

# A CLUSTER-BASED TECHNOLOGY ROADMAPPING APPROACH FOR STRATEGIC MANAGEMENT OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE

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Technology roadmapping is a key strategic concern for companies. The aim of this study is to propose a cluster-based technology roadmapping approach using patent documents. The proposed approach is applied to artificial intelligence (AI) technology. The proposed approach provides evidence-based decision-making in healthcare management by identifying and prioritizing artificial intelligence (AI) technology domains with high long-term success potential. Unlike existing studies in the literature, the proposed approach integrates weighted evaluation criteria with market trends and product feature characteristics, enabling a more comprehensive assessment of technological relevance from a managerial perspective. The applicability of the proposed approach is demonstrated through an empirical case study on AI applications in the healthcare domain. The findings suggest that medical image processing, diagnosis and treatment support systems, electronic communication technologies, interactive robotic systems, and acoustic and haptic feedback technologies are expected to play a significant role in the long-term development of healthcare services.

**Keywords:** Technology Roadmapping, Healthcare Management, Artificial Intelligence, Strategic Decision Making, Patent Analysis

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## 1. INTRODUCTION

Technologies are developing rapidly, and this affects investment decisions (Dong *et al.*, 2023). Sustainable competitive advantage cannot be achieved if technology trends cannot be forecasted and planned. For this reason, technology forecasting is needed to plan future developments (Abdou and Mahmoud, 1977). It is very important for decision makers to forecast the success of future technologies and make technology investment decisions (TIDs) accordingly (Altuntas *et al.*, 2015). Forward-looking TIDs are not simple because of uncertainty, especially when it comes to coordinating the development of multiple technologies (Bray and Garcia, 1997). In this situation it should be a linkage between TIDs and business requirements (Garcia and Bray, 1997).

The evolutionary paths of technologies can be investigated with a technology management perspective (Zhang *et al.*, 2023). TRMs are one of the technology management tools. TRMs help make better TIDs by identifying critical technologies or technology gaps according to product/service requirements and customer/market needs/trends (Bray and Garcia, 1997). It is known that roadmapping helps to make investment decisions (Kostoff and Schaller, 2001). Roadmapping should be applied to forecast developments in the sector and technology in large, technology-intensive and high-cost markets.

Studies on technology forecasting based on criteria have been reported (i.e., Altuntas *et al.*, 2015; Yuan and Cai, 2021; Ghaffari *et al.*, 2023). In these studies, it is seen that technology candidates are ranked only according to criteria for forecasting the future development trend of alternative technologies. They do not examine market trends and product/service features. In this study, TRM is built by aligning technologies with product requirements and market trends to link investment decisions and requirements.

Unlike traditional TRM models that rely heavily on subjective, workshop-based expert opinions, this study introduces a data-driven forecasting framework. While prior approaches, such as those by Altuntas *et al.* (2015) and Jin *et al.* (2015), focus on evaluating individual patents or isolated technologies independently, our methodology differentiates itself by introducing a new evaluation criterion and shifting the analytical focus to technology clusters containing multiple interrelated technologies. By synthesizing text-mined criteria weighting based on relative importance degrees with cluster-level analysis, this approach overcomes the subjective biases of conventional TRMs. Consequently, it embeds an objective, cluster-based technology success forecasting capability directly into the roadmap architecture, a methodological integration not previously established in the independent utilization of existing models.

While the core technology forecasting pipeline and roadmap derivation rely exclusively on a curated patent dataset, scientific publications are selectively integrated into the methodology solely to inform the criterion weighting calculations. This study establishes the criteria to forecast future technology success. According to Altuntas *et al.* (2015), different results are obtained from each of the criteria used for technology forecasting. In addition, Yuan and Cai (2021) emphasize that the weight method for criteria leads to forecasting results that are more objective and accurate. Furthermore, Keskin and Delice (2022) suggest that different perspectives and calculation procedures should be applied to weight method. For all these reasons, in this study, the degree of importance of the criteria is obtained by taking advantage of the ability of text mining to find previously unknown useful patterns in big data, inspired by Jin *et al.* (2015).

The usefulness and potential of the proposed approach are demonstrated on AI applications in the health domain. It is seen that the development of technology and information systems in recent years has activated the health sector (Yorgancioglu Tarcan *et al.*, 2024). Many different applications, such as digitalization and monitoring of patient data, analysis of images, and the use of virtual assistants, are preferred (Bohr and Memarzadeh, 2020). Empirical data underscores this rapid expansion, noting that the global healthcare AI market, which was valued at approximately USD 15.1 billion in 2022, is projected to surge to USD 187.95 billion by 2030 (Zhukovska *et al.*, 2023).

It is known that investing in the health domain, where the costs of quality and intellectual property rights are high, means investing in both costly and risky innovation (Dzau *et al.*, 2017). Therefore, forecasting the success of future technologies is very important for decision makers (Altuntas *et al.*, 2015).

In this study, patents of AI applications in healthcare are accessed, and the patent abstracts are examined. Data are subjected to cleaning and pre-processing according to text mining methods. First of all, Social Network Analysis (SNA) is preferred. Since appropriate results could not be obtained with SNA, hierarchical clustering is then performed. The clusters are evaluated according to the criteria (Diffusion speed (DS) and Patent power (PP)). The information/indicators/components they use are, respectively, citation information and IPC codes. The DS criterion considers that the forward citations of each patent in the cluster come from different applicants. In this way, the connections and information flows between technologies can be measured. The breadth of the technology is measured with the PP criterion, inspired by Altuntas *et al.* (2015). The process of weighting the criteria is based on the word vector and similarity measurement (Jin *et al.*, 2015). The most promising cluster is obtained by criterion weighting. The technologies in this cluster are associated with product features and market trends, and a TRM with a future time horizon is built.

Compared to existing studies, this study has differences and advantages:

- 1) Structured and unstructured patent data are used for technology success (i.e., patent abstracts, claims, patent application date, patent applicants, IPC codes and forward citation information are utilized).
- 2) According to Bray and Garcia (1997), since importance is given to the development of multiple technologies in TIDs, a cluster-based study is conducted in the proposed approach.
- 3) The degree of importance of the criteria for technology success forecasting is found by text mining.
- 4) The criteria, DS and PP are established to find the most promising cluster. In order for firms to innovate, it is recommended that they explore external knowledge as well as internal knowledge (Carrasco-Carvajal *et al.*, 2023), and that firms competing with each other ensure knowledge transfer (Rosa *et al.*, 2020). Inspired by these explanations, through the dissemination of information, the diffusion of technology is measured by the DS criterion in the international dimension. PP is used in the subclass of IPC classifications, not only four-digit IPC codes.
- 5) TRM is built to present technology success results to decision makers by showing the relationship between product features and market trends. By determining the technology trend creating the future time horizon of TRM and placing the TRM elements/drivers in layers is completed.
- 6) This research addresses the need to determine future technologies in artificial intelligence applications in the healthcare field through data-driven analysis.

The flow in the following sections of this study is organized as follows: “Literature Background” is given in the second section. The third section, “Research Design and Methodology”, includes the suggested methodology steps and a case study. The fourth section, “Findings”, accounts for the results of TRM. The last two sections specify the contributions to the literature and implications for practice, and suggestions for future studies are given.

## 2. LITERATURE BACKGROUND

### 2.1. AI applications in healthcare

AI was first defined by John McCarthy in 1956 as the science and engineering of producing smart machines (Malik *et al.*, 2019). The healthcare ecosystem is realizing the importance of AI-powered tools in next-generation healthcare technology. AI brings improvements to healthcare services such as cost savings, digitalization of data, patient monitoring, image analysis, and virtual assistants (Bohr and Memarzadeh, 2020). Examples of applications include ensuring the effectiveness, efficiency and accuracy of the disease treatment and drug development cycle, reducing workload, disease diagnosis, increasing patient consultation times thanks to individualized health management, facilitating immediate intervention in critical cases, better personalized monitoring of patients, long-term cost savings and online appointment scheduling (Malik *et al.*, 2019).

The increase and complexity of data in healthcare means that AI will be increasingly applied in this field (Davenport and Kalakota, 2019). AI applications have great potential in improving healthcare services (Lämmermann *et al.*, 2024). Since AI applications include promising technologies, they will transform the healthcare sector in terms of better diagnosis and treatment in the coming years (Wen and Huang, 2022). For this reason, significant investments need to be made in this process to develop infrastructure and activities (Sjödin *et al.*, 2021). Since it includes technologies that require high investments, it is important to prioritize investments by making plans for the technology and product features of AI applications. In this study, future developments are forecasted in this field.

### 2.2. Technology forecasting

Attempting to predict future trends in technologies is called technology forecasting. Since new technologies always involve risk and uncertainty, technology forecasting is important (Li *et al.*, 2019a). As technology becomes increasingly widespread and important, forecasting future technology trends becomes important (Calleja-Sanz *et al.*, 2020).

Many methods are being developed for technology forecasting (Cho and Daim, 2013). These methods are categorized as qualitative and quantitative (Jun *et al.*, 2012). The Delphi method, also called a judgmental forecasting technique, can be given as an example of qualitative methods (Mitchell, 1992). Quantitative methods involve the examination of historical data (Walk, 2012); for example, support vector clustering (Jun *et al.*, 2012), trend extrapolation (Coates *et al.*, 2001; Tsai *et al.*, 2023), growth models and leading indicators (Coates *et al.*, 2001), etc.

Studies on technology forecasting are briefly presented in Table 1. It is observed that existing studies frequently benefit from patent data. However, both patent data and scientific publications are used within this study. Core forecasting analysis relies exclusively on patent data, while scientific publications are integrated solely within the criterion weighting process in Section 3.5.

Table 1. Summary table of studies related to technology forecasting

| Author(s) (year)                     | Technology                                                   | Method(s)                                                                              |
|--------------------------------------|--------------------------------------------------------------|----------------------------------------------------------------------------------------|
| Choi and Jun (2014)                  | The humanoid robot system technology                         | Bayesian patent clustering methodology                                                 |
| Chang <i>et al.</i> (2014)           | Dental implant technologies                                  | Patent map                                                                             |
| Altuntas and Dereli (2015)           | Telecommunication technology                                 | DEMATEL method and patent citation analysis                                            |
| Noh <i>et al.</i> (2016)             | 5G                                                           | Patent data analysis + Bibliographic coupling + Text mining                            |
| Lim (2018)                           | Liquid Crystal Displays (LCD)                                | Data Envelopment Analysis                                                              |
| Dehghani Madvar <i>et al.</i> (2019) | Biofuel technologies                                         | Patent data analysis + Technology life cycle                                           |
| Kim <i>et al.</i> (2019)             | Wireless power transfer technology                           | Patent data analysis + Time series analysis                                            |
| San Kim and Shon (2020)              | Motor vehicles + Signal transmission and telecommunications. | Link prediction + Semantic analysis + Machine learning algorithms                      |
| Cho <i>et al.</i> (2021)             | Electric motors                                              | Technology convergence with IPC codes                                                  |
| Altuntas and Aba (2022)              | Unmanned aerial vehicle technologies                         | Hierarchical S-curves                                                                  |
| Kwon <i>et al.</i> (2022)            | Logistics technology                                         | Topic modeling + Trend analysis + Network analysis + Technology Level Map + Patent map |
| Yang <i>et al.</i> (2023)            | Green hydrogen technology                                    | Patent analysis + Network analysis                                                     |

| Author(s) (year)              | Technology                                      | Method(s)                                                                     |
|-------------------------------|-------------------------------------------------|-------------------------------------------------------------------------------|
| Feng <i>et al.</i> (2024)     | Green technologies in the construction industry | Knowledge network + Bibliometrics + Semantics analysis                        |
| Forestal <i>et al.</i> (2024) | Nanotechnology                                  | Patent maps + Bibliometric analysis                                           |
| Hu <i>et al.</i> (2024)       | The new energy vehicle technologies             | The Vector Autoregression (VAR) model                                         |
| Zhao <i>et al.</i> (2024)     | Pharmaceutical technology                       | Subject-Action-Object (SAO) structures + Link prediction + Multilayer network |

### 2.3. Criteria

Scientific publications that make technology forecasting using performance indicators/criteria are summarized in Table 2. It is seen that criteria are often created based on structured data from patents/academic publications.

Table 2. Summary table of studies related to technology forecasting by criteria

| Author(s) (year)                | Metrics/criteria they use in their studies                                                                                                                                                                                                                            |                                                                                             |
|---------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|
| Bengisu and Nekhili (2006)      | Number of patents and scientific publication citations (Gompertz and logistic growth models)                                                                                                                                                                          |                                                                                             |
| Altuntas <i>et al.</i> (2015)   | Comparing the success of technologies according to the following 3 metrics;<br>- Technology diffusion speed,<br>- Patent power,<br>- Expansion potential                                                                                                              |                                                                                             |
| Park and Moon (2017)            | Development in the number of publications and patents in the relevant field (Fisher-Pry and Gompertz models)                                                                                                                                                          |                                                                                             |
| Kim and Bae (2017)              | - Forward citations,<br>- Triadic patent families,<br>- Claims                                                                                                                                                                                                        |                                                                                             |
| Cho <i>et al.</i> (2018)        | Trend analysis, Object-Solution (OS) matrix analysis:<br>- Patent family size,<br>- Patent citations,<br>- Patent application numbers                                                                                                                                 |                                                                                             |
| Kim and Ju (2019)               | Prioritization of technologies according to PBS (Potential Boundary Spanner) features                                                                                                                                                                                 |                                                                                             |
| Li <i>et al.</i> (2019a)        | Technology forecasting is done by collecting patent documents and scientific papers in the relevant field and obtaining the following metrics using Social Network Analysis;                                                                                          |                                                                                             |
|                                 | - Average degree,<br>- Density,<br>- H-Index,<br>- Degree of centralization,<br>- Connectedness,                                                                                                                                                                      | - Average distance,<br>- Diameter,<br>- Compactness,<br>- Efficiency,<br>- Scaling exponent |
| Li <i>et al.</i> (2019b)        | Collecting patent documents and scientific papers in the relevant field and clustering them according to topics and determining the time lag between the years in which the topics were included in the past, as well as forecasting their inclusion in future years. |                                                                                             |
| Erzurumlu and Pachamanoa (2020) | The following evaluation headings were applied to the topics extracted by topic modeling with patents in the relevant field:<br>- Expert opinions,<br>- CPC codes,<br>- Commercial applicability                                                                      |                                                                                             |
| Ghaffari <i>et al.</i> (2023)   | Current status and growth rate of patent activity trend                                                                                                                                                                                                               |                                                                                             |
| Aminullah (2024)                | Examining the economic growth of technologies in the relevant field (before and after the pandemic)                                                                                                                                                                   |                                                                                             |
| Cai <i>et al.</i> (2024)        | Topic density and patent score                                                                                                                                                                                                                                        |                                                                                             |

It is significant that current technology forecast indicators are based on patents (Chang *et al.*, 2009). Because the inputs of the forecasting method are available and accessible, it will ensure that the method can be carried out easily (Altuntas *et al.*, 2015). Similarly, since patent data is open to public use and free of charge, patent data is used in our study. There are different types of indicators regarding patent data, such as citations, patent age, IPC codes and claims (Altuntas *et al.*, 2015).

Patent citation information enables information flows into and out of organizations (Suh and Jeon, 2019). According to Chang *et al.* (2009), when a patent is cited by subsequent patents, it means that the cited patent is disseminated, implemented and valuable. Furthermore, Huang and Wang (2011) emphasize in their study that technologies can be diffused, and technical knowledge can be transferred by different organizations/countries/companies. Knowledge can be transferred among organizations by means of collaborating. Inspired by these situations, within the scope of our study, the DS indicator (Equation 1), unlike Altuntas *et al.* (2015), discusses the forward citations of the patents made by different applicants. It can be interpreted that the higher the numerical value obtained by the ratio, the higher the diffusion speed.

$$DS = \frac{\sum_{i=1}^n F_i}{A}, \quad (1)$$

where

$i$  : the individual patent index ( $i = 1, 2, \dots, n$ )

$n$  : the total number of patents within the given cluster

$F_i$  : the number of different applicants in the forward citations

$A$  : the number of forward citations

Another indicator related to patent data is IPC codes. The number of different IPC codes that patents have demonstrates the expansion potential, meaning that the technologies contained in the patents are associated with a large number of different technologies (Altuntas *et al.*, 2015). The reason for considering subclasses of IPC codes in the PP criterion (Equation 2) within the scope of this study is to evaluate whether the technologies are widespread across different sectors/areas. With the numerical value obtained through the ratio, patents covering different technical fields can be handled. Within the scope of the study, the higher this ratio is, the more valuable patents are covered. The criteria suggested within the scope of the approach are applied to all clusters obtained as a result of clustering.

$$PP = \frac{\sum_{i=1}^n IPC_i}{T}, \quad (2)$$

where

$IPC_i$  : The number of IPC codes for  $i^{\text{th}}$  patent

$T$  : The total number of patents within the given cluster

## 2.4. Text mining and clustering

According to Madani and Weber (2016), it is stated that text mining is used to extract useful information and textual patterns from technical documents, especially patents. Text mining performs information discovery by placing labels on each document based on keywords that stand out from unstructured texts (such as claims, abstracts) (Yoon and Park, 2004). The output of text mining is clusters consisting of groups of documents that are similar to each other according to a certain threshold value (Fattori *et al.*, 2003). Patent clustering is carried out in order to determine dominant technologies, forecast future technological trends, detect patent violations and identify technological vacuum points (Wodehouse *et al.*, 2017).

Including patents with similar features in the same group reduces the complexity of the dataset. Documents with similar terms are identified using some similarity measurements (Yang and Watada, 2011). Similarity measurements (metrics such as Cosine, Edice, Ejaccard) are used to create the similarity matrix of the documents. Jaccard similarity measurement is applied within this study. The clustering in the proposed approach is performed using the similarity matrix of the texts. Since data clustering can be done with SNA (Yu, 2007; Singh *et al.*, 2016), clustering is first performed through SNA. Centrality and clustering coefficient are used to meaningfully explain the connection between nodes (Basfirinci, 2016). The clustering coefficient takes a value between 0 and 1 (Li *et al.*, 2017). Link prediction is considered as a binary classifier, where each pair of nodes can be 0 or 1; A value of 0 indicates that there is no relationship between the neighbors of a node, while a value of 1 indicates that the neighbors of the node have formed a complete connection (Zalaghi, 2015). Accordingly, if the nodes are fully connected with their neighboring nodes, meaningful results cannot be obtained.

When it is not known which group the data belongs to before the cluster analysis, the cluster analysis performed with machine learning is known as the unsupervised learning method (Bulut, 2023). In this case, secondly, the hierarchical clustering method is applied under unsupervised learning methods for unlabeled data (Li *et al.*, 2022). Additionally, due to

the computational costs in large data sets, the most efficient method for unlabeled data is the hierarchical clustering method (Bouguettaya *et al.*, 2015).

## 2.5. Text mining and the degrees of importance of criteria

It is emphasized in the literature that the criteria may have degrees of importance and that the criteria can be weighted accordingly (Yuan and Cai, 2021; Ersoy, 2022). In Yuan and Cai (2021), which weights the criteria, the entropy, one of the objective criteria weighting methods, is used.

As can be seen in the presented literature review, studies on calculating the degree of importance of the criteria and their weighting are rarely carried out. In addition, in studies on technology forecasting based on criteria, the number of studies weighting the criteria is very limited. Also, an approach based on the use of text mining methods in creating the degree of importance is not recommended.

This study is inspired by Jin *et al.* (2015) to find the degree of importance of the criteria. They aim to prepare a technology-driven roadmap based on quantitative methods to find new product/market opportunities. For this purpose, they associate it with the Quality Function Deployment (QFD) methodology; keywords are extracted from 15 products and 14 patents, and these keywords are placed in the matrices. The frequencies of the keywords and the similarity measurements of the documents are multiplied (Jin *et al.*, 2015).

In this study, keyword metrics and document similarity analysis were used in combination to go beyond raw linguistic word counts in determining strategic decision weights for technology roadmaps. The strategic weights obtained within this text mining framework represent the structural information density of technology clusters within the academic whole and the proximity of documents, going beyond simple frequencies.

Selecting the abstracts of scientific publications as a dataset for corporate technology investments allows firms to simultaneously track the most current scientific and technological developments that have not yet been reflected in the commercial market and industry. Publication and patent activity in academic literature is a leading indicator of products that will be commercialized in the future. Therefore, the frequency and similarity analysis-based weighting performed on this dataset directly functions as a current trend tracking mechanism in firms' R&D and investment decisions.

Methodologically, the use of document similarity values obtained in this way serves as an objective and data-driven alternative to traditional Multi-Criteria Decision Making (MCDM) methods such as AHP or Delphi. While traditional MCDM tools rely on subjective expert opinions and surveys to map relationships between criteria, making them susceptible to cognitive biases, this study mathematically extracts these relationships directly from the collective and current knowledge base of the literature. This ensures that the final roadmap weights reflect an unbiased and dynamic synthesis of global technology trends, aiming to avoid subjective errors stemming from human factors.

## 2.6. Technology roadmap

TRM is a long-term strategic planning tool that can be prepared at the firm, sector and national level (Ding and Hernandez, 2023). According to Willyard and McCless (1987), Motorola's purpose in using TRM is to focus on a single technology and use TRM to forecast the progress of this technology, in addition to evaluating its own capabilities and comparing these capabilities with its competitors, both today and in the future. TRM is one of the easily applied methods for technology forecasting (Cho *et al.*, 2014). In addition, with the help of TRM, the development of new applications in the sector can be demonstrated (Lu *et al.*, 2023).

As a result of the systematic literature review carried out by Ding and Hernandez (2023), considering 79 studies, it is seen that the manufacturing sector and energy and renewable resources are the leading areas where TRM is frequently built. Only 5% of these 79 TRMs are in the field of "Health and Biotechnology". It is observed that there are few TRMs prepared in the field of health. Additionally, in another study, Wang and Lin (2023), it is observed that the time axis of the TRM prepared in the field of health included past periods. Huang and Lee (2024) proposed a network-based method for constructing a technology roadmap.

TRM should be prepared in the future time horizon (Phaal *et al.*, 2004). Due to the few numbers of TRMs prepared in the health sector and the fact that existing studies do not reflect the future time horizon, within this study, the future trends of AI applications in health services are estimated, and the product needs of the technologies, market trends and relationships are presented in the TRM. The TRM presented is based on the Market, Product features and Technology enablers layers in the TRM format used by Kulshrestha and Daim (2021).

Within the scope of the study, time axes named short (0-2 years), medium (3-5 years) and long term (+6 years) are determined in order to prepare the TRM with a future vision. To determine the elements/drivers to be included under these axes, the emergingness and trend information of the most promising cluster obtained in our study is considered. These two parameters are used in Lee *et al.* (2018) to detect new product/market opportunities. The aforementioned two parameters are

evaluated separately for 3 different time axes of TRM in this study. These values facilitate decision-making in short-medium-long term technology planning (Lee *et al.*, 2018), considering the application years of the patents to which the relevant patents receive forward citations. For example, for the short-term, forward citation values of 0-2 years are considered.

Lee *et al.* (2018) explain what the factors in Equation (3-4) mean in their study.  $Emergingness_t$  is the weighted sum of the number of patents in value categories issued in time  $t$  in Equation (3), and also  $trend_{t,\Delta t}$  measures the increasing and decreasing rate of a technology's emergingness in Equation (4). If the values of these two indicators (emergingness and trend) for a subject technology are greater than those of another period, the subject technology is emerging in the present, and this trend will deepen in the future. In this study,  $w_i$  means the weight of the citation value of  $i$ . patent,  $(PC)_i$  means the value of  $i$ . patent,  $i$  means the total number of patents in the cluster. The weight of the patent is determined by the number of citations the patent has received in the relevant period, and the patent value is determined by the number of IPC codes. In Equation (4), the change in the emergingness value over time is taken as the basis.

$$Emergingness_t = N * \sum_{i=1}^N w_i * (PC)_i, \quad (3)$$

$$trend_{t,\Delta t} = \frac{emergingness_{t+\Delta t} - emergingness_t}{\Delta t}. \quad (4)$$

### 3. RESEARCH DESIGN AND METHODOLOGY

This study revises the method proposed by Altuntas *et al.* (2015) and Yuan and Cai (2021) to forecast technology success/trend in three aspects. According to Lee *et al.* (2010), patent citation knowledge spillover analyzes the diffusion process of a specific firm's patent to other firms or industries. So, first, the DS criterion is established in this study. Second, the subclass IPC classifications are used in this study. Previous studies use the four-digit IPC codes, so they need to establish an extra criterion (the expansion potential criterion) to examine the types of IPCs. However, in this study, there is no need to create extra criteria because different IPC code numbers are measured by subclasses of IPCs. Third, to evaluate multiple technologies, a cluster-based study is conducted in the proposed approach. Text documents that are similar to each other are in the same group; that is, they are clustered (Al-Anazi *et al.*, 2016). For this reason, patents are clustered to work with a compact data set. The proposed approach is explained in Figure 1.

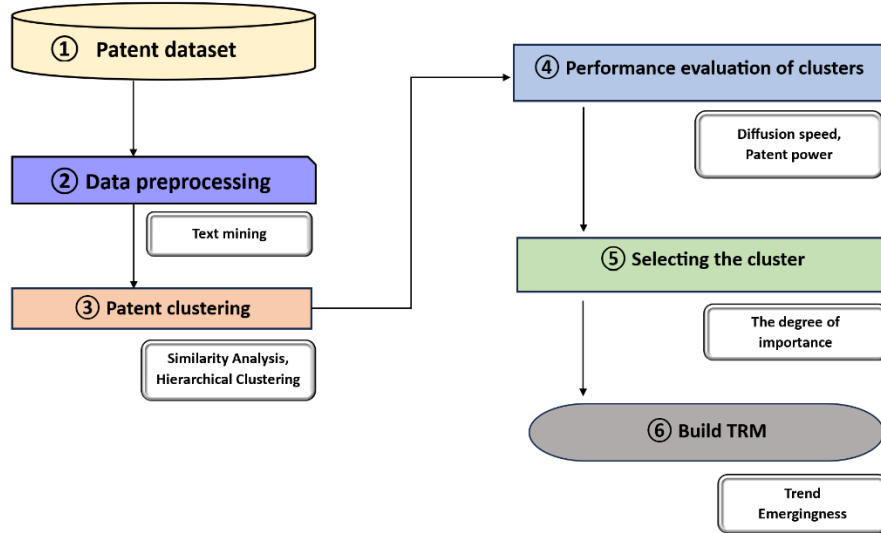


Figure 1. The proposed approach

By accessing the patent data, the patent abstracts are preprocessed for text mining. Since patent abstracts consist of sentences, the aim of the preprocessing is to remove prepositions and stopwords, punctuation marks, and numerical values from the dataset (Yan *et al.*, 2022). Patents are clustered. In addition, since it is anticipated that different criteria will provide different results when evaluating the clusters, the degree of importance of each criterion is calculated. The degrees of importance of the criteria, inspired by Jin *et al.* (2015), are measured. For weighting criteria, the scientific publications working on patent-based technology forecasting are accessed through WoS. These publications are grouped according to the

input parameters of the criteria in this study. Input parameters are considered as keywords; accordingly, the frequencies of the relevant keywords in each group and the similarity values of the publications (according to their abstracts) and adding the multiplied values. In this way, the most promising cluster is determined. Finally, the elements/drivers belonging to the “Market”, “Product” and “Technology” layers of TRM are obtained in the most promising cluster. To place the elements/drivers on the time axis of TRM under the short-, medium-, and long-term columns, the formulations of the “emergingness” and “trend” values are inspired by Lee *et al.* (2018).

### 3.1. Patent dataset

The search queries used to access patents on AI technologies and applications in the field of healthcare are shown in Table 3. The search queries are taken from Benjamins *et al.* (2023). They found 10,967 patents between January 2012 and July 2022 in their study. 7,332 of these patents (66.9%) were obtained from the Chinese Patent Office, 191 (1.7%) were obtained from the European Patent Office (EPO), and the remaining patents were obtained from the Japanese Patent Office (1.5%), the Korean Patent Office (4.7%) and the USPTO (25.2%), respectively. Within the scope of the study, 356 patents were obtained by filtering patent documents with “Active” as patent status, “EPO” as patent registration institution, “English” as patent language and patents with forward citation value (cited by value>0) according to the date range specified in the patent application dates filter. A notable temporal limitation of our filtering framework is that explicitly excluding patents with zero forward citations systematically eliminates very recently published, cutting-edge innovations that have not yet had sufficient time to accumulate citations. Given that these newly emerging patents often contain critical indicators for immediate technological shifts, their omission may introduce a conservative bias or partially restrict the roadmap’s short-term forecasting accuracy.

In order to verify all the information for 356 patents, the patents are checked with their application numbers from Espacenet.

Table 3. Search Strategies and Explanations for AI Applications in Healthcare

| Search Strategies        | Explanations                                                                                                                                                       |
|--------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Patent Access Platform   | lens.org ( <a href="https://www.lens.org/">https://www.lens.org/</a> )                                                                                             |
| Patent Application Dates | 01/01/2003-12/31/2023                                                                                                                                              |
| Patent Office            | European Patent Office                                                                                                                                             |
| Patent Status            | Active                                                                                                                                                             |
| Forward Citation Status  | Yes                                                                                                                                                                |
| Search Queries           | ((deep learning) OR (machine learning) OR (deep neural networks) OR (artificial intelligence)) AND ((medical) OR (medicine) OR (healthcare) OR (health) OR (G06N)) |

According to Ernst (1997), the S-curve is used to see the growth potential of patents. To evaluate the technological lifecycle and growth dynamics of the studied system, a logistic growth model was fitted to the cumulative data. It is known that the axes of the S-curve show the cumulative R&D expenditures over time (Krubasik, 1982, as cited in Ernst, 1997) or the cumulative number of patent applications over time (Ernst, 1997). In this study, the S-curve is created via the LogletLab platform according to the cumulative patent application numbers over time and is presented in Figure 2. According to the explanation of Urbina-Suarez *et al.* (2024), K, r and  $t_m$  are model parameters that define the saturation value of the system in terms of the number of publications, the speed or growth rate and the time interval, respectively. In our study, these values are considered according to the number of patents. The K parameter, which is one of the statistical values of the S-curve, is evaluated as the carrying capacity and the maximum limit point in the applied data is shown on the graph. It is interpreted that the higher the r value, the higher the growth rate will be (<https://logletlab.com/>). The statistical results of this analysis, corresponding to the S-curve in Figure 2, indicate an exceptionally strong fit with a coefficient of determination ( $R^2$ ) of 0.981 and a highly significant p-value ( $p = 2.33 \times 10^{-14}$ ). The model estimates the saturation limit (K) of this technology phase as 408 units, with a growth rate parameter (r) of 0.323. The inflection point ( $t_m$ ), which represents the time of maximum growth rate where the technology transitions from acceleration to deceleration, is identified as the year 2013. The model's projection stages demonstrate that the technology reached 1% of its potential in 1999, progressed to 10% in 2006, passed the midpoint (50%) in 2013, and reached the 90% maturity level in 2020. It is estimated to reach 99% saturation by 2027. The low error metrics, including a Mean Absolute Percentage Error (MAPE) of 0.0673 (6.73%) and a Standard Error (SE) of 7.93, further confirm the high predictive accuracy and robustness of the fitted S-curve. If the r value in Figure 2 were smaller than specified, a graph with a flatter S shape could be seen. It is known that a parameter indicates where the data starts; that is, it expresses the initial population size of the data set. In addition to the error margins for the accuracy of the model, the fact that the  $R^2$

value is more than 90% indicates that the model established through LogletLab has a high accuracy rate (Urbina-Suarez *et al.*, 2024).

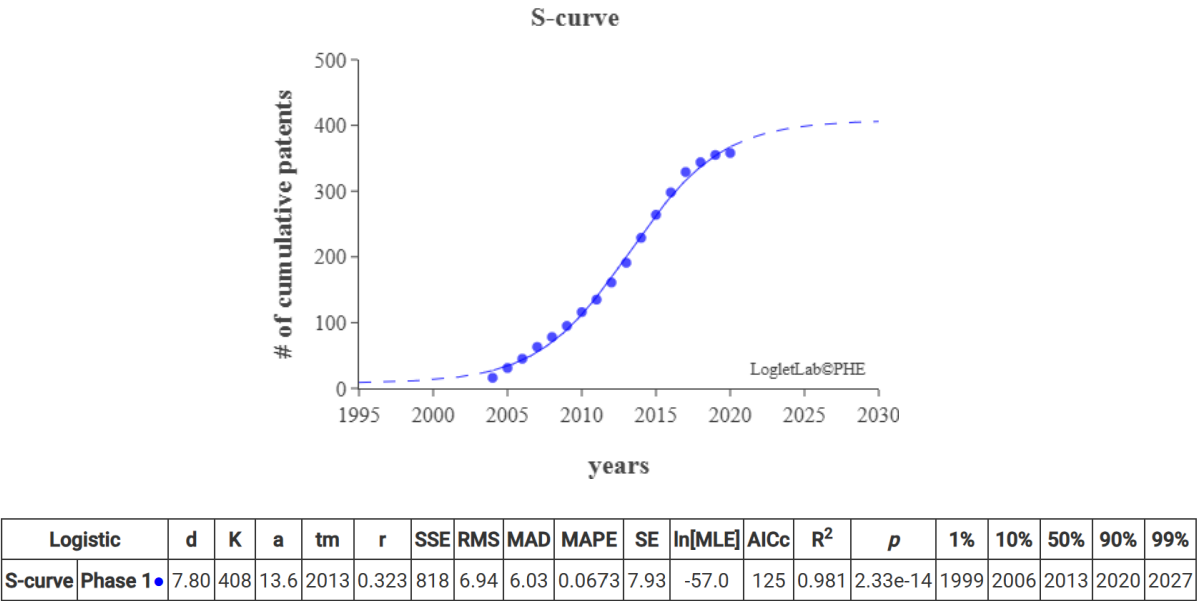


Figure 2. S-curve of Patents for AI Applications in Healthcare

The S-curve analysis (Figure 2) provides the empirical baseline for the overall context of the TRM. The accelerating growth trajectory confirmed by the curve statistically validates that AI applications in healthcare are in a highly active expansion phase. This macro-level trend establishes the necessary justification for the subsequent pipeline, ensuring that the individual technological clusters are mapped and evaluated within a dynamic, non-mature innovation window.

3.2. Data preprocessing

The data preprocessing steps required by text mining are applied to the patent abstracts. These steps include removing punctuation marks, numbers, symbols, characters and stopwords from sentences in the abstracts of patents, adjusting case sensitivity and creating word stems. Data preprocessing is implemented through the R programming language.

3.3. Patent clustering

As indicated in Figure 1, similarity matrices of patent documents are created after data preprocessing. The Jaccard Similarity matrix is applied to the patent abstracts through the R programming language. Firstly, SNA is applied to the obtained similarity matrix. The number of clusters suggested by SNA is three. Also, as shown in Figure 3, three clusters are obtained as indicated by the colors. It is observed that no results in accordance with the clustering logic can be obtained from the SNA application. Because the clusters in Figure 3 do not appear to show the most similarity within themselves and the greatest difference between clusters; on the contrary, they appear to be nested. The fact that a cluster seen at the end of the circle in the figure contains only one element supports the fact that a meaningless result is obtained (Altuntas *et al.*, 2020). Also, by comparing two parameters (clustering coefficient and eigenvector centrality) obtained with SNA, it is tested whether the clustering process is meaningful or not. In addition, with the clustering coefficients obtained (1.0 and 0.997325), it is understood that almost all nodes are fully connected to each other and no meaningful results are obtained. Additionally, the eigenvector centrality value is obtained at three different values (1.0; 0.998518; 0.524882). By looking at these values, a central node could not be found, and the nodes with the highest impact on the network could not be determined meaningfully. In other words, in this study, no significant difference could be seen between the network graph and the documents, and no grouping could be made.

To explore underlying technology relationships, SNA was initially applied in Gephi by treating the Jaccard similarity coefficients directly as edge weights in a weighted network. However, SNA produced highly unbalanced groups (including single-element clusters). Consequently, SNA was used strictly for preliminary exploratory visualization and was not employed for the final technology clustering. For this reason, an alternative method is investigated for clustering patents.

Instead, Hierarchical Clustering was adopted to construct balanced and methodologically robust technology clusters. Since the patent dataset included in the analysis does not contain any class information, the Unsupervised Learning technique is preferred for clustering the abstracts of patents according to their similarities. It is concluded that four clusters should be created with the hierarchical clustering method. It is proven that it would be more appropriate to use the hierarchical clustering method within this study, as it works with a large data set with sensitive similarity values, and no meaningful results can be obtained when SNA is applied. The preliminary network-based partitioning attempted via SNA resulted in degenerate clusters where a cluster contained only a single element (patent). In clustering methodology, a single-element cluster is analytically invalid for trend identification and leads to highly misleading conclusions. To prevent this misclassification and ensure that technological clusters represent collective trends rather than isolated documents, the SNA approach was abandoned.

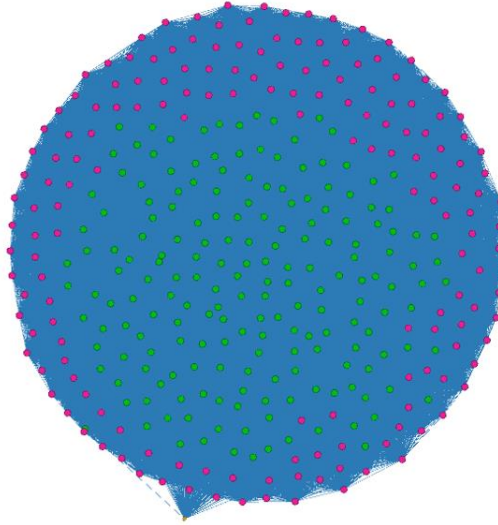


Figure 3. Clustering representation obtained with SNA

To evaluate the quality of the hierarchical clustering solution and assess how well the dendrogram preserves the original pairwise distances of the data, the cophenetic correlation coefficient was calculated. The analysis yielded a cophenetic correlation coefficient of approximately 0.6373. While a coefficient closer to 1.0 indicates perfect preservation, a value of 0.6373 represents a moderate-to-good fit, which is commonly observed and accepted in complex, multidimensional, and qualitative-driven data structures.

### 3.4. Performance evaluation of clusters

The criteria in Equation (1-2) are applied. Firstly, the forward citation counts of the patents in each cluster are obtained and shown in Table 4. The situation where the forward citations of the patents are received from different applicants is explained as follows: for example, it is recorded that 135 forward citations belonging to Cluster 1 are received from 98 different applicants (such as institutions/companies/organizations/universities). Cluster 1 has the highest DS.

Second, the number of patents in each cluster obtained as a result of the clustering process and the number of IPC codes owned by the patents are considered. IPC code numbers are accessed, and the numbers are shown in Table 5. IPC codes are considered according to their subclasses; for example, the patent with application number “EP 14713780 A” has one IPC code (“G06T7/00”). It is concluded that Cluster 1 has the highest PP.

Table 4. Values of DS

| Clusters  | Necessary information for DS                    |                        | DS values (~) |
|-----------|-------------------------------------------------|------------------------|---------------|
|           | # of* different applicants in forward citations | # of forward citations |               |
| Cluster 1 | 98                                              | 135                    | 0,726         |
| Cluster 2 | 167                                             | 244                    | 0,684         |
| Cluster 3 | 71                                              | 115                    | 0,617         |
| Cluster 4 | 137                                             | 331                    | 0,414         |

\*# of means the number of.

Table 5. Values of PP

| Clusters  | Necessary information for PP |              | PP values (~) |
|-----------|------------------------------|--------------|---------------|
|           | # of IPC codes               | # of patents |               |
| Cluster 1 | 324                          | 71           | 4,563         |
| Cluster 2 | 465                          | 132          | 3,523         |
| Cluster 3 | 218                          | 55           | 3,964         |
| Cluster 4 | 335                          | 98           | 3,418         |

### 3.5. The most promising cluster

This section identifies the most promising cluster. Since the criteria produce different results using different inputs, the degrees of importance of the criteria are calculated. It is seen in Section 3.4 that the criteria use different input parameters. For example, the input parameter used within the scope of the DS criterion is the number of forward citations of patents. For this purpose, scientific publications working on patent-based technology forecasting are accessed through the Web of Science (WoS). The accessed publications are grouped according to the input parameters of each criterion. The input parameters for the DS and PP criteria consist of the words citation and IPC code, respectively.

On April 22, 2024, 40 studies on patent-based technology forecasting were accessed through WoS. The criteria we used in our study were not used as input in 15 scientific publications. For this reason, these studies were removed from the dataset. Among the remaining 25 publications, there are 11 publications using citation information, 10 publications using IPC code information, and 4 publications using both citation and IPC code information. Publications that used citation and IPC code information together are added separately to those that used citation information (11 publications) and publications that used IPC code information (10 publications). Accordingly, the number of studies using citation information has increased to 15, and the number of studies using IPC code information has increased to 14.

Two input parameters are considered separately; firstly, the occurrence frequency of the word “citation” in 15 studies using citation information is examined. Then, the cosine similarity matrix of these 15 scientific publications is obtained through the R programming language (see Table 6). As a result, the input parameter "citation" is considered as a keyword, and accordingly, the frequencies of the relevant keywords in each group and the similarity values of the publications (according to their abstracts) are multiplied (Jin *et al.*, 2015). The matrix in Table 6 is presented in a diagonal form for easy review by readers. In the same way, another input parameter is also considered in Table 7. For example, the total value is 77.4 for Document 14 (D14) in Table 7. It is calculated as follows:  $6 * (0.992 + 0.991 + 0.993 + 0.993 + 0.992 + 0.993 + 0.995 + 0.993 + 0.991 + 0.994 + 0.993 + 0.992 + 0.994) \approx 77.4$ .

Table 6. Cosine similarity matrix of publications that use "citation" information

|            | The occurrence frequency | D1 | D2    | D3    | D4    | D5    | D6    | D7    | D8    | D9    | D10   | D11   | D12   | D13   | D14   | D15              | Total   |
|------------|--------------------------|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------------------|---------|
| <b>D1</b>  | 48                       | -  | 0.991 | 0.992 | 0.99  | 0.991 | 0.99  | 0.99  | 0.992 | 0.991 | 0.992 | 0.99  | 0.993 | 0.991 | 0.99  | 0.99             | 665.9   |
| <b>D2</b>  | 9                        |    | -     | 0.993 | 0.99  | 0.993 | 0.993 | 0.992 | 0.994 | 0.993 | 0.995 | 0.99  | 0.99  | 0.991 | 0.993 | 0.991            | 125     |
| <b>D3</b>  | 35                       |    |       | -     | 0.994 | 0.994 | 0.993 | 0.991 | 0.994 | 0.993 | 0.994 | 0.994 | 0.994 | 0.995 | 0.993 | 0.992            | 486.7   |
| <b>D4</b>  | 33                       |    |       |       | -     | 0.992 | 0.991 | 0.989 | 0.992 | 0.991 | 0.992 | 0.992 | 0.992 | 0.993 | 0.991 | 0.99             | 458     |
| <b>D5</b>  | 14                       |    |       |       |       | -     | 0.992 | 0.991 | 0.994 | 0.993 | 0.995 | 0.991 | 0.992 | 0.993 | 0.993 | 0.99             | 194.5   |
| <b>D6</b>  | 108                      |    |       |       |       |       | -     | 0.989 | 0.992 | 0.992 | 0.993 | 0.991 | 0.991 | 0.992 | 0.993 | 0.991            | 1,499.3 |
| <b>D7</b>  | 96                       |    |       |       |       |       |       | -     | 0.993 | 0.992 | 0.992 | 0.989 | 0.989 | 0.99  | 0.99  | 0.988            | 1,331   |
| <b>D8</b>  | 9                        |    |       |       |       |       |       |       | -     | 0.994 | 0.996 | 0.991 | 0.992 | 0.993 | 0.993 | 0.992            | 125.1   |
| <b>D9</b>  | 71                       |    |       |       |       |       |       |       |       | -     | 0.994 | 0.991 | 0.991 | 0.991 | 0.992 | 0.991            | 986.1   |
| <b>D10</b> | 37                       |    |       |       |       |       |       |       |       |       | -     | 0.991 | 0.991 | 0.992 | 0.995 | 0.992            | 514.4   |
| <b>D11</b> | 14                       |    |       |       |       |       |       |       |       |       |       | -     | 0.993 | 0.996 | 0.991 | 0.99             | 194.3   |
| <b>D12</b> | 43                       |    |       |       |       |       |       |       |       |       |       |       | -     | 0.993 | 0.991 | 0.99             | 596.9   |
| <b>D13</b> | 17                       |    |       |       |       |       |       |       |       |       |       |       |       | -     | 0.992 | 0.99             | 236.1   |
| <b>D14</b> | 12                       |    |       |       |       |       |       |       |       |       |       |       |       |       | -     | 0.91             | 165.6   |
| <b>D15</b> | 15                       |    |       |       |       |       |       |       |       |       |       |       |       |       |       | -                | 208     |
|            |                          |    |       |       |       |       |       |       |       |       |       |       |       |       |       | <b>Total (~)</b> | 7,787   |

A mathematical constraint of the document weighting framework lies in the narrow numerical range (0.989–0.996) observed for pairwise cosine similarity values in Tables 6 and 7. This high degree of uniformity implies that the cosine similarity component contributes minimally to differentiating between publications, causing the total document scores to be predominantly governed by keyword frequency metrics (e.g., “citation” or “IPC code”). While this represents a boundary condition on the discriminating power of the criterion weights, future work could address this by adopting alternative similarity metrics to enhance discriminatory capability.

Table 7. Cosine similarity matrix of publications that use "IPC code" information

|            | The occurrence frequency | D1 | D2    | D3    | D4    | D5    | D6    | D7    | D8    | D9    | D10   | D11   | D12   | D13   | D14             | Total   |
|------------|--------------------------|----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----------------|---------|
| <b>D1</b>  | 2                        | -  | 0.995 | 0.992 | 0.994 | 0.993 | 0.992 | 0.993 | 0.993 | 0.992 | 0.994 | 0.994 | 0.993 | 0.993 | 0.992           | 25.8    |
| <b>D2</b>  | 8                        |    | -     | 0.991 | 0.993 | 0.992 | 0.992 | 0.991 | 0.992 | 0.991 | 0.993 | 0.994 | 0.992 | 0.993 | 0.991           | 103.2   |
| <b>D3</b>  | 13                       |    |       | -     | 0.994 | 0.993 | 0.993 | 0.994 | 0.993 | 0.992 | 0.994 | 0.995 | 0.993 | 0.994 | 0.993           | 167.8   |
| <b>D4</b>  | 219                      |    |       |       | -     | 0.995 | 0.994 | 0.994 | 0.994 | 0.994 | 0.996 | 0.995 | 0.995 | 0.995 | 0.993           | 2,830.7 |
| <b>D5</b>  | 70                       |    |       |       |       | -     | 0.993 | 0.993 | 0.994 | 0.993 | 0.995 | 0.995 | 0.994 | 0.995 | 0.992           | 904.1   |
| <b>D6</b>  | 36                       |    |       |       |       |       | -     | 0.993 | 0.994 | 0.992 | 0.994 | 0.994 | 0.993 | 0.994 | 0.993           | 464.7   |
| <b>D7</b>  | 13                       |    |       |       |       |       |       | -     | 0.994 | 0.991 | 0.995 | 0.994 | 0.993 | 0.994 | 0.995           | 167.8   |
| <b>D8</b>  | 5                        |    |       |       |       |       |       |       | -     | 0.994 | 0.995 | 0.995 | 0.995 | 0.995 | 0.993           | 64.6    |
| <b>D9</b>  | 5                        |    |       |       |       |       |       |       |       | -     | 0.994 | 0.995 | 0.996 | 0.995 | 0.991           | 64.5    |
| <b>D10</b> | 27                       |    |       |       |       |       |       |       |       |       | -     | 0.996 | 0.995 | 0.996 | 0.994           | 349.1   |
| <b>D11</b> | 31                       |    |       |       |       |       |       |       |       |       |       | -     | 0.996 | 0.996 | 0.993           | 400.8   |
| <b>D12</b> | 33                       |    |       |       |       |       |       |       |       |       |       |       | -     | 0.995 | 0.992           | 426.4   |
| <b>D13</b> | 7                        |    |       |       |       |       |       |       |       |       |       |       |       | -     | 0.994           | 90.5    |
| <b>D14</b> | 6                        |    |       |       |       |       |       |       |       |       |       |       |       |       | -               | 77.4    |
|            |                          |    |       |       |       |       |       |       |       |       |       |       |       |       | <b>Total(~)</b> | 6,138   |

It is suggested that important elements/drivers should be included on TRM (Bielsky and Daim, 2021). Therefore, a single cluster is determined as the most promising cluster. According to the results obtained in Table 8, the cluster with the highest score is Cluster 1. In this way, the cluster containing the most promising patents is shown on the TRM.

$$T_j = \sum_{m=1}^M W_m * V_{jm}, \quad (9)$$

where

$T_j$ : The total score of  $j^{\text{th}}$  cluster

$M$ : The total number of criteria

$W_m$ : The weight coefficient of  $m^{\text{th}}$  criteria

$V_{jm}$ : The value of  $j^{\text{th}}$  cluster for  $m^{\text{th}}$  criteria

The total value is derived using a weighted sum approach, multiplying the static parameter weights (DS and PP) by the respective cluster-specific values. For example, the total score for Cluster 1 ( $T_1 = 33.65$ ) is explicitly computed based on the new Equation (5) as follows:  $T_1 = (7.787 \times 0.726) + (6.138 \times 4.563) = 5.6533 + 28.0076 = 33.65$ .

Table 8. The result values for clusters

|           | 7,787 | 6,138 | Total |
|-----------|-------|-------|-------|
|           | DS    | PP    |       |
| Cluster 1 | 0.726 | 4.563 | 33,65 |
| Cluster 2 | 0.684 | 3.523 | 26,95 |
| Cluster 3 | 0.617 | 3.964 | 29,13 |
| Cluster 4 | 0.414 | 3.418 | 24,2  |

Although the DS criterion exhibits a higher weighting coefficient (7,787) compared to PP (6,138), this difference is influenced by sample size and keyword frequencies within the underlying document groups. Furthermore, because PP raw values (3.4–4.6) are an order of magnitude larger than DS values (0.41–0.73), the PP criterion exerts a larger actual impact on the final cluster scores in Table 8. Consequently, criteria importance should be interpreted in conjunction with raw value scales rather than sole reliance on weighting coefficients.

### 3.6. Building TRM

To create the time axis of TRM, "emergingness" and "trend" values are obtained according to the forward citation values of the patents in Cluster 1 in the 0-2 years, 3-5 years and +6 years. Equation (3) and Equation (4) are applied to all patents in the cluster for short-, medium-, and long-term. The parameter values that need to be obtained for the application of Equation (3) within the scope of 0-2 years are explained in Table 9. Among the patents in Cluster 1, those with forward citation values within 0-2 years from the date of publication are filtered. In Cluster 1, 7 patents with the value of forward citation with forward citation value greater than zero are found. Similarly, as seen in Tables 10-11, the "emergingness" values are shown for the other time axes of TRM (3-5 years, +6 years, respectively).

Table 9. Emergingness of Cluster 1 for short-term (0-2 years)

| # | Patent Application No | $N$ value | $w_i$ values | $(PC)_i$ values | Total |
|---|-----------------------|-----------|--------------|-----------------|-------|
| 1 | EP 15854012 A         | 7         | 1            | 13              | 91    |
| 2 | EP 10251785 A         |           | 1            | 1               | 7     |
| 3 | EP 16150482 A         |           | 1            | 3               | 21    |
| 4 | EP 16738215 A         |           | 2            | 3               | 42    |
| 5 | EP 17882344 A         |           | 1            | 3               | 21    |
| 6 | EP 18833609 A         |           | 1            | 3               | 21    |
| 7 | EP 17775856 A         |           | 1            | 21              | 147   |
|   |                       |           |              | TOTAL           | 350   |

Table 10. Emergingness of Cluster 1 for medium-term (3-5 years)

| No    | Patent Application No | $N$ values | $w_i$ values | $PC_i$ values | Total |
|-------|-----------------------|------------|--------------|---------------|-------|
| 1     | EP 12150097 A         | 27         | 1            | 1             | 27    |
| 2     | EP 14763789 A         |            | 1            | 14            | 378   |
| 3     | EP 13752166 A         |            | 1            | 2             | 54    |
| 4     | EP 09795990 A         |            | 1            | 1             | 27    |
| 5     | EP 14738672 A         |            | 1            | 4             | 108   |
| 6     | EP 16774765 A         |            | 1            | 1             | 27    |
| 7     | EP 17195826 A         |            | 1            | 8             | 216   |
| 8     | EP 11185225 A         |            | 1            | 5             | 135   |
| 9     | EP 12730419 A         |            | 1            | 1             | 27    |
| 10    | EP 17702561 A         |            | 1            | 5             | 135   |
| 11    | EP 19188893 A         |            | 1            | 4             | 108   |
| 12    | EP 09807801 A         |            | 1            | 5             | 135   |
| 13    | EP 17813586 A         |            | 1            | 7             | 189   |
| 14    | EP 17305475 A         |            | 1            | 3             | 81    |
| 15    | EP 18737430 A         |            | 1            | 1             | 27    |
| 16    | EP 14811421 A         |            | 2            | 4             | 216   |
| 17    | EP 14753949 A         |            | 1            | 4             | 108   |
| 18    | EP 17870742 A         |            | 2            | 5             | 270   |
| 19    | EP 17871692 A         |            | 1            | 13            | 351   |
| 20    | EP 17882344 A         |            | 1            | 3             | 81    |
| 21    | EP 12854522 A         |            | 1            | 4             | 108   |
| 22    | EP 15203108 A         |            | 1            | 13            | 351   |
| 23    | EP 14803880 A         |            | 1            | 3             | 81    |
| 24    | EP 15834564 A         |            | 1            | 8             | 216   |
| 25    | EP 17751246 A         |            | 1            | 2             | 54    |
| 26    | EP 16729146 A         |            | 1            | 5             | 135   |
| 27    | EP 18189288 A         |            | 1            | 2             | 54    |
| TOTAL |                       |            |              |               | 3,699 |

Table 11. Emergingness of Cluster 1 for long-term (+6 years)

| No    | Patent Application No | $N$ value | $w_i$ values | $PC_i$ values | Total  |
|-------|-----------------------|-----------|--------------|---------------|--------|
| 1     | EP 09712991 A         | 43        | 1            | 2             | 86     |
| 2     | EP 07736107 A         |           | 1            | 3             | 129    |
| 3     | EP 04808461 A         |           | 18           | 3             | 2322   |
| 4     | EP 10740837 A         |           | 1            | 8             | 344    |
| 5     | EP 13752166 A         |           | 15           | 2             | 1290   |
| 6     | EP 15854012 A         |           | 1            | 13            | 559    |
| 7     | EP 05706657 A         |           | 1            | 5             | 215    |
| 8     | EP 09750109 A         |           | 2            | 3             | 258    |
| 9     | EP 13811103 A         |           | 1            | 2             | 86     |
| 10    | EP 20151462 A         |           | 1            | 9             | 387    |
| 11    | EP 10251785 A         |           | 1            | 1             | 43     |
| 12    | EP 13706379 A         |           | 1            | 4             | 172    |
| 13    | EP 13749145 A         |           | 4            | 4             | 688    |
| 14    | EP 06815799 A         |           | 8            | 5             | 1720   |
| 15    | EP 06719427 A         |           | 1            | 4             | 172    |
| 16    | EP 07837227 A         |           | 3            | 1             | 129    |
| 17    | EP 14822501 A         |           | 1            | 4             | 172    |
| 18    | EP 12781419 A         |           | 1            | 3             | 129    |
| 19    | EP 09807801 A         |           | 1            | 5             | 215    |
| 20    | EP 16710700 A         |           | 1            | 1             | 43     |
| 21    | EP 12802356 A         |           | 1            | 5             | 215    |
| 22    | EP 17164941 A         |           | 1            | 2             | 86     |
| 23    | EP 14827347 A         |           | 2            | 7             | 602    |
| 24    | EP 13863449 A         |           | 2            | 4             | 344    |
| 25    | EP 05104250 A         |           | 1            | 3             | 129    |
| 26    | EP 15177855 A         |           | 1            | 3             | 129    |
| 27    | EP 08718501 A         |           | 1            | 2             | 86     |
| 28    | EP 11741573 A         |           | 1            | 1             | 43     |
| 29    | EP 12733550 A         |           | 1            | 2             | 86     |
| 30    | EP 10792683 A         |           | 1            | 3             | 129    |
| 31    | EP 14185144 A         |           | 1            | 13            | 559    |
| 32    | EP 15720669 A         |           | 2            | 5             | 430    |
| 33    | EP 11004723 A         |           | 1            | 4             | 172    |
| 34    | EP 11840840 A         |           | 1            | 3             | 129    |
| 35    | EP 12854522 A         |           | 2            | 4             | 344    |
| 36    | EP 13785045 A         |           | 2            | 4             | 344    |
| 37    | EP 13895842 A         |           | 1            | 7             | 301    |
| 38    | EP 18164800 A         |           | 1            | 4             | 172    |
| 39    | EP 13836691 A         |           | 2            | 7             | 602    |
| 40    | EP 09791851 A         |           | 1            | 3             | 129    |
| 41    | EP 20190682 A         |           | 1            | 2             | 86     |
| 42    | EP 08162469 A         |           | 5            | 3             | 645    |
| 43    | EP 13775280 A         |           | 1            | 4             | 172    |
| TOTAL |                       |           |              |               | 15,093 |

Trend values are obtained by applying Equation (4). The trend values are calculated by dividing the difference between the emergingness values of the relevant time axes by the time differences. As seen in Table 12, the value of the +6-year column on the TRM time axis is obtained as  $(15,093 - 3,699)/1 = 11,394$ . The value of the 3- 5-year column on the TRM time axis is obtained as  $(3,699 - 350)/3 = 1,116$ . The 0- 2-year column on the TRM time axis is obtained as  $(350 - 0)/2 = 175$ , since there is no axis before it. The expected result from Table 12 is the placement of the elements/drivers according to the time axes of TRM. Information about a technology's emergingness in the present and in the future can be obtained by

Equation (3) and Equation (4) (Lee *et al.*, 2018). According to Lee *et al.* (2018), if the values of these two indicators for a subject technology or cluster are greater than those of another, the subject technology or cluster is emerging in the present, and this trend is anticipated to deepen in the future. If the value of emergingness is greater than that of another but the value of trend is less than that of another, the subject technology or cluster is emerging in the present, but this trend is anticipated to be lost in the future. For this reason, elements/drivers that develop in the 0-2 year term will only be included in the short-term column. The elements/drivers that will develop in the 3-5 year term will exist in the present and will deepen in the future; therefore, it is concluded that the elements/drivers that will develop in the 3-5 year term should be included in both the short and medium term columns, and the elements/drivers that will develop in the +6 year term should be included in the short, medium and long term columns.

Table 12. Emergingness and trend values for Cluster 1

|              | 0-2 years | 3-5 years | +6 years |
|--------------|-----------|-----------|----------|
| Emergingness | 350       | 3,699     | 15,093   |
| Trend        | 175       | 1,116     | 11,394   |

#### 4. FINDINGS

Within the scope of the study, criteria are applied for forecasting technology success. The criteria use different input parameters and produce different results; their contribution to the analysis process is not the same or not the equal. In order to examine these contributions in the study, the importance levels of the criteria are calculated. TRM is created by examining the patents owned by Cluster 1 because the most promising cluster is Cluster 1. The placement of the time axis on the TRM is based on Table 12. Short-term elements/drivers in the TRM in Figure 4 are highlighted in yellow. Wireless network security and management is an example of a short-term driver. This driver requires a product feature that will be supported by electromagnetic signature analysis. The technology enabler that will meet this product feature is the Internet of Things.

In Figure 4, the block colors are systematically applied across all three layers to represent different strategic time horizons, ensuring high readability and easy tracking. Specifically, elements/drivers operating in the short-term horizon are highlighted in yellow, those in the medium-to-long-term horizon are highlighted in turquoise, and those developing strictly in the long-term are highlighted in green. Additionally, elements/drivers that span a broad time period across the short, medium, and long term are highlighted in pink.

The time dimensions are determined by the horizontal timeline alignment and the width of the boxes, allowing readers to trace the periods regardless of color perception or grayscale printing:

- Yellow elements indicate the short-term horizon, physically positioned within the Year 1 and Year 2 columns.
- Blue elements represent the medium-term horizon, covering the Year 3, 4, and 5 columns.
- Turquoise elements represent the medium-to-long-term horizon, spanning between Years 3 and 6.
- Green elements define the long-term horizon, located in the Year 6 and +6 Years columns.
- Pink elements dynamically span across all-term horizons.

This spatial layout ensures the roadmap remains functional without relying solely on color, which serves as a secondary visual aid.

To reduce tracking ambiguity for the cross-layer paths, we have clearly separated the arrow functions:

- Black arrows represent the Product Feature layer to the Market layer.
- Red arrows map cross-layer paths from the Technology Enabler layer directly to the Market layer. Because these red arrows traverse the intermediate layer, individual Product Features are distinctly numbered, and the red arrows are coded based on the specific numbers they intersect.

In this way, the readability and interpretability of TRM is increased. At the same time, in order to make it easier to follow the arrows, the elements in the Product Features (PF) layer are numbered and shown with black arrows. The red arrows are used to show the relationships between the Technology Enabler layer and the Market layer. While the relationship between the market and technology layer is shown with the red arrows, the required product features are also shown with the numbered expressions on these arrows (for example, PF13). For example, the Technology Enabler (Medical and surgical implant technologies and tele-rehabilitation) required by PF9 (Reducing noise data in the dataset and controls) is carried over the red arrow with the numbered PF9 and brought together with the driver it is associated with in the Market layer (Correcting mis-sized problems).

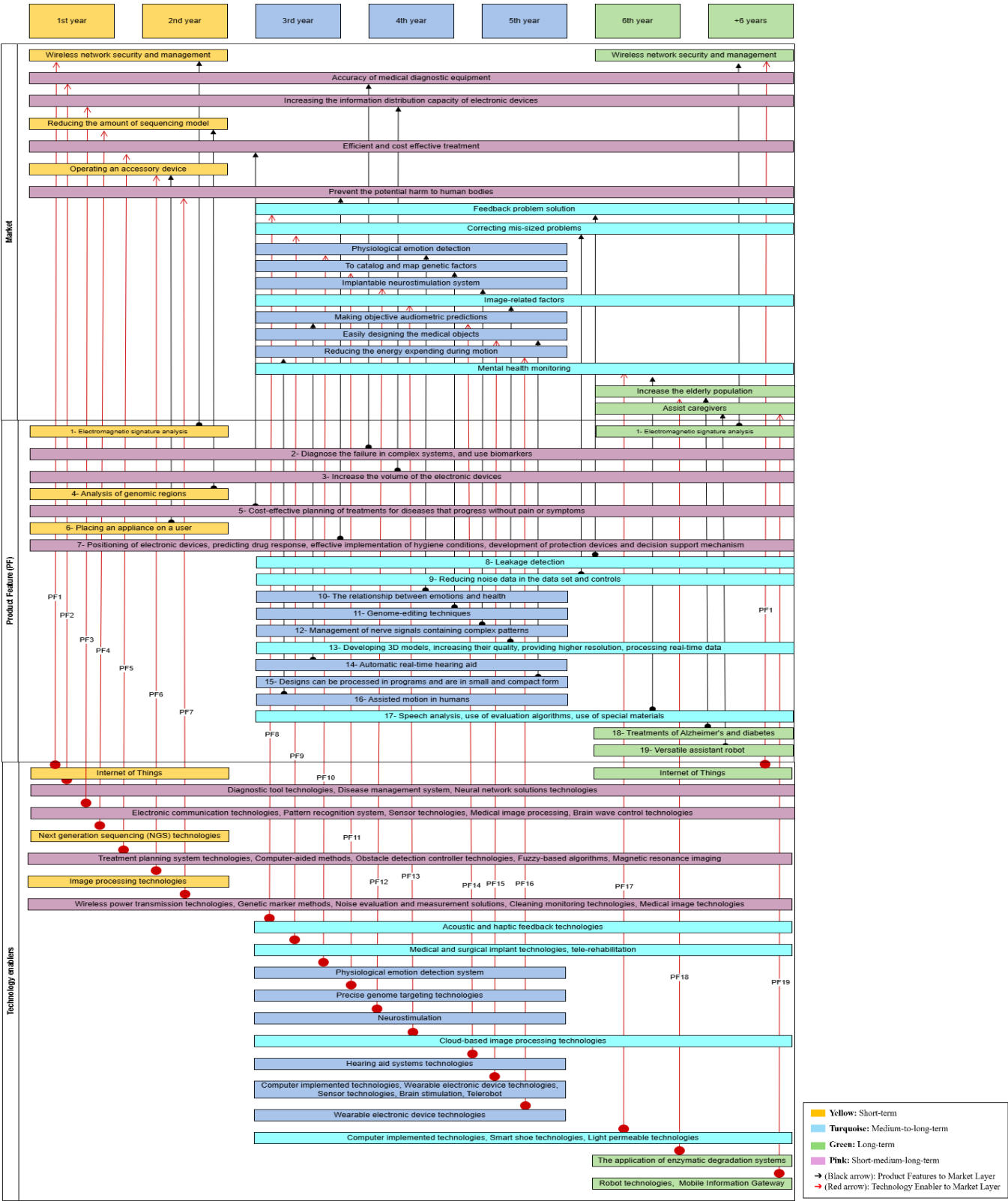


Figure 4. TRM

To construct the structural map in Figure 4, unstructured patent abstracts within Cluster 1 were analyzed through expert qualitative coding. Domain experts conducted a thematic manual evaluation of the text to extract, code, and map the 19 distinct Product Features and their corresponding Technology Enablers based on recurring functional mechanisms.

Thanks to the TRM obtained, it is obvious that the field that will develop in the long term will be Cloud-based image processing technologies. Possible product features that will provide a guiding move in meeting the investment need for image processing technology include developing 3D models, increasing their quality, providing higher resolution and processing real-time data. By examining the patents in Cluster 1, it is predicted that artificial intelligence systems that can improve the early diagnosis process, shorten the diagnosis period, reduce errors, select the appropriate treatment or increase the quality and efficiency of medical imaging; research on medical image processing in digital pathology, especially including pathology and its sub-branches and artificial intelligence-supported cancer screening systems from medical/microscopic images will gain value. Medical imaging and remote sensing processes can be carried out by supporting algorithms such as artificial intelligence and machine learning in the field of medical image processing.

Other promising areas when TRM is examined are diagnostic tool and treatment planning systems technologies, electronic communication tools, acoustic and haptic feedback technologies and robot technologies. In addition, it is anticipated that improving the performance of human physicians in terms of accuracy, speed and cost in diagnosing the types of cancer that are commonly seen today will gain importance. It is also predicted that the number of key players and start-up companies in this field will increase (IDtechex, 2020). Robotic technology will be used to provide patient care, perform surgeries, bring the concept of telemedicine back to the agenda after the COVID period and provide support to healthcare personnel, like human assistants, to carry out diagnosis, treatment and follow-up processes by sending physiological signals between remote centers.

## 5. DISCUSSION

### 5.1. Theoretical Contributions

This study aims to enable the forecasting of technology success based on criteria by considering the knowledge spillover and expansion potential to find potential emerging multiple technologies. The research framework seeks to demonstrate the necessity of establishing the relationships between the market trends, product requirements and technologies for TIDs. This study contributes to academic studies in five ways. First, the criteria created within the scope of the study enable measurements to be made differently from existing studies. Because the knowledge spillover in different organizations is analyzed with the DS criterion, and the PP criterion measures the relevance and expansion potential of technologies in patents to many different technologies. Also, there is no need to establish an extra criterion to measure the expansion potential, as in previous studies, because of using the subclass of IPC codes. Therefore, technology forecasting based on criteria literature is contributed to with these criteria.

Second, the degree of importance of criteria is discussed with a novel approach within the scope of text mining. In rapidly changing market environments, predicting and following technological innovations are important ways to increase the competitiveness of organizations. So, it is important to forecast the future success of technologies in dynamic, complex and unstable conditions. The point that is aimed at being proven within the scope of the analysis is to show that not all criteria have the same importance and do not contribute to the analysis to the same degree.

Third, unlike existing studies, the cluster-based study is performed instead of considering technologies one by one and in limited numbers. The cluster-based studies in the literature are quite few (i.e., Ghaffari *et al.*, 2023). Previous studies consider a certain number of technologies; for example, three technologies are evaluated in Altuntas *et al.* (2015), and four technologies are ranked in Yuan and Cai (2021). Clusters are created from patent data, allowing the evaluation of a larger number of technologies in this study because the development of multiple technologies is coordinated for the health domain.

Fourth, the results of the study are presented with the TRM to provide the opportunity to monitor the change of these evaluations over time. TRM is built according to emerging technology theory in the literature (Conger and Mazey, 2022). The contribution of this study is to the literature on TRM applications developed for emerging technologies to make investment decisions. The market trend/needs, product features and technology enablers can be examined in short-, medium- and long-term terms with the TRM prepared at the end of the proposed approach. For example, it is seen that "wireless network security and management" represents an important need in the health sector; the technical features or functions that AI products should include to meet this need should provide "electromagnetic signature analysis" and finally, the technology enabler that will meet the need of the product features is "Internet of Things". Other drivers that need to be monitored in the long term are the "increase in the elderly population" and the spread of "assist caregivers". The necessity of developing tools for the increasing elderly population, especially "treatments of Alzheimer's and diabetes", is emphasized. In addition, it is concluded that care assistance will accelerate in the future and that this will be achieved with versatile assistant robots and mobile devices that are large enough and flexible enough to enter households.

Finally, previous studies only rank some technologies according to criteria (i.e., Altuntas *et al.*, 2015; Yuan and Cai, 2021). However, an understanding of how to align the technology with market needs/trends and product requirements is very important to find potential emerging technologies before making TIDs to monitor technologies.

Integrating patent data into the formulation of TRMs offers systematic and objective decision support for corporate innovation management. Unlike traditional roadmapping methods that often rely on subjective expert opinions, patent-based TRMs utilize codified, global technological intelligence. From an innovation management perspective, this data-driven approach contributes to several key processes:

1. Technology Intelligence and Forecasting: It maps the evolutionary trajectories of emerging technologies, enabling firms to detect disruptive shifts early and avoid technological obsolescence.
2. R&D Portfolio Management: By identifying unexploited technological areas and crowded domains, firms can optimize their resource allocation and mitigate R&D duplication risks.
3. Strategic Alignment and Competitor Analysis: It bridges the gap between commercial market demands and technical capabilities while monitoring competitors' technological positioning, thereby strengthening the firm's overall intellectual property strategy and open innovation practices.

## 5.2. Practical implications

The benefit of the proposed method is demonstrated on AI applications in healthcare. The health domain is chosen to demonstrate the usefulness of the proposed approach because it involves intensive technology and high costs. Current studies in the field of health are based on the use of a specific technique, device or treatment for a particular disease. Within this study, all AI applications in the field of health are considered from a broad perspective and associated with market trends and product features.

Questions sought to be answered within the scope of the study: (1) Which technologies will develop when, and what is the prioritization among technology clusters? (2) What criteria can be used to measure future technology success? (3) Do these criteria contribute to the process in the same way? By using the proposed method, decision makers, managers, or researchers may find promising technology areas based on the success of technology clusters. In addition, thanks to the TRM, which is the output of the study, people working in the health domain can follow the technological developments that they will encounter and need to implement in their business lives.

Although the effects and alternatives of AI applications in the health sector are becoming more remarkable day by day, studies on the monitoring and management of technologies in this field are quite few. Through this study, a practical TRM application is presented to forecast, track and manage the future success of AI applications. Since it is known that the most important elements/drivers should be included in TRM, TRM is prepared with the cluster of the most promising AI applications. Individuals or institutions that may benefit from the TRM built within the scope of the study are supported to easily and correctly incorporate these developments into their organizations according to the profile of their own organizations. Within the framework of the proposed approach, it is possible to see the future of AI applications in many areas such as health, medicine and patient care, thanks to a comprehensive perspective without ignoring the trends and needs in the market. The findings of the study show that the areas that will develop in the long term are diagnostic tool and treatment planning systems technologies, electronic communication tools, acoustic and haptic feedback technologies and robot technologies.

## 5.3. Limitations and future research directions

This study has some limitations; First, the patent search queries are obtained from a single academic publication. The search queries can be expanded to reach a larger dataset. Second, some filters (date range, patent office, patent status) are applied to the patent documents. These filters can be reduced in future studies. The third limitation of the study is that the occurrence of the frequency of these criteria in academic publications is examined in order to determine the importance levels of the criteria. In order to provide comparative results, expert opinions can be consulted, and evaluation can be made using Multi-Criteria Decision Making methods. However, the point that should be taken into consideration here is that the analysis should not be created using qualitative methods; in other words, evaluations should not be made based solely on expert opinions. Fourth, in addition to using blog pages or specific reports when preparing the Market layer of TRM, documents showing important trends in the market such as expert opinions, sector reports, and whitepapers may also be used.

Further studies may be applicable to technology-intensive industries or applications. The number of criteria affecting technological success can be increased. For example, these criteria can consist of financial indicators that also consider the size of investments made in technologies. In addition, in the studies of Son *et al.* (2012), it is stated that patent vacuum points have development potential. These vacuum points can be considered to forecast technology success. Also, patents that are not included in a certain cluster and have low similarity with other patents, in other words, "outlier patents" (Rodriguez *et*

*al.*, 2016), are more likely to find innovation points and points open to development, so these points can also be considered for the forecasting of technology success. When preparing the TRM in the coming years, it is necessary to consider the needs of the market in detail and to give importance to relying on hybrid methods. The product features that need to be determined for the product feature layer of TRM can be obtained from various documents such as customer reviews, blog pages, and product manuals.

## 6. CONCLUSIONS

This study proposes a novel TRM for forecasting technology success by finding the most promising cluster. Although a substantial body of literature exists on technology forecasting, this study provides a unique contribution by establishing and weighting criteria as a cluster-based study. The obtained results extend both TRM applications and the literature of future technology success forecasting and contribute to how organizations will make decisions about technology investment for short-medium-long term. Thanks to this study, AI applications in the healthcare field are established in the generally accepted TRM format (as stated in EIRMA, 1997) by associating them with both market trends and product features in the future time horizon. In order to prove the reliability and accuracy of the obtained TRM, the results presented in studies working in the similar field (for example, Bajwa *et al.* (2021) and Deloitte (2019) studies) are compared with the TRM within this study and the findings of this research framework are proven to be largely supported.

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