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MAPPING INNOVATION DOMAINS USING TOPIC MODELING

Abstract: Innovation plays a crucial role in driving economic growth and development, improving competitiveness, and creating new opportunities for individuals and businesses. It can lead to higher living standards and improved quality of life by addressing some of the world's most pressing challenges, such as climate change, health crises, and poverty. In recent years, artificial intelligence (AI) has emerged as one of the most influential forces shaping everyday life. It is also revolutionizing the innovation process by supporting R&D activities, automating complex tasks and enabling data analysis at speeds far exceeding human capabilities. The adoption of AI technologies accelerates the development of new products and business models while fundamentally transforming decision-making processes. Consequently, companies are required to restructure their innovation processes in response to rapid technological advancement and evolving workforce roles. AI is widely perceived as a source of unlimited possibilities, and its increasing adoption is strongly reflected in the expanding body of scholarly work. The number of papers addressing innovation and AI has grown significantly in recent years. To illustrate, assess and map research at the intersection of AI and innovation, this study analyzes published work indexed in the Elsevier Scopus databases. The research examines thousands of publications related to innovation by analyzing titles, abstracts, and keywords, employing BERTopic modeling and bipartite graph analysis to identify emerging patterns. The findings reveal five distinct innovation technology domains and systematically map their relationships with various AI methods. The results indicate that AI-related innovations are not isolated phenomena but are widely integrated across multiple domains, highlighting the importance of cross-departmental collaboration to maximize system-wide benefits.
Keywords: Artificial Intelligence (AI), innovation, innovation management, BERTopic, bipartite graph models, SCOPUS.

1. INTRODUCTION

Technological innovation developments in organizations have attracted increasing scholarly attention over the last few decades, as firms have rapidly learned to use technology to enhance their innovativeness and performance (Beilin et al., 2019; Bai and Li, 20020; Hoffman et al., 1988; Musiolik et al., 2020). More specifically, organizations have soon learned that they can blend innovative technologies with their capabilities to enhance their competitive advantage (Porter, 1985). Among digital technologies that are constantly allowing firms to innovate in the digital age, there is artificial intelligence (AI), which is increasingly affecting how firms innovate (Kakatkar et al., 2020; Mariani and Fosso Wamba, 2020; Wamba and Mishra, 2017) and how consumers respond to AI-informed innovations (Mustak et al., 2021).

Economists have recently sought to understand the impact of AI on innovation (Cockburn et al., 2019) and have called for more research at both the industry and organizational levels. So far, management scholars dealing with technology-driven innovation have focused mainly on themes such as the barriers in the implementation of AI systems in organizations (Desouza et al., 2020; Haefner et al. 2021), and ways through which AI can support organizational processes (Frank et al., 2019), decision making (Kakatkar et al., 2020; Verganti et al., 2020), operations (Belhadi et al., 2021), business models (Di Vaio et al., 2020) and the achievement of organizational objectives (Hutchinson, 2021). While this body of research is very recent, it apparently displays several features: (1) there are indicators on research fragmentation (2) its nature is mostly exploratory; (3) innovation scholars do not have a clear, holistic, and comprehensive picture of what has been researched and where are the most relevant new research gaps that might provide fruitful avenues for further enquiry in the focal domain.

More specifically, despite AI being increasingly critical in innovation studies, so far, no systematic effort has been made to synthesize and assess comprehensively and quantitatively through a systematic literature review (SLR) the knowledge produced on the role of AI in innovation management. Furthermore, innovation management scholars miss a structured framework that clearly maps extant literature in relation to the drivers and outcomes of AI adoption in the innovation field. To bridge these research gaps, and in line with the tenets of literature review research (Donthu et al., 2021), we conduct an SLR to answer the following research question: What is the emerging intellectual structure of the innovation literature on AI?

To answer this research question, we conduct an SLR to identify the evolution of research on AI and innovation, to investigate the scientific knowledge produced to date, and to portray the advancement of innovation research pertaining to AI. Having identified the relevant sample for the review (N = 16950 articles), an SLR approach is used to identify the drivers and outcomes of AI adoption for innovation purposes. Adopting an SLR allows researchers to embrace a systematic, transparent, and reproducible approach that can reduce bias (Snyder, 2019).

This paper makes several contributions to the intersection of innovation and AI by adopting a multidisciplinary perspective. First, we provide an updated overview of the volume and trends in research outputs at the intersection of AI and innovation, thereby contributing to the field of innovation management. Second, we single out economic, technological, and social factors as drivers of AI adoption in firms willing to innovate. Third, we identify firms' economic, innovation, competitive, and organizational factors as key outcomes of AI adoption in firms aiming to innovate. Fourth, we leverage a bibliometric analysis to uncover seminal work in the field of AI in innovation research and to map the research field over time. Fifth, we contribute to the innovation literature by developing an interpretive framework that elucidates the drivers and outcomes of AI adoption for innovation, thereby offering a theoretical contribution to the field of innovation management. Sixth, we identify the most frequently used theories to provide clear directions for further inquiry. Seventh, we develop a rich research agenda that contributes to expanding the field's perimeter while revealing new research gaps that can lead to fruitful avenues for further enquiry in the focal field.

The article is structured as follows. In section 2, we review the recent debate on AI in the innovation domain. Section 3 describes the methodology adopted in this study. Section 4 portrays the findings in relation to the descriptive statistics of extant publications, major themes and topics that emerged from the bibliographic coupling analysis, theoretical lenses deployed in the literature, and a comprehensive framework to identify drivers and outcomes of AI adoption. Section 5 elucidates the major contributions and illustrates the limitations while developing a rich research agenda.

2. RECENT DEBATE ON AI IN INNOVATION STUDIES

As the aim of this study is to map the intellectual structure of innovation literature dealing with AI, we first introduce several key concepts and definitions to better inform this systematic literature review.

Several scholars in business and management have recognized that AI has multiple ramifications. These ramifications have been theorized recently by Davenport and Ronanki (2018) and Huang and Rust (2018). For instance, Davenport and Ronanki (2018) distinguish three types of AI: process automation, cognitive insight and cognitive engagement. More recently, AI has been defined as "the use of computational machinery to emulate capabilities inherent in humans, such as doing physical or mechanical tasks, thinking, and feeling" (Huang and Rust,2018, p.31). In innovation contexts, AI has been defined as systems developed with the "objective of creating human-like behaviour in machines for perception, reasoning, and action" (Prem, 2019, p.2). AI has gained power due to rapid advances in computational capabilities and a huge variety of new technologies (e.g., computer vision, machine learning, and natural language processing) (Mariani et al. 2022), as well as a blast of available data to train algorithms (Bornet et al., 2021).

The increasing relevance of AI in innovation is witnessed by the production of several studies on topics such as AI supporting innovation analytics (Kakatkar et al., 2020), AI enabling digital experimentation and digital innovation (Mariani and Nambisan, 2021), AI and sustainable business models (Di Vaio et al., 2020), AI in supply chain management (Toorajipour et al., 2021), strategic uses of AI (Borges et al., 2021), AI and big data integration within business processes

(Wamba and Mishra, 2017), and AI capabilities in industrial markets (Akter et al., 2021). However, to the best of our knowledge, there is only one literature review focusing on AI within innovation: Haefner et al. (2021) review the literature on AI and innovation management using the behavioural theory of the company to identify the application of AI systems in the innovation process, and illustrate the challenges that firms may face during the innovation process.

Our study is unique and distinct from the mentioned literature review on AI and innovation management, for several reasons. First, our study embraces a bibliometric and quantitative approach to examine the relevant literature, whereas Haefner et al. (2021) adopted a narrative approach. Second, the work of Haefner et al. (2021) is confined to "innovation management", while our study captures holistically the way AI has been researched in innovation studies. Third, bibliometric techniques allowed us to dig in depth about several key topics, and to portray the scholarly debate on the drivers and outcomes of AI adoption by firms trying to pursue product, process, and business model innovation.

As such, this work makes the following contributions. First, to the best of our knowledge, our study is the first (or among the first) to conduct a SLR on AI in the wider innovation research context (without a mere focus on innovation management) and to provide an integrated and holistic view of this emerging research area. Second, we leverage several bibliometric techniques (e.g., citation analysis, co-citation analysis, bibliographic coupling, and co-word analysis) as well as network analysis to scrutinize the intellectual structure emerging from the literature, and subsequently, provide a comprehensive framework that sheds light on the drivers and outcomes of AI adoption for innovation. Third, we single out and examine the wide range of theoretical lenses adopted in this research area to enable a better theoretical and conceptual interpretation of AI in innovation research.

3. RESEARCH METHODOLOGY

It is assumed that the input data consists of text files containing abstracts of scientific publications related to the fields of innovation and artificial intelligence.

The purpose of the research methodology developed was:

1. Identification of concepts related to artificial intelligence area,
2. Identification of main issues related to innovation area,
3. Analysis of relationships between AI and innovation topics.

3.1. The identification of AI concepts

Computer Science Ontology (available at: https://cso.kmi.open.ac.uk/home) was used to identify concepts related to AI . In this ontology, the concept "artificial ontology" is a direct descendant of the root node "computer science" and has 1,826 descendants, 36 of which are direct descendants, while the rest are indirect descendants. Each concept has a label containing its name (e.g., "machine learning"). After collecting all concepts related to the field of AI , an embedding was assigned to each of them using a model all-MiniLM-L6-v2, which produces 384-dimensional embedding vectors. Word's embedding can be treated as its coordinates in semantic space (it means that in this space words with similar meaning are places close together). The all-MiniLM-L6-v2 model is one of the most popular tools for calculating embeddings for English words. Determining the distance between word embeddings allows us to assess their semantic similarity. This property has been used in research to identify the alignment between each analyzed sentence and concepts characteristic of a selected field of knowledge. To use this feature, the same model was used for calculating embeddings for every sentence taken from descriptions of publications (titles, keywords, abstracts). To assign concepts to specific sentences, the distance between the concept's location in the semantic space and the location of every sentence was calculated. If the calculated distance was less than the specified threshold value, the concept was assigned to the given sentence. In the study, the Euclidean formula was used to calculate the distance, and the threshold value was set at 0.9 The threshold value was determined experimentally, based on an assessment of the accuracy of concept assignment to the analyzed set of example sentences. In the last step, for every AI concept that was found in documents, the upper-level concepts being the direct descendants of the "artificial intelligence" concept were identified. These concepts (called "main AI sub-concepts) were used for further analysis.

3.2. The identification of main areas in the field of innovations

Due to the lack of a generally accepted ontology describing the field of innovation, the concept of identification process was conducted using an unsupervised learning procedure. The procedure consisted of two steps. In the first step, the main topics discussed in the publication descriptions were identified. The analysis identified 40 topics. It was assumed that the number of topics identified would exceed the number of innovation-related issues planned for identification, as it was expected that some of the topics appearing in the texts would not refer to the analyzed area.. For topic identification BERTopic algorithm was used (Grootendorst, M., (2022)).

In the next step of the analysis, the identified topics were grouped into categories corresponding to the issues most frequently discussed in the literature regarding the field of innovation. Finally, it was decided that the following five issues would be included in the subsequent analysis:

1. Digital and Intelligent Technological Enablers
2. Sectoral and Industrial Application Environments
3. Sustainability and Energy Transformation Drivers
4. Analytical and Modelling Support for Innovation
5. Innovation Systems and Diffusion Context

For each of the innovation-related issues identified in this way, aggregated word frequencies were calculated to indicate the frequency of specific words in the texts assigned to each group. These values served as the basis for creating word cloud charts illustrating the issue under consideration.

3.3. Analysis of relationships between AI concepts and innovation areas

Bipartite graph models (Lula et al., 2019) were used to show relationships between AI main sub-concepts. Bipartite weighted graph shows the number of occurrences of concepts belonging to two separate sets (AI and innovation) and the strength of connections between them (expressed as a number of cases in which two given concepts belonging to different sets occur at the same time). A bipartite graph presenting relationships between innovation and AI issues was presented in the form of a Sankey diagram.

4. RESULTS OF EMPIRICAL RESEARCH

4.1. General description of the publications analyzed

As part of the empirical research, an analysis was conducted of abstracts, keywords, and titles of papers published in 2025, indexed in the Scopus database, and related to the topic of "innovation and management". The total number of publications meeting the criteria defined above was 16,950.

The scope of the analyzed works is presented in Figure 1 in the form of a word cloud.

Figure 1. The scope of the analyzed works
Source: The authors

Word clouds show the importance of words and phrases used in text documents. The importance of a given phrase is proportional to the font size used to display it. The content of the figure indicates that the following concepts should be considered particularly important: artificial intelligence, machine learning, sustainable development, supply chain, innovation, digital transformation and technology.

4.2. Topics identified in the area of AI

The method used to identify the main thematic areas within the field of AI was of a different nature. It was based on a semantic search within publication descriptions for concepts associated with the field of AI in Computer Science Ontology (https://cso.kmi.open.ac.uk/home).

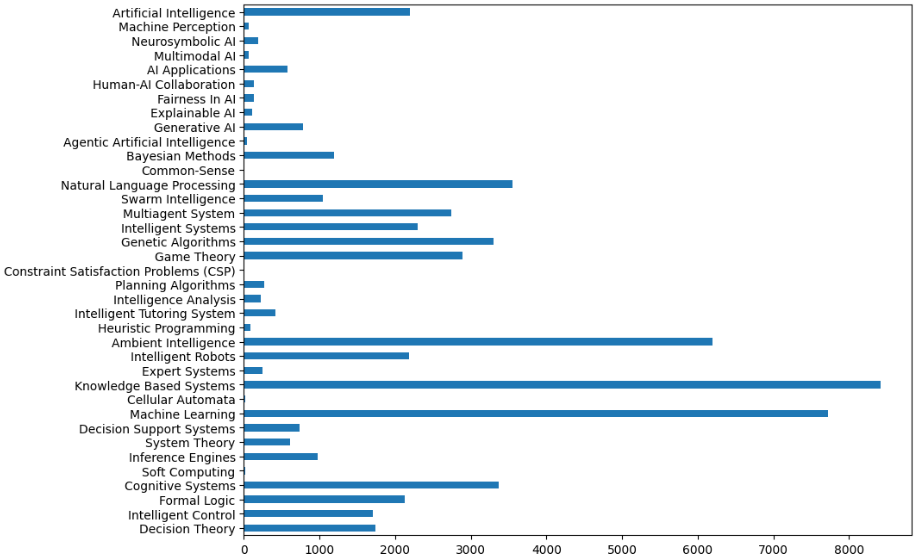


Figure 1: The number of references to AI main subareas.
Source: The authors

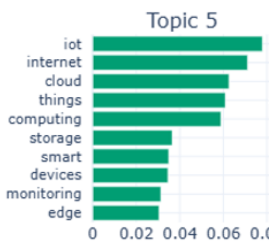
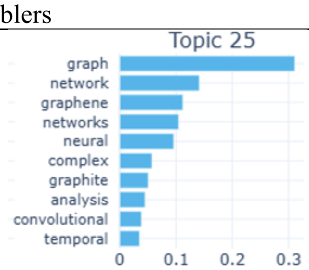
The figure shows that knowledge based systems, machine learning and ambient intelligence belong to the group of the most important concepts in AI area.

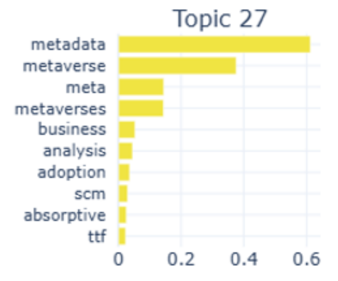
4.3. Topics identified in the area of innovations

The process of identifying the main issues in the field of innovation consisted of two main stages. During the first stage, 40 topics were identified using the BERTopic algorithm. The identified topics were then assigned to five areas.

The first area was identified as "Digital and Intelligent Technological Enablers". The description of topics assigned to this area is presented in Table 1. This domain encompasses digital and computer technologies that enable the development of innovation. Identified technologies are not innovations by themselves but represent the infrastructure that empowers big data processing, process automation, and the development of new digital functionalities.

Table 1. The characteristics of the "Digital and Intelligent Technological Enablers" area

Digital and Intelligent Technological Enablers		
		



Source: The authors

The word cloud created with the use of texts assigning by BERTopic method to topics belonging to the "Digital and Intelligent Technological Enablers" area is presented in Figure 1.

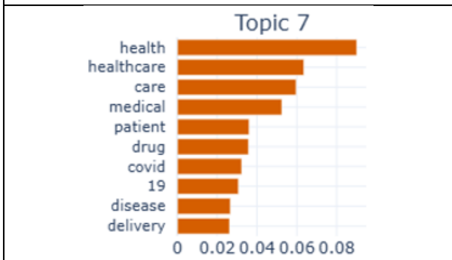
Figure 3. Word cloud for the "Digital and Intelligent Technological Enablers" area
Source: The authors

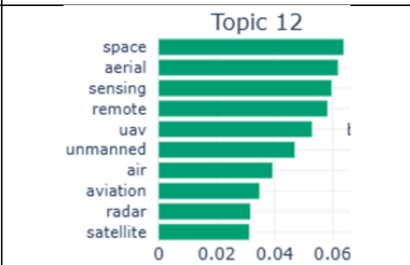
The content of the figure confirms the importance of issues related to knowledge management, data analysis, and the technological aspects of the implemented solutions.

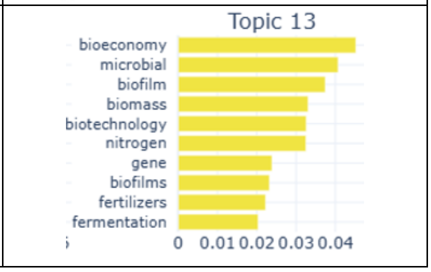
The characteristics of the "Sectoral and Industrial Application Environments" area are presented in Table 2. These domains represent the sector and industry contexts in which innovations are developed and applied. It can be interpreted as a concrete technology application or development of new products, services, or technological solutions adjusted to customer requirements in the specific industry.

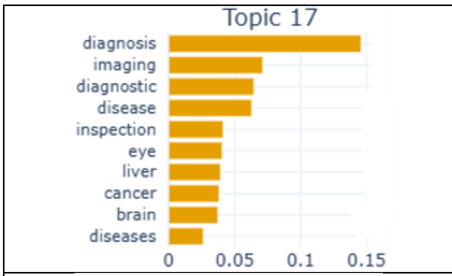
Table 2: The characteristics of the "Sectoral and Industrial Application Environments" area

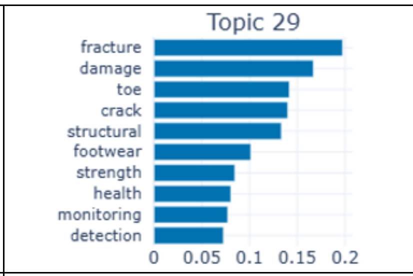
Sectoral and Industrial Application Environments

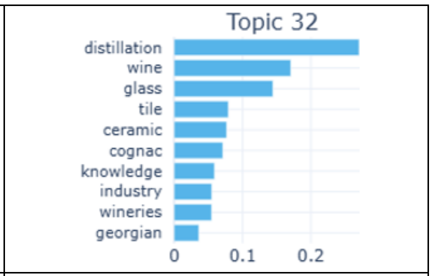


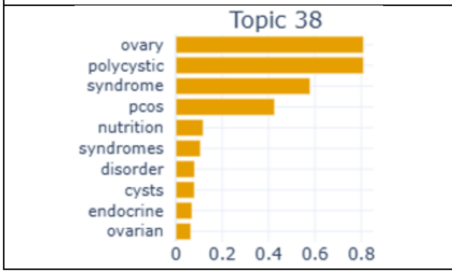












Source: The authors

The word cloud for the "Sectoral and Industrial Application Environments" is presented in Figure 3.

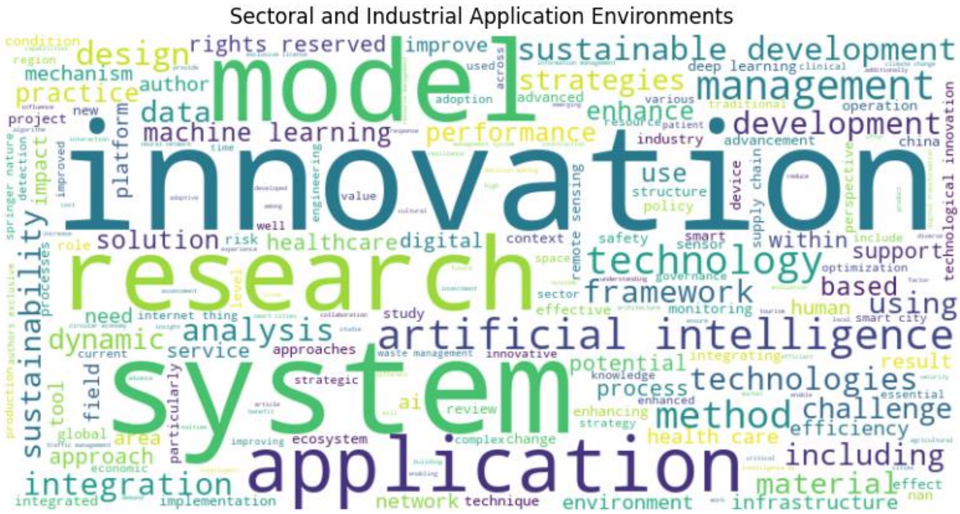


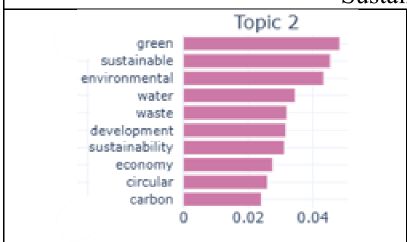
Figure 4: Word cloud for the "Sectoral and Industrial Application Environments" area
Source: The authors

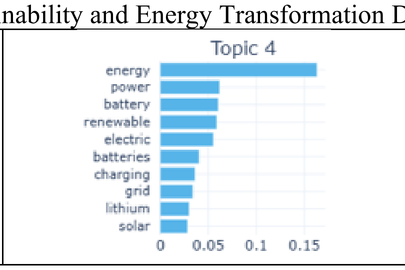
The resulting plot confirms that the most important issue in the area "Sectoral and Industrial Application Environments" is the implementation of the innovative solutions that have been developed.

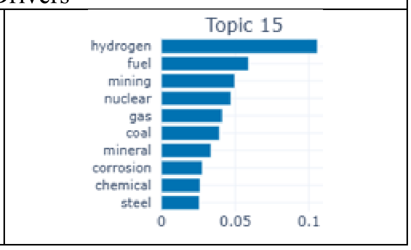
Next, an analysis of the "Sustainability and Energy Transformation Drivers" area was conducted. The description of topics that were assigned to this area is presented in Table 3. Dominant concepts include renewable energy, hydrogen, energy efficiency, ESG principles, etc. These topics reflect global efforts to reduce emissions and the development of sustainable technological solutions. This area is especially significant in current innovation policies that emphasize the transition towards sustainable energy solutions.

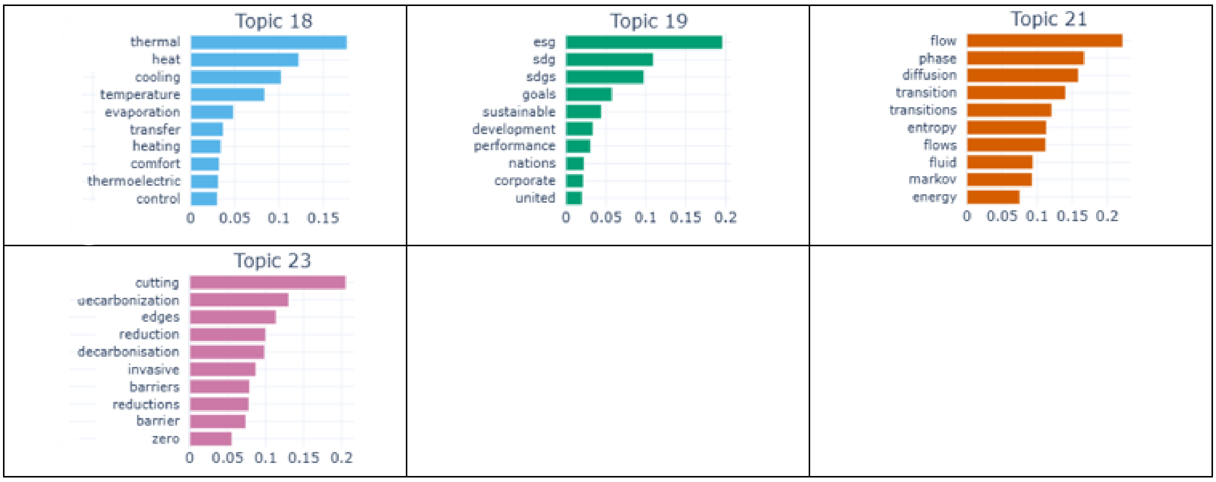
Table 3: The characteristics of the "Sustainability and Energy Transformation Drivers" area

Sustainability and Energy Transformation Drivers









Source: The authors

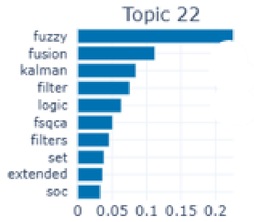
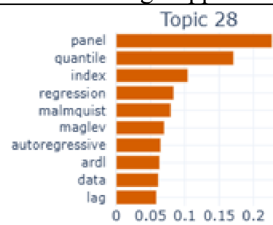
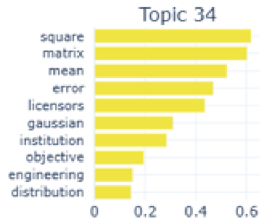
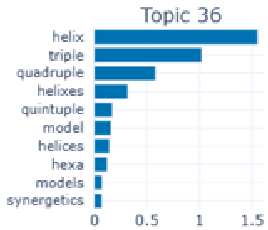
Main issues discussed in the area "Sustainability and Energy Transformation Drivers" are presented in Figure 4.

Figure 4: Word cloud for the „Sustainability and Energy Transformation Drivers" area
Source: The authors

The most important concepts related to the "Sustainability and Energy Transformation Drivers" area include: sustainable development, green innovation, waste management, circular economy and climate change issues.

"Analytical and Modelling Support for Innovation" was another area identified during the research process. It was presented in Table 4. This domain encompasses mathematical, statistical and analytical methods used for modelling and evaluation of innovation processes. Models enable innovation feasibility, resource optimization and informed decision making during new product or service development.

Table 4: The characteristics of the "Analytical and Modelling Support for Innovation" area

Analytical and Modelling Support for Innovation		
		
		

Source: The authors

The word cloud for the "Analytical and Modelling Support for Innovation" is presented in Figure 5.

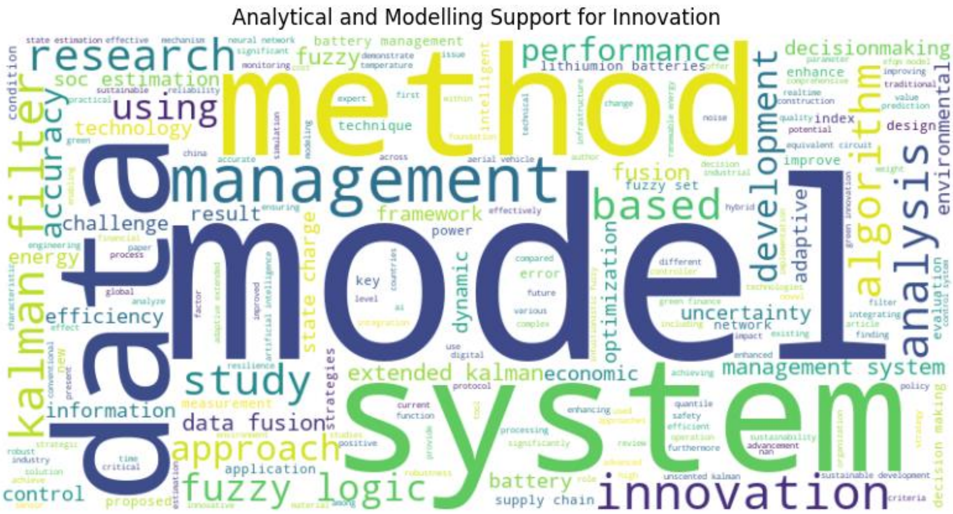
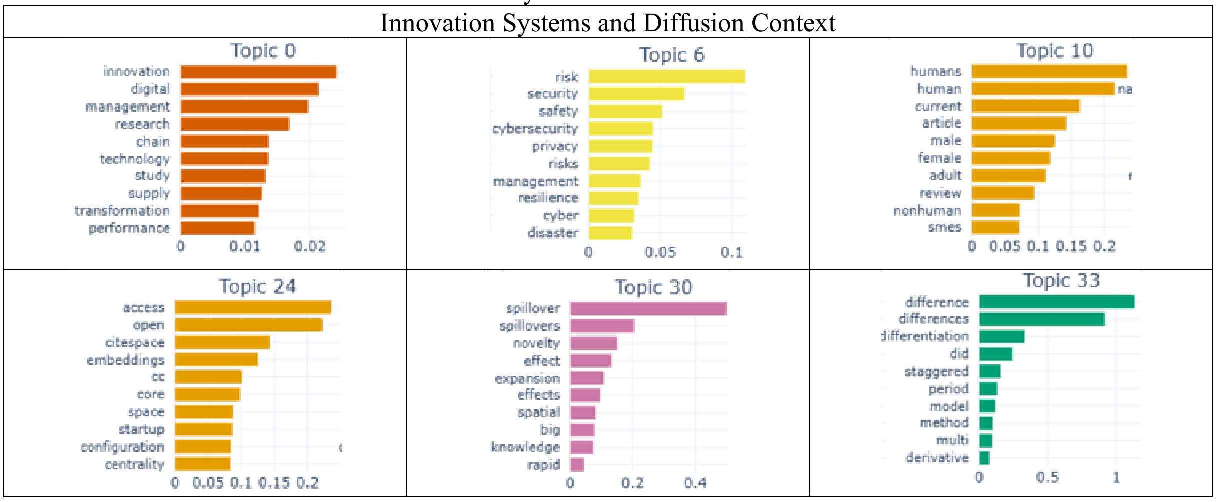


Figure 5: Word cloud for the „Analytical and Modelling Support for Innovation" area
Source: The authors

Data, models, methods, analysis and performance belong to the most important issues connected with "Analytical and Modelling Support for Innovation" area.

The area "Innovation Systems and Diffusion Context" is presented in Table 5. The domain includes organizational, social and institutional factors that shape development and diffusion of innovation. It is very important for understanding the process of how innovation passes through development phase to phase of commercialization and adoption.

Table 5. The characteristics of the “Innovation Systems and Diffusion Context” area



Source: The authors

Main issues belonging to the area “Innovation Systems and Diffusion Context” are presented in Figure 6.

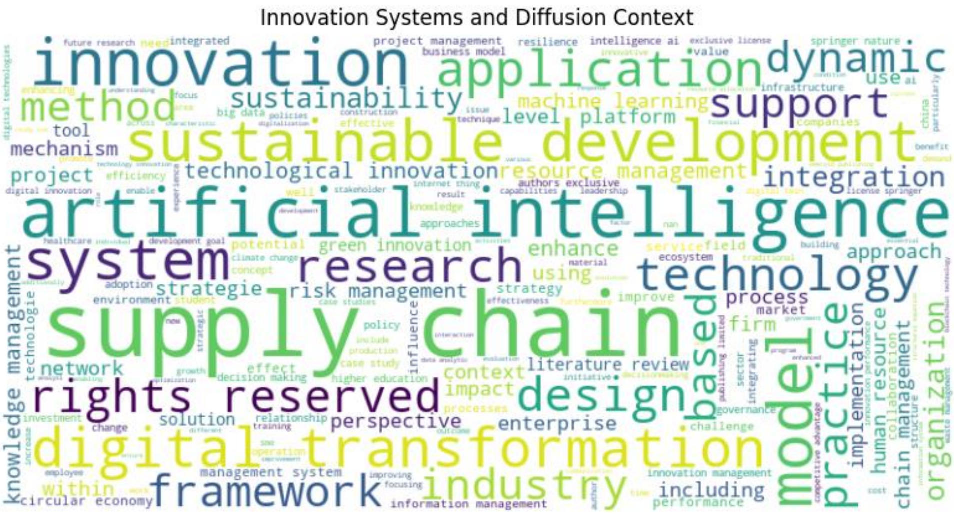


Figure 6: Word cloud for the „Innovation Systems and Diffusion Context” area
Source: The authors

Phrases presented in Figure 6 indicate issues related to the application of innovation solutions.

The significance of areas identified within the innovation field is presented in Figure 7. Values presented in this figure show the number of references to topics belonging to five main innovation areas.

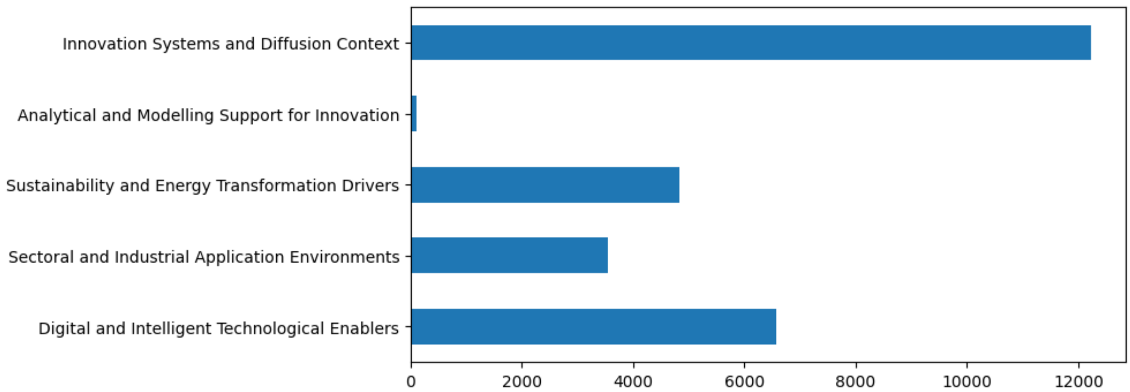


Figure 7: The number of references to main areas defined within innovation field
Source: The authors

4.4. Analysis of relationships between main AI sub-areas and main areas belonging in innovation field

The relationships between AI subareas and main areas within the innovation field are presented in Figure 8 in the form of a Sankey diagram.

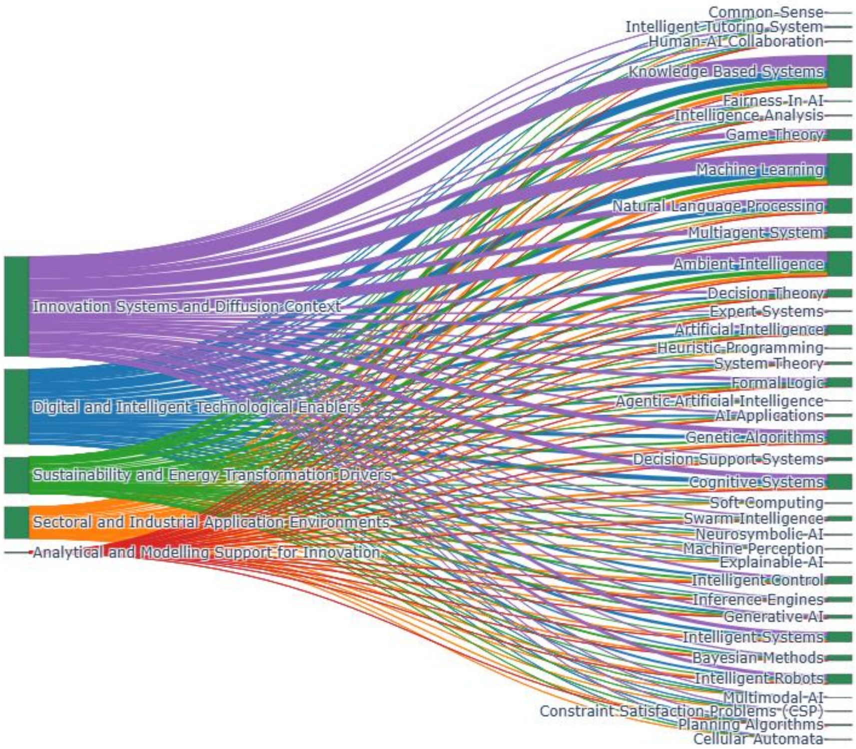


Figure 2: Relationships between main AI subareas and areas within innovation field

Source: The authors

In the document corpus under study, from the perspective of innovation-related topics, the following areas were of the greatest significance:

- Innovation Systems and Diffusion Context
- Digital and Intelligent Technological Enablers
- Sustainability and Energy Transformation Drivers

The following areas were significantly underrepresented:

- Sectoral and Industrial Application Environments
- Analytical and Modelling Support for Innovation

Knowledge-based systems, machine learning and ambient intelligence should be considered one of the most important concepts in the field of AI. Particularly strong connections emerge between the aforementioned fields of artificial intelligence and the “Innovation Systems and Diffusion Context”.

Analysis of the graph confirms the high specificity of the concepts under examination—which indicates a high degree of variation in the strength of connections between the concept under consideration (belonging to the first set) and the concepts belonging to the second set.

5. CONCLUSIONS

The analysis confirms the existence of a strong link between AI and innovation. In the context of innovation, the following areas of AI should be considered particularly important: knowledge-based systems, machine learning, ambient intelligence, cognitive systems, natural language processing and genetic algorithms.

It should be noted that the importance of AI concepts in various areas of innovation is not evenly distributed.

From the theoretical aspect, the identified clusters and their subsequent classification into broader areas contribute to a better understanding of the complex and multidimensional nature of innovation. The resulting clusters provide an insight into the latent thematic structures within the literature, whereby innovations are not viewed as a single phenomenon, but as a result of the interaction of various technological, sectoral, analytical and systemic factors.

The research results provide a practical tool for researchers, decision-makers, and organizations developing innovative solutions. Identification of these areas and their relationships allows easier recognition of the key factors that influence the success of innovation activities, as well as identification of areas with the greatest potential for the development of new technologies. The primary problem identified during the research was the lack of a widely accepted ontology describing the field of innovation. In their future work, the authors of this paper aim to address this issue by proposing an ontology that includes a set of concepts related to innovation and their interrelationships.

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