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Bibliometric Analysis of Computational and Mathematical Models of Innovation and Technology in Business

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Abstract: There is consensus, both in academia and in the business world, that one of the main resources of a company is the incorporation of technology and, along with this, its capacity to generate innovation. Therefore, knowing the development of a company's research becomes essential. The aim of this work is to develop a bibliometric analysis of the literature published in the Web of Science database to analyze the advances and trends in the development of research. The methodology analyzed bibliometric quantity and quality indicators using Bibliometrix, VOSviewer, and SciMAT software. The results show the evolution of the topic as well as recognition of the different lines along which research has organized the debate.

Keywords: innovation; technology; model; computing; business

MSC: 62-XX; 68-XX

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1. Introduction

There is consensus, both in academia and in the business world, that one of the main resources of a company is the incorporation of technology and, along with this, its capacity to generate innovation [1] and elements that provide greater dynamism, better business performance, and bases for developing competitive advantages to stay ahead of the competition. [2–4]. This situation is accelerating with the emergence of new technologies, such as artificial intelligence, machine learning, the Internet of Things, blockchain, and data science. Companies are automating repetitive tasks, patenting their developments, gaining in-depth knowledge of buyers with statistical and computational models, optimizing the management of value chains, digitizing their processes, and developing new products and services for their customers [5–9]. The accelerated growth of technologies and their impact on innovation are important determinants for societal development [10], as seen in the adoption of sustainable development and opportunities for digital activities [11].

Due to the changing nature of digitization and the advancement of technologies, which significantly accelerated during the COVID-19 crisis [12], digital transformation has spread rapidly in all types of organizations, including commercial enterprises, governments, and nonprofit institutions [13]. Therefore, this growth has increased the volume of literature on technology and innovation issues, given the sales and disadvantages debate that this digital transformation has caused [14,15].

The study of innovation and technology in business has been approached from different perspectives. First, systemic approaches have emphasized the importance of institutions (laws, norms, institutions, financing, and programs) and collaboration among the multiple actors involved in the innovation process, such as companies, governments, and universities. These approaches include national innovation systems [16], regional innovation systems [17], clusters [18], triple helixes [19], innovation technology systems [20], and innovation ecosystems [21]. Secondly, analyses that focus on firms were recorded and reviewed the external and internal factors that lead firms to innovation [8,22], the development of dynamic, digital, and ambidextrous capabilities [9,23,24], and innovation management processes [25,26]. Third, some studies focused on a specific type of innovation and technology in business. For example, blockchain [6], artificial intelligence and machine learning [27,28], computational modeling [29], the Internet of Things, and big data [30,31].

Technology is one of the fundamental concepts of our time [32], even though the word only became commonplace in the mid-20th century [33]. Historically, there are two divergent traditions for referring to technology [33]. On the one hand, the instrumental perspective describes technology as technical rationality stripped of creativity and values. On the other hand, technology is a cultural perspective that is understood as a set of human practices used to transform the material world, including practices related to the creation and use of material things.

In the social sciences, technology has three different uses [34]. The first is the use of technology as machines and devices. The second is technology as a technique or stylized behavior or cognition. The third is technology as an organization, i.e., specific tools, people, and task arrangements.

Similarly, the concept of technology has been the subject of many different definitions in business management literature [35]. The multitude of definitions has led to technology becoming a misleading term that admits several plausible interpretations and is, therefore, subject to misunderstandings [35,36].

Innovation is also a term with multiple meanings. It has been used as a synonym for other concepts, such as creativity, knowledge, or change, subject to numerous classifications, levels of analysis, and perspectives [8,37,38]. For example, innovation can mean both an activity and an outcome [22]. This multiplicity of meanings detracts from the clarity of the research [39].

A fundamental distinction can be made between invention and innovation [40]. Invention is the first occurrence of an idea for a new product or process, and innovation refers to the first attempt to put an idea into practice. Innovation creates or adopts new ideas [38]. Para [41] states, "Innovation is the generation, acceptance, and implementation of new ideas, processes, products, and services".

Innovation can be analyzed from multiple levels, e.g., global, national, and industrial. Organizational innovation considers factors that executives can influence at the firm, team, or individual level [37]. Additionally, innovation can be new to the individual, group, organization, or society [38]. From the organizational process perspective, ref. [42] states, "Innovation is the multi-stage process whereby organizations transform ideas into new/improved products, services or processes, to advance, compete and differentiate themselves successfully in their marketplace".

Innovations are usually classified by type. Schumpeter, for example, recognized the following types of innovation: products, production methods, sources of supply, exploitation of new markets, and ways of organizing business [40]. The literature also distinguishes between technological innovations, associated with product and process innovations, and non-technological innovations, associated with marketing and organizational innovations [8]. In its 2018 version, the Oslo Manual states that "An innovation is a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)" [22]. This definition condenses the previous categories of product, process, organizational, and marketing innovation into two categories: product innovation and business process innovation. In [37], the authors proposed that innovation is the production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems. It is both a process and an outcome. Other authors focus on innovation in business models, which they understand as the search for and discovery of new business logic and new ways of creating and capturing value for stakeholders [43].

On the other hand, a computational or mathematical model is an abstract representation of a system, process, or phenomenon constructed using techniques and tools. These models can be used to simulate the behavior of complex systems, analyze, and understand their behavior, predict results, optimize processes, and make decisions [44]. In this sense, computational or mathematical models can be valuable tools for innovation in business models and for improving the competitiveness and sustainability of companies in a constantly changing environment.

In scientific research, it is common to use computational and mathematical models to represent studied phenomena. These models are designed to capture patterns or regularities in empirical data by manipulating parameters that correspond to the variables affecting the phenomenon [45] (Myung et al., 2009). Although computational and mathematical models may appear similar, an important distinction is that mathematical models hypothesize about relationships, variables, and magnitudes, whereas computational models hypothesize about mechanisms or processes [46]. Thus, computational models are a powerful tool for understanding phenomena. This also implies that models are more productive when the reasons behind the suitability of a model are understood [45].

In contrast, two of the characteristics of mathematical models are that the same model can occur and be used successfully in fields with very different subject matter [47] and that they are used to describe processes that would otherwise be difficult to analyze. Thus, when using a model to make predictions in a specific context, it may be necessary to calibrate the model using observed data [48].

On the other hand, it is increasingly recognized in the social sciences that one of the best ways to build valuable theories of group phenomena is to create functional computational models of social units (such as individuals, households, firms, or nations) and their interactions [49]. Additionally, while computational models of cognition are increasingly advancing as explanations of behavior, the success of this line of research depends on the development of sound methods to guide the evaluation and selection of these models [50]. To cope with the large amount of data being processed today and to understand these new phenomena, techniques for processing large amounts of data are being introduced, using as examples different scientific fields, such as engineering, medicine, astronomy, and computer science [51].

In recent years, knowledge production has accelerated at an incredible speed but, at the same time, remains fragmented and interdisciplinary, generating difficulties when analyzing state-of-the-art and the latest advances in research [52]. Therefore, bibliometric studies have gained importance since they provide quantitative and objective information on the scientific production, visibility, and impact of research works on a given topic [53]. Bibliometric studies are an approach that evaluates and monitors the progress of specific disciplines using statistical techniques to classify the data, such as citations, author affiliations, keywords, topics covered, and methods employed, in the studies published within those disciplines [54]. Bibliometric studies provide quantitative and objective information on research papers' scientific output, visibility, and impact [55].

Compared to peer review, which has limitations in research, bibliometric methods allow unlimited quantities of publications to be examined. Bibliometrics has provided a scalable tool that can be applied at the micro and macro levels [56].

Conducting bibliometric studies has led to the development of various approaches, methods, and indicators that reflect the evolution and complexity of research [57–60]. This increase in the complexity and importance of bibliometric studies has led to a greater need for strengthening the teaching of bibliometrics, and other metrics, as a research tool and requiring rigorous and critical review before accepting and publishing these types of studies [61]. Bibliometric analysis is a popular and thorough method for exploring and analyzing large volumes of scientific data. It makes unraveling the evolving nuances of a specific field possible and sheds light on emerging areas in that field [62].

Despite the significant contributions made in recent bibliometric research [63–67], two primary aspects justify this study. First, previous analyses have addressed innovation or technology at the managerial or process level without specifically analyzing the models associated with them. Second, the exponential growth of the literature has reached a level of complexity within the domain, making it essential to identify boundaries and highlight advances with a unifying view of the literature.

Given these considerations, this study aims to conduct a bibliometric analysis of computational and mathematical models of innovation and technology in business. By performing an analysis of previous bibliometric studies that have addressed the topic in question, we have determined specific gaps, which will be handled via the following research questions:

According to bibliometric indicators, what is the composition of research on computational and mathematical models of innovation and technology in business?

What are the trends in the concepts studied on computational and mathematical models of innovation and technology in business?

The methodology used for this study will be detailed in the following section, followed by a presentation of the results obtained through the bibliometric analysis and their discussion. Finally, the relevant conclusions obtained from this analysis are presented.

2. Materials and Methods

Bibliometric studies serve to monitor and trace scientific research [68,69]. They help to make important research decisions by analyzing specialized topics [70] since useful information can be extracted [71], and they constitute an alternative to other types of reviews [72]. Different indicators can be used for a bibliometric analysis [73]. Activity indicators are oriented to measure productivity, quality indicators are oriented to measure citation frequency, and relationship indicators are based on keywords [74,75]. A summary of the indicators is presented in Table 1. This work follows the guidelines of [62], which established the following steps for bibliometric analyses: Step 1: Define the objectives and scope of the bibliometric study; Step 2: Choose the techniques for the bibliometric analysis; Step 3: Collect the data for the bibliometric analysis; and Step 4: Execute the bibliometric analysis and report the results.

Table 1. Types of Indicators.

Types of Indicators	Indicators
Activity indicators	Number of publications Number of contributing authors Number of journals Number of countries
Quality indicators	Total number of citations received Average number of citations per publication Impact factor H-Index
Relationship indicators	Co-citation Bibliographic Coupling Co-word Co-authorship Degree of centrality

The information for the documents was retrieved from the SCI-Expanded for the "Web of Science" of "Clarivate Analytics", including the bases: Science Citation Index Expanded, the Social Sciences Citation Index, and the Arts and Humanities Citation Index. The Web of Science has traditionally been the primary source for scientific publications, and it has been established that the Web of Science has a significant advantage over other databases in coverage [76,77].

Figure 1 shows the search strings used in the Web of Science Topic field (TS), which searches for terms in the title, abstract, keywords, and keyword-plus-words ® [78].

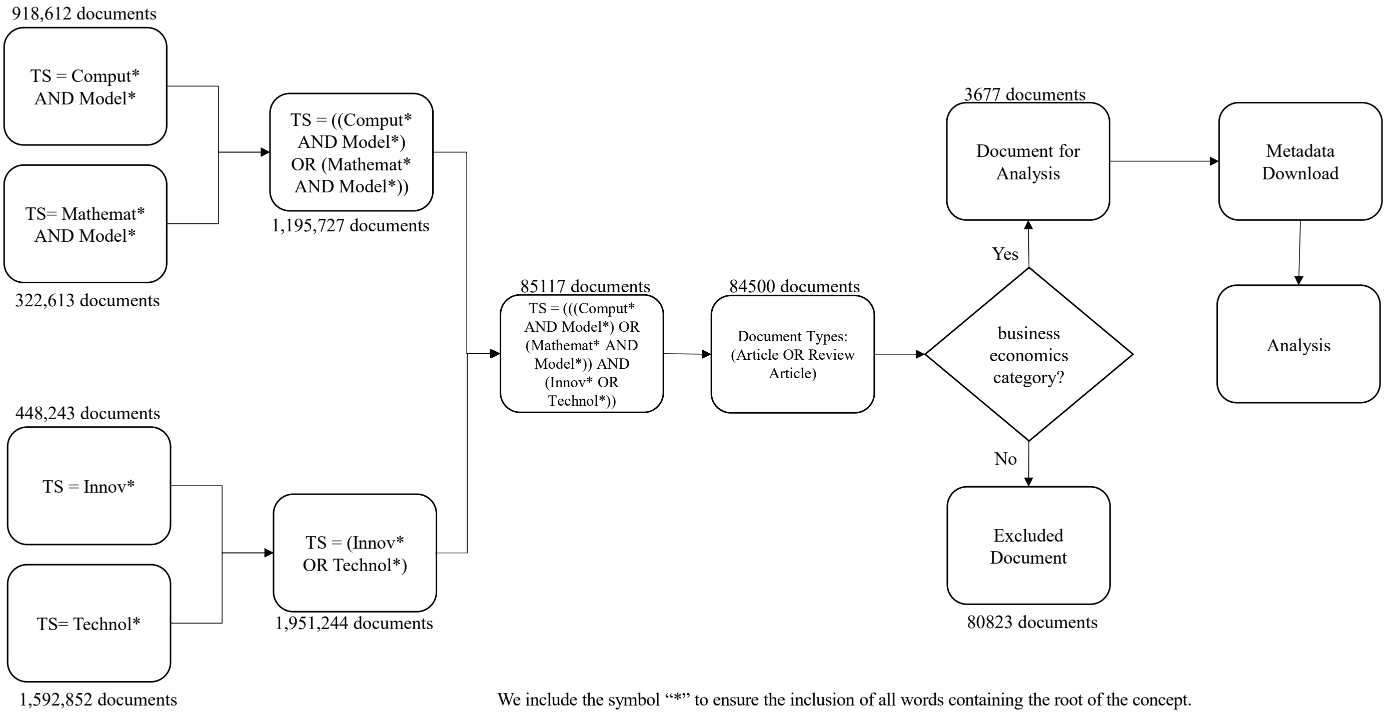

Figure 1. Prisma Flowchart.

After performing each of the searches, we grouped and excluded repeated results. In addition, we filtered only articles and reviews. Finally, we limited the scientific field to the category of "business economics". The Web of Science establishes this category and groups the journals indexed in the areas of business and economics. With the search results, a single database was created in a file containing the complete record of each publication.

Centrality and density measures were used to represent the detected networks. Callon centrality [79] measures the degree of interaction of a network in contrast to other networks. It was identified as indicated in Equation (1), where "k" represents a word belonging to the subject, and "h" is a keyword belonging to another topic.

$$c = 10\sum e_{kh} \tag{1}$$

Callon's density [79] measures the internal strength of a network and can be defined as Equation (2), where "i" and "j" are keywords belonging to the topic, and "w" is the number of keywords (nodes) framing the topic.

$$d = 100\frac{\sum e_{ij}}{w} \tag{2}$$

Given both measures, the research topics could be classified into four groups [80]: (i) Driving Themes (upper right quadrant), which represent topics important for structuring the field and that are also well developed; (ii) Specialized Themes (upper left quadrant), which are well-developed themes that are less important for the field; (iii) Emerging or Declining Themes (lower left quadrant), which represent less developed and less important themes; and (iv) Basic and Crosscutting Themes (lower right quadrant themes), which are crucial for a research field, although not sufficiently developed.

The tools used for the analysis are the freely available VOSviewer software that allows the construction of bibliometric maps [81], the Bibliometrix software, which is an open-source package proposed to perform comprehensive bibliometric analysis [82], and the SciMAT software that allows the construction of strategic maps based on density and centrality [83].

3. Results

A total of 3677 articles met the search criteria, and 8327 authors from 102 countries were responsible for the number of articles published. These papers have been published in 515 journals and have received 235,986 citations over time. Thirty-four percent of the citations came from the management area, 15% from the economics area, and 7% from supply chain and logistics and sustainability science. The remaining 37% came from 108 other disciplines. Of the total number of countries registered as research producers, the USA made the most considerable contribution with 43%, followed by China and England with 9%, Canada with 6%, and Germany with 5%.

A historical citation network considers the relationships or links between two documents, which implies the existence of knowledge flow and thematic similarity between the documents. The more citations a paper accumulates, the more basic or essential it is believed to be because there are knowledge flows from that document to many other documents, which provide insight into the dominant paradigms and their changes [84]. As illustrated in Figure 2, the historical citation network demonstrates that the main articles attempt to respond to the usability and acceptance of technology.

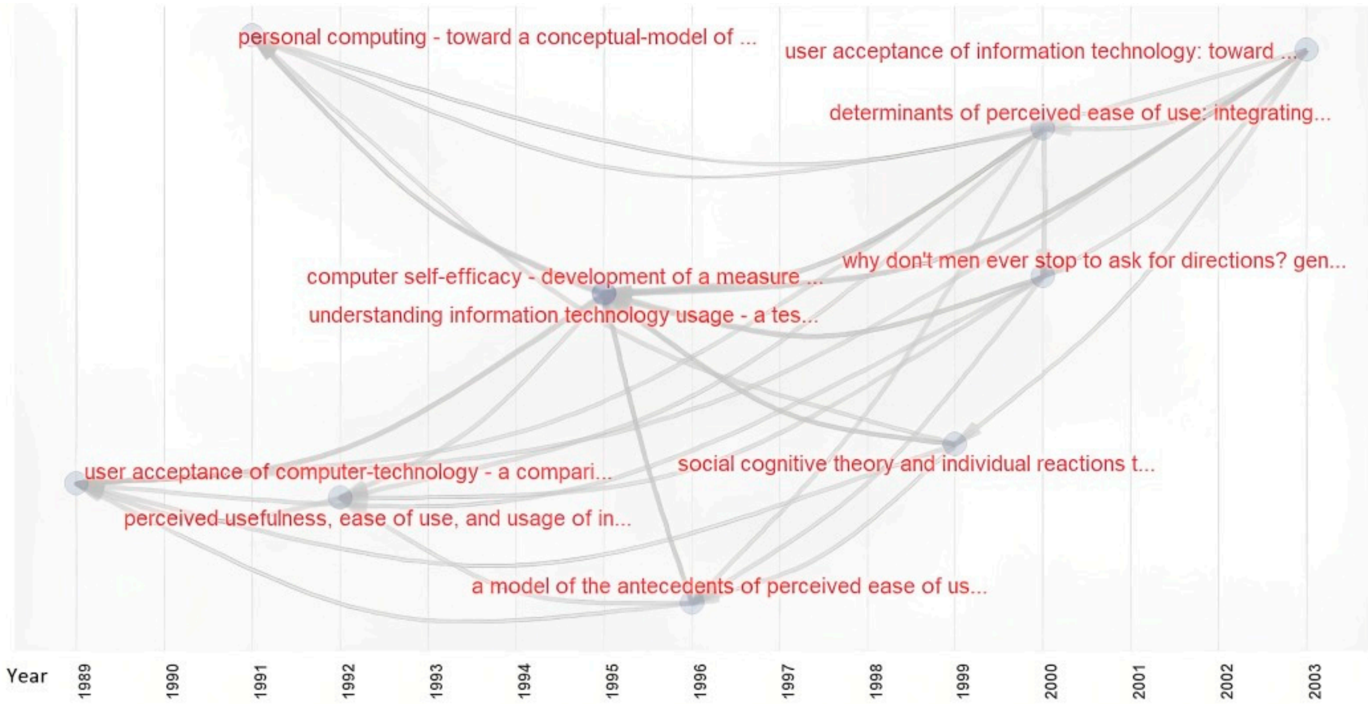

Figure 2. Historical Direct Citation Network. Source: Software Output Bibliometrix.

We used a keyword network (Figure 3) to identify the concepts associated with the models. The keywords mentioned together are linked, and the strength of the links between the keywords corresponds to the intensity of their respective relationships. The most robust connections to the models are related to information, computers, productivity, optimization, and strategies. On the other hand, a linked group refers to industry 4.0 technological concepts, such as big data, cloud computing, the internet, knowledge, and management. A third linked group also refers to technology acceptance models and the associated determinants in this process.

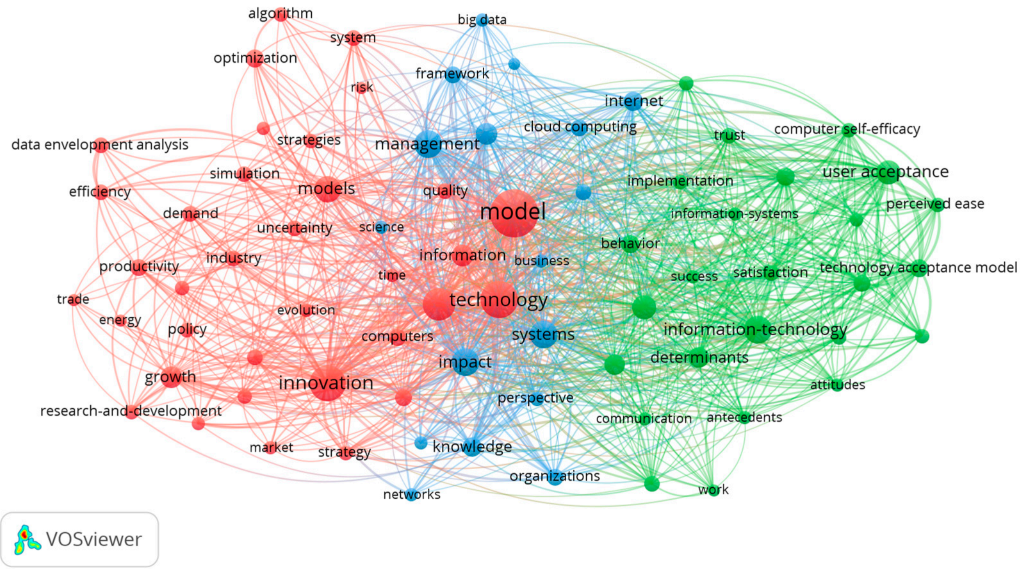

Figure 3. Keyword Network. Source: Software Output VOSviewer.

An investigation of the evolution of keywords over time provides a complementary analysis of the keyword network. Figure 4 shows the evolution, where it is possible to review that although the development of the models started in the 1990s, it was after 2000 that the trend began to develop. Initially, with the concepts of mathematical programming and implementation, from 2004 to 2014, the concepts of technological acceptance, social networks, technological change, and programming emerged. Since 2014, the development of ideas has been linked to Industry 4.0 technologies and their application in data, business models, supply chain management, and game theory.

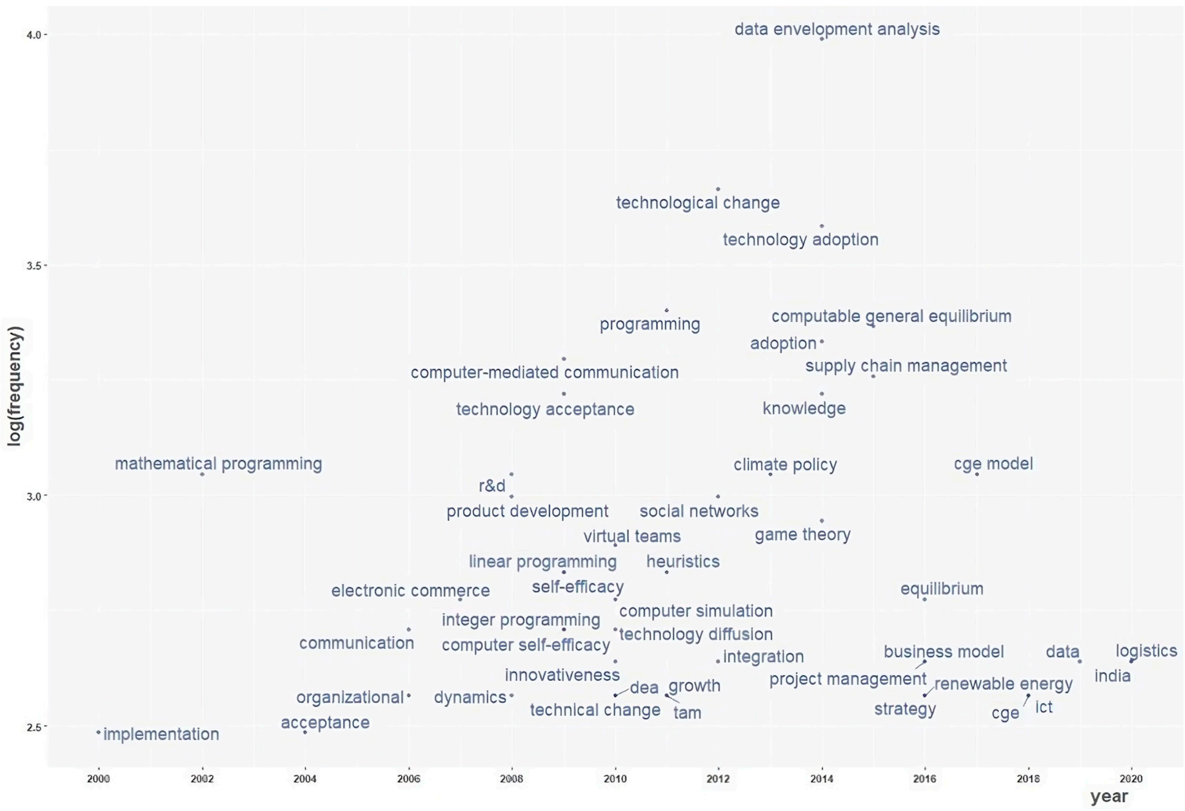

Figure 4. Trend Topics. Source: Software Output Bibliometrix.

The bibliometric analysis of the network is presented below. Figure 5 shows the strategic map, and Figure 6 shows the thematic evolution structure. Figure 5 shows 17 clusters, three (3) of which are classified as motor themes, six (6) as basic and transversal themes, two (2) as emerging or declining themes, and six (6) as highly developed and isolated themes. The size of each cluster is proportional to the number of core documents associated with the theme, followed by the total H-Index (in brackets). Table 2 details the nodes associated with the three driving themes, including their H-index value, the number of citations, and the number of documents in each node.

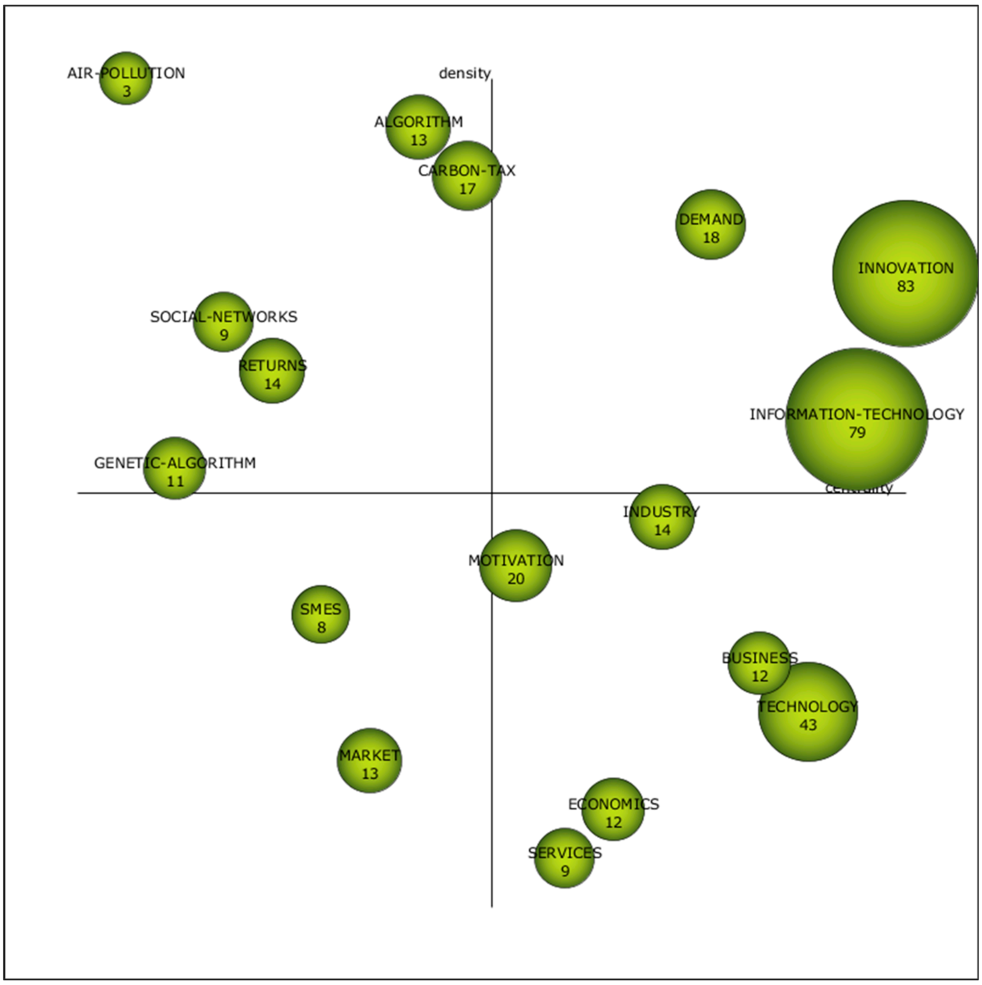

Figure 5. Strategic Map. Source: Software Output SciMAT.

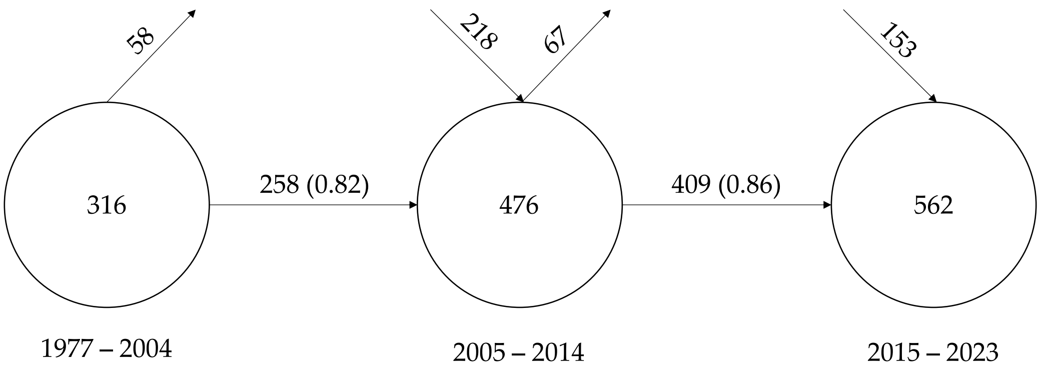

Figure 6. Graph of Overlapping Elements. Source: Software Output SciMAT.

Table 2. Thematic Networks Motor Themes.

Theme	Centrality	Density	h-Index	Citations	Nodes	Docs
Innovation	27.9	3.84	83	25,966	Capabilities	56
					Diffusion	97
					Firms	85
					Innovation	430
					Model	929
					Networks	82
					Organizations	122
					Patents	20
					Product	45
					Strategy	139
Information Technology	24.46	2.67	79	43,285	Attitudes	68
					Behavioral Intention	23
					Communication	61
					Computers	139
					Computer-Mediated Communication	92
					Determinants	130
					Impact	267
					Information Technology	367
					Social Influence	20
Demand	8.31	3.99	18	2638	Demand	84
					Elasticities	12
					Inequality	37
					Investment	75
					New-Product	4
					Personal-Computers	18
					Price	53
					Price-Indexes	7
					Task	20

We analyzed the evolution of the research in three time periods. Figure 6 shows the graph of overlapping elements according to [85]. The number inside the circle indicates the total number of keywords used in the period; the arrows between periods represent the number of keywords they share, represented in parentheses. The incoming arrows indicate new words, and the outgoing arrows indicate words no longer used.

In addition, the evolution map is shown in Figure 7; the spheres represent the clusters, and their volume is proportional to the number of documents. The characteristics of the line define the quality of their relationships, representing the weight of the "evolutionary link" between the articles of two consecutive periods. More specifically, the solid line means the linked clusters share the main element (usually the most significant). In contrast, the dotted line means that the topics share characteristics that are not the main element, describing features relatively distant from the main components [86]. The thickness of the edges is proportional to the inclusion index, which reflects the proportion of the number of documents published in each cluster [87].

We conducted a multiple correspondence analysis (MCA) to examine the relationship between the keyword items, i.e., the conceptual structure of the field. The output was the map presented in Figure 8, according to the number of factorial axes selected. The resulting map summarizes 32.7% for the domain we called management and 11.7% for the domain we called technology.

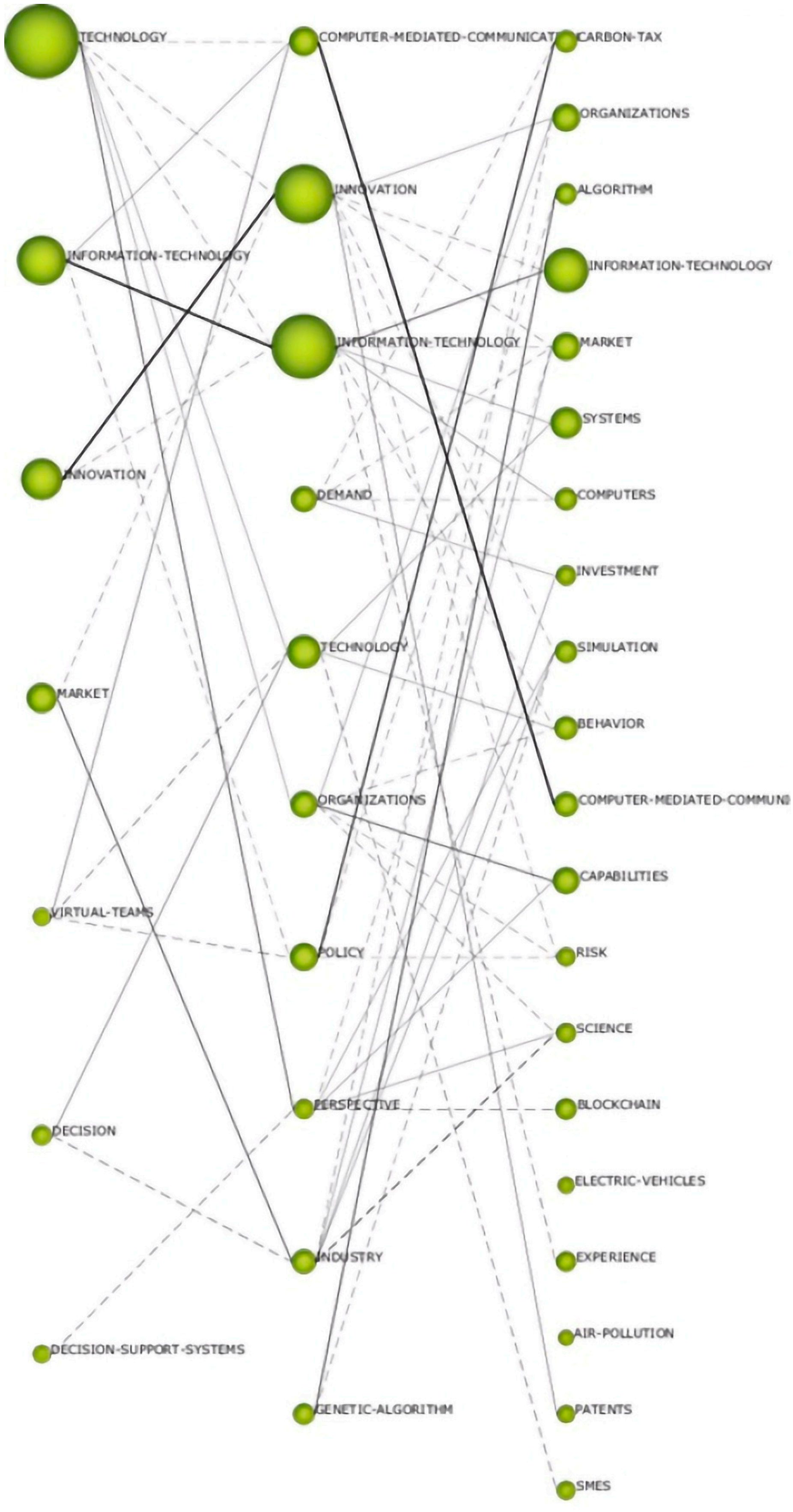

Figure 7. Thematic Evolution Structure. Source: Software Output SciMAT.

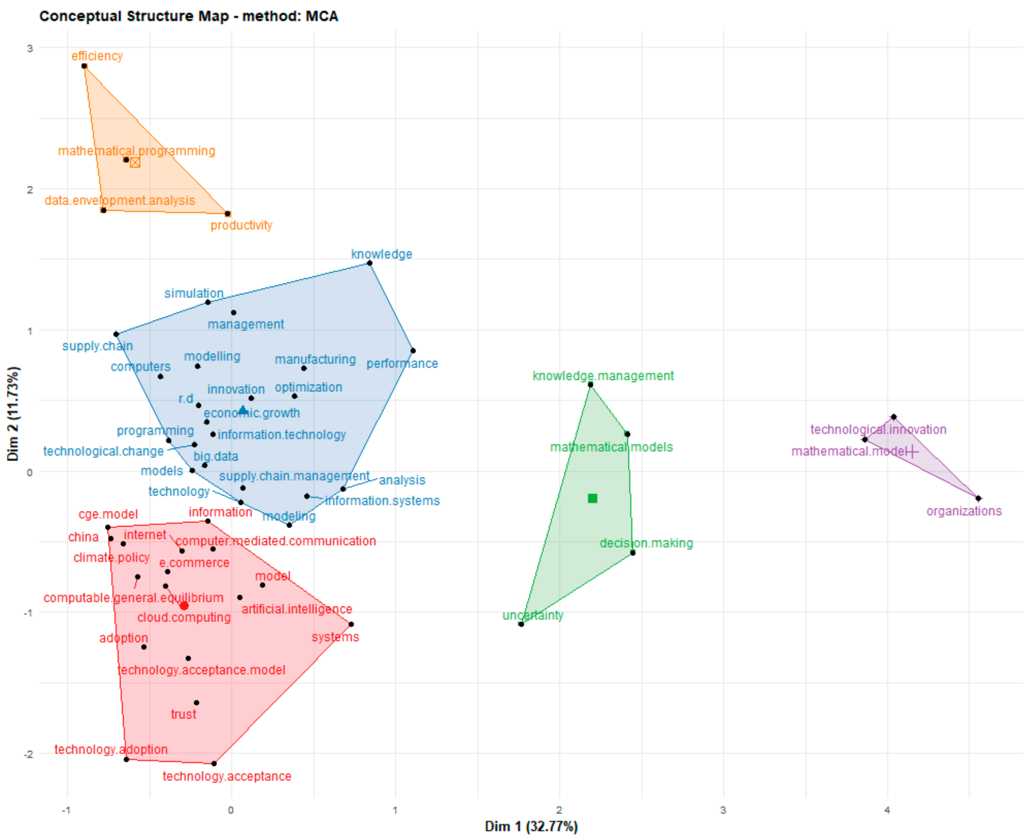

Figure 8. Conceptual Structure Map. Source: Software Output Bibliometrix.

4. Discussion

In the following, we discuss the main results of our work. Concerning the first question, the research was supported by several papers that develop models to explain behavior in the face of technology use and innovation. From the analysis of the historical citation network, the most important works in the analysis dealt with technological acceptance models and technology's role in organizational change.

The first of the referent articles to emerge from the analysis was the work of [88], which analyzed the challenges of users' acceptance of computer technology and compared two theoretical models, the Theory of Reasoned Action (TRA) [89] and the Technology Acceptance Model (TAM) [90], to predict and explain users' acceptance and rejection of computer technology. Results showed that intentions predicted use, and both TRA and TAM explained a significant proportion of the variance in behavioral intention. TRA and TAM are reference models describing people's behavior for incorporating technologies and innovation.

The second article that emerged as a reference was the work of [91], who used the theory of attitudes and behavior from [92] to understand the factors that influence the use of personal computers (PCs) in optional-use environments. The study identified social norms and three components of expected consequences (complexity of use, fit between work and PC capabilities, and long-term consequences) as the main determinants of behavior. Overall, the article provided information on the factors influencing the adoption and use of PCs in the workplace.

In the third referent article [93], they proposed Adaptive Structuration Theory (AST) as a framework for studying the role of advanced information technologies in organizational change. AST examines the change process from two perspectives: the types of structures that advanced technologies provide and the structures that emerge in human action when people interact with these technologies. The theory suggests that technological structures act as opportunities and constraints within which appropriation occurs, and the nature of appropriation will vary depending on the internal system of the group. Adaptive Structuration Theory (AST) is a theoretical approach that emphasizes the interaction between technology and the social process of technology use, illuminating how multiple outcomes can result from applying the same technology. AST argues that advanced information technologies trigger adaptive structuring processes that, over time, can change the norms and resources that organizations use in social interaction.

When analyzing the co-occurrence map, one can see several clusters or groups of closely connected words. For example, there is a cluster of words that focus on the idea of "artificial intelligence", which includes terms such as "algorithms", "neural networks", and "machine learning". Another significant grouping is "software", which includes words such as "applications", "development", and "programming".

Some words function as "bridges" between different clusters. For example, the term "data" is connected to both the "artificial intelligence" cluster and the "software" cluster, suggesting that it is a critical concept linking these two themes. In addition, the word "technology" is a connecting point for many of the clusters, suggesting that it is a central concept in this diagram.

The word "technology" is central to several word groupings, suggesting that it is a central and crucial concept in the set of related words represented in the image. On the one hand, the term "technology" is closely associated with the cluster of words that refer to "innovation", including words such as "disruption", "change", and "transformation". This suggests technology is an important driving force behind innovation and change in different fields.

Further, the word "technology" is also connected to groupings that refer to "software development" and "artificial intelligence". This suggests that technology is also seen as an important tool in these fields and that innovation in these fields is driven by technological advances. The analysis suggests that technology is a central and connective concept in the related words. Technology is seen as a driving force behind innovation and change and an essential tool for software development and artificial intelligence.

According to [94], three perspectives can be distinguished in the literature on the role of technology in business and society. First, the dominant perspective in the area is the instrumental perspective that understands that technology "refers to both the artifacts and arrangements that are developed as solutions to problems and to make life easier and to the knowledge and ingenuity to develop and use them, for better and worse" [94]. The standard view is to understand technology as a tool developed to solve problems in each context or natural use [95,96].

In strategic management, innovation and technology management, and international business, technology is conceived as something that can be managed, as a tool, a resource, or a capability related to a competitive advantage, while in economics, it is associated with productivity gains, new opportunities, and in relation to previous technology [94]. In management science and engineering, technologies are described as systems of interrelated components forming part of an industrial process [97]. Technology is defined as a set of skills or the integration of applications that allow people, using particular resources and means, to conduct a productive activity, provide a service, or achieve a goal or objective [36]. The latter authors also recognize that from a technical-economic perspective, technology means the state and knowledge of production systems and the leading techniques and skills necessary for these systems to function effectively. Technology is related to science, as highlighted by [98], in defining technology as the application of scientific knowledge to determine ways of doing things in a reproducible manner.

The second perspective on technology is that technology is value-laden, which considers that technology is socially constructed and is, therefore, the result of the dispute between different cultural preferences, social values, and political interests; thus, behind its declared search for effectiveness and efficiency, these conflicts are hidden [94,99]. It is recognized that technology is a broader socio-technological phenomenon than equipment, labor skills, or management systems with a macro approach that includes cultural, social, and psychological processes, institutions, and the culture of countries [100,101]. This view opens the line of research on what and how specific values and interests are embodied in technology [94]. For example, the development process and effects of "surveillance capitalism" [102] or "data capitalism" [103].

The third and most recent perspective approaches technology as relationally agentic [94,104,105]. This perspective considers not only that society shapes technology but that technology shapes society. Technology has agency in the sense of "the capacity of an entity to be causally effective in the production of events and states of affairs, including how "we", human beings, think and behave" [94]. Additionally, the TAM model is one of the most effective and widely used information system theoretical frameworks [106].

The results show that the trends in concepts are related to the modeling and integration of advanced technologies, such as artificial intelligence, automation, data analytics, and supply chain. Recently, there has been an emphasis on applying technologies to address social challenges from business through technology-based business models to contribute to sustainability, for example, electric vehicles and environmental management with solutions for air pollution or public policy, such as a carbon tax.

Examining the development of thematic structures makes it evident that the focus has shifted from an organizational perspective to an individual one. This change has resulted in a greater emphasis on people's capabilities, experiences, and behaviors regarding innovation. Researchers have increasingly turned their attention to topics such as managing technological innovations, models for technological advancements, and the impact of these innovations. Mathematical models have emerged as crucial tools for future innovations, providing the analytical tools to understand, simulate, and predict the behavior of technological innovations and their impact on business models. Different scenarios can be evaluated through mathematical models, optimized resources, and informed decisions based on quantitative data.

Moreover, with the explosive rise of artificial intelligence (AI), further study and empirical analysis of these technologies are required [107]. Mathematicians are fundamental models in this context, as they allow the development of hybrid models that combine the participation of humans and machines. These hybrids are especially relevant as they take advantage of the strengths of both parties, generating more efficient innovations and sustainable models. For example, the emergence of AI creation automation techniques, or AutoAI, will radically change the role of data scientists in technology companies, raising new research questions. Among them is what role AI will play—will it be a co-collaborator, an advisor, a teacher, or a team member? On the other hand is how stakeholders (e.g., executives and customers) perceive AutoAI. How is the customers' willingness to pay for a model developed by AutoAI affected? How important is the role of humans in the development of models for customers? What factors influence stakeholders' trust in AutoAI? When companies delegate decisions to AIs, research questions arise that require further empirical studies to address, such as how to prevent biases that AI models may have, how to ensure that decision-making processes and structures that include AIs represent improvements over traditional decision-making, and what the effects of these new human-AI configurations are.

In another example, from a marketing perspective, consumers may perceive AI-based micro-targeting marketing as reducing their autonomy. They may alter their evaluations and choices to assert self-determination [108]. Consequently, it will be necessary for research to understand what factors determine the perceived value of autonomy in AI-mediated choice environments and to what extent while further addressing the adoption and use of hybrid technologies that combine human and machine participation and determining how they improve decision-making efficiency and outcomes in different contexts. Trust, communication, accountability, and coordination between human and technological actors should be considered. It would also be interesting to delve into the ethical aspects of using advanced technologies, such as artificial intelligence, including privacy, accountability, algorithmic discrimination, bias, and the social impact of these technologies.

On the other hand, with this study oriented at the company level, it would be of interest in future research to also consider the analysis of the adoption of computational and mathematical models to optimize the implementation of circular economy strategies. This involves examining the flow of materials and resources, identifying opportunities for recycling and reuse, and assessing these practices' environmental and economic impact.

There may be other areas of research that could be developed considering a systemic approach and a company-level approach. From a systemic point of view, one could analyze the effects of new technologies arising from computational and mathematical models on society, work, and social relations, differentiating between developed and developing countries by economic sectors and territories. On the other hand, the simultaneous adoption of new technologies by companies, such as blockchain and artificial intelligence, could be analyzed. It is also crucial to understand their effects on business performance, the development of new business models, and the development of capabilities to adapt these new models.

5. Conclusions

This study analyzed research on using computational models in technology and business innovation through a bibliometric literature review.

The study results indicate that publications in high-impact journals correspond to diverse areas, such as management, technology, computer science, and social sciences. Additionally, the areas in which such articles are cited are extensive, including, for example, numerical methods, quantum mechanics, bioengineering, sociology, psychiatry, and medical sciences, denoting the importance of these studies in the development of science.

A relevant aspect of our analysis is the scarce contribution made by Latin American countries, which contributed 1.6% of the total number of works analyzed together. Therefore, a call should be made to develop literature in these geographic areas, considering the region's characteristics and that Latin American economies have particularities that make it necessary to analyze data from these contexts. Additionally, the results can have a better impact on public policies and the management of organizations, allowing them to incorporate innovation and technology with greater precision.

Another interesting aspect is that although the scope of this research is business, the theoretical references are from the areas of psychology and behavior. The theoretical references are from the areas of psychology and behavior. These have allowed us to support the theories that explain the acceptance of technologies in the participants of the companies.

A bibliometric analysis based on mathematical and computational models can be the foundation for becoming a Digital Assets Management (DAM) system. This enables organizations to efficiently store, organize, and retrieve digital assets, ensuring easy access and retrieval of relevant publications, patents, and other research outputs.

Several practical advantages arise from this approach within organizations. A company can identify influential researchers in specific scientific areas or disciplines through bibliometric analysis. By extracting information from a large number of publications and scientific citations, bibliometric comment empowered by DAM helps identify Key Opinion Leaders (KOLs) who have the potential to contribute to innovative collaborations or serve as expert advisors. Furthermore, it can be used to monitor the research and patents of competitors, enabling the identification of emerging technologies and potential market gaps. By analyzing patent citations and tracking scientific publications from competitors, companies can strategically position themselves to seize new opportunities and stay ahead in the market.

Lastly, DAM facilitates the sharing and dissemination of research outcomes within and outside the organization. Companies can foster a culture of open innovation by providing a platform for researchers to collaborate, exchange knowledge, and publish their work. DAM also supports licensing and intellectual property management, allowing organizations to monetize their digital assets while ensuring proper attribution and compliance.

From the analysis of the results of our research, the progress of technology and innovation raises the need to investigate not only the economic but also the cultural and social implications of the use of systems that include innovation and technology, which we can call intelligent systems. One of the cases in which innovation and technologies could be incorporated in companies is Smart Manufacturing, where H-AI (Human-AI collaboration) has significant potential, where humans and AI systems can interact and work together towards common goals. For example, collaborative robots have enabled human-robot collaboration in companies such as BMW, Mercedes, GM, Skoda, Ford, and Tesla, improving production efficiency. However, achieving a better balance in the human-robot relationship is crucial. With H-AI advancements, humans can guide robots using cognition, while machines have their thoughts and engage in bidirectional communication. This enhanced collaboration can significantly improve intelligent manufacturing efficiency [107]. Another business case is the proposal of SPChain, a blockchain-enabled digital asset management framework known for its enhanced intelligence and privacy features while also adhering to the General Data Protection Rules (GDPR). This framework adopts a decentralized InterPlanetary File System to address the challenge of a single point of failure (SPOF). Furthermore, integrating artificial intelligence models with digital assets expands accessibility to a broader range of applications and promotes greater creativity. In this design, independent and virtualized containers execute artificial intelligence models invoked through intelligent contracts. The SPChain framework's applicability extends to the digital art management field, providing a comprehensive implementation based on the Hyperledger Fabric. Stakeholders, such as model developers, digital art creators, collectors, service providers, and third parties, benefit from securely managing digital assets, integrating them with AI models, and adhering to the GDPR [109].

Despite the strengths of bibliometric analysis, it has limitations that can be addressed by developing a systematic or meta-analysis. Scopus databases could also be included to analyze research for other purposes.

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