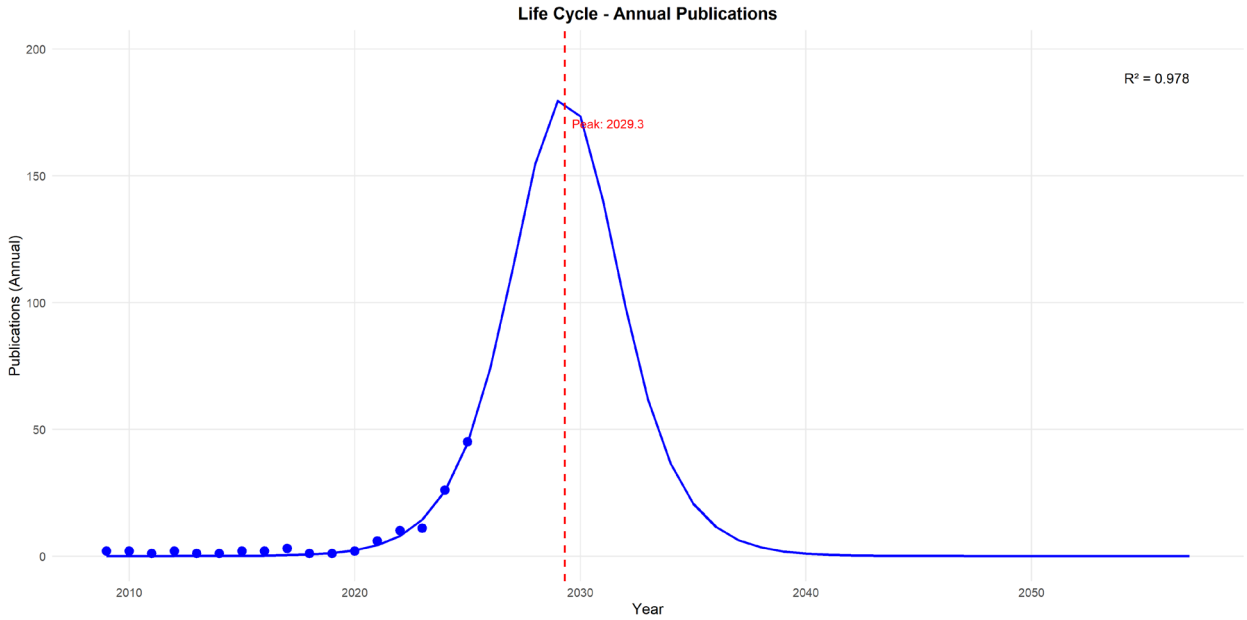

Fig. 3. Predicted Life Cycle and Trend of Annual Publications (2010–2055)

In Fig. 3, logistic regression shows an extremely high fit of the observed publication data to the predicted growth curve (R^2 = 0.978). This result confirms that the model is well tuned to fit the realities of the research field. A key realization from this analysis is an inflection point around the year 2029.3. Thus, the inflection point may occur when growth levels off as the field matures in logistic growth models. Additionally, the current dataset runs only until 2025, and so these results suggest that the field is still within the steepest portion of the S-curve. As well as predicting the inflection point, the logistic model also presents estimates of the field's carrying capacity, which reflects the maximum expected level of publication output once a research domain has reached steady state. While developments in technology may alter this figure, the model indicates that academic output will still grow exponentially over the next 10 years. And critically, these results are consistent with broader patterns in technology. AI-based innovation research is rapidly expanding, demonstrating how artificial intelligence has developed embedded (or at least part of the rhetoric) in organizational strategies for innovation (Verganti et al., 2020). Additionally, organizations in many other sectors will continue to adopt intelligent systems for improving NPD and innovative performance (Cooper & Brem, 2024; Cooper, 2025). Thus, the life cycle assessment recommends that the research field is still far from development, presenting ample options for future academic activities.

4.4 Journal and Source Publications

Another key aspect of bibliometric analysis is attached to the distribution of publications through academic journals. A summary of the journals from which this dataset originates is presented in Fig. 4.

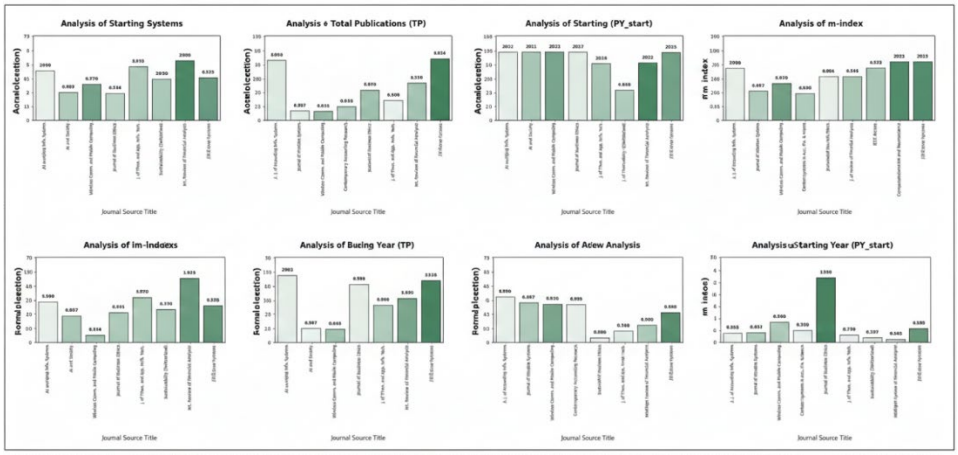

Fig. 4. Comparative Bibliometric Analysis of Journal Source Titles.

First, a few highly cited articles are issued in journals specializing in the fields of innovation management and product development (e.g., Journal of Product Innovation Management, Research-Technology Management). They are also the outlets of choice for research that investigates the managerial implications of such AI-driven innovation.

Conversely, the dataset is also complemented by contributions from journals in information systems, machinery management, and computer science. Examples include several notable papers investigating AI applications to innovation management issued in the IEEE Transactions on Machinery Management (Brem et al., 2021; Jiang et al., 2023). Additionally, as evidenced by inclusion of a number of the research issued in journals such as Tech novation and Business strategy and the Environment it is maturing through becoming more entwined with sustainability and digital transformation research. For example, Plantec et al. (2023) investigated how innovative design is being confirmed through exploring AI-embedded systems included within automotive design procedures for problem solving purposes. Likewise, modern technologies like digital twins are starting to receive more research attention within machineering and manufacturing. Van Dyck et al. (2023) highlights the importance of interconnected digital twins to digital manufacturing systems for the future.

The journal division analysis evidences the interdisciplinary nature of this research space combining lenses from executives' science, machine ring design, information systems, and sustainability papers.

4.5 Highly Cited Documents and Intellectual Anchors

In addition to the trends in publication, searching for highly cited articles can supply a guide on the scholarly basis of the field. Table 2 summarizes the top 10 cited articles. Among those publications are the works of Barbieri et al. (2018) included a total of 3 impact factor citations conversations alongside global industrial strategies. According to Srai and Lorentz (2019), in a similar spirit and Hallikas et al. also gaining 120 + citations, leading the suggestion of encompasses it all When you have making digital in design procedures for procurement and supply chain.

Table 2
Top 10 Highly Cited Articles

No.	Authors	Title	Source Title	Cites	Cites per Year
1	Barbieri et al. (2018)	What do we know about manufacturing reshoring?	Journal of Global Operations and Strategic Sourcing	133	14.78
2	Srai & Lorentz (2019)	Developing design principles for the digitalisation of purchasing and supply management	Journal of Purchasing and Supply Management	123	15.38
3	Hallikas et al. (2021)	Digitalizing procurement: the impact of data analytics on supply chain performance	Supply Chain Management: An International Journal	123	20.5
4	Narasimhan et al. (2004)	Exploring flexibility and execution competencies of manufacturing firms	Journal of Operations Management	110	4.78
5	Gong et al. (2020)	Consistency and consensus modeling of linear uncertain preference relations	European Journal of Operational Research	108	15.43
6	Flechsig et al. (2022)	Robotic Procedure Automation in purchasing and supply management: A multiple case study on potentials, barriers, and implementation	Journal of Purchasing and Supply Management	104	20.8
7	Bag et al. (2021)	Barriers to adoption of blockchain technology in green supply chain management	Journal of Global Operations and Strategic Sourcing	97	16.17
8	Sharma & Joshi (2023)	Digital supplier selection reinforcing supply chain quality management systems to develop firm's performance	The TQM Journal	93	23.25
9	Dolfsma & Seo (2013)	Government policy and technological innovation—a suggested typology	Technovation	92	6.57
10	Choudhury et al. (2021)	Digital supply chain to unlock new agility: a TISM approach	Benchmarking: An International Journal	90	15

But if the painting examines citations by year, a different picture occurs. A median annual citation rate of 6.5 was determined by Sharma and Joshi (2023), representing that recent scholarship about digital supplier selection and QMS have operated under terms requiring particularly fleet onset of academic attention. These most-cited publications importantly make three intellectual leaders of the field of research.

Multiple high-impact papers deliberation on design and knowledge management enabled by AI systems: these analyses identify forms in which AI can authorize stimulated processes and other decisions correlated to modernization (Botega & Da Silva, 2020).Second, a second set of papers that transactions with cloud-allowed products and digital source chains (Wong et al., 2021), concrete a path for the increasingly important role of digital programs in allowing agile modernization ecosystems.

Thirdly, there have been more papers addressing digital innovation ecosystems used by encompasses companies that leverage AI-technologies, big data analytics, and collaborative networks to confirm innovation processes that are more simplified

(Plantec et al., 2023). Collectively these early papers afforded a foundation to work on for most of the following research on AI-enabling product innovation.

4.6 Author Keywords Analysis

4.6.1 Network Visualization: Thematic Clusters

To scratch deeper into the abstract structure of the literature, a keyword co-occurrence analysis was capable through VOSviewer. The outcome of this network visualization (Fig. 5) highlights six prominent thematic clusters.

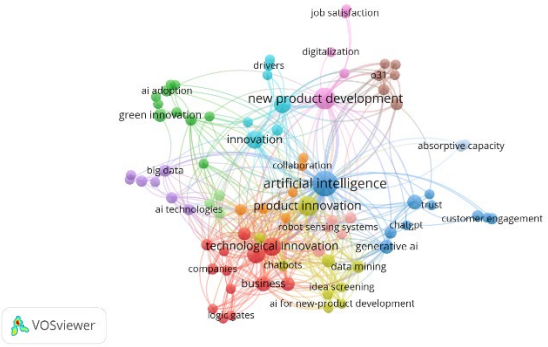

Fig. 5. Network Visualization of Co-occurring Keywords in AI and Product Development Literature

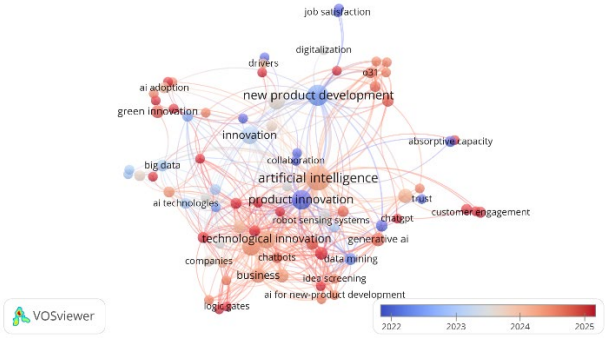

Fig. 6. Keyword Evolution by average publication year Overlay vision

The initial cluster focuses on AI and machine learning applications within the realm of product design and optimization, considering how intelligent algorithms can assist with complex machineering decisions (Garbuio & Lin, 2021). While the second cluster identifies CC programs for collaborative product development, the role of "digital infrastructures" for distributed innovation systems (Robertson et al., 2021). The third one relates to digital twins and smart product machineering, which enable organizations to simulate how well a product will perform, as well as enabling them to optimize their design procedures even before they start manufacturing (Van Dyck et al., 2023). The fourth group focuses on data analytics and predictive innovation systems that utilize big data technologies to confirm forecasting, decision making, and evaluation of innovation performance (Ghorbani & Ghousi, 2019). The fifth cluster is making its way into a new frontier, as it relates to generative AI and intelligent design automation, an extension of how products are born by assembling bits, analogically speaking. The sixth cluster is open innovation ecosystems, where cloud programs facilitate collaborative product development across organizational boundaries.

4.6.2 Overlay Visualization: Themes Over Time

Lastly, the overlay visualization shown in Fig. 6 reflects how research themes evolve over time. In the first generation (2009–2015), it decorated cloud infrastructures, computer-aided design (CAD) incorporations, and developing data-driven creation design systems. The successive phase of expansion (2016–2020) focused on big data analytics, collaborative digital modernization ecosystems, and cloud programs. Only now, with the acceleration phase (2021–2024), have we been distinguished by the AI-powered design systems, deep algorithms, and virtual twins. Regarding the short-term outlook and 2024 expectations & faithfulness in research, the visualization shows associated key frontiers of emergence beyond the 2025 horizon i.e., generative AI for creation gene Expression, and improve collaboration in invention development environments for product development. In conclusion, the thematic evolution analysis clearly shows that this field is continuously evolving at high pace with AI technologies which are becoming accepted nor included into innovation management and product development procedures.

5. Discussion

5.1 Synthesizing Intellectual Structure and Thematic Convergence

The bibliometric results show a fast-changing range of research, where various technological and managerial fields are increasingly conversing. Particularly, the nexus of AI, CCs and digitals innovation ecosystem is the key intellectual apparatus that defines it. Past research on innovation and NPD focused on organizational procedures, customer engagement, and cross-functional collaboration (Carbonell et al., 2009; Markham et al., 2010). The traditional models of innovation were soon being enhanced with computational tools to facilitate complex decision making and knowledge generation procedures as digital technologies matured. As a result, literature increasingly evidences a trend towards data-driven product innovation paradigms in which large-scale data analytics and machine learning algorithms inform product design, market analysis, and strategic decision-making. Research examining predictive analytics and data mining presents evidence of how organizations can apply

data-driven perceptions to be able to predict market trends and develop innovation performance (Ghorbani & Ghousi, 2019). Similarly, bibliometric analyses of adjacent technology domains reveal that digital ecosystems surrounding big data and online programs have accelerated innovation dynamics (Esfahani et al., 2019; Salimi et al., 2019).

Concurrently, increasing connectivity in AI and innovation management results in the formation of digital innovation ecosystems as organizations depend on intertwined technological infrastructure to augment complex development procedures. Beca apply cloud-based computational architecture authorities the software programs to delegate their resources, complement distributed parties and formulate accessible programs for innovation (Robertson et al., 2021). Thus, AI-Powered analytics became the reasoned backbone that would empower ventures to transform unstructured data to structured awareness necessary for product development systems (and therein innovation perceptions). Then the field methodically arranges its towers of thought from disbursed technological applications to embedded digital modernization systems where artificial intelligence (AI), clouds infrastructure, and collaborative innovation networks.

5.2 From Digital Tools to Intelligent Innovation Systems

Alongside this technological convergence, the results also suggest a broader intangible shift taking place in the improvement of management literature. Digital technologies are no longer passive to confirm actors backing human decision-makers; rather they are evolving into intelligent innovation systems that can actively shape the actual product development procedure. At first, from computer-aided design systems to cloud collaboration programs, digital technologies had been the human creativity and coordination approve tool. In the meantime, machine learning and natural language procedure Ing moved on to transform the AI world. To illustrate, AI knowledge management systems are now available to help innovative groups choose appropriate creativity techniques and recognize forthcoming design alternatives (Botega & Da Silva, 2020). Similarly, algorithms for machine learning have also sustained effectiveness at pinpointing potential product ideas by examining vast amounts of user-generated content in online communities (Christensen et al., 2017; Hoornaert et al., 2017). More recently, generative AI technologies are modifying this transformation. Instead of just helping designers, they can generate new product ideas and full design solutions. Research on transformer-based language models demonstrates how AI can complement human creativity groups by generating creative ideas during the ideation or design stages (Bouschery et al., 2023). As a result, the innovation procedure is increasingly one of human–AI co-creation, with intelligent systems acting as active partners rather than tools. This shift also has major consequences for the innovative life cycle. Conventional models of innovation outline a linear path for product development, from ideas to commercialization. Yet AI technologies accept continuous data-driven feedback loops that let businesses iteratively streamline products. To illustrate, manufacturing organizations are increasingly leveraging artificial intelligence to harness operational data whilst continuously refining their product designs through cyclic learning loops (Jiang et al., 2023). Subsequently, the innovative lifecycle is transforming to be more adaptive, dynamic and data driven.

5.3 Implications for Theory

In parallel with this technological convergence, the results also imply a broader shift in thinking as the innovation management literature is being carried out. Digital technologies no longer play a passive role instead of smart actors assisting human algo decision-makers; systems that would progress the actual product development process. Digital, at least early on, meant technics as contradictory as computer-aided design systems and cloud collaboration programsXML. Now technology has been restored and connected, human imagination and coordination confirm tool. In the meantime, after a few years, machine learning and natural language processing developed the AI world. To exemplify, AI knowledge management systems are accessible to support creativity groups in selecting adequate creativity methods and identifying potential design solutions (Botega & Da Silva, 2020). Likewise, the power of machine learning algorithms in successfully identifying prospective product-ideas based on user-authored data draws from large online communities (Christensen et al., 2017; Hoornaert et al., 2017). More recently generative AI technologies are turbocharging this transformation. Instead of merely supplementary designers, instead they may generate original product designs and complete design solutions. Transformer-based language models research shows me how AI can aid human creative groups by proposing imaginative ideas in the ideation or design phases (Bouschery et al., 2023). Consequently, the advance process is becoming more one of human–AI co-creation; intelligent systems are now active partners instead of simple tools.

This change has massive inferences for the innovative life cycle, too. Traditional models of innovation describe a linear progression for product development, from ideas to commercialization. But AI technologies embrace continuing data-driven feedback loops that enable companies to gradually improve products. For instance, industrial firms are beginning to use artificial intelligence for harvesting operational data and improving their designs in constant loops of learning (Jiang et al., 2023). Hence, the innovative lifecycle is evolving to be agile, more dynamic and data driven.

5.4 Implications for Practice

Additionally, to contributing theoretically, the study also verified results have a few practical implications for organizations requesting to integrate AI and cloud in their product development efforts. In the first place, firms need to hypothesis strategic skeletons for embedding AI talents into their improvement actions. Instead of bolting on one-off technological fixes, firms

should develop holistic plans for digital innovation that connect AI systems to expansive organizational goals. Recent superintendent literature argues that successful adoption of AI in organizations changes on prearranged investments across multiple dimensions, including technological infrastructure, organization-level capabilities, and novelty culture (Cooper & Brem, 2024; Cooper, 2025). AI and cloud programs also have the potential to considerably increase the collaborative procedures of innovation among geographically dispersed groups. Digital collaboration environments enable organizations to effect designers, machinery, and external stakeholders together into common virtual workspaces. Cloud-based development environments, for instance, accept the separation of data in real time and allow collaborative problem-solving, thus increasing dominance across a network of distributed groups implicated in innovative procedures (Robertson et al., 2021). Nonetheless, along with these possibilities, organizations must contend with some critical risks around AI-driven development systems. One of the most pressing challenges lies in data governance and intellectual property maintains. As procedures for innovation develop progressively more data-intensively, organizations need to mature well-defined policies around the respective rights that manage ownership of individual datasets and access to them given privacy concerns. Overall, AI algorithms being used for decision-making techniques also makes us rethink transparency and answerability. The other arising concern is the ethical enigma of AI permitted innovation. AI systems have developed progressively more freely, so organizations should make sure their technological applications align with higher societal reliability and sustainability goals. Past research underscores that organizations must consider ethical, environmental, and governance factors when adopting progressed technological systems if responsible apply of AI is to be achieved (Lin et al., 2024; Schwaeke et al., 2025). As such, embedding sustainability consequences in digital inventions could potentially except for a more responsible evolution of technology.

5.5 Recommendations for Future Research

Despite some expensive perceptions from accessible literature on AI-permitted product innovation, there are still moderately a few unmapped opportunities for future research. A remarkably interesting line of work explores compassion in human–AI collaboration, particularly in (product) design. While recent research shows that AI can thrive alongside humans to develop some forms of creative output, the study knows little about the practical interaction of innovative groups and intelligent systems. Thus, future research could specifically explore the cognitive and organizational procedures that underlie human–AI collaboration in innovation environments (Bouschery et al., 2023).

Another key research direction relates to governance and ethics in AI-driven innovation systems. AI, Ethics, and organizations: With the increased importance of data-driven decisions, scholars must develop new frameworks for ethical apply of AI algorithms that help organizations ensure transparency, accountability, and fairness in algorithmic procedures. Primarily, explainable AI frameworks might contribute to further assuring stakeholders in the responsible adoption of technology. Besides, future research can further encompass cross-industry comparisons of AI-permitted product development practices. While a substantial portion of the current body of literature centers around manufacturing industries, AI technologies are progressively revolutionizing innovative procedures in service industries and software development environments. Understanding this remains hard as reasonable papers across regions might scale more light on how technological capabilities and organizational forms of shape AI passed innovation performance. And lastly there is a demanding need for methodological revolution in the research domain. Most existing papers are either qualitative case based or impalpable frameworks. Further research may detect hybrid analytical approaches which integrate technical AI performance metrics and innovation management statistics. Incorporating such advances would enable scholars to assess not only the organizational technological efficiency of AI systems, but also their implications on the organization's innovation performance. In general, these research trajectories better the understanding of the incomplete growth and diversification of this domain as AI technologies continue to trickle their way into innovative ecosystems.

6. Conclusion

This study not only grants the first consolidative bibliometric analysis into AI-permitted and cloud-confirmed product upheaval but also serves as a rich foundation for further exploration of this growing research avenues' its development over time, their intellectual structure, and their thematic evolution. Analysis of 118 publications from 2009 to 2025 showed that the research domain is still growing miraculously fast with a large growth rate, interdisciplinary collaboration strengthening as well as considerable academic influence. The results reveal that the domain has gone through developmental stages starting from early adoption and investigation of digital technologies in revolution management, before evolution into experienced AI confirmed innovation systems. The bibliometric results also suggest that the research domain is still in a dynamic growth phase and will develop, as modern technologies like generative AI and digital twins are frequently transforming innovative procedures. Only time will tell, even so, as future product modernization ecosystems will be shaped by advancing trends in computer attentiveness through artificial intelligence (AI), cloud infrastructures systems-based technology and collaborative digital programs. Simultaneously, the growing prevalence of AI technologies also gives rise to key questions around ethical supremacy, transparency, and sustainability. As such, while future research needs to consider advances in technology, it also must address the wider societal impacts of AI-permitted innovation. The eventual success of these solutions, However, will differ on the practical implementation of responsible, sustainable, and human-centered innovative systems capable of encouraging positively impactful modern technologies that develop organizational performance while satisfying society's needs.

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