


# DATA-DRIVEN TECHNOLOGY INTELLIGENCE: AN APPLICATION TO AIRCRAFT ENGINE MAINTENANCE

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## Abstract

In rapidly evolving technological environments, research and development (R&D) organizations require effective Technology Intelligence (TI) methods to support evidence-based decision-making and maintain strategic advantages. This paper presents a data-driven TI methodology tailored to application-oriented research environments. The methodology combines bibliometric analysis, co-occurrence networks, and quantitative indicators of research activity and trend development to identify and prioritize relevant technologies. The approach is demonstrated and validated through an application in aircraft engine maintenance, focusing on engine inspection and resulting in a technology portfolio that indicates promising research directions including non-destructive testing or deep learning. The results show the practical applicability of the proposed approach for R&D units. However, further refinement of assessment metrics and the integration of diverse data sources are recommended to enable more comprehensive analyses.

**Keywords:** technology intelligence, maintenance, engine inspection, bibliometrics

## 1. Introduction

Technology Intelligence (TI) refers to systematic determination, acquisition, evaluation, and dissemination of technology-relevant information to enable timely and evidence-based decision-making in research and development (R&D) [1]. For corporate R&D units and research institutes operating in close proximity to industrial practice, rapidly increasing information volumes, shorter technology life cycles, and tight budget constraints demand lean, transparent, and reproducible TI processes that can be implemented using openly available and user-friendly tools. Addressing these challenges, this paper develops and validates a data-driven TI methodology specifically tailored to application-oriented research environments. The approach consists of three phases: systematic determination of information requirements, structured information acquisition, and quantitative evaluation of technological domains. The iterative framework enables evidence-based identification, monitoring, and prioritization of technological topics through bibliometric analysis, technology clustering, and publication trend analysis. The framework is validated through a use case in aircraft engine maintenance, with a focus on engine inspection — a domain characterized by stringent constraints such as accessibility in confined geometries, high defect-detection performance at low false-alarm rates, repeatability, and high operational throughput. Based on this use case, we examine the following research question:

*'What technologies are relevant for engine-inspection research in an application-oriented context?'*

To address the research question, we generate a co-occurrence network of publication keywords to identify salient technologies and thematic clusters. Subsequently, these technologies are assessed using quantitative indicators of *research activity* and *trend development*, producing a portfolio-based decision matrix as the final output. The results demonstrate the practical applicability of the proposed approach for research-intensive environments. Following this, the contributions of this paper are threefold:

- a reproducible data-driven TI process,
- an application to aircraft engine maintenance,
- a quantitative technology prioritization framework based on bibliometric indicators.

## 2. Fundamentals

### 2.1 Technology Intelligence

As a core element of technology management, TI comprises systematic determination, acquisition, evaluation, and dissemination of technology-related information to support strategic and operational decision-making in R&D [1]. By continuously monitoring technological developments, TI enables organizations to identify emerging technologies, assess their relevance, and derive actionable knowledge under conditions of increasing technological complexity [2].

Common TI frameworks [1, 3, 4] divide the process into four iterative phases, which can also be operated in parallel. First, information requirements are determined by identifying relevant technological search domains and information needs, which can be defined by a leading research question. Second, information is obtained from appropriate sources, such as scientific publications, patents, or expert knowledge. Third, the collected information is analyzed and evaluated using qualitative or quantitative approaches to assess, for example, technological relevance or development, depending on the respective organization, use case, and research question. Finally, the resulting knowledge and insights are communicated to decision makers to support technology-related decisions.

TI operations can involve the application of a wide variety of methods [5, 1]. These methods can generally be categorized as qualitative or quantitative [1]. Qualitative approaches, such as expert interviews, brainstorming, delphi studies, or scenario techniques, rely on expert knowledge and are particularly useful for assessing emerging technologies in the early stages with limited data and critical implicit knowledge [6, 1]. Quantitative methods can be applied to analyze large amounts of information or explicit knowledge using indicators derived from publications, patents, or other technology-related sources [1]. Common examples are trend and lifecycle analyses, simulations, or bibliometric network graphs. Increasingly, modern TI combines qualitative and quantitative approaches to address information uncertainty, complexity, and scalability [1, 7, 8, 9].

### 2.2 Data-Driven Bibliometric Analysis

The increasing availability of digitally accessible information [10] has encouraged the adoption of data-driven methods in TI [11, 12]. Compared with purely expert-based approaches, these methods enable the systematic analysis of large volumes of data to identify weak signals in technological developments, emerging research topics, and relationships between technological domains [11].

Among data-driven approaches, bibliometric methods have become well established for analyzing technologies based on scientific publications [13, 14]. By exploiting publication metadata, such as authors, keywords, or citations, bibliometric analyses provide quantitative insights into the structure, activity, and relations of research fields. Common techniques include publication mapping to obtain co-citation or co-occurrence networks, or frequency analyses which enable the identification of research trends, emerging or relevant topics, thematic relationships between technologies or even their historical evolution [11, 15, 16, 17].

Depending on the application, bibliometric analyses may be complemented by additional innovation indicators [14], such as patents or funding, to gain a broader perspective on technological dynamics. The combination of multiple indicators supports a more comprehensive and robust assessment than relying on a single data source alone [14, 1].

### 2.3 Aircraft Engine Maintenance

Maintenance of aircraft engines is one of the main operations within aircraft maintenance and includes all activities required to ensure the continued airworthiness, safety, and operational reliability of aircraft engines throughout their useful life. Therefore, engine maintenance represents a major share of aircraft maintenance costs, accounting for approximately 42% of total maintenance costs on

average [18]. These high costs are primarily driven by the complexity of aircraft engines with numerous integrated components and their limited accessibility during maintenance. Engine components are subject to significant mechanical and thermal loads, making them susceptible to wear and damage. As a result, maintenance activities often require extensive disassembly, leading to increased labor, downtime, and costs. An example of an aircraft in the hangar being prepared for engine maintenance tasks can be seen in Figure 1. Due to the limited accessibility, inspections being carried out regularly to assess component condition and detect defects, represent a particularly demanding task within complex engine geometries. Consequently, a wide range of technologies — including advanced imaging, robotics, artificial intelligence, and non-destructive testing (NDT) — are being investigated to enhance inspection capabilities. [19]



Figure 1 – Aircraft engine maintenance

## 3. Methodology

This section introduces the proposed data-driven TI methodology. The presented methodology utilizes a structured, three-phase framework consisting of (1) *Determination of information requirements*, (2) *Acquisition of information*, and (3) *Evaluation of information*. As depicted in Figure 2, the framework comprises clearly delineated phases — each characterized by distinct input and output criteria — thereby ensuring systematic comprehensibility. Although, as mentioned in subsection 2.1, relevant frameworks from literature often include 'communication of results' as a fourth phase, whereas our framework focuses on systematic identification and assessment of technologies as the value-adding TI core elements. However, we recommend that information and knowledge dissemination be carried out on a case-specific basis and throughout the process.

*Phase (1), determination of information requirements:*

This initial phase serves as the foundational step in systematically identifying essential information needs. It incorporates the understanding and specification of the research problem or question to be analyzed, its technological scope, the distribution of available resources, and the exact definition of suitable evaluation indicators, such as research activity and trend development, to analyze the data later in the process. To address the respective research question of this paper,

*'What technologies are relevant for engine-inspection research in an application-oriented context?'*,

we measure relevance for application-oriented research in two dimensions with *research activity* and *trend development*.

The first dimension, research activity, consists of three indicators:

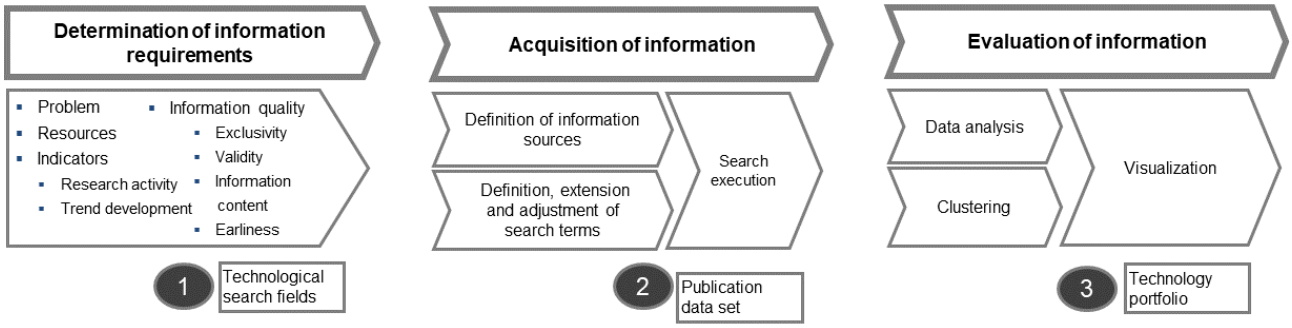



Figure 2 – Methodological framework

- Absolute number of publications,
- Research funding,
- Startup funding.

The second dimension, trend development, is defined by one single indicator:

- Publication growth.

Although startups are usually not considered in the context of research indicators, we integrate startup funding into the research activity calculation to consider the inherent technology transfer potential. In particular, for application-oriented research institutions, the potential for technology transfer is a crucial aspect for research and resource planning.
Ideally, the project team starts the process with a kickoff workshop to discuss and define a problem statement, resources, and organizational planning of the TI project. Techniques such as brainstorming, basic literature research, mind mapping, and technology trees can help to increase and structure the understanding of the given technical problem. Furthermore, this step sets the quality criteria for the required information based on the needs of the problem. In this case and according to [1], we define exclusivity, validity, content or value of the information, and the earliness of the information. These criteria will crucially influence later steps regarding the acquisition of information. The primary output of this phase is the precise definition of technological search fields, such as NDT, acoustics, robotics, or measurement engineering, providing the conceptual basis and ensuring a focused direction for subsequent phases.

*Phase (2), acquisition of information:*
The second phase focuses on the systematic acquisition of relevant information. This phase begins with two activities that can be performed in parallel. First, appropriate information sources are selected on the basis of the previously defined search fields and information quality requirements, as the choice of data sources is critical to the reliability of subsequent analysis. Second, the technological search fields are translated into specific search terms, which are iteratively refined and expanded using boolean operators as well as controlled vocabularies, such as thesaurus and taxonomies, to ensure comprehensive coverage of the technological domain. The finalized search strategy is subsequently executed, resulting in an appropriate data set of scientific publications.
For instance, the starting search query for the first iteration was:

*Inspection AND (Aircraft OR Airplane OR Jet) AND (Propulsion OR Engine OR Turbine OR Propeller OR "Power Train" OR Motor)*.

In this research, we utilized the widely known publication database *Scopus* to obtain a scientific foundation with publication data for the years 2000 to 2020. In addition, we used the commercial technology scouting platform *Mapegy Scout* to obtain additional data streams for the indicators research funding and startup funding. Enhanced by using the IEEE-standard thesaurus [20] and taxonomy

[21], the search query could be refined with several search iterations to ensure coverage of relevant technological developments. To achieve this, internal engine maintenance experts discussed the search results for each iteration until the established set of publication data was appropriate enough.

*Phase (3), evaluation of information:*
The concluding phase encompasses detailed analytical evaluation with the aim of transforming the acquired publication data into a decision-relevant portfolio of suitable technologies through bibliometric analysis and visualization. First, the data set is analyzed to uncover meaningful patterns of keywords, technologies, and their relationships in network-based thematic clusters. With the defined indicators measuring research activity and trend development, a technology selection can be quantified and ranked.
The results are subsequently visualized in a portfolio matrix, in which technologies are positioned according to the selected indicators to support their evaluation and prioritization. Finally, the resulting technology portfolio provides a transparent basis for deriving technology-related recommendations. Since insights gained during the evaluation can reveal additional technologies or refine existing search fields, the acquisition and evaluation phases can be performed iteratively to continuously improve the comprehensiveness and quality of the results.
For this research work, the collected publication data were analyzed and represented as a co-occurrence network graph using the free bibliometric mapping tool VOSviewer [22] after manual data cleansing. Consequently, different clusters of technologies could be identified, of which 16 technologies were selected based on their frequencies and expert discussions according to the relevance for application-oriented engine inspection research. Following this, the aforementioned indicators were derived for each of the identified technologies. The results were then visualized in a strategic portfolio structure, allowing further discussions and the formulation of informed strategic decisions.

## 4. Results

The proposed methodology was applied to the domain of aircraft engine inspection research to identify and prioritize relevant technologies. Based on the publication data set obtained from Scopus, authors' keywords were analyzed to identify thematic relationships and emerging technological domains. The identified technologies were subsequently evaluated using quantitative indicators that measure research activity and trend development before being integrated into a portfolio representation.

Generally, the number of publications on aircraft engine inspection research is increasing, indicating a growing research activity. Based on the analysis of authors' keyword frequencies and their development over time, the technology fields NDT and unmanned aerial vehicle (UAV) seem to have dominant roles. Furthermore, robotics and ultrasonic testing turn out to be frequently used publication keywords. Figure 3 visualizes an exemplary network of co-occurrences of authors' keywords on aircraft engine inspection derived from the publication data set after the first iteration of the search. Frequently co-occurring keywords form connected clusters representing related technological topics and research areas. In addition to inspection-specific terminology, the network contains numerous enabling technologies, demonstrating that aircraft engine inspection is inherently multidisciplinary and strongly connected to developments in adjacent technological fields. The network therefore provides the basis for identifying coherent technology clusters for further evaluation.

Each search iteration generated new data sets and therefore new networks with different topic clusters. For instance, from the first iteration, technologies such as eddy current testing, computer simulations, or finite element method (FEM) could be derived. In addition, new and more specific search terms could be integrated into existing search queries. Subsequent focused cluster analyses with respectively adjusted search queries were performed on specific topic domains such as health technology, image processing, or NDT, which uncovered new, more concrete technologies like computerized tomography (CT), augmented reality (AR), or virtual reality (VR). Based on this approach and after three iterations of the co-occurrence analysis, related keywords were consolidated into technology domains, resulting in the final technology network shown in Figure 4. The network diagram

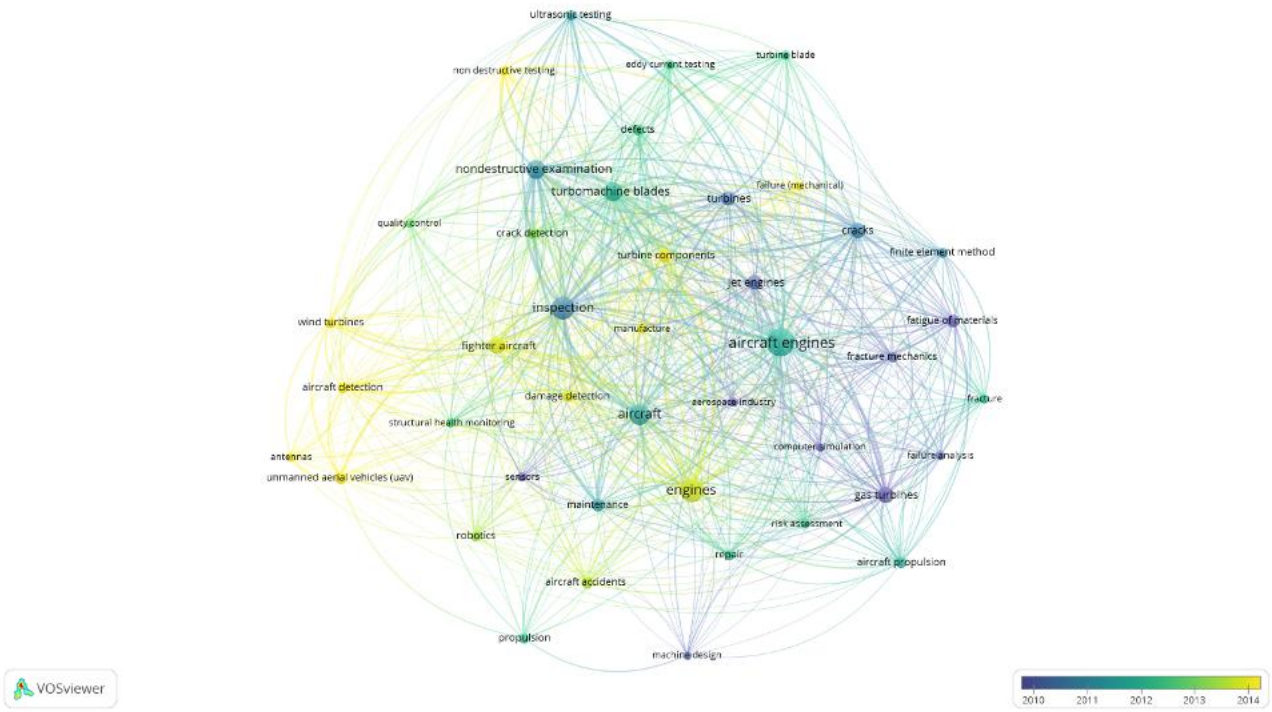



Figure 3 – Co-occurrence network example based on publication keywords after the first iteration

structures specific technologies around the application domain of turbine inspection and reveals relationships between inspection technologies and enabling disciplines such as machine vision or image processing, health technologies, UAV, or NDT. Technologies including thermosonics, FEM, computer simulation, acoustic variable control, and bayesian networks were excluded from further consideration and are therefore shown in gray. Although these technologies are related to engine inspection, they were not considered suitable as in-situ inspection technologies within the scope of this research. Following this, a total of 16 technologies could be identified for subsequent evaluation.

The identified technologies were then evaluated using the research activity indicator defined in Eq. (1). Research activity combines the number of scientific publications $P_{publication\,number}$ from Scopus with the amount of research funding $P_{research\,funding}$ and startup funding $P_{startup\,funding}$ from the platform Mapegy Scout for each technology.

$$I_{research\,activity} = 0.8 \cdot P_{publication\,number} + 0.1 \cdot P_{research\,funding} + 0.1 \cdot P_{startup\,funding} \tag{1}$$

Therefore, specific search queries were used, such as *'CT OR "Computerized Tomography" OR "Computed Tomography"'* for CT technology. Publications were assigned the highest weighting, while funding indicators provide additional evidence of technological relevance for application-oriented or high-mature research beyond scientific output. The weighting reflects the central role of scientific publications as the primary sub-indicator of research activity, while research funding and startup funding are integrated as complementary sub-indicators. Table 1 summarizes the resulting research activity values for the identified technologies. Technologies such as robotics, X-ray, neural networks, and deep learning exhibit particularly high research activity, whereas technologies including laser ultrasound and eddy current testing show comparatively lower activity.

For the trend development indicator, the publication growth rate, $P_{publication\,growth}$, was calculated for the period 2000 to 2020 for each technology. The resulting values of $P_{publication\,growth}$ and $I_{research\,activity}$ are summarized in Table 2. The publication growth rates were then qualitatively adjusted based on the publication dynamics curves to derive the final indicator of trend development, $I_{trend\,development}$, thus addressing recent developments that are not adequately reflected by the overall growth rate, such as

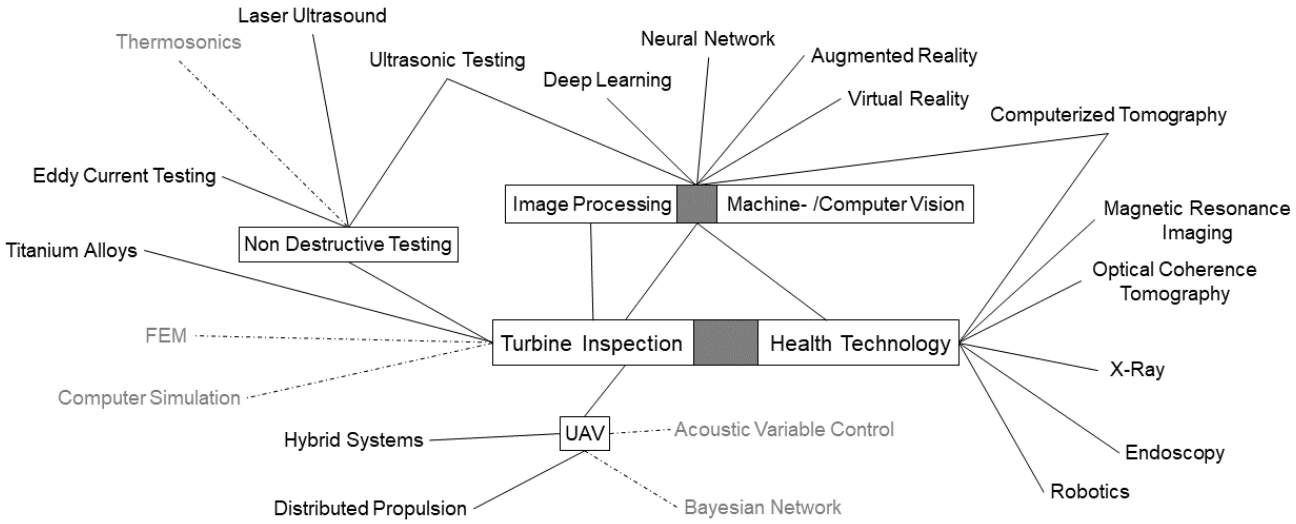



Figure 4 – Identified technology network

stagnating publication activity during the last five years.

Based on the two final indicators, research activity and trend development, the technology portfolio shown in Figure 5 was generated. To improve readability, the y-axis representing dimensionless $I_{research\,activity}$ is displayed on a logarithmic scale with an axis break to accommodate the large differences between technologies. The x-axis represents $I_{trend\,development}$, with technologies that exhibit a stronger trend development positioned further to the right. Technologies located in the upper-right region exhibit both high research activity and strong trend development, indicating considerable momentum and future relevance. In contrast, technologies with high research activity but lower trend development represent mature research fields, whereas technologies with low research activity and weak trend development currently appear less promising for future research investment. According to the portfolio, robotics, neural networks, AR, and deep learning emerge as the most promising technology domains due to their combination of relatively strong research activity and significant growth. While OCT exhibits a medium intensity of research, it shows a notably high trend development, which makes it particularly relevant for future considerations. Furthermore, eddy current testing displays an interesting position, revealing medium to high publication growth and significantly low research activity. Therefore, the aforementioned technologies represent promising candidates for future research in the application of aircraft engine inspection.

## 5. Conclusion

This paper presented a data-driven TI methodology for systematic identification and prioritization of technologies in application-oriented research environments. The proposed framework and its application comprised three phases: the determination of information requirements, the structured acquisition of scientific publication data, and the quantitative evaluation of relevant technologies using bibliometric methods. The methodology was validated using the application domain of aircraft engine inspection. Consequently, the first phase led to potential technological search fields such as health technology or image processing. With these, robust search queries could be established and iteratively refined, yielding to publication data as an interim output of the second phase. In the third phase, bibliometric analyses, such as clustering through co-occurrence networks based on publication keywords, enabled the identification of relevant technology domains like NDT or robotics and their relationships. Finally, the combination of research activity and trend development indicators allowed the prioritization of 16 technologies in a portfolio representation, resulting in an effective basis for the derivation of promising future research directions including AR, deep learning, OCT, or eddy current testing.

The approach provides a transparent and reproducible framework for addressing evidence-based

Table 1 – Research activity values for the identified technologies

| Technology | $P_{publication\,number}$ [absolute frequency (2000–2020)] | $P_{research\,funding}$ [k€] | $P_{startup\,funding}$ [k€] |
|---|---|---|---|
| AR | 19757 | 335000 | 15120000 |
| CT | 658867 | 477000 | 661080 |
| Deep Learning | 9917 | 227000 | 6720000 |
| Distributed Propulsion | 337 | 93000 | 22680 |
| Eddy Current Testing | 6837 | 1400 | – |
| Endoscopy | 162502 | 218000 | 804720 |
| Hybrid Systems | 12405 | 222000 | 2100000 |
| Laser Ultrasound | 2076 | 5000 | – |
| MRI | 802487 | 1300000 | 1428000 |
| Neural Network | 437497 | 321000 | 9240000 |
| OCT | 71462 | 141000 | 31080 |
| Robotics | 253159 | 4000000 | 40320000 |
| Titanium Alloys | 62484 | 24000 | 417480 |
| Ultrasonic Testing | 15916 | 29000 | 1512000 |
| VR | 111613 | 284000 | 3528000 |
| X-RAY | 1413096 | 1100000 | 10080000 |

Table 2 – Final indicator values for the identified technologies

| Technology | $I_{research\,activity}$ [–] | $P_{publication\,growth}$ [growth rate (2000–2020)] |
|---|---|---|
| AR | 184715806 | 23.4 |
| CT | 114335094 | 4.5 |
| Deep Learning | 694739934 | ∞ |
| Distributed Propulsion | 11568269 | 3.2 |
| Eddy Current Testing | 145470 | 3.6 |
| Endoscopy | 102402002 | 1.8 |
| Hybrid Systems | 232209924 | 6.2 |
| Laser Ultrasound | 501661 | 1.3 |
| MRI | 273441990 | 2.8 |
| Neural Network | 956449998 | 5.0 |
| OCT | 17265170 | 39.0 |
| Robotics | 4432202527 | 8.0 |
| Titanium Alloys | 44197987 | 4.5 |
| Ultrasonic Testing | 154112733 | 3.2 |
| VR | 381289290 | 3.0 |
| X-RAY | 1119130477 | 1.3 |

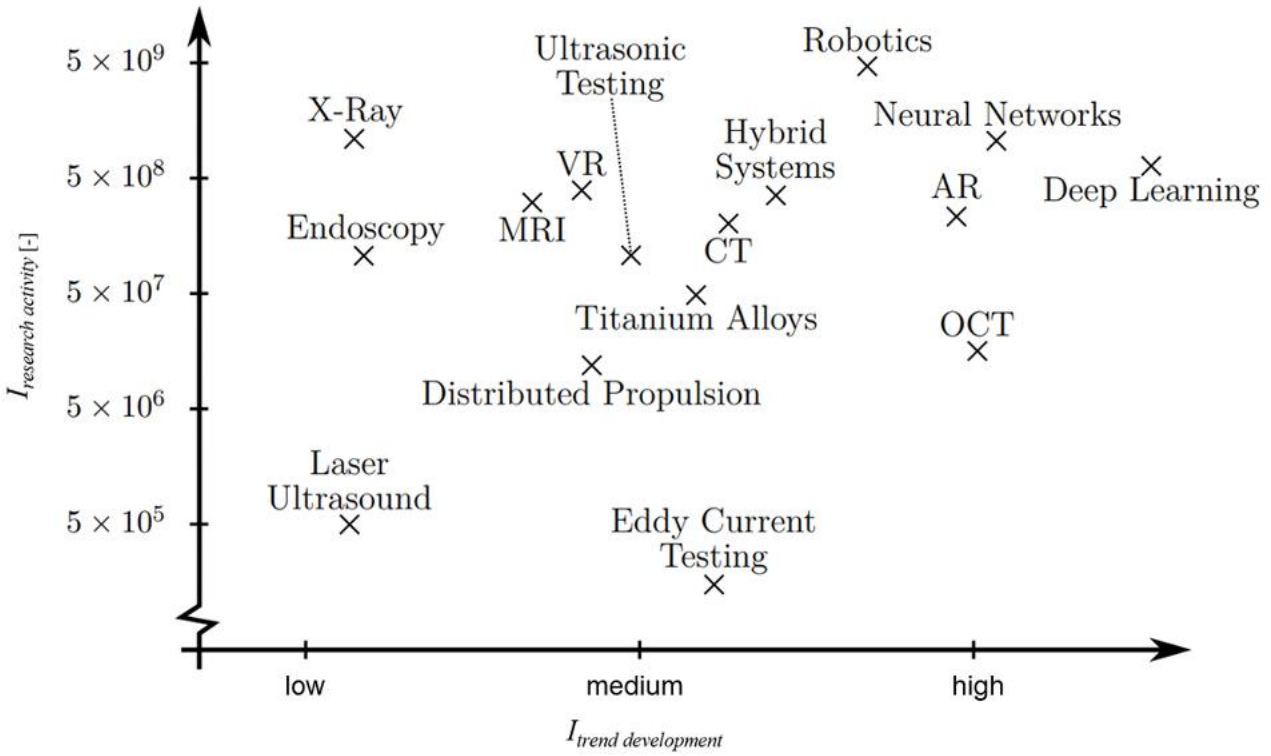



Figure 5 – Technology portfolio

TI by leveraging existing data. Furthermore, the results confirm the practical applicability of the proposed methodology and its potential to support technology-related decision-making in R&D environments.

Although the proposed methodology proved suitable for the presented use case, several opportunities for further development remain. Future work should investigate additional quantitative evaluation indicators, integrate further data sources, such as patents or industrial data, and evaluate the quality of results with expert surveys and retrospective studies. Moreover, the methodology should be validated in additional application domains to assess its transferability.

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