Lisbon School of Economics & Management
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ECONÓMICA E EMPRESARIAL

PROJECT

# ARTIFICIAL INTELLIGENCE IN EMERGENCY DEPARTMENTS: A COMPARATIVE ANALYSIS OF PUBLICATIONS AND PATENTS

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*To my grandfather,*

*who always encouraged me to do my best.*

*Thank you for giving me much more*

*than the inspiration for this thesis.*

# ABSTRACT

Emergency departments face increasing pressure from overcrowding, long waiting times, and limited human and material resources. In this context, artificial intelligence may improve clinical and operational performance, but it remains unclear whether scientific progress is being translated into protected technologies.

This study examines the main evolutionary trends in the application of AI in emergency departments by comparing scientific publications and patents. The data was collected from Scopus and WIPO Patentscope. The methodology combined descriptive bibliometric analysis, term co-occurrence mapping and thematic clustering, and integrated semantic network analysis. Together, these three approaches enabled distinguishing the main areas of scientific interest, protected technologies, and potential fields for future development.

The results show strong growth in both papers and patents, particularly since 2018. However, they revealed a partial misalignment: papers focus mainly on predictive models, AI adoption, clinical outcomes, medical imaging, and diagnostic applications. In comparison, patents emphasis on implementable systems involving clinical workflow, monitoring, patient data, healthcare information systems, and imaging technologies. Nevertheless, both domains converge around clinical decision support, emergency care, AI and ML terms, and patient description and diagnosis. These findings are important because they show that research growth does not necessarily correspond to patent activity. Overall, AI presents a significant potential for imaging, workflow optimization, monitoring and analysis of patient data, and diagnosis-related topics. Nevertheless, its protected technological development still depends on real-world validation, transparency, accountability, and clinical trust.

KEYWORDS: Artificial Intelligence; Emergency Departments; Bibliometric Analysis; Innovation; Clinical Decision Support.

## RESUMO

Os serviços de urgência enfrentam uma pressão crescente devido à sobrelotação, aos longos tempos de espera e à escassez de recursos humanos e materiais. Neste contexto, a inteligência artificial pode contribuir para melhorar o desempenho clínico e operacional. No entanto, ainda não é claro se o progresso científico está a ser traduzido em aplicações tecnológicas que contribuam efetivamente para essa melhoria.

Este estudo analisa as principais tendências de evolução da aplicação da inteligência artificial nos serviços de urgência, através da comparação entre publicações científicas e patentes. Os dados foram recolhidos nas bases de dados Scopus e WIPO Patentscope. A metodologia combinou o uso de uma análise bibliométrica descritiva, mapeamento da coocorrência de termos e agrupamento de dados, bem como análise integrada de redes semânticas. Em conjunto, estas três abordagens permitiram distinguir as principais áreas de interesse científico, de proteção tecnológica e o potencial de desenvolvimento futuro.

Os resultados mostram um forte crescimento tanto das publicações científicas como das patentes, sobretudo desde 2018. No entanto, foi identificado um desalinhamento. A investigação concentra-se em modelos preditivos, adoção da inteligência artificial, resultados clínicos, imagiologia médica e aplicações de diagnóstico. Nas patentes destacam-se os fluxos de trabalho clínicos, monitorização, dados dos doentes, sistemas de informação em saúde e tecnologias de imagiologia. Apesar destas diferenças, ambos os domínios convergem nos sistemas de apoio à decisão clínica, cuidados de emergência, conceitos relacionados com IA e aprendizagem automática, bem como a caracterização e o diagnóstico dos doentes. Estes resultados são relevantes porque demonstram que o crescimento da investigação não corresponde necessariamente à proteção tecnológica. A adoção prática destas soluções depende ainda da sua validação, integração em sistemas, transparência e confiança dos profissionais de saúde no futuro.



KEYWORDS: Inteligência Artificial; Serviço de Urgência; Análise Bibliométrica; Inovação; Apoio à Decisão Clínica

# GLOSSARY

AI - Artificial Intelligence

ED - Emergency Department

GPT – Generative Pre-trained Transformer

ICU - Intensive Care Unit

IPC - International Patent Classification

LLM - Large Language Model

MCP - Multiple Country Publications

ML - Machine Learning

NLP - Natural Language Processing

NTC - Normalized Total Citation

PCA - Principal Component Analysis

SCP - Single Country Publications

WIPO - World Intellectual Property Organization

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Finally, I declare that this project was composed independently. Generative AI tools such as ChatGPT, Google Gemini, and Claude AI were used strictly for basic linguistic checks, spelling corrections, and translation verification. No generative text models were utilized to create, restructure, or expand upon the scholarly arguments or data presented in this document.

# 1. Introduction

## *1.1. Context and Motivation*

In Portugal, emergency departments within the National Health Service (SNS) provide continuous 24 hour care for urgent and life-threatening conditions. Despite their central role in the healthcare system, these services face persistent structural challenges, including shortages of human and material resources, a high waiting time and a high volume of patients. In 2023, Portugal recorded the highest number emergency department visits within the SNS, with 77 visits per 100 people (OECD, 2025). This level of demand places considerable pressure on workflows and negatively affects the operational efficiency of emergency departments.

Several initiatives have been introduced to address these pressures. These include the Working Group for Emergency Services (GT-SU), created to analyze organizational models and propose strategies to improve urgent care delivery (*Ministério Da Saúde. (2019). Despacho n.º 696/2019. Diário Da República.*, n.d.). The Health Literacy Action Plan, which seeks to place individuals at the center of healthcare interventions while promoting the continuous improvement of health literacy in Portugal (*Plano de Ação Para a Literacia Em Saúde 2019–2021*, n.d.). However, despite these efforts, overcrowding in public hospital emergency departments remains a persistent challenge within the national healthcare system.

In this context, the integration of artificial intelligence (AI) into healthcare systems can be considered a promising approach. One of the most relevant areas of AI application is medical science, where AI algorithms and deep learning tools increasingly support physicians in managing health records, assisting diagnosis and decision-making, prescribing treatments, assessing mental health conditions, and analyzing medical images (Srivastava, 2024). These technologies enable professionals to access relevant information more quickly, thereby improving both the quality and efficiency of healthcare delivery.

From this perspective, AI has the potential to address existing challenges in emergency departments (EDs) by improving triage processes, helping manage resource shortages, overcrowding, and waiting times. These improvements can be achieved through machine learning models that predict intensive care unit (ICU) admissions, resource utilization, waiting room occupancy and individualized patient waiting times, potentially outperforming traditional approaches (Sitthiprawiat et al., 2025), (Vural et al., 2025), (Gloyn et al., 2026).

However, it remains unclear whether current research is keeping pace with the protected technological development of AI-based processes in emergency departments. This is an important issue to analyze, as the relevance of studies in this field lies in their potential to be translated into practical solutions that improve emergency department settings.

To examine whether a gap exists between research and protected technologies, it is important to compare the main evolutionary trends found in scientific papers and patents. This comparison allows for a more comprehensive understanding of the current state of application, while also identifying areas that may require further improvement in the future. Additionally, analyzing both scientific publications and patents provides a broader perspective on technological evolution and helps identify potential opportunities for future development (Liu et al., 2024).

This study explores opportunities to improve emergency department performance and, consequently, contribute to the improvement of EDs in Portugal. Its main objective is to examine whether scientific research and protected technologies of AI, in this field, are evolving at a similar pace, by analyzing the main evolutionary trends in the use of AI in emergency departments.

### *1.2. Research Question and Objectives*

The rapid development of artificial intelligence and its wide range of capabilities raises a central research question: How does scientific research on AI in Emergency Departments translate into healthcare innovation?

To address the research question, this study aims to identify and compare the evolutionary trends in the application of AI in Emergency Departments. This central goal is operationalized through four specific objectives, beginning with an analysis of the evolution of scientific research and patent activity related to AI in EDs. This will be achieved through bibliometric analysis, focusing on key metrics to understand how the interest in this topic has evolved over time.

The second objective is to distinguish the main topics present in both papers and patent documents. This will be achieved through network analysis, which enables the visualization of keyword relationships and the generation of thematic clusters. By analyzing these clusters separately for papers and patents, it will be possible to understand which topics dominate scientific research and which areas are more strongly represented in protected technologies.

The third objective is to identify the areas of convergence between papers and patents. This will be achieved through semantic network analysis using combined data from both sources. By examining multiple network metrics, this approach will help reveal which topics are shared by research and patents, as well as identify relevant indicators between these two.

The last objective is to highlight the fields of AI application that appear most relevant for emergency departments. This will be achieved by combining the results of the bibliometric analysis, network analysis, and semantic network analysis. By integrating these three techniques, the study will provide a broader understanding of the most significant AI applications in emergency departments, highlighting areas with strong scientific attention, protected technology and potential development fields.

### *1.3. Structure of the Master's Final Work*

This academic work begins with a literature review that establishes the theoretical foundations of artificial intelligence applications in emergency departments, including key concepts in innovation and healthcare management. Next, the methodology is presented. It describes the data preprocessing steps, the descriptive analysis conducted with Bibliometrix, and the network analysis performed with VOSviewer and SciPat to examine relationships among concepts. The results are then presented and discussed. Finally, the study concludes by addressing its main limitations and suggesting directions for future research.

# 2. LITERATURE REVIEW

## *2.1. Science and Innovation*

Science can be understood as a cumulative process through which knowledge is preserved, tested, and refined across generations. In this sense, scientific progress does not consist merely of storing information, but of continuously questioning inherited ideas and confronting them with observation and experience. This view is consistent with (*Feynman_what-Is-Science_68.Pdf*, n.d.), which emphasizes that scientific knowledge advances through doubt, verification, and the correction of error.

This scientific perspective is closely related to innovation, as scientific knowledge often underpins the development of new technologies, processes, and services. Innovation is commonly defined as the generation, acceptance, and implementation of new ideas, products, or processes (Thompson, 1969). From this perspective, science contributes to innovation by creating knowledge from which protected technologies can emerge.

Technology transfer represents the stage at which knowledge and innovation move towards a protected technological development. It may be understood as the process through which scientific or technical knowledge is adopted, adapted, and implemented in products, services, or organizational practices. Accordingly, science, innovation, and technology transfer should be viewed as interdependent concepts: science generates knowledge, innovation transforms that knowledge into new solutions, and technology transfer supports its diffusion and implementation (Dubickis & Gaile-Sarkane, 2015; *Evolution and Development of Technology Transfer Models and the Influence of Knowledge-Based View and Organizational Learning on Technology Transfer*, n.d.).

This relationship can also be examined through patents, since they contain relevant technical knowledge and reflect how ideas are transformed into potential technological opportunities. Patent data can be used to construct knowledge networks, where technological concepts and their relationships are analyzed to discover future opportunities for innovation. This reinforces the connection between science, innovation, and technology transfer. As patents enable observation of how knowledge is structured, evaluated, and directed toward a practical implementation. (Liu et al., 2024).

From this perspective, a meaningful connection can be established between scientific publications and the practical realization of innovation. Research papers capture the development of scientific knowledge, whereas protected technologies reflect the transformation of that knowledge into technological and organizational outcomes (Fey & Rivin, 1997).

## 2.2. Papers and Patents from an Innovation Perspective

Within this innovation process, patents play a central role because they are designed to protect and encourage inventive activity. In general, an invention may be patented when it satisfies three core criteria: novelty, non-obviousness, and usefulness. Novelty requires that the invention has not been publicly disclosed before the patent application. Non-obviousness implies the presence of an inventive step that would not be evident to a specialist in the field, and usefulness requires that a protected technological development is capable of generating value (Tidwell & Liotta, 2012).

The relationship between papers and patents is therefore especially relevant from an innovation perspective. Scientific publications usually reflect the generation and dissemination of knowledge, whereas patents tend to represent efforts to formalize and protect their practical development. Analyzing both sources together enables comparison of scientific development with patent activity and assessing whether emerging research directions are also being translated into applied innovation.

This perspective is particularly important in the early stages of the innovation process, where decision quality can strongly influence the future success of products or services. Prior research shows that innovation can be evaluated through indicators such as the number of ideas generated, their commercialization potential, dependence on complementary products, and customer orientation (Dziallas & Blind, 2019). These indicators help identify which ideas are more likely to progress from scientific development to protected technologies.

## 2.3. Application of AI in emergency departments

Artificial intelligence is increasingly applied in healthcare, particularly for diagnostic support, workflow optimization, and clinical prioritization. Although many machine learning systems have been developed for areas such as radiology, cardiology, and pathology, the emergency department has emerged as an especially promising setting due to its need for rapid assessment, timely decision-making, and efficient resource management.

In the diagnostic domain, AI has been used to support follow-up after ED discharge and to improve adherence to clinical protocols. Natural language processing (NLP) systems, for example, can analyze medical reports in real time, helping clinicians identify relevant patterns, monitor compliance with guidelines, and strengthen clinical decision-making (Moulik et al., 2020). However, multiple steps in ED do not deal exclusively with diagnosis.

These non-diagnostic stages can also benefit from AI integration. Although there is no database for these applications, ongoing commercial development shows that AI can support multiple workflow tasks, including order entry, study protocoling, scan scheduling, demand forecasting, image acquisition, hanging protocols, and report generation. Overall, these tools have the potential to optimize emergency department workflow and improve efficiency (Al-Dasuqi et al., 2022).

In triage, AI and ML-based models have shown stronger predictive performance than conventional triage approaches in outcomes such as hospital admission, ICU transfer, sepsis, and bacteremia. These tools may help reduce ED overcrowding by enabling more efficient prioritization, bed management, and allocation of clinical resources, thereby shortening waiting times and improving operational responsiveness (El Arab & Al Moosa, 2025). Recent reviews also emphasize that implementation remains constrained by issues such as bias, integration with clinical workflows, transparency, and the need for real-world validation. In this regard, AI adoption should also be understood as an organizational and sociotechnical process rather than only a technical implementation problem. Costa, Aparício, Aparício, and Aparício (2024) argue that AI democratization depends on extending access to AI technologies beyond technical specialists, while also addressing governance, literacy, responsible use, and institutional readiness. This perspective is relevant to emergency departments because the effective use of AI requires that clinicians, managers, and support teams are able to interpret, trust, and incorporate AI outputs into time-critical clinical workflows.

### *2.4. Bibliometric Analysis*

Bibliometric analysis is a set of techniques used to explore and interpret large volumes of scientific information. It allows researchers to identify patterns, trends, and structural relationships within a field without the need to examine each document individually. In studies involving both publications and patents, bibliometric analysis is particularly useful because it provides a systematic way to compare scientific production with technological development. This methodological orientation is also consistent with recent work by Aparicio, Aparicio, and Costa (2023), who use bibliometric analysis to clarify the structure and methodological boundaries of design science in information systems and computing, and with Aparicio and Costa (2026), who apply systematic literature review and bibliometric techniques to identify opportunities, challenges, and emerging trends in AI-related domains.

A common distinction in bibliometric studies is between performance analysis and science mapping. Performance analysis focuses on quantitative indicators of research activity, such as the number of publications, citation counts, publication growth over time, and contributions by authors, journals, or countries. These indicators help characterize the productivity and visibility of a research domain.

Science mapping, in turn, aims to identify and visualize relationships among research constituents, such as terms, documents, authors, or thematic areas. Its general workflow typically includes data retrieval, preprocessing, network extraction, normalization, mapping, analysis, and visualization (Donthu et al., 2021). In the context of this study, these techniques are appropriate because they support both a descriptive comparison of papers and patents and a structural analysis of how themes evolve across scientific and technological domains.

# 3. METHODOLOGY

## *3.1. Research Objective and Analytical Design*

The methodology was designed to address the study's main objective: to identify the main evolutionary trends in the application of AI in emergency departments by comparing scientific research and patent activity. To operationalize the objectives, the study followed six analytical stages: defining the research focus, constructing the search strategy, selecting the data sources, collecting and cleaning the data, and applying bibliometric techniques suited to each sub-objective (Passas, 2024; Ragazou et al., 2022).

## *3.2. Operationalization of the Research Scope*

The search strategy was defined to support the core analytical objective: capturing the intersection of artificial intelligence and EDs across scientific and technological domains. More specifically, the query was structured to reflect three sub-objectives: identifying AI approaches, identifying the emergency care context, and detecting management and decision-related applications such as workflow, resource allocation, triage, predictive analytics, and clinical decision support.

This process began with the following initial query:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("emergency room" OR "emergency department" OR "urgent care" OR "trauma center") AND ("hospital" OR "healthcare" OR "medical facility" OR "clinic") AND ("Portugal" OR "Portuguese" OR "Lisbon" OR "Porto") AND ("patient care" OR "treatment" OR "diagnosis" OR "workflow") AND ("decision support" OR "predictive analytics" OR "resource allocation" OR "triage")

However, due to the limited number of results retrieved from both Scopus and Patentscope, the geographical location component of the query was removed. As a result, the analysis was no longer restricted to a specific region, leading to a substantial increase in the number of retrieved documents. After several iterations and considering the objectives of the study, some health-related concepts that had initially been grouped together were separated to improve the relevance of the results. Furthermore, the results of the query were expanded, by removing the restriction to terms referring to emergency departments within hospitals or medical facilities. Following these adjustments, the final query was defined as follows:

Query: ("clinical decision" OR "predictive analytics") AND ("workflow" OR "resource allocation" OR "triage") AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("emergency room" OR "emergency department" OR "urgent care" OR "trauma center")

## *3.3. Selection of Comparative Data Source*

The selection of data sources was guided by the study's comparative objective. Because the analysis seeks to contrast scientific knowledge production with protected technology development, two complementary sources were used: Scopus to represent academic research and WIPO Patentscope to represent patent activity. This choice allows the study to compare how the topic evolves in scientific literature and in applied innovation.

## *3.4. Data Collection for Scientific and Technological Analysis*

### *3.4.1. Scopus*

The extraction of publication data was intended to support the sub-objective of characterizing the field's scientific evolution. Using the previously defined query, records were retrieved from Scopus, with the search applied across all fields, limited to English-language documents, and covering the period from 1984 to 2026. This process yielded 3,522 documents, forming the basis for analysis of publication growth, citations, sources, authorship, and thematic development.

The extracted fields were selected according to their analytical relevance. Citation, bibliographic, abstract, and keyword information were retained because they support the descriptive and relational analysis required to identify trends, influential contributions, and thematic patterns within the scientific literature.

The CSV file extracted from Scopus is presented in Appendices 1 and 2, and the description of each column is below in Table 1.

Table 1: Description of columns from Scopus extraction

| Field | Description |
|---|---|
| Authors | Names of the authors who contributed to the document. |
| Authors full names | Full names of the authors who contributed to the document. |
| Author(s) ID | A unique identifier assigned to individual researchers to distinguish their work from others with similar names. |
| Title | The title of the research paper or document. |

| Field | Description |
|---|---|
| Year | The year the document was published. |
| Source Title | The name of the journal, conference, or book where the document was published. |
| Volume | The volume number of the journal in which the document appears. |
| Issue | The issue number of the journal in which the document appears. |
| Article Number (Art. No.) | A unique identifier assigned to a specific article or publication within a journal or a collection of works. |
| Page Start | The page number on which the document begins within the journal or book. |
| Page End | The page number on which the document ends within the journal or book. |
| Cited By | The number of times the document has been cited by other documents. |
| DOI (Digital Object Identifier) | A unique alphanumeric string assigned to the document for identification and access. |
| Link | Link to the document. |
| Abstract | A summary of the document's content. |
| Author Keywords | Specific keywords provided by the authors. |
| Index Keywords | Keywords assigned by indexing services. |
| Correspondence Address | Contact information for the corresponding author. |
| Editors | Individuals who hold editorial roles in academic journals. |
| Publisher | The entity responsible for publishing the document. |
| ISSN (International Standard Serial Number) | Identifies serial publications such as journals and magazines. |
| ISBN (International Standard Book Number) | Identifies books and non-serial publications. |
| CODEN | Identifies scientific and technical journals. |
| PubMed ID | Identify articles indexed in the PubMed database. |
| Language of Original Document | The language in which the document is written. |
| Abbreviated Source Title | Shortened version of the journal's name for citation purposes. |
| Document Type | The type of document, such as article, review, or conference paper. |

| Field | Description |
|---|---|
| Publication Stage | Status of the article in the publication process. |
| Open Access | Indicates whether the article is freely accessible. |
| Source | Name of the journal or publication. |
| EID | Unique identifier for documents in Scopus. |

### *3.4.2. Patentscope*

The extraction of patent data aimed to support the complementary sub-objective of characterizing technological development in the same domain. For this purpose, the same query was applied in Patentscope, with the search limited to English-language documents and conducted across all fields. The publication date range was set from 2002 to 2026, resulting in 1,123 records. The dataset provides a basis for analyzing how AI applications in emergency departments are being translated into technological solutions.

Given the objective of comparing patents with publications, the patent fields retained were those that best describe the technological scope, filing context, and application domain of each record. The resulting file is illustrated in Appendix 3, and a summary of its columns is presented below.

Table 2: Description of columns from Patentscope extraction

| Field | Description |
|---|---|
| Application ID | A unique internal identifier used in the database. It distinguishes each record within the system (not the official patent number). |
| Application Number | The official patent application number. |
| Application Date | The date when the patent application was filed. |
| Country | The country where the application was filed or published. |
| Title | The title of the invention. Provides a short description of what the patent is about. |
| Abstract | A summary of the patent. |
| IPC (International Patent Classification) | A standardized system used to classify patents by technological area. |

## 3.5. Data Cleaning

### 3.5.1. Scopus file

Data cleaning was performed to ensure that the analyzes would reflect meaningful patterns rather than artifacts in the datasets. For the Scopus file, duplicate records were identified in the title and abstract fields, and documents without abstracts were removed because they could not contribute to the thematic and network analysis. After cleaning, the final Scopus dataset contained 3,403 records.

This step was essential for the sub-objective of identifying reliable thematic trends, since incomplete or duplicated records could distort term frequencies, clustering, and comparative interpretation.

### 3.5.2. Patentscope file

A similar cleaning procedure was applied to the Patentscope dataset to ensure comparability with the publication dataset. Duplicate records, blank entries, unreadable titles and abstracts, and formatting codes irrelevant to the analysis were removed. This was particularly important because the patent data required additional normalization before it could be used in text-based thematic analysis.

Removing markup-like codes and unreadable content improved the interpretability of the textual fields and reduced the risk of biased results in the mapping of technological themes. After this stage, the final cleaned patent dataset contained 1,093 records.

## 3.6. Selection of bibliometric techniques

The bibliometric techniques were selected based on the specific analytical sub-objectives of the study rather than on the tools themselves. First, descriptive bibliometric analysis was used to characterize the evolution, volume, and visibility of publications and patents over time. Second, science mapping techniques were used to identify thematic structures and relationships among concepts. Third, a combined analysis of papers and patents was used to examine how scientific and technological themes co-evolve across the two domains. Figure 1 summarizes how these analytical objectives are operationalized (Taques, 2025).

To implement these analyzes, the study used Bibliometrix for descriptive indicators, VOSviewer for term co-occurrence mapping, and SciPat for the integrated analysis of papers and patents. These tools were selected because each one supports a different analytical need derived from the study's objectives.

For the descriptive component, Bibliometrix was used to identify indicators such as annual production, document age, citation patterns, source relevance, country contribution, and keyword frequency. These indicators support the objective of describing how the field has evolved and which actors and themes have been most prominent.

For the thematic mapping component, VOSviewer was used to analyze co-occurrence patterns in titles and abstracts. This step supports the sub-objective of identifying the main thematic clusters and conceptual relationships in each dataset (van Eck & Waltman, n.d.).

Because Patentscope does not provide a keyword field equivalent to Scopus, the comparison between datasets relied on titles and abstracts as the common textual basis for mapping. For this reason, the patent data were structured to support the same type of term co-occurrence analysis, enabling a more consistent comparison between scientific and technological themes.

Finally, to address the integrative objective of analyzing the co-evolution of papers and patents, SciPat was used to generate combined semantic analyzes across the two datasets (Arsenio et al., 2026). This made it possible to examine publication dynamics, semantic balance between papers and patents, keyword communities, and temporal evolution, thereby extending the analysis beyond isolated descriptive and mapping results. Lastly, the data to support this analysis is on GitHub - Catsilva4/TFM.

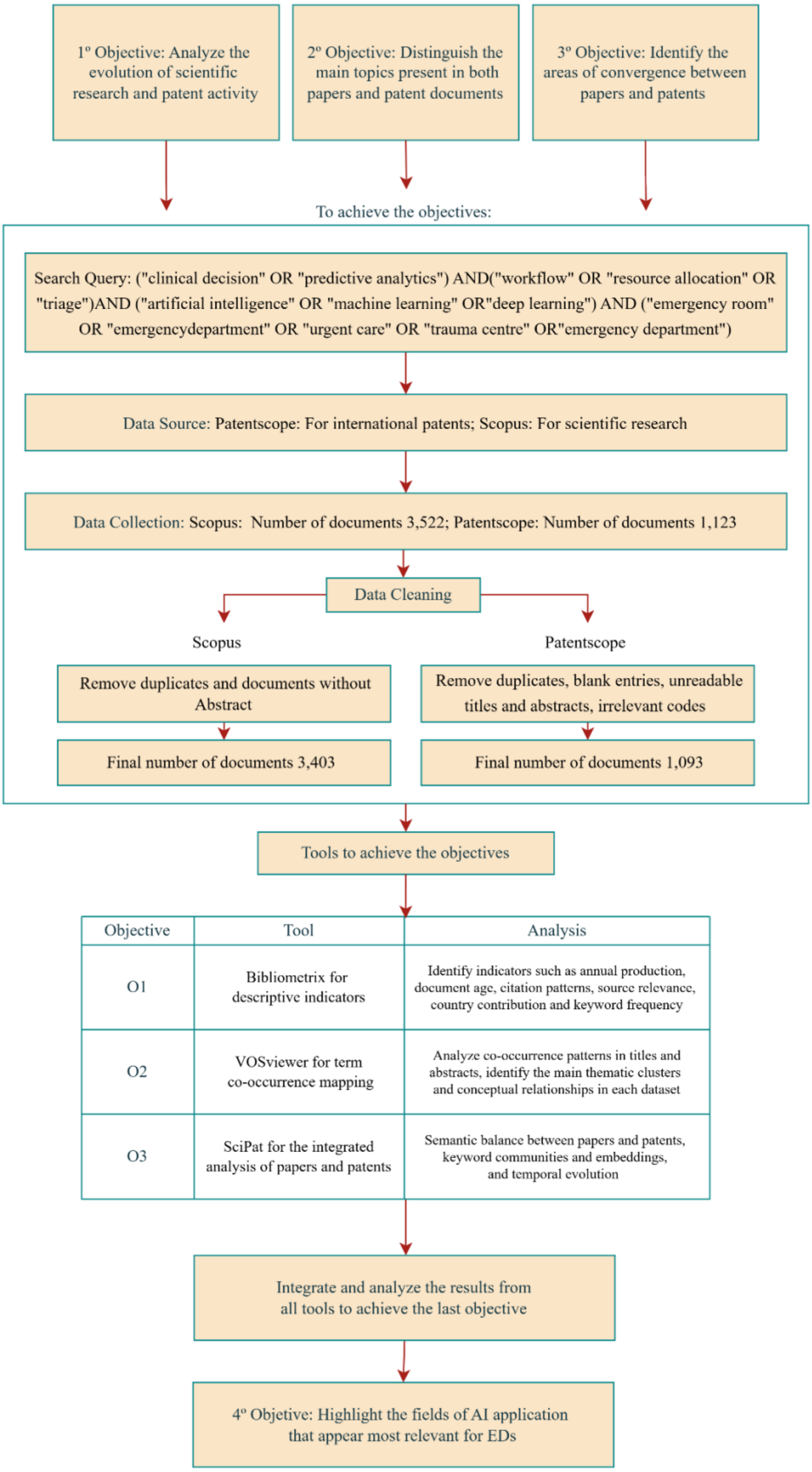


Figure 1: Methodology diagram

# 4. Results

## 4.1. Evolution and Descriptive Comparison of Papers and Patents

### 4.1.1. Scientific Development in the Literature

This subsection addresses the study's first objective: to characterize how scientific research on AI in emergency departments has evolved over time. Using the cleaned Scopus dataset, the descriptive results show the scale, growth, visibility, and thematic emphasis of academic literature.

The annual growth rate was 8.26%, indicating a steady increase in the number of publications over time and reflecting growing academic interest in this field. Moreover, the average document age of 3.83 years indicates that this is a relatively recent and evolving research area. The annual scientific production analysis presented in Figure 2 shows a significant increase in the number of publications from 2018 onward. Over the last decade, the number of publications increased substantially, from 35 documents in 2015 to 934 documents in 2025. In addition, between 2024 and 2025 alone, there was an increase of 340 publications, highlighting the quick expansion of research in this field.

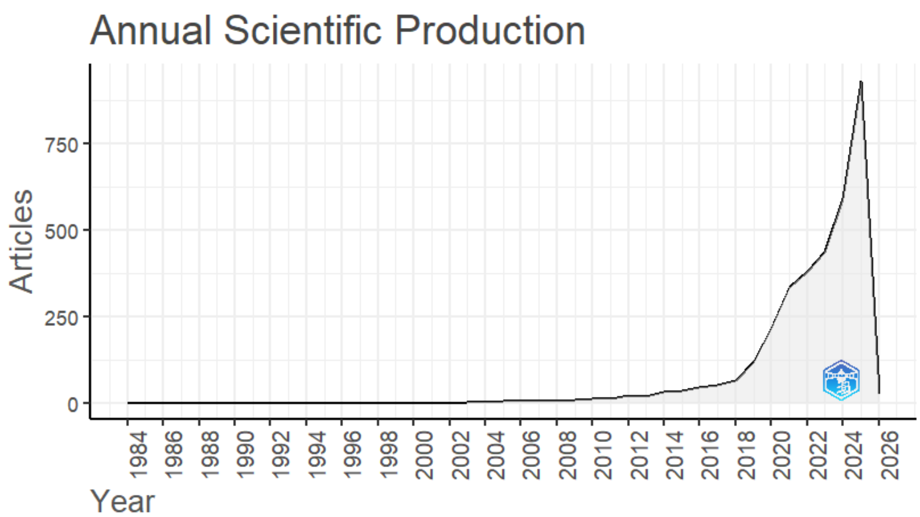


Figure 2: Annual Scientific Production

The dataset contains 1,123 different sources. The most relevant were the Journal of Medical Internet Research, the International Journal of Medical Informatics, Scientific Reports, and the Journal of the American Medical Informatics Association. However, 345 documents lacked information on the publication source.

Regarding document types, articles were the most common type, with 2,032 publications, followed by 798 review papers and 290 conference papers. The high number of review articles suggests that the field already has a considerable body of literature, allowing researchers to conduct reviews.

The citation indicators also demonstrate a strong academic impact. The papers received an average of 25.28 citations per document and 4.289 citations per year per document. The most cited publication was Topol EJ (2019), Nature Medicine, with 5,154 citations and an average of 644.2 per year. This publication also achieved a Normalized Total Citation (NTC) score of 51.68. NTC represents the normalized citation impact of a document relative to other publications from the same year, indicating that this article had a high impact within its publication period. The second-most-cited paper was Garg AX, 2005, Journal of the American Medical Association, with 2,521 citations.

The graph in Figure 3 shows the average total citations per year. The results indicate that citation impact was very low between 1984 and 2000. After this period, the number of citations began to increase, reaching a significant peak around 2005, indicating that publications from that year had a strong citation impact. Following this peak, the values decreased but remained relatively stable until 2019, when a smaller secondary peak in total citations can be observed.

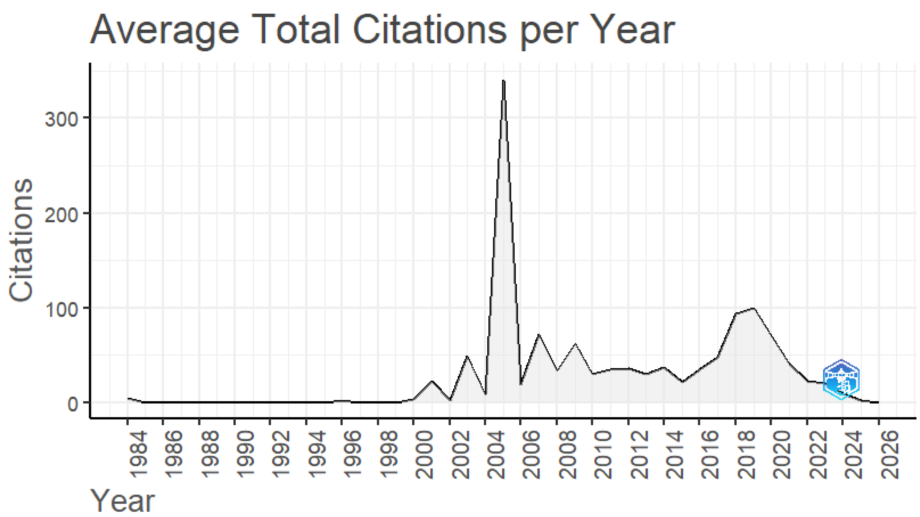


Figure 3: Average Total Citations per year

Regarding geographic indicators, the United States presented the highest total number of citations, with 29,609 citations, followed by Canada with 7,412 and the United Kingdom with 6,245. However, Canada achieved a higher average citation per article than the United States and the United Kingdom.

The dataset included 16,239 authors and 22,854 author appearances, with an average of 6.72 co-authors per document, and only 140 documents were single-authored. These indicators demonstrate that the field is highly collaborative. International co-authorship accounted for 27.86% of publications, indicating a moderate level of international collaboration.

When considering authors' countries in Figure 4, the United States was the leading contributor, with 857 published articles. It also had the highest number of Single Country Publications (SCP), with 702 publications produced exclusively by authors affiliated with the United States, and 155 Multiple Country Publications (MCP). China was ranked second with 307 publications, followed by the United Kingdom with 182 and Canada with 154 documents.

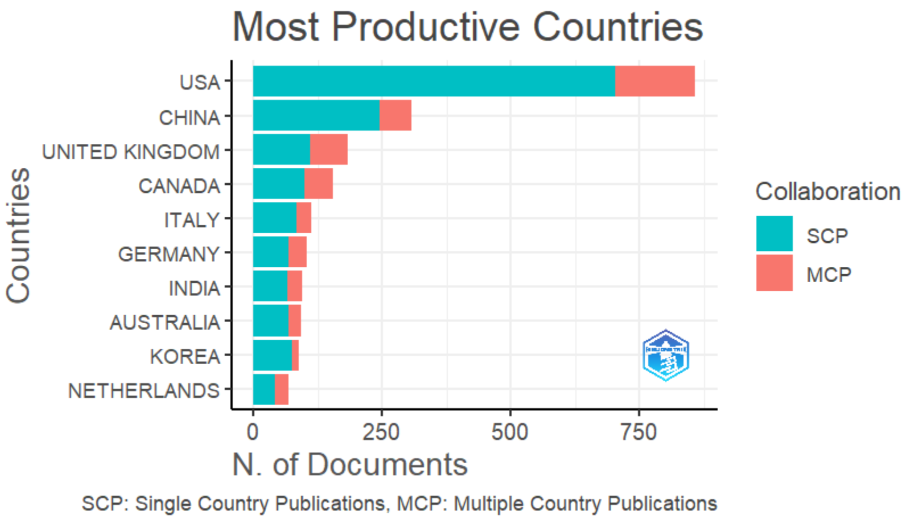


Figure 4: Number of documents per Country

The keyword analysis highlights the main concepts of the dataset. The most frequent author keywords were machine learning (751 occurrences), artificial intelligence (699), emergency department (227), deep learning (180), triage (165), and clinical decision support (164). These results confirm that the dataset is strongly aligned with the search query and emphasize the intersection between artificial intelligence methods, emergency care, triage systems, and clinical decision support.

The article keywords present a different perspective. The most frequent keywords were human (2,132), humans (1,515), female (1,347), artificial intelligence (1,330), male (1,322), and machine learning (1,289). This indicates that author keywords are more closely related to the search query and the study's focus, while article keywords provide context for the biomedical aspects of the papers.

### *4.1.2. Technological Development in Patents*

This subsection addresses the complementary objective of identifying how the same domain is evolving from a technological and application-oriented perspective. Using the cleaned patent dataset, the analysis characterizes the growth, concentration, and technological orientation of patent activity in AI for emergency departments.

The analysis revealed an annual growth rate of 6.8%, indicating a sustained increase in patent activity in AI and emergency healthcare. The average patent age was 6.04 years, suggesting that the field is relatively recent, though slightly more mature than the scientific publication dataset from Scopus.

The bibliometric analysis presented zero citations for all documents. This was expected because the Patentscope dataset lacked citation information, so the function was unable to retrieve citation metrics. Similarly, the related indicators do not accurately reflect the actual data, as the original dataset did not include author information. Nevertheless, these fields were required as inputs for the function to run correctly.

Regarding annual patent publication activity (Figure 5), patent activity began to increase in 2017, when 32 patents were published. The highest number of patent publications was recorded in 2024, with 116 patents. The apparent decrease in 2025 should be interpreted cautiously, as recent patent records may be affected by publication and indexing delays.

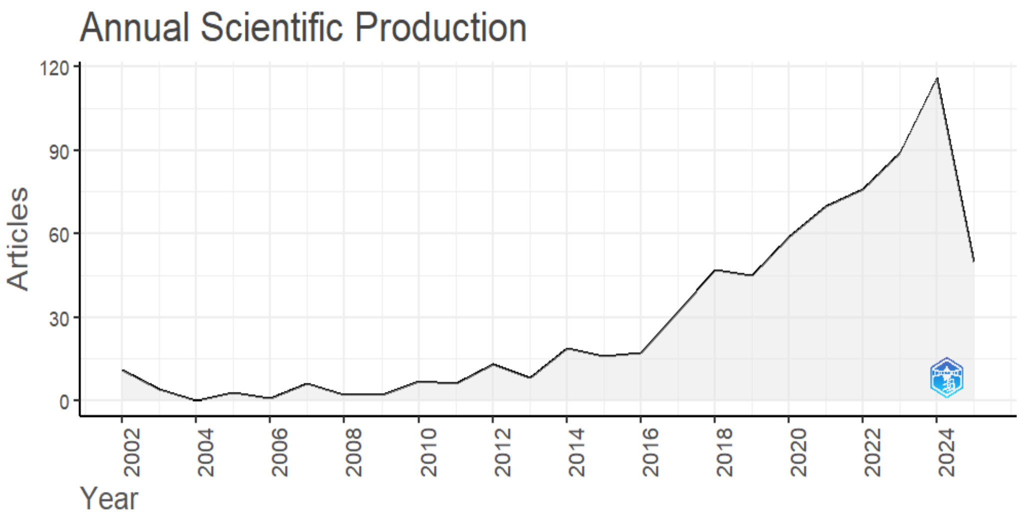


Figure 5: Annual Patent publication activity

The keyword analysis provides important insights into the main topics of the patents. The interpretation below is based on the most frequent keywords and is based on International Patent Classification (IPC) codes (*IPC Publication*, n.d.).

- **G16H 50/20:** Computer-aided diagnosis
- **G16H 10/60**: Patient-specific data
- **A61B 5/00:** Measuring for diagnostic purposes
- **G16H 50/30:** Calculating health indices for individual health risk assessment
- **G16H 40/20:** Management or administration of healthcare resources or facilities
- **G06F 19/00:** Digital computing or data processing equipment or methods, specially adapted for data processing systems or methods specially adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes
- **G06N 20/00**: Machine learning
- **G16H 50/70:** Mining of medical data
- **G16H 40/67:** Remote operation
- **G06T 7/00**: Image analysis

The G16H classification was the most frequent IPC code in the dataset and represents healthcare informatics and communication technologies specifically designed to handle medical and healthcare data. This result is consistent with the objective of the query, which aimed to analyze the technological dimension in healthcare, particularly the application of artificial intelligence and digital systems in emergency departments. The IPC codes A61B and G06 were also considered relevant, as they relate to the fields of diagnosis and computing, respectively.

To analyze the geographical indicators, a new bar plot was created outside the *biblioanalysis* function, as shown in Figure 6. In this analysis, the “Country” column was used, which may refer to countries, other entities, or intergovernmental organizations.

As observed in the image, the United States (US) has the highest number of patent publications, with 485, followed by WO, an abbreviation of an entity, in this case the World Intellectual Property Organization (WIPO) (*HANDBOOK ON INTELLECTUAL PROPERTY INFORMATION AND DOCUMENTATION – ST.3*, n.d.). In third place is the European Patent Office (EP) with 32 patent publications.

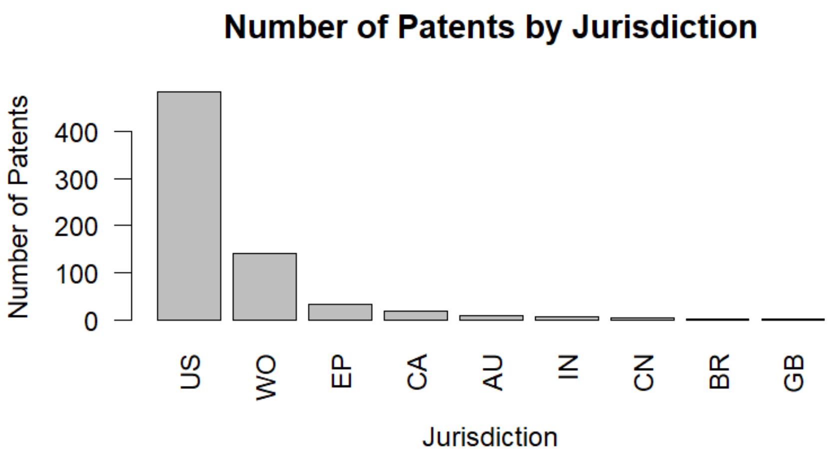


Figure 6: Number of Patents by Jurisdiction

## *4.2. Thematic Structures and Co-evolution Across Scientific and Technological Domains*

### *4.2.1. Thematic Structures in Scientific Literature*

To address the objective of identifying the main thematic structures within the scientific literature, the analysis examined patterns of term co-occurrence in titles and abstracts. This makes it possible to identify the dominant research themes and to observe how the scientific field is organized conceptually.

In the next step, a thesaurus file was included and a minimum occurrence threshold of 10 was selected, resulting in 1,580 terms being included in the analysis. After generating the network, one cluster was identified as containing terms that were not relevant to the study. These terms were considered textual noise and were therefore removed from the analysis. The resulting co-occurrence network reveals the main research themes within the dataset by grouping related terms into distinct clusters, as shown in Figure 7.

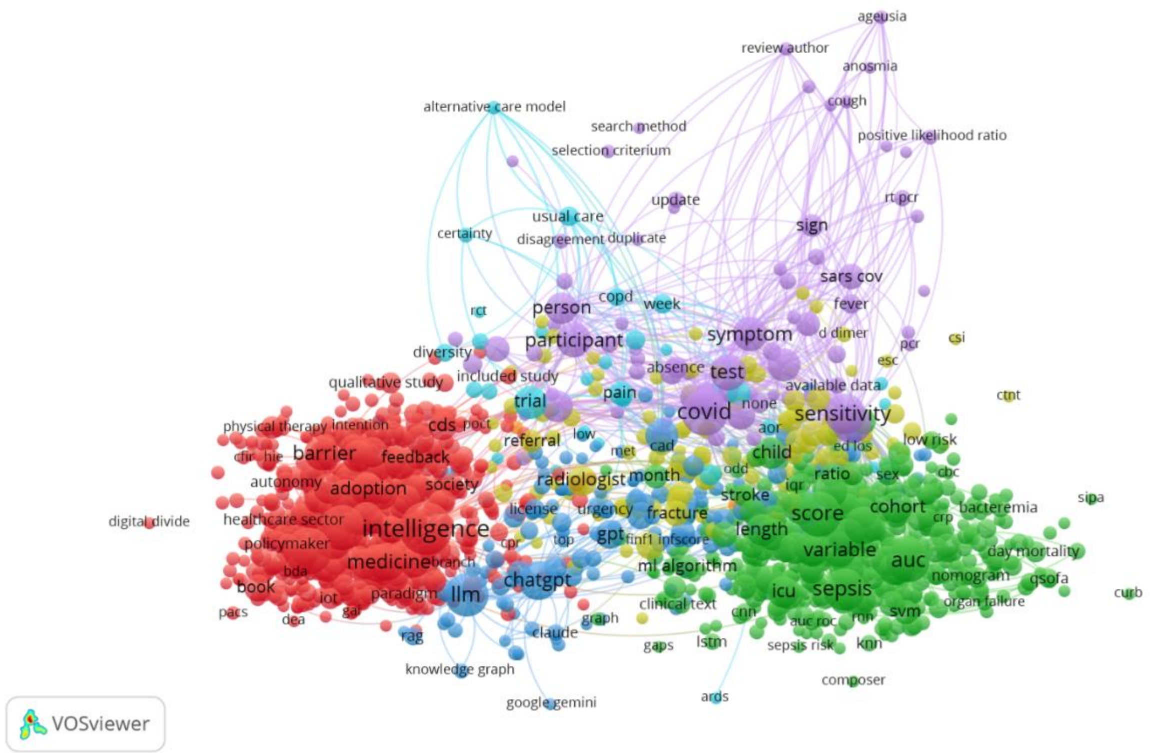


Figure 7: Network analysis (Scopus)

The clusters were generated using VOSviewer, and Table 3 summarizes the clustering results. Each cluster was assigned a name based on the fifteen most frequent terms identified in the map CSV file extracted from VOSviewer. The main items represent the keywords that are most representative of each cluster, and the number of occurrences indicates the total occurrences in that cluster.

Table 3: Clustering of Scientific Research

| Cluster | Main Items | Number of occurrences |
|---|---|---|
| **Digital Health Adoption** | Intelligence, healthcare, technology, medicine and adoption | 29,863 |
| **Prediction Models** | Score, prediction model, machine learning model, logistic regression and sepsis | 24,540 |
| **COVID-19-related applications** | COVID, test, infection, sensitivity and symptom | 6,615 |
| **AI Adoption** | LLM, ChatGPT, GPT, models and agreement | 5,679 |
| **Medical Imaging** | Radiologist, fracture, probability, confidence interval and trauma | 4,420 |
| **Clinical Trials Research** | Trial, comorbidity, pain, usual care and registry | 1,289 |
| **Clinical Decision Support Tools** | Calculator and medical calculator | 51 |

*4.2.2. Thematic Structures in Patent Activity*

To address the corresponding objective for patents, the analysis examined the thematic structures present in patent titles and abstracts. This allows the identification of the main application domains and technological problem areas emphasized in patent activity. Figure 8 shows the co-occurrence network, grouping related terms into distinct clusters.

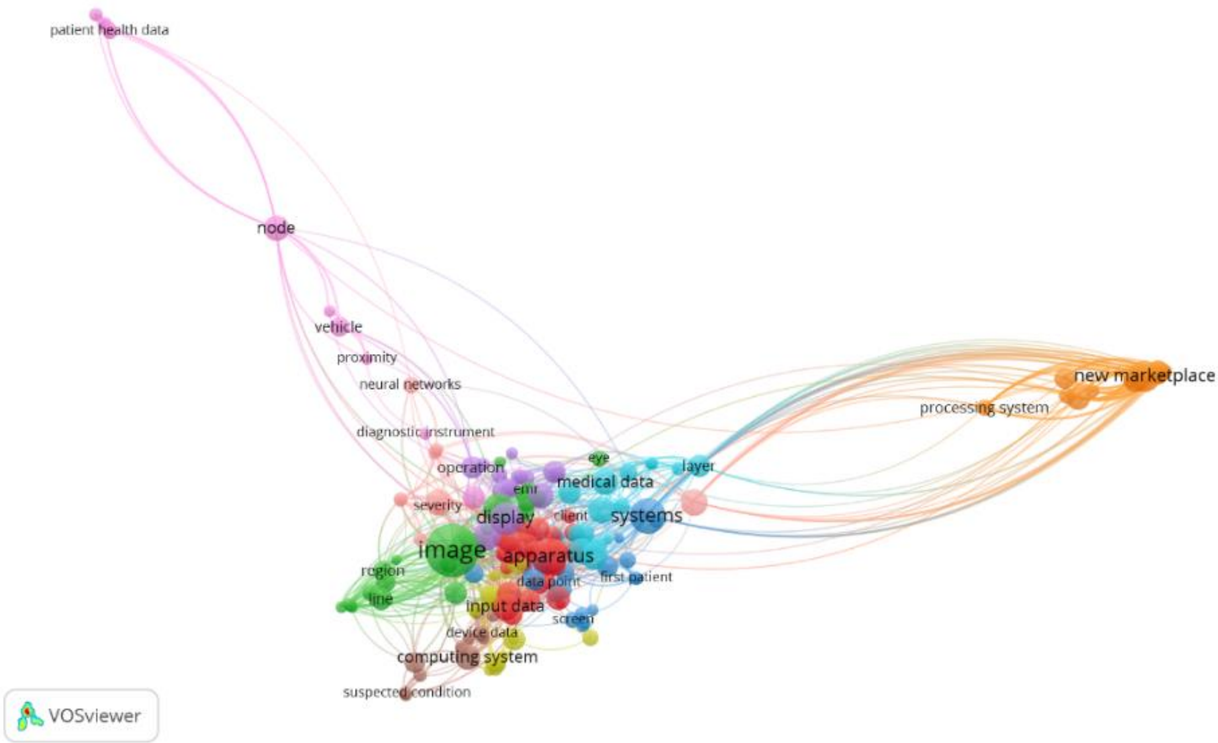


Figure 8: Network analysis (Patentscope)

The patent clusters were generated using VOSviewer, and Table 4 summarizes the clustering results. Each cluster is named following the same methodology applied to the Scopus dataset.

Table 4: Clustering of Patent Activity

| Cluster | Main Items | Number of occurrences |
|---|---|---|
| **Medical Imaging** | Image, location, region, code, and memory | 1,143 |
| **Clinical Workflow** | Apparatus, input data, assessment, workflow, and image data | 884 |
| **Monitoring and Medical Reporting** | Display, portion, risk score, equipment, and operation | 564 |
| **Patient Data** | Server, patient information, medical data, health, and layer | 558 |
| **Healthcare Information Systems** | Systems, user device, access, task, and member | 539 |
| **Marketplace** | New marketplace, data resource, configuration, marketplace, and architecture | 482 |
| **Inovation in Healthcare** | Change, computer program product, data signal, medication, and computer system | 394 |
| **Diagnostic imaging** | Type, measurement, report, neural networks, and severity | 285 |
| **AI Adoption** | Node, use, vehicle, survivability, and patient health data | 246 |
| **Triage Systems** | Computing system, triage, device data, recipient, and imaging data | 239 |

#### *4.2.3. Integrated Analysis of Papers and Patents*

The objective of this chapter is to compare papers and patents to identify areas of convergence and divergence between scientific research and technological application. This integrated analysis helps to reveal whether the themes most visible in the literature are also reflected in patents, and how both domains co-evolve over time.

Since the query was applied to All Fields, it may retrieve some records that are not directly relevant to the main research topic. To address this limitation, the analysis focuses on the giant component of the semantic graph, which includes publications semantically connected to the main body of literature. This helps ensure that the analysis is based on the most coherent and relevant set of publications.

Figure 9 illustrates the comparison of the number of publications by year. At first glance, it's visible that the number of scientific papers exceeds the number of patents included in the study. It also highlights a substantial increase in publication activity after 2018, as previously noted, which may be linked to the growing interest in artificial intelligence during this period. In 2025, 960 scientific research papers were published, making it the year with the most publications. However, 2022 was the year with the highest number of patent publications, with 144 patents. These figures result from a different data cleaning procedure used in this analysis, which explains the discrepancy with the results obtained through the bibliometric analysis.

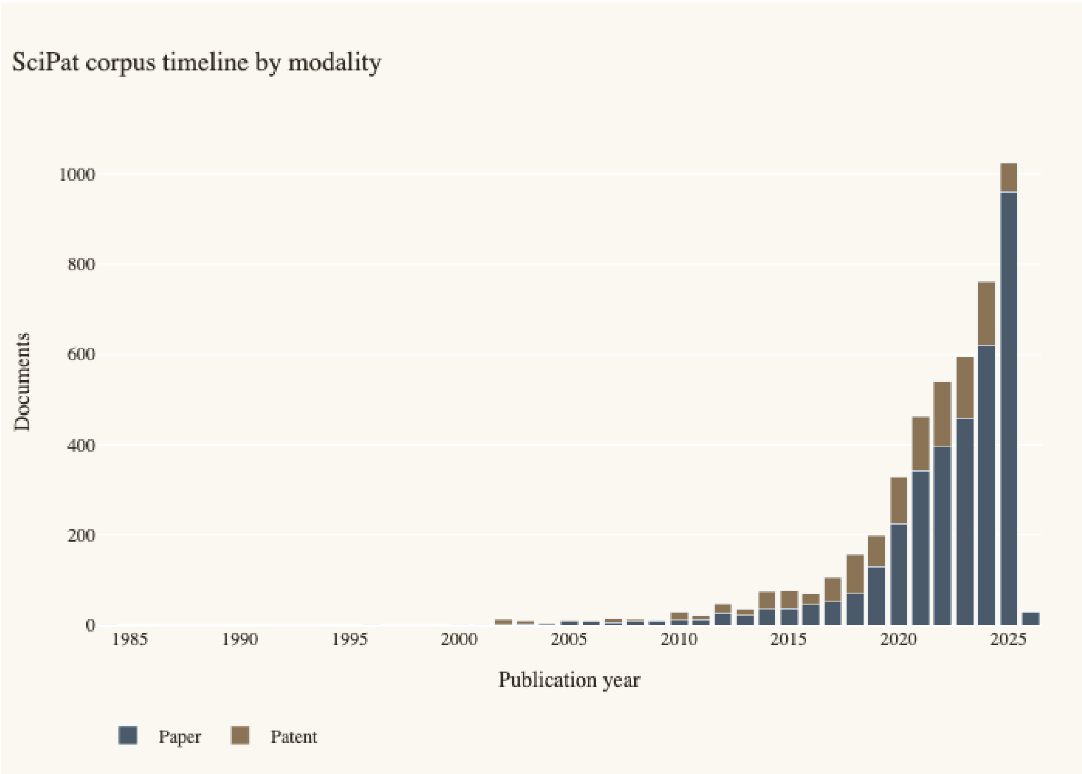


Figure 9: Publication year comparison

The paper vs patent semantic balance network is visualized in Figure 10. This distribution is more paper-heavy, meaning that papers mainly support most keywords. By hovering over the circles on the dashboard, you can identify which keywords have stronger paper or patent support. In this image, the keywords “artificial”, “intelligence”, “monitoring”, “health” and “risk” show a stable, balanced level of support near 0% from both patents and papers.

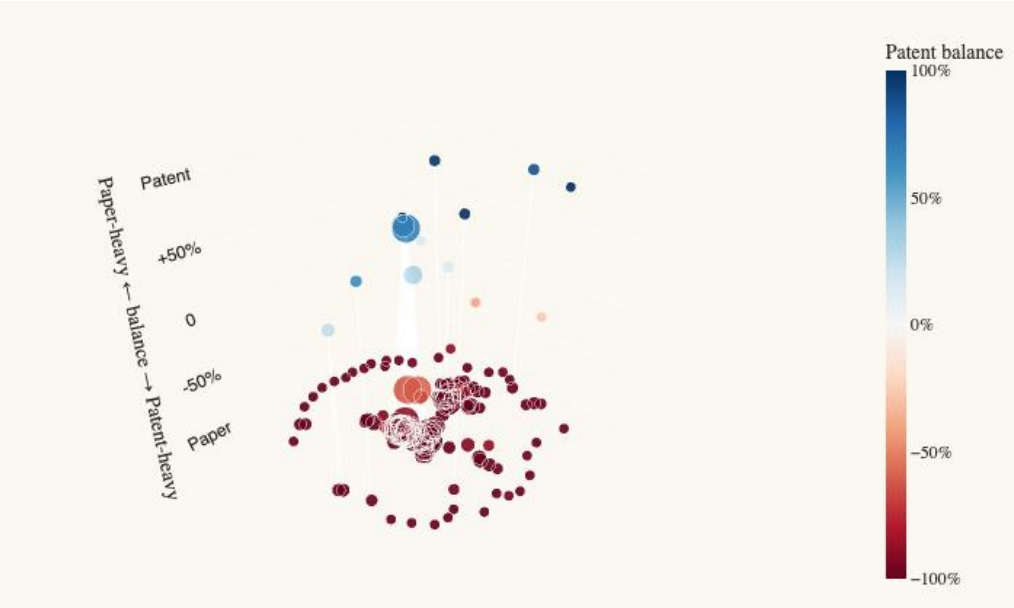


Figure 10: Semantic balance network

In the SciPat methodology, network analysis is based on semantic connections between words. The analysis was done by using three algorithms: Louvain, Greedy Modularity, and Label Propagation. The bar chart in Appendix 4 displays the number of communities identified by each algorithm, along with their modularity values.

The Greedy Modularity algorithm identified fewer communities and achieved the highest modularity value, 0.625. This suggests that the nodes are more strongly connected within communities than between communities, indicating a well-defined community structure. Therefore, Greedy Modularity could be expected to provide a stronger result. However, the Louvain algorithm showed greater stability. In this context, stability refers to the consistency of the results across several runs, whereas the Greedy algorithm produced less consistent outcomes (Aparicio et al., 2026). For this reason, the Louvain algorithm will be used in this analysis. In Figure 11, the semantic network of papers and patents is shown.

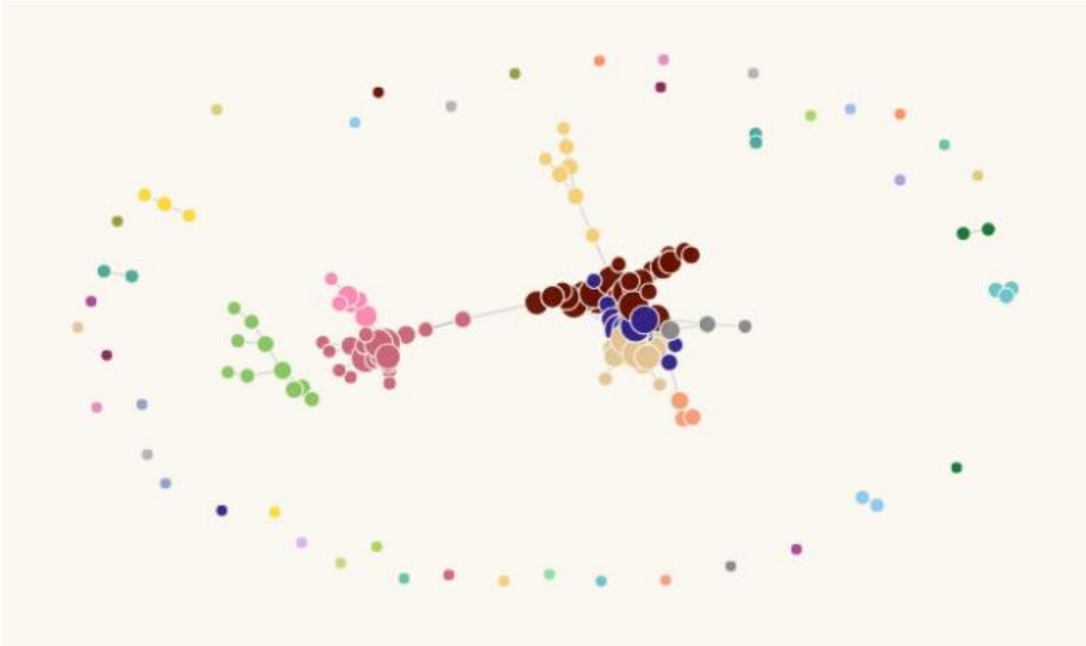

Figure 11: Semantic keyword network

The Figure shows different communities, many of which contain only a single keyword. Nevertheless, Table 5 presents the names of the communities and the keywords with the highest weighted degree. The weighted degree represents the weight of the semantic similarity between each keyword and its neighbors [Appendix 5].

Table 5: Community Summary

| Communities | Keywords |
|---|---|
| **Community 9 – Clinical Decision Support** | Clinical, patient treatment, clinical research, clinical outcome, clinical practice |
| **Community 17 - Hospital emergency department** | Hospital, emergency care, emergency medicine, emergency service, hospitals |
| **Community 1 – AI / ML Terms** | Machine learning, artificial Intelligence, machine-learning, neural networks, deep learning |
| **Community 34 – Medical care** | Medical, patient care, health care system, health care, healthcare |
| **Community 23 – Patient Description** | Adult, aged, middle aged, male, very elderly |
| **Community 20 – Diagnosis** | Diagnostic accuracy, diagnostic imaging, diagnosis, diagnostic test accuracy study, prognosis |

The Principal Component Analysis (PCA) projection of the keyword embeddings shows how the selected keywords are distributed according to their semantic similarity. The visualization in Figure 12 indicates a separation between clinical and healthcare-related terms, on the left side, and more computational or AI-related terms, on the right side.

The projection suggests that the keywords are spread mainly along Component 1, indicating that this component captures a distinction between different areas. On the left side of the graph, there is a concentration of healthcare and clinical-related terms, such as emergency service, emergency care, clinical outcome, and clinical study. These terms appear relatively close to each other, suggesting a similar semantic relationship around them. On the right side of the graph, the keywords are more associated with computational and artificial intelligence topics, including terms such as machine learning and artificial neural networks.

Component 2 keywords located higher on the graph may represent operational healthcare, like emergency care and emergency service. In contrast, keywords positioned lower on the graph, such as clinical outcome, major trauma, and clinical study, are more related to clinical research and patient outcomes.

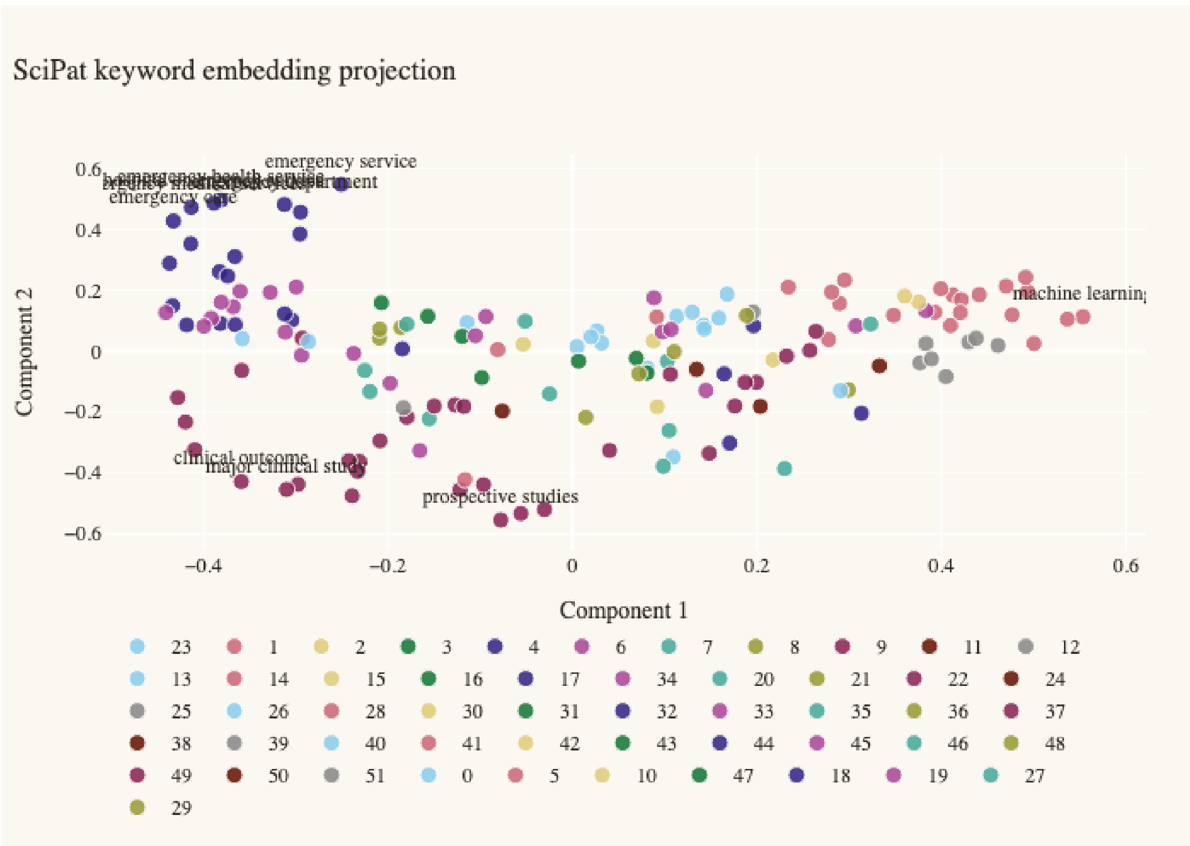


Figure 12: Keyword embedding projection

The next analysis is a keyword salience map, Figure 13, based on the weighted degree and betweenness centrality. While the weighted degree indicates how well a node is connected to its neighbors, the betweenness centrality measures the extent to which a node acts as a bridge between other nodes in the network.

At the top of the graph, the terms “decision support system”, “decision tree”, and “data mining” are highly relevant because they play an important role in linking different parts of the network. On the right side of the graph, keywords such as “medical”, “hospital”, “emergency care”, and “patient care” can be observed. This is consistent with the other analysis because these keywords represent the main topic across the documents and therefore show stronger semantic connections.

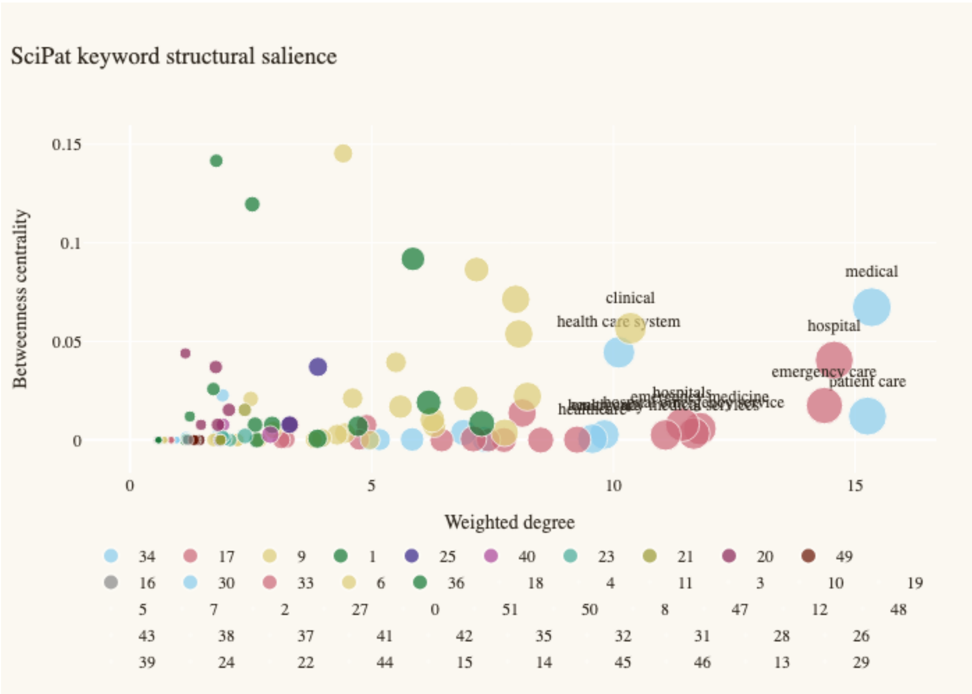


Figure 13: Keyword Structure salience

In this section, a threshold sensitivity analysis was conducted to determine the most appropriate threshold for the network analysis. The results shown in Figure 14 indicate that when the threshold is set to 0.55, the number of communities is approximately half of the number obtained with a threshold of 0.75. This indicates that the threshold has a significant influence on the community structure of the network.

The effect of changing the Louvain resolution was also analyzed. Louvain resolution is a parameter that controls the size of the detected communities, influencing whether the algorithm identifies larger or smaller groups. However, the results show that changing the Louvain resolution does not significantly affect the number of communities.

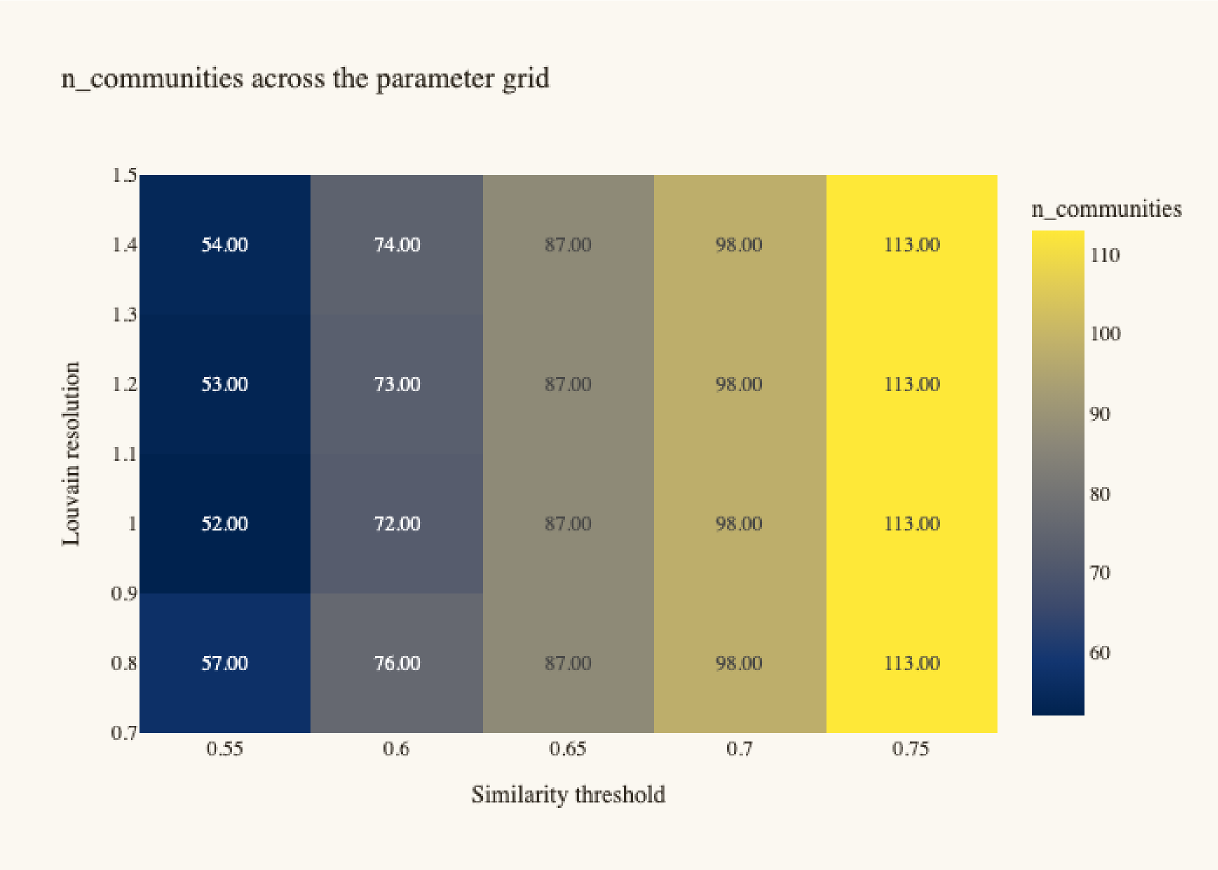


Figure 14: Number of communities across the parameter

Figure 15 shows the main keywords identified in the patents, which are similar to the results obtained in Bibliometrix. The G16H code is the most frequent, followed by A61B, which also represents a significant part of the patents. The results indicate that healthcare informatics and diagnostic measurement are the two main technological areas covered by the patents.

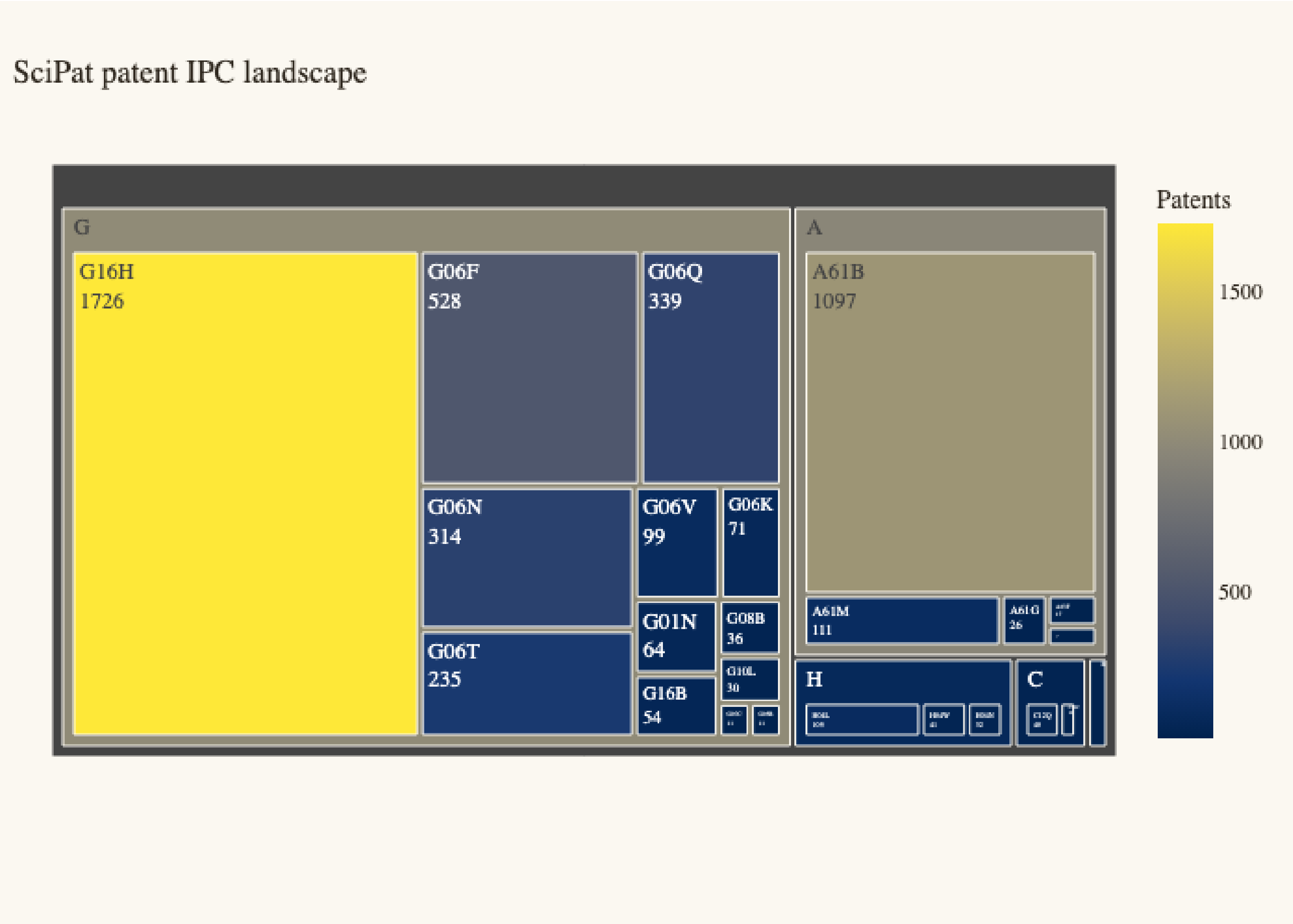


Figure 15: IPC Patentscope

# 5. DISCUSSION

This study sought to identify the main evolutionary trends in the application of artificial intelligence in emergency departments by comparing scientific publications with patent activity. The discussion, therefore, focuses not on restating the descriptive results but on interpreting whether the patterns observed in the two datasets are consistent with prior literature and what they reveal about the current stage of development of this field.

The scientific literature identified in this study is strongly oriented toward predictive models, digital health, medical imaging, and COVID-19-related applications. This pattern is broadly consistent with prior reviews showing that research on AI in emergency departments has developed mainly around diagnostic support, risk prediction, and triage-related modeling rather than around fully embedded operational systems (Boonstra & Laven, 2022; El Arab & Al Moosa, 2025; Moulik et al., 2020). The prominence of COVID-19 in the scientific clusters is also expected, as the pandemic accelerated experimentation with AI-based screening, testing, and decision-support tools in acute care settings (Ravikumar et al., 2023; Vaishya et al., 2020).

By contrast, the patent results are more concentrated on medical imaging, workflow, monitoring, reporting, patient data, and health information systems. This suggests that technological development is moving more directly toward implementable and operational solutions than the scientific literature alone would indicate. The contrast between the two datasets is meaningful: whereas papers emphasize model development and evaluation, patents appear to emphasize system integration, data handling, and clinical workflow support. This distinction aligns with the literature on innovation and technology transfer, which holds that scientific production and technological application typically evolve in related but non-identical ways (Dubickis & Gaile-Sarkane, 2015; *Evolution and Development of Technology Transfer Models and the Influence of Knowledge-Based View and Organizational Learning on Technology Transfer*, n.d.; Fey & Rivin, 1997).

The integrated analysis reinforces this interpretation. The dominance of the clinical decision support community, together with the centrality of emergency care, diagnosis, and AI/ML terms, indicates that the field is structured around decision-oriented applications. This is consistent with previous studies reporting that the most visible uses of AI in emergency departments involve prediction of admission, sepsis, mortality, deterioration, waiting times, and prioritization decisions during triage (Boonstra & Laven, 2022; El Arab & Al Moosa, 2025; Kuttan et al., 2025). In this sense, the present results do not contradict literature, rather, they confirm that decision support remains the core interpretive frame linking research and protected technologies.

Table 6 summarizes the main themes identified across the three components of the analysis, distinguishing between paper-heavy, patent-heavy, and balanced terms. This comparison highlights an important imbalance between papers and patents. Several themes that are highly visible in the literature do not appear with the same intensity in patent activity, particularly those related to general predictive modeling and broad AI adoption. This may suggest that not all research directions are progressing toward protected or market-oriented applications at the same pace. Such a gap is plausible in healthcare, where translating model performance into real-world deployment is constrained by clinical validation requirements, regulatory uncertainty, interoperability issues, and institutional resistance (Boonstra & Laven, 2022; Kuttan et al., 2025).

This interpretation also helps explain why workflow, monitoring, and information systems are more explicit in the patent clusters. Prior literature has emphasized that the practical value of AI in emergency departments depends not only on prediction accuracy but also on its capacity to fit time-critical workflows, support coordination, and reduce operational pressure (El Arab & Al Moosa, 2025; Moulik et al., 2020). The patent landscape captured in this study appears to reflect that implementation logic more directly than the paper landscape, because it focuses on systems and processes that can be embedded in clinical environments.

Triage deserves particular attention in this comparison. While in the literature it is repeatedly described as one of the most promising areas for AI adoption in emergency medicine (Da'Costa et al., 2025; El Arab & Al Moosa, 2025), in the integrated analysis, triage is not a prominent keyword. The fact that triage is present but not overwhelmingly dominant in either the scientific or patent structures may indicate that it functions less as an isolated topic and more as a cross-cutting application area that intersects diagnosis, workflow, risk prediction, and resource allocation. This interpretation is consistent with recent reviews describing AI-driven triage as a bridge between clinical decision support and operational management (Da'Costa et al., 2025; Kuttan et al., 2025).

The weaker-than-expected visibility of clinical decision support in the patent structure may also reflect known barriers discussed in the literature. Although AI-based clinical decision tools are widely studied, their implementation raises concerns about bias, transparency, explainability, accountability, and clinician trust. These constraints may slow the conversion of research concepts into protected technological solutions, especially in areas where decisions directly affect patient safety (Boonstra & Laven, 2022; Kuttan et al., 2025).

Thus, the present findings support the view that the bottleneck in emergency AI is not only technical development, but also safe and credible integration into clinical practice.

Table 6: Summary of the main terms identified in each analysis

| Paper-heavy terms | Patent-heavy terms | Balanced terms |
|---|---|---|
| Digital health<br>Predictive models<br>COVID-19-related applications<br>AI Adoption<br>Medical imaging<br>Clinical Trials Research<br>Clinical Decision Support Tools | Medical imaging<br>Workflow<br>Monitoring and Medical Reporting<br>Patient data<br>Health information systems<br>Marketplace<br>Innovation in Healthcare<br>Diagnostic imaging<br>AI Adoption<br>Triage Systems | Clinical decision support<br>Hospital emergency department<br>AI/ML terms<br>Medical care<br>Patient Description<br>Diagnosis |

The confrontation between results and literature suggests that the field is expanding rapidly but unevenly. The literature points to strong scientific momentum in predictive and diagnostic AI, while the patent data shows stronger movement toward operational and infrastructural applications. Together, these findings indicate that AI in emergency departments is evolving along two partially overlapping trajectories: one centred-on model development and evaluation, and another centred-on implementation, integration, and workflow support. This dual pattern is coherent with innovation theory, which treats papers and patents as complementary but distinct manifestations of knowledge production and application (Dziallas & Blind, 2019; Fey & Rivin, 1997; Tidwell & Liotta, 2012).

These findings also help clarify the practical areas in which AI is most likely to consolidate in emergency departments. The literature reviewed in this study highlights triage, urgent neurological detection, cardiovascular assessment, trauma care, and pre-hospital support as promising domains for application (Da'Costa et al., 2025; Hunter et al., 2023). The present results support this view, particularly through the prominence of imaging, workflow, monitoring, and diagnosis-related themes. Rather than indicating a single dominant application, the evidence suggests that AI is becoming relevant across multiple interconnected functions of emergency care.

# 6. LIMITATIONS

The initial limitation is that the Patentscope dataset did not have the same structure as the Scopus dataset and contained less information, particularly citations and authors. As a result, some indicators of the patents could not be analyzed.

A second limitation is related to the query used. Since the search was limited to terms such as workflow, resource allocation, clinical decision, predictive analytics, and triage, within the emergency department, the document retrieval and field exploration may have been restricted. Therefore, the results obtained should be understood as a consequence of that query.

Furthermore, the query may have generated false positives, particularly in the patent dataset, by retrieving documents that contained the selected keywords but were not directly related to the specific context or objectives of this study. The inclusion of these potentially irrelevant documents may reflect broader technological fields rather than developments specifically associated with emergency department operations. Therefore, the cluster analysis and its interpretation should be interpreted with caution.

Additionally, the algorithms used to generate the network visualization in VOSviewer differ from those used in SciPat. Therefore, the resulting clusters and communities are different. However, the purpose of using two different methods was to observe how the datasets responded to different algorithmic approaches.

The paper-oriented nature of the selected keywords may also be limited in the accuracy of the analysis in representing the relationships between scientific publications and patents. This imbalance may have led to the underrepresentation of certain patent technologies and weakened the links observed between scientific research and technological innovation. Finally, a patent does not necessarily demonstrate practical application in a hospital setting, but rather the legal protection of an innovation.

# 7. CONCLUSION

This project contributes to the ongoing debate on whether AI can help improve the operational performance of emergency departments by comparing scientific publications and patent activity. The initial results demonstrate that this field has expanded rapidly, particularly since 2018. Both scientific production and patent activity have increased. This trend reflects the growing academic and technological interest in using AI to address the clinical and operational challenges faced by emergency departments.

The following comparison between scientific research and technological production revealed a partial misalignment. Scientific publications primarily focus on predictive models, AI adoption, clinical outcomes, medical imaging, and diagnostic applications. In contrast, patents place greater emphasis on implementable systems involving clinical workflow, monitoring, patient data, healthcare information systems, and imaging technologies. In the integrated analysis, both domains share central themes such as clinical decision support, emergency care, AI and ML terms, and patient description and diagnosis. The results suggest that scientific advances are not always translated into protected technological solutions at the same pace.

In this study, AI shows significant potential to improve emergency departments, especially in imaging, workflow optimization, monitoring and analysis of patient data, and diagnosis-related themes. These applications may support faster prioritization, more informed clinical decisions, better resource allocation, and more efficient patient flows. However, technological development alone is insufficient to ensure successful implementation. AI systems must be validated with diverse, real-world clinical data, while challenges related to transparency, explainability, bias, accountability, and clinical trust must also be addressed. Future progress will therefore depend on closer collaboration among researchers, healthcare professionals, technology developers, institutions, and regulators. Aligning scientific development with clinical needs and implementation requirements will be essential to transform AI research into safe, trustworthy, and practical solutions for emergency care.

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# Appendix

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Authors | Author full | Author(s) I | Title | Year | Source titl | Volume | Issue | Art. No. | Page start | Page end | Cited by | DOI | Link | Affiliations | Authors wi | Abstract | Author Key | Index Keyw |
| 2 | Mangio, A. | Mangio, Ar | 60208748! | Machine le | 2026 | Internatior | 207 | | 106181 | | | 0 | 10.1016/j. | https://ww | Medicine & | Mangio, Ar | Backgroun | Aged care; | Clinical re |
| 3 | Vecsey-Na | Vecsey-Na | 57195724: | CT Angiogr | 2026 | European J | 195 | | 112556 | | | 0 | 10.1016/j. | https://ww | College of | Vecsey-Na | Purpose Tl | Acute che: | beta adrer |
| 4 | Avci, V.; H | Avci, Veli ( | 41560903! | A Novel Bic | 2026 | IRBM | 47 | 1 | 100921 | | | 0 | 10.1016/j. | https://ww | Departme | Avci, Veli, | Introductic | Appendicit | biological |
| 5 | Wang, H.; | Wang, Hac | 36077203: | Generative | 2026 | American J | 100 | | | 62 | 69 | 0 | 10.1016/j. | https://ww | Departme | Wang, Hac | Backgroun | Ambulanc | adult; amb |
| 6 | Asif, S.; Ha | Asif, Sohai | 57221248: | The impac | 2026 | Computer | 59 | | 100847 | | | 0 | 10.1016/j. | https://ww | Zhejiang C | Asif, Sohai | Large lang | GPT; Large language r | |
| 7 | Lin, E.A.; R | Lin, Eugen | 57219931: | AI-Enabled | 2026 | Hand Clini | 42 | 1 | | 75 | 83 | 0 | 10.1016/j. | https://ww | Departme | Lin, Eugen | Artificial in | Artificial in | Article; art |
| 8 | Breuler, C. | Breuler, Cl | 57031880: | Ethics and | 2026 | Hand Clini | 42 | 1 | | 85 | 93 | 0 | 10.1016/j. | https://ww | Section of | Breuler, Cl | Artificial in | Artificial in | Article; art |
| 9 | Lee, M.-H. | Lee, Meihu | 57224102 | Alignment- | 2026 | Biomedica | 112 | | 108401 | | | 0 | 10.1016/j. | https://ww | Departme | Lee, Meihu | Accurate a | Bacteria ic | Alignment |
| 10 | Liu, T.; Hu, | Liu, Tianyi | 60132065( | A portable | 2026 | Biosensor: | 292 | | 118071 | | | 0 | 10.1016/j. | https://ww | Whiting Sc | Liu, Tianyi, | Protein bic | Automatic | Biomarker |
| 11 | Kavsak, P. | Kavsak, Pe | 66022218: | ALARRM: A | 2026 | Clinica Ch | 579 | | 120630 | | | 0 | 10.1016/j. | https://ww | McMaster | Kavsak, Pe | Backgroun | Acute corc | biological |
| 12 | Strohmeie | Strohmeie | 16043513( | Beyond av | 2026 | Expert Sys | 296 | | 128954 | | | 0 | 10.1016/j. | https://ww | Chair of M | Strohmeie | As algorith | AI Principl | Artificial ir |
| 13 | T.; Seo, C.; | ; Seo, Chri | 60220505( | Using artif | 2026 | Artificial In | 171 | | 103316 | | | 0 | 10.1016/j. | https://ww | Humber Ri | null, null, F | Objective | Artificial intelligence; | |
| 14 | Ormaza-Si | Ormaza-Si | 59258533! | Mobile Apr | 2026 | Communic | 2393 CCIS | | | 44 | 55 | 0 | 10.1007/9 | https://ww | Research ( | Ormaza-Si | Respirator | biomedica | Biomedica |
| 15 | Castro, G. | Castro, Gi | 58513871( | Automatec | 2026 | Artificial In | 171 | | 103302 | | | 0 | 10.1016/j. | https://ww | Departme | Castro, Gi | Machine L | Automatec | Classifica |
| 16 | Savvadelli, | Savvadelli, | 60193654! | A Literatur | 2026 | IFIP Advan | 761 | | | 376 | 388 | 0 | 10.1007/9 | https://ww | Departme | Savvadelli, | This paper | cyber threa | Case base |
| 17 | Reddy, J.R. | Reddy, Jee | 60138152( | Time-Critic | 2026 | Lecture Nc | 1608 LNNS | | | 11 | 20 | 0 | 10.1007/9 | https://www.scopus.( | | Reddy, Jee | New healtl | Clinical De | Diagnosis; |
| 18 | Younesi, A | Younesi, A | 57771797 | HealthCar | 2026 | Internet of | 35 | | 101815 | | | 0 | 10.1016/j. | https://ww | Departme | Younesi, A | The rising | 6G communication; A | |

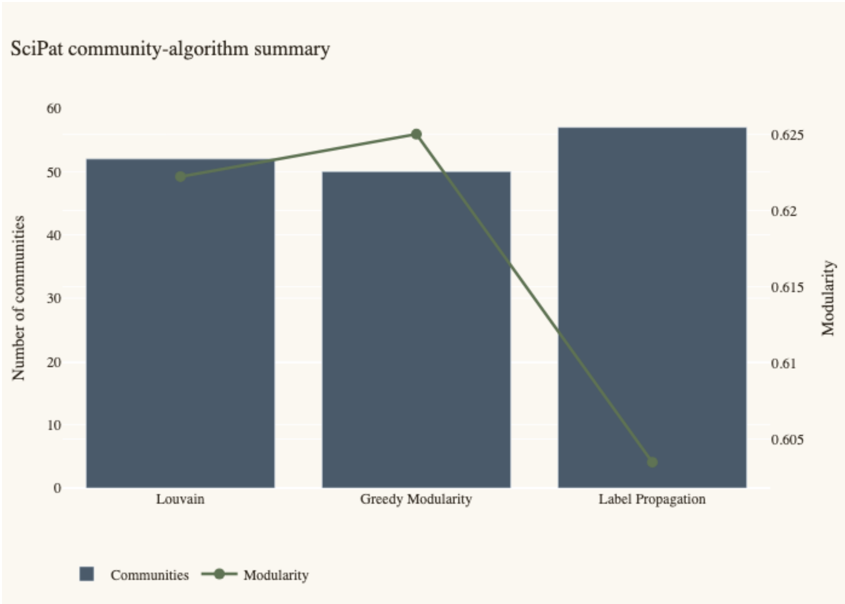
Appendix 1: Csv file extraction from Scopus part 1

| | R | S | T | U | V | W | X | Y | Z | AA | AB | AC | AD | AE | AF | AG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| t | Author Keywords | Index Keywords | Correspon | Editors | Publisher | ISSN | ISBN | CODEN | PubMed ID | Language | Abbreviate | Document | Publicatio | Open Acce | Source | EID |
| un | Aged care; Artificia | Clinical research | R. Dendere; Centre fo | | Elsevier Ire | 13865056 | | IJMIF | 41308275 | English | Int. J. Med. | Review | Final | All Open A | Scopus | 2-s2.0-10502 |
| Tl | Acute chest pain; C | beta adrenergic r | A. Varga-Szemes; De | | Elsevier Ire | 0720048X | | EJRAD | 41275631 | English | Eur. J. Rad | Article | Final | All Open A | Scopus | 2-s2.0-10502 |
| :tic | Appendicitis; Biom | biological marker | M.T. Huyut; Departme | | Elsevier M | 19590318 | | | | English | IRBM | Article | Final | | Scopus | 2-s2.0-10502 |
| un | Ambulance; Emerg | adult; ambulance | H. Wang; Department | | W.B. Saun | 7356757 | | AJEME | | English | Am. J. Eme | Article | Final | | Scopus | 2-s2.0-10502 |
| ng | GPT; Large language model (LLM); Me | | D. Xu; Taizhou Key Lal | | Elsevier Ire | 15740137 | | | | English | Comput. S | Review | Final | | Scopus | 2-s2.0-10502 |
| l in | Artificial intelligenc | Article; artificial i | K.J. Renfree; Departm | | W.B. Saun | 7490712 | | HACLE | 41206191 | English | Hand Clin. | Article | Final | | Scopus | 2-s2.0-10501 |
| l in | Artificial intelligenc | Article; artificial i | H. Prescher; Section ( | | W.B. Saun | 7490712 | | HACLE | 41206192 | English | Hand Clin. | Article | Final | | Scopus | 2-s2.0-10501 |
| e a | Bacteria identificat | Alignment; Antibi | Y.-C. Chang; Graduat | | Elsevier Lt | 17468094 | | | | English | Biomed. Si | Article | Final | | Scopus | 2-s2.0-10501 |
| bic | Automatic sample | Biomarkers; Cher | T.-H. Wang; Departm | | Elsevier Lt | 9565663 | 97801280: | BBIOE | 41066993 | English | Biosens. B | Article | Final | | Scopus | 2-s2.0-10501 |
| un | Acute coronary syn | biological marker | P.A. Kavsak; Departm | | Elsevier B. | 98981 | | CCATA | 41022274 | English | Clin. Chim | Article | Final | All Open A | Scopus | 2-s2.0-10501 |
| ith | AI Principles; Algori | Artificial intelliger | S. Strohmeier; Saarlai | | Elsevier Lt | 9574174 | | ESAPE | | English | Expert Sys | Article | Final | All Open A | Scopus | 2-s2.0-10501 |
| ve | Artificial intelligence; Emergency dep | | T. Gloyn; Humber Rive | | Elsevier B. | 9333657 | 97890519! | AIMEE | 41313968 | English | Artif. Intell | Review | Final | All Open A | Scopus | 2-s2.0-10502 |
| tor | biomedical devices | Biomedical equip | A.C. Villa-I | Narváez, F | Springer Sc | 18650929 | 9789819671748; 978981966461 | | | English | Commun. | Conferenc | Final | | Scopus | 2-s2.0-10502 |
| L | Automated Machin | Classification (of | T.A. Almeida; Departr | | Elsevier B. | 9333657 | 97890519! | AIMEE | 41273806 | English | Artif. Intell | Article | Final | | Scopus | 2-s2.0-10502 |
| er | cyber threats; cybe | Case based reas | E. Savvade | Furnell, S.; | Springer Sc | 18684238 | 9783032007766; 978303196230 | | | English | IFIP Advan | Conferenc | Final | | Scopus | 2-s2.0-10502 |
| alth | Clinical Decision S | Diagnosis; Disea | J.S. Pokkal | Swaroop, A | Springer Sc | 23673370 | 9789819652372; 978303193105 | | | English | Lect. Note | Conferenc | Final | | Scopus | 2-s2.0-10502 |
| ig ( | 6G communication; Artificial intellige | | A. Younesi; Departme | | Elsevier B.V. | | | | | English | Internet. T | Review | Final | All Open A | Scopus | 2-s2.0-10502 |

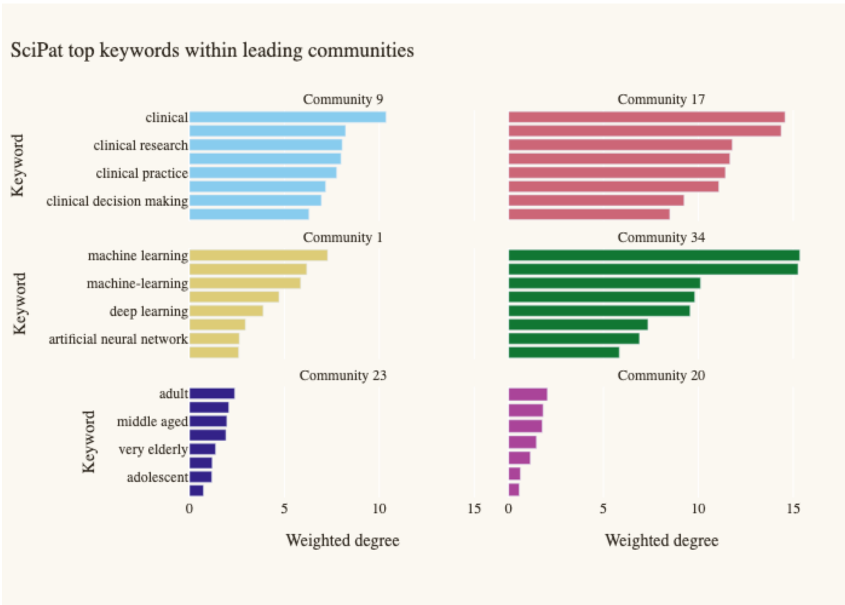
Appendix 2: Csv file extraction from Scopus part 2

| | A | B | C | D | E | F | G | H | I | J | K | L | M |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Time: | 08.12.2025 18:14:09 | | | | | | | | | | | |
| 2 | Query: | EN_ALL:(("clinical decision" OR "predictive analytics" ) AND ("workflow" OR "resource allocation" OR "triage" ) AND ( "artificial intelligence" OR "machine learning" OR "deep learning" | | | | | | | | | | | |
| 3 | SortBy: | Relevance | | | | | | | | | | | |
| 4 | | | | | | | | | | | | | |
| 5 | Application Id | Application Number | Application Date | Country | Title | Abstract | I P C | | | | | | |
| 6 | WO2023107595 | PCT/US2022/052212 | 08.12.2022 | WO | HUMAN RESOURC | A method to optimiz | H04W 4/90 | | | | | | |
| 7 | US447975816 | 18717342 | 08.12.2022 | US | HUMAN RESOURC | <p id="p-0001" num | G16H 40/20; G06N 20/20 | | | | | | |
| 8 | WO2025129165 | PCT/US2024/060327 | 16.12.2024 | WO | MULTISPECTRAL C | A camouflage defeat | G06V 10/74; G06V 20/40; G06V 20/52 | | | | | | |
| 9 | US458063342 | 18982178 | 16.12.2024 | US | MULTISPECTRAL C | <p id="p-0001" num | G06V 10/80; G06V 10/143; G06V 20/40; G06V 20/50; G06V 40/10; G06V 40/40 | | | | | | |
| 10 | US448392241 | 18798710 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | A61B 5/00; G16H 10/60; G16H 40/67 | | | | | | |
| 11 | US448393505 | 18798716 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | G16H 40/20; G16H 10/60; G16H 15/00; G16H 40/67 | | | | | | |
| 12 | WO2025035023 | PCT/US2024/041554 | 08.08.2024 | WO | INFORMATION MA | A computer-implem | G16H 10/60; G16H 50/20; G16H 50/30; G16H 20/00; G06F 21/60; G06F 11/00; G08B 2: | | | | | | |
| 13 | US448393509 | 18798670 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | G16H 40/40; G16H 40/60 | | | | | | |
| 14 | US448393511 | 18798706 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | G16H 40/67; A61B 5/00 | | | | | | |
| 15 | WO2025035017 | PCT/US2024/041546 | 08.08.2024 | WO | INFORMATION MA | A computer-implem | G16H 10/60; G16H 50/20; G16H 50/30; G16H 20/00; G06F 21/60; G06F 11/00; G08B 2: | | | | | | |
| 16 | US448393477 | 18798686 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | G16H 10/60; G16H 40/20 | | | | | | |
| 17 | US448393506 | 18798721 | 08.08.2024 | US | Information Manag | <p id="p-0001" num | G16H 40/20; G16H 15/00 | | | | | | |

Appendix 3: Csv file extraction from Patentscope




Appendix 4: SciPat Communiy algorithm summary




Appendix 5: Top keywords within leading communities