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Assessing Interdisciplinary Research Within an Emerging Technology Network: A Novel Approach Based on Patents in the Field of Bioplastics

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***Abstract*—Interdisciplinary research is an increasingly crucial source of emerging technologies like artificial intelligence, or bioplastics with the potential to alleviate the grand challenges of the 21st century. Nonetheless, assessing the degree of interdisciplinary research and resulting emerging technology networks remains somewhat ambiguous, as integrating and recombining knowledge from distant domains is a complex phenomenon. By drawing upon patents, patent citations, and their technology classification, this article seeks to elucidate how interdisciplinary research can be assessed, monitored, and visualized by taking technological knowledge areas as the unit of analysis. For our novel approach, we employ the case of bioplastics as an example of an emerging technology within the highly interdisciplinary Bioeconomy. We demonstrate, inter alia, how the importance of interdisciplinarity across technological knowledge areas has increased over time in the case of bioplastics, how different technological knowledge areas link up to form an emerging technology network, and, more generally, how this novel approach can help scientific and industrial actors to guide and plan their interdisciplinary research in emerging technologies. With regard to policy-makers, our novel operationalization of interdisciplinarity provides guidance for developing and monitoring the impact of science and innovation policies that are able to foster interdisciplinary research and emerging technologies.**

***Index Terms*—Bioeconomy, emerging technologies, interdisciplinary research, patents.**

I. Introduction

INTERDISCIPLINARY research (IDR) is an increasingly crucial source of emerging technologies, innovations, and science-based ventures [1]–[4]. Most scholars agree that IDR can be conceptualized as research that integrates two or more bodies of specialized knowledge or research practices [5], [6]. Greater appreciation of the relevance of IDR for scientific and industrial actors is triggered by the empirical observation that the most impactful technological innovations often emerge from the integration of diverse knowledge areas [7]–[11]. Accordingly, IDR has gained tremendous interest from science policy-makers given its potential to alleviate the grand challenges of the 21st century, such as climate change [1], [12], [13]. Prominent examples of IDR with the potential to foster the emergence of novel technologies include bioinformatics, nanobiotech, nutrigenomics, artificial intelligence, or bioplastics, all of which are emerging between two or more knowledge areas [12], [14]–[17]. All these examples represent, and, thus, demonstrate, the need to pay closer attention to developments at the integration of two or more knowledge areas.

However, the assessment of emerging technologies from IDR is a complex phenomenon, which presents numerous challenges for scientific and industrial actors as well as (science) policy-makers [14], [18], [19]. Amongst others, one challenge is to understand the interdisciplinary degree of the involved technological knowledge areas as well as how interlinkages between these areas link up to form an emerging technology network [7], [11], [19], [20].

Evaluating the interdisciplinary character of the involved technological knowledge areas, and the underlying technology network of emerging technologies, is pivotal during the highly uncertain and ambiguous early phase of emergence [14], [18]. Thus, a novel operational approach for *assessing*, *monitoring,* and *visualizing* the emergence of technology networks formed by IDR appears especially desirable for scientific and industrial actors. Such approaches have the potential to facilitate and direct learning processes for actors involved in the development of emerging technologies, by identifying which of the diverse knowledge areas are relevant and providing insight on how to manage knowledge integration across boundaries [19], [20].

Yet, despite the potential for better assessment and its increasing relevancy, measures and indicators that can both evaluate diverse technological knowledge areas and help to monitor their emerging connections in the form of novel technology networks—the basis of emerging technologies—are still lacking in literature. Thus, this article proposes a novel approach that alleviates the ambiguities associated with emerging technologies, by specifically enabling scientific and industrial actors as well as (science) policy-makers to better *assess* the interdisciplinary nature of technological knowledge areas that form emerging technologies, *monitor* the respective processes and outcomes,

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and identify and *visualize* central as well as key bridging technological knowledge areas for the development of emerging technologies.

To this end, we draw upon patents, patent citations, and patent classification codes as proxies used for the development of indicators enabling assessing, monitoring, and visualizing the emergence of a novel technology network. We chose bioplastics as an emerging technology resulting from IDR for a number of reasons. First, bioplastics (i.e., plastics resulting from renewable and biological resources) represent a prominent case of the so-called knowledge-based Bioeconomy [21], [22], and one requiring the integration of technological knowledge from multiple areas like chemistry, biology, or materials science. Thus, we expect a large amount of interlinkages among different technological knowledge areas [23], [24]. Second, we highlight bioplastics as an example of an emerging technology resulting from IDR that has the potential to alleviate the grand challenges such as climate change. Third, we expect that this emerging technology also lends itself to our approach given the increasing patenting activity. In this way, bioplastics offers an initial case to validate our approach before, ultimately, applying it to other emerging technologies where IDR plays a crucial role.

II. Foundations of Emerging technologies: Interdisciplinary Research, Technology Knowledge areas, and Emerging Technology Networks

The integration and recombination of various scientific and technological knowledge fields within IDR often lead to the emergence of new technologies [7], [11], [19], [20]. According to Rotolo *et al.* [14], five attributes qualify a technology as an emerging technology, namely 1) radical novelty, 2) relatively fast growth, 3) coherence, 4) prominent impact, and 5) uncertainty and ambiguity. Understanding the developments of emerging technologies and thereby reducing 5) the involved uncertainty and ambiguity is of key interest for a broad range of actors [25]. More precisely, one particular challenge is the identification of the origins of emerging technologies [14], [18]. In this regard, Rotolo *et al.* [14] provided an overview of methods and frameworks for operationalizing emerging technologies, which can be grouped into five main categories: 1) indicators and trend analysis, 2) citation analysis, 3) coword analysis, 4) overlay mapping, and 5) hybrid approaches (combination of two or more of the above). To this end, various data sources can be used for the assessment of emerging technologies, such as publications or patent data [26], [27].

Moreover, Burmaoglu *et al.* [18] carried out an extensive review of the concept of technology emergence from the viewpoint of the philosophy of science and complexity. Accordingly, Burmaoglu *et al.* [18] examined the concept of technology emergence from three different theoretical backgrounds: philosophy of science, complexity theory, and evolutionary economics [18]. Through this extensive review, five aspects characterize technological emergence, namely 1) qualitative novelty, 2) qualitative synergistic, 3) irregular trend, 4) high functionality, and 5) continuity. Burmaoglu *et al.* [18] focused on understanding the individual technology in microstate (microperspective) [18], while Rotolo *et al.*, 2015 focused on understanding emerging technologies from a macroperspective, when different technological areas are combined in one field [14].

The focus of existing studies is mainly on detecting rather than on characterizing emerging technologies [14], [18], [26]. In addition, we see a particular challenge for the assessment (as well as monitoring and visualization) of emerging technologies resulting from IDR, as such a task requires the identification of the combined technological knowledge areas, i.e., the underlying technology network forming the bases of emerging technologies. Accordingly, this article seeks to complement existing approaches by focusing on the involved technological knowledge areas that form a technology network. While assessing the emerging technology network, actors are enabled to better understand the development of the emerging technology, enhance their awareness of the relevant technological knowledge areas, and more efficiently anticipate the future impact of the emerging technology on an organization's current knowledge base. More precisely, such an assessment supports the learning capacity of the involved actors by enabling them to timely become aware of knowledge gaps and identify partners with complementary knowledge at an earlier stage [19].

In what follows, we use the term IDR[1] from a technological innovation perspective, defined as the integration of knowledge from two or more areas [3], [5]. Thus, along with its empirical relevancy—that technological innovations often arise from the integration of diverse knowledge areas [7], [9], [11], [19], [20]—IDR is also increasingly receiving attention from management scholars [6], [17], [28]–[30]. The concepts of IDR and technology convergence are related, the first refers to a rather temporary interdisciplinary action and not necessarily reflecting a long-lasting convergence process [31], whereas technology convergence or technology fusion describe a type of phenomenon that leads to novel (merged) functions by combining at least two or more existing technologies into hybrid technologies [32], [33]. This article does not analyze the subsequent convergence process, but it aims at characterizing emerging technologies resulting from IDR. The evolving research stream on IDR has examined the more general features of interdisciplinarity, including the particularities of IDR, such as resource complementarity [17] or its potential disadvantages with regard to, e.g., peer-review evaluations, which tend to favor disciplinary excellence [34]. Moreover, as IDR is becoming more significant, there is growing appreciation of the need to manage and facilitate knowledge integration, especially between and among the diverse actors aiming to leverage the insights of IDR [9], [19], [35].

Hence, we consider knowledge integration as a crucial process within IDR in order for scientific and industrial actors as well as (science) policy-makers to benefit from the newly combined and subsequently integrated areas of hitherto distant areas of

[1]Recent studies suggest closely connected concepts for IDR and collaborations, such as multidisciplinary or transdisciplinary. The concept of multidisciplinary is defined as collaboration with a low degree of integration across disciplines or knowledge (Klein, 2008), transdisciplinary is defined as collaboration between not only disciplines but also integrating nonscientific actors (Klein, 2008).

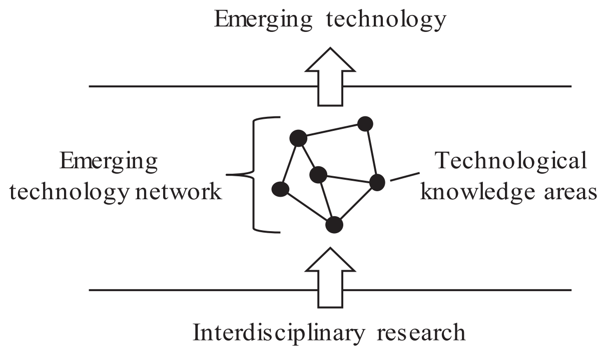

Fig. 1. IDR integrates technological knowledge areas that form a technology network and results in an emerging technology.

knowledge [7], [9], [19]. Here, we follow the definition of Tell *et al.* [19], who describe knowledge integration as the *"coordination and recombination of knowledge from different individuals, disciplines, technologies, and functions"* [19, p. 6]. Additionally, since *"knowledge integration is not only a process of combining and fusing different knowledge bases but also a process of creating new knowledge needed for this integration to succeed"* [36, p. 7], we consider knowledge recombination [7], [9], [37] as a synonym for knowledge integration within the context of IDR. To sum up, knowledge integration within IDR leads to interlinkages between diverse knowledge areas, which, as a result, form a technology network building the foundation of an emerging technology.

As depicted in Fig. 1, we conceptualize an emerging technology network with regard to the interlinkages of hitherto-unrelated technological knowledge areas. Triggered by IDR, these different technological knowledge areas are increasingly integrated and build technological networks, ultimately resulting in the formation of emerging technologies. Despite IDR often results in the formation of new technologies [1]–[4], it needs to be pointed out that not every collaborative research leads to an emerging technology. In this regard, IDR might lead to knowledge integration and interlinkages between diverse knowledge areas, which does only result in an emerging scientific field without being observed at technological level. On the other side, emerging technologies may involve a potential dark side that can be manifested by harmful effects on the environment or on human health or by unintended consequences (e.g., security threats or implications on privacy) [38].

For the most part, extant studies attempting to assess IDR have focused on the level of integrating different scientific knowledge areas measured, inter alia, in terms of research publications [6], [14]. Given the aforementioned potential of IDR for innovation, however, it seems evident that a mere assessment of interdisciplinarity at the level of scientific knowledge alone is unlikely to suffice. Although scientific knowledge forms the basis of emerging technologies, it is ultimately the new combinations of technological knowledge, which potentially trigger the emergence of technology networks and resulting emerging technologies. Thus, a novel approach is required that enables actors to assess IDR at the level of technological knowledge areas.

III. Assessment of Interdisciplinary Research at the Level of Scientific and Technological Knowledge

Given that the ability to transfer technology across knowledge areas is necessary for the benefits of IDR to be realized, a number of methodological and conceptual advances are currently being pursued. Nonetheless, the ability to assess and understand IDR remains somewhat ambiguous [6]. To structure the present research, we distinguish between assessment of IDR at the level of a) scientific knowledge and b) technological knowledge (compare Table I).

A. Assessing Interdisciplinary Research at (a) the Level of Scientific Knowledge

Extant research has largely focused on assessing IDR at the level of scientific knowledge [6], [39]–[41]. As listed in Table I, common approaches use coauthorship analysis [39], [40], a method that employs departmental/institutional affiliation of authors, or coclassification analysis, an approach that analyzes the assignment (classification) of articles to different journal categories. The more recent approaches to assess IDR make use of cocitation analysis, a method that draws upon citations of publications outside their own scientific knowledge area as an indicator for interdisciplinarity. Cocitation analyses were found to capture the interdisciplinary knowledge more accurately than coauthorship analysis or coclassification analysis [39], [42]. Additionally, text (semantic) analyses to identify frequently used words across publications, have also been employed [43].

Furthermore, a high number of studies have combined cocitation analysis of publications with additional indicators. For instance, network indicators (e.g., betweenness centrality) were used to assess IDR [28], [44]. Morillo *et al.* 2001 described relationships among scientific knowledge areas according to the quantity of their links (number of related areas) and their quality (with close or distant areas, diversity, and strength of links) by using coauthorship and cocitations analyses [45]. The Shannon entropy and the Simpson index, indices that reflect the distribution of the cited references in different scientific knowledge areas, were used by [46], [47] as indicators for IDR. Porter *et al.* [39] developed a knowledge integration indicator based on publications that accounts not only for the distribution of the cited references in different scientific knowledge areas but also for the degree to which those areas are closely related. Porter and Rafols [2] used several indicators, e.g., variation, integration index, citations within subject category to show how the degree of IDR has changed from 1995 to 2005.

In addition, Rafols and Meyer [46] built upon Porter *et al.* [39] and Stirling [48] to develop a new set of indicators to assess IDR at scientific level: diversity (it captures disciplinary heterogeneity of the set of scientific knowledge areas), and coherence (it measures similarity between scientific knowledge areas). Moreover, Cassi *et al.* [49] or Solomon *et al.* [50] used the Rao-Stirling index, a diversity measure that is computed as the relative share of references citing two different scientific knowledge areas and the degree of relatedness between these two areas, respectively. The Leinster-Cobbold index, as employed by [16], is a diversity index similar to Shannon or Simpson indices

TABLE I
EXTANT APPROACHES TO ASSESS IDR AT THE LEVEL OF SCIENTIFIC AND TECHNOLOGICAL KNOWLEDGE

Knowledge area	Scientific knowledge	Technological knowledge
Predominantly used data source	Publications	Patents
Proxies and indicators for assessing interdisciplinarity	▪ Co-Authorship / Affiliation (e.g. Bordons et al., 1999) ▪ Co-Classification (journal category) (e.g. Morooka et al., 2014) ▪ Co-Citation (e.g. Rafols and Meyer, 2007) ▪ Text (semantic) (e.g. Xu et al., 2016) ▪ Social network indicator (e.g. Leydesdorff et al., 2018) ▪ Shannon entropy (e.g. Barjak, 2006) ▪ Simpson index (e.g. Rafols and Meyer, 2010) ▪ Knowledge integration indicator (e.g. Porter et al., 2007) ▪ Rao-Stirling index (e.g. Cassi et al., 2017) ▪ Leinster-Cobold index (e.g. Mugabushaka et al., 2016)	▪ Co-Inventor / Assignee (e.g. Sorenson et al., 2006) ▪ Co-Classification (patent class) (e.g. Aharonson and Schilling, 2016) ▪ Co-Citation (e.g. Yan and Luo, 2017) ▪ Text (semantic) (e.g. Whalen, 2018) ▪ Social network indicators (e.g. Sorenson et al., 2006) ▪ *Interdisciplinarity index and technology network indicators* *(our study)*

that also includes a sensitivity parameter (from 0 to infinity) that controls "the relative emphasize that the user wishes to place on common and rare elements" [16, p. 600].

B. Assessing Interdisciplinary Research at (b) Level of Technological Knowledge

Fewer studies have employed patent data to examine IDR drawing upon different technological knowledge areas. Some studies use patent classifications (e.g., International Patent Classification (IPC)[2]) in order to operationalize technological areas [51], [52]. Additionally, some studies have used technological knowledge areas, to which the classification codes of the patented invention can be assigned [53].

As depicted in Table I, scholars have employed (co-) inventor or assignee analyses, coclassification analysis, e.g., based on IPC codes, or cocitation analysis. Inventor analyses, for example, enable the identification of experts relevant and necessary for conducting R&D [7]. Coclassification analyses, a method that categorize patents in IPC codes, were used to map technology distance [51], [52]. Additionally, cocitations of patents were applied to map technological knowledge areas and distance among these [54] and to locate the relative technological position of an organization's patenting activity [55]–[57], or to identify boundary spanning inventions [1]. Furthermore, some of the abovementioned studies (e.g., [55], [57]) have provided a way to create visualizations of technological knowledge areas based on cocitations, or based on co-occurrence of IPC codes in the same patent [51], [52].

However, most of these studies focus on the individual's perspective of either an inventor or a company and, yet, neither developed indicators dedicated to the assessment or monitoring of the process of IDR nor did they analyze or visualize the emerging technology network perspective as such. Also, these studies lack the combination of visualizations with the creation of indicators that can specifically be used to assess, monitor, and visualize the degree of interdisciplinarity of technological knowledge areas that are involved in the development of emerging technologies or the respective underlying technology network. Consequently, most research has focused on the question of *how* to best integrate (or recombine) different disciplines.

This article builds on extant work and further seek to elucidate *what* is the degree of interdisciplinarity of technological knowledge areas forming a technology network and *what* technological knowledge areas appear most relevant and, thus, ought to be integrated in R&D based on their centrality or their potential bridging function while focusing on emerging technology networks. Thus, we add to extant literature by developing interdisciplinarity indicators as well as applying network indicators and visualization approaches that can be employed to identify central and bridging technological knowledge areas within emerging technologies. The availability of such indicators and visualization approaches enables the involved actors to not only *assess* and *monitor* IDR but also to identify and *visualize*

[2]IPC is a hierarchical system of codes established by World Intellectual Property Organization that matches patents with categories. The IPC structures patents into eight different sections: i.e., from A to H, followed by a sub-structuring into classes, subclasses, groups, and subgroups, ultimately leading to>70 000 different IPC codes.

the most relevant technological knowledge areas in emerging technology networks—a necessary condition for knowledge integration [19].

IV. Data and Methods

This article draws upon patent data to assess, monitor and visualize IDR at the level of technological knowledge areas in a technology network. Moreover, to operationalize technological knowledge areas, we refer to [53] who coined the term technology area and developed the IPC-Technology Concordance Table. This is a well-established classification system that matches IPC codes (on subclass level) with technological areas. More precisely, this article draws upon the IPC Technology Concordance Table (version 2018), which is divided into five major sectors, including Electrical engineering, Instruments, Chemistry, Mechanical engineering, and Other fields. These sectors are subdivided into 35 different technological areas based on IPC codes. For example, the IPC subclass C12Q corresponds to the technological area of Biotechnology. Following the logic of [53], we will refer to technological knowledge areas as technology areas (TA)—we, thus, draw on TAs derived from [53] to operationalize the theoretical concept of technological knowledge areas.

A. Interdisciplinary Research: The Case of Bioplastics

The case of bioplastics represents an example of an emerging technology within the highly interdisciplinary Bioeconomy. The concept of the Bioeconomy has been introduced as an important part of the solution to the grand challenges [58]. It relies on the application of research and innovation across knowledge from different areas with the potential to trigger a transition toward more sustainable economies by creating technologies and products from renewable biological resources [22]. Examples herein include biopharmaceuticals, biofuels, biogas, as well as bioplastics, all of which can be used in agriculture, forestry, fisheries, food and pulp, and paper production, as well as parts of chemical, biotechnological, energy industries, or medicine [22].

Bioplastics, defined as plastics derived completely or partially from biomass [59], represent a case example within the highly interdisciplinary Bioeconomy and require the combination of technological knowledge from multiple areas like Chemistry, Biology, or Materials Science [23], [24]. Applications of these materials include replacement of plastic materials in a wide range of industries mostly in the packaging industry in the form of plastic bags and bottles. Other industries include automotive, catering products, consumer electronics, construction and housing, horticulture and agriculture, medicine, packaging, pharmaceuticals, personal care, or textiles [59]. In addition, likewise other studies on IDR such as [42], [46], who draw upon biomolecular motors as a case example, the research setting of bioplastics qualifies as a relevant case as it fulfils the idea of the basic definition of IDR: integration of knowledge from two or more areas [3], [5].

B. Data Collection and Categorization

The data collection process (see Table II) consisted of extracting the patent sample and the cited patent sample from the Derwent Innovation patent database.

1) Extraction of the Patent Sample: In the first step, we generated an overall patent sample. We selected keywords based on technology names of the field under investigation, i.e., bioplastics. This task was carried out in an iterative process whereby different keywords and queries were tested by collecting information from patent databases and validating the results with an expert. As such, our search string[3] included the following biobased and biodegradable polymers: PLA, PHAs, PBS. The sample was limited by the publication data and the time frame between 1995 and 2015 was selected. We started our analyses with the year 1995 since it represents the time where the market and economic importance of bioplastics initially became visible [60]. This search resulted in 890 INPADOC patent families. In the second step, the IPC codes of each patent in our sample were translated into TAs based on the IPC-Technology Concordance Table [53]. In total, 1705 IPC codes (on IPC subclass level) distributed into 29 TAs were obtained in our patent sample.

2) Extraction of the Cited Patent Sample: In the third step, we focused on the backward citations of our patent sample to demonstrate how the interdisciplinarity of TAs for the development of bioplastics has increased over time and capture the underlying technology network, which is formed by the integration of diverse TAs and, thus, builds the basis of an emerging technology. Backward citations are previous patents (references) on which the new invention is based upon. Backward citations allow to trace back the origin of ideas and identify what ideas are based upon, e.g., if a patent builds on knowledge from a particular TA or builds upon the integration of knowledge from two or more TAs [3]. This search resulted in 8979 patent applications. In the fourth step, the IPC codes of each cited patent were translated into TAs based on the IPC-Technology Concordance Table [53] following the same process carried out in the second step. In total, 23160 IPC codes (on IPC subclass level) distributed into 32 TAs were obtained.

C. Data Analysis

The data analysis process, as depicted in Table III, followed three main steps: 1) the generation of the matrices, 2) the calculation of indicators based on the matrices, 3) the computation of different visualization approaches to depict interdisciplinary dynamics and relationships among TAs in an emerging technology network.

1) Matrix Generation: In the first step, the matrices were generated following two steps. First, we classified all of the patents into four subperiods according to their application year in

[3]CTB=((bioplastic* OR biopolymer* OR bioplastic* OR biopolymer* OR biobased ADJ plastic* OR biobased ADJ polymer* OR biobased ADJ plastic* OR biobased ADJ polymer*) AND (poly ADJ (lactic ADJ acid) OR polylactic ADJ acid OR polylactide OR polyhydroxyalkanoate* OR poly ADJ (butylenesuccinate) OR polybutylene ADJ succinate)) AND DP>=(19950101) AND DP<=(20151231)

TABLE II
REPRESENTATION OF THE DATA COLLECTION AND CATEGORIZATION STEPS. SOURCE: AUTHORS

I. **Patent sample**		II. **Cited patent sample**	
1 Sample creation	**2 Sub-sample creation**	**3 Sample creation of cited patents**	**4 Sub-sample creation of cited patents**
Extracting patent sample representative for the field of bioplastics N = 890 patent families from 1995 to 2015	Matching IPC codes of patents with TAs (based on IPC-Technology Concordance Table) N_{IPC} = 1,705 IPC codes distributed into 29 TAs	Extracting patents cited by our patent sample N = 8,979 cited patents included in our patent sample	Matching IPC codes of cited patents with TAs (based on IPC-Technology Concordance Table) N_{IPC} = 23,160 IPC codes distributed into 32 TAs

TABLE III
REPRESENTATION OF THE DATA ANALYSIS STEPS. SOURCE: AUTHORS

I. Matrix generation	**II. Calculation of indicators based on matrices to assess and monitor interdisciplinarity in a technology network**		**III. Visualizations of interdisciplinarity in a technology network**
	2.1 Indicators based on citations sent	**2.2 Indicators based on citations received**	
Generating matrices across time sub-periods. The number in each cell of the matrix is the frequency of citations	Developing and calculating novel indicators assessing and monitoring interdisciplinarity at technological level (micro perspective)	Calculating centrality indicators to identify central TAs as well as bridging TAs within the emerging technology network (macro perspective)	Generating interdisciplinary portfolio at technological level (micro perspective) Generating network maps that show relationships among TAs (macro perspective)

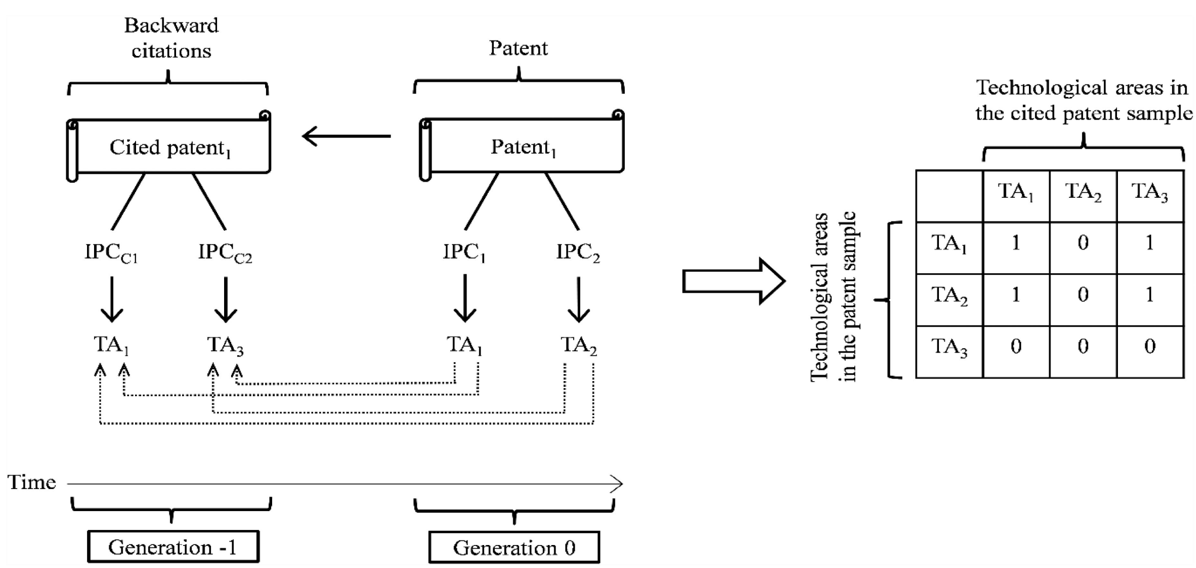

Fig. 2. Schema for patent citations showing how the matrices are constructed taking the example of one patent. Dotted arrows indicate where the technological knowledge is originating from.

our patent sample: ≤2000[4], 2001–2005, 2006–2010, 2011–2015 and over all time span: ≤2000–2015. These subperiods were defined based on the phases of the innovative activity of bioplastics. The starting year (1995 in our patent sample) matches the time where the market and economic importance of bioplastics initially became visible [60]. Particularly, the four subperiods used for the analysis: ≤2000, 2001–2005, 2006–2010, 2011–2015 correspond to distinct phases of innovative activity that can be distinguished according to the descriptive analysis on the evolution of bioplastics.

Second, we computed five citing-to-cited matrices corresponding to the four subperiods (≤2000, 2001–2005, 2006–2010, 2011–2015) and over all time span (≤2000–2015). A depiction of the process of constructing the matrices taking the example of one patent is shown in Fig. 2. For example, patent_1 includes two IPC codes classified in two different TAs, and

[4]The patents with the oldest application year in our patent sample are from 1994 (DE4420223C1 and CA2156718A1) but for a matter of simplification, we will name ≤2000 the first subperiod of analysis along the article.

TABLE IV
LIST OF INDICATORS DEVELOPED TO ASSESS AND MONITOR INTERDISCIPLINARITY AT TECHNOLOGICAL LEVEL. SOURCE: AUTHORS

Indicator	Description	Interpretation
$I_{(i)}$(Total interdisciplinarity technological area)	It measures the number of self-citations a TA draws upon relative to the total number of citations	A high degree of interdisciplinarity TA would imply that TAs build upon technological knowledge from different TAs.
$Is_{(i)}$(Total interdisciplinarity sector)	It measures the diversity of sectors involved in the citations a TA draws upon	A high degree of interdisciplinarity sector would imply that TAs build upon technological knowledge from different sectors.
$TI_{(i)}$(Total interdisciplinarity index)	It combines the total interdisciplinary TA and the total interdisciplinary sector	A high interdisciplinarity index would imply that TAs build upon technological knowledge from different TAs and from different sectors.
$Dc_{(i)}$(Degree centrality)	It measures the number of citations a TA receives	Central TA: A high degree centrality would imply that TAs have more power within the technology network.
$Bc_{(i)}$(Betweenness centrality)	It measures the capacity of a TA to serve as a bridge within a network	Bridging TA: A high betweenness centrality would imply that TAs are considered to act as 'bridges' and thus, have potential to coordinate relations to other TAs within the technology network.

it cites a patent (Cited patent$_1$) that includes two IPC codes classified in two different TAs. Each row and column in the matrix represent a TA. The number in each cell of the matrix indicates how often each TA in our patent sample cites each TA in our sample of cited patents. For example, we place a 1 in a cell of the matrix as TA$_1$ cites TA$_1$ and TA$_3$, however, we place a 0 as TA$_1$ does not cite TA$_2$. Therefore, these matrices represent relationships among TAs, i.e., leading to the formation of the emerging technology network, with 32 rows and columns corresponding to the total number of TAs extracted from our sample of cited patents. A higher value in a cell indicates that this pair of TAs is highly cited, implying that patents rely on knowledge from those TAs.

2) Calculation of Indicators Based on Matrices: In the second step, with the aim of identifying the most interdisciplinary TAs that are integrated in the development of the emerging technology of bioplastic as well as the most central and bridging TAs within the underlying technology network, we calculated a series of indicators explained below (see Table IV). These indicators consider 1) number of citations of a TA stemming from the own TA (self-citations), 2) number of citations of a TA stemming from outside the own TA, and 3) the number of sectors cited (referring to technological diversity following [42], [46]).

The *total interdisciplinarity technological area* measures the self-citations relative to the total number of citations. According to this, a higher number of self-citations over the total number of citations point to less interdisciplinary TAs. The *total interdisciplinarity technological area* is defined as follows:

$$I_{(i)} = 1 - \left[\frac{Cs_i}{\sum_i C}\right]$$

where i is the focal TA, Cs_i is the number of backward citations of the focal TA stemming from the own TA and C is the sum of backward citations the focal TA draws upon. The ratio is subtracted from one (1), hence, the closer the value of $I_{(i)}$ is to 1, the more interdisciplinary the focal TA i is.

The *total interdisciplinarity sector* is calculated as the ratio of the different sectors that a TA draws upon to five (5), thereby corresponds to the total number of sectors following the IPC-Technology Concordance Table. The total interdisciplinarity sector is defined as follows:

$$Is_{(i)} = \left[\frac{ns_i}{5}\right]$$

where i is the focal TA, and ns_i is the number of sectors that the focal TA draws upon. The closer the value of $Is_{(i)}$ is to 1, the higher the number of sectors a TA draws upon, and thus, the more interdisciplinary the focal TA i is.

In the final step, the total interdisciplinarity TA is multiplied by the total interdisciplinary sector, yielding the *total interdisciplinarity index* ($TI_{(i)}$)

$$T\,I_{(i)} = I_{(i)}\ \text{x}\ Is_{(i)}.$$

Furthermore, network analysis indicators were used to determine the central TAs within the underlying emerging technology network that is built by the interlinkages of TA that are involved in the development of bioplastics. A typical indicator to assess the relative importance of a node is its centrality, which is subdivided into degree centrality, closeness centrality, and betweenness centrality [61], [62]. This article uses degree centrality and betweenness centrality to identify the most important nodes. The *degree centrality* of a TA explains the extent to which a TA may be integrated in the network and is defined as follows:

$$Dc_{(i)} = \frac{\sum_{j=1}^{n} a_{ij}}{n-1}$$

where i is the focal TA, j is another TA in the network, and a_{ij} is the sum of all citations that the focal TA receives. The numerator is divided by the maximum number of TAs (n) in the network minus one (1). If a TA in an (emerging) technology network has a high degree centrality value, it has a strong power or prestige in the network [63] and can, therefore, be considered as a central TA.

The *betweenness centrality* of a TA measures the extent to which a TA lies between the other TAs in the network. It reflects the TA's influence as a communication channel between the other TAs in a network and is regarded as the extent to which a TA serves as a bridge [61], [62]. Betweenness centrality is calculated as the shortest paths that contain the node, among all the shortest paths between each pair of the other TAs in the network and is defined as follows:

$$Bc_{(i)} = \sum_{s \neq t \neq i \epsilon V} \frac{\sigma_{st}(i)}{\sigma_{st}}$$

where i is the focal TA, V is the set of all TAs in the network, $\sigma_{st}(i)$ is the total number of shortest paths between TA s and t that pass through i, and σ_{st} is the total number of shortest paths between s and t. A TA with a high betweenness centrality value has a strong possibility of acting as a bridge in transferring technological knowledge within the network [62], [64], and it can, thus, be considered as a bridging TA.

3) Visualization: In the third step, to enable the visualization of the interdisciplinarity of TAs as well as the emerging technology network, different maps were computed. First, *scatter plots* were created to depict the evolution of interdisciplinarity by TAs based on the *total interdisciplinarity technological area* ($I_{(i)}$) and the *total interdisciplinarity sector* ($Is_{(i)}$). Second, TAs and relationships among TAs involved in the innovative activity in the field of bioplastics were visualized by means of *network analysis*. In doing so, the aggregated matrices constituted the input for the computation of network maps using UCINET 6 [63]. These visualizations are based on citing-to-cited relationships among the TAs derived from the IPC codes of our patent samples. TAs are the unit of analysis and are presented as nodes, which are connected by lines on the map. The lines represent the citation relationship, which represents that a TA is related to another TA. The evolved network of relationships indicates the internal knowledge structure of the emerging technology under examination, i.e., bioplastics. The most connected nodes are on the center of the map and the least connected nodes are located on the periphery.

V. Results

A. Indicators to Assess and Monitor IDR Within Emerging Technologies

1) Characterization of the Most Interdisciplinary Technological Areas: This section seeks to assess and monitor the degree of interdisciplinarity behind the technological knowledge of our patent sample. In order to determine the degree of interdisciplinarity that each TA related to bioplastics has, we developed and calculated the interdisciplinary indicators defined in 4.3.2, namely the *total interdisciplinarity technological area*, the *total interdisciplinarity sector* and the *total interdisciplinarity index*. The TAs shown in Table V indicate the *Total interdisciplinarity technological area*, the *Total interdisciplinarity sector* and the *Total interdisciplinarity index* classified by sectors across time subperiods: ≤2000, 2001–2005, 2006–2010, 2011–2015 and over all time span: ≤2000–2015.

Table V shows the dynamics of interdisciplinarity by TAs across time subperiods, identifying whether these have become more interdisciplinary over time. Overall, according to the total interdisciplinarity index ($TI_{(i)}$), the three TAs showing the highest degree of interdisciplinarity are: “Audio-visual technology” ($TI_{(i)}$ = 0.970), “Chemical engineering” ($TI_{(i)}$ = 0917), and “Pharmaceuticals” ($TI_{(i)}$ = 0.904). The first refers to consumer electronics, the second to applications in pharma, and the latter covers technologies at the interface of chemistry and engineering, referring to apparatus and processes for the industrial production of chemicals. Moreover, 11 out of 29 TAs that are relevant for the development of bioplastics have become more interdisciplinary over time, as the total interdisciplinarity index ($TI_{(i)}$) appears to increase across time sub-periods. The cases of chemical engineering and pharmaceuticals are interesting in that their $TI_{(i)}$ has increased to around 210% for chemical engineering[5] and around 104% for pharmaceuticals[6] over the whole time period. Therefore, chemical engineering and pharmaceuticals can be described as TAs characterized by a rapid increase of interdisciplinarity, as many other different TAs are becoming relevant (see networks maps in Section V-B2).

2) Characterization of the Central and the Key Bridging Technological Areas: To determine the importance that each TA related to the emerging technology network of bioplastics has on the overall network, we calculated the degree centrality (see Table VI) and the betweenness centrality (see Table VII) of each TA classified by sectors across time subperiods: ≤2000, 2001–2005, 2006–2010, 2011–2015 and over all time span: ≤2000–2015. For both cases, normalized centrality values were calculated. Hence, the dynamics of TAs over time subperiods are shown in Tables VI and VII to help identifying whether TAs have been central (degree centrality) or acted as bridging (betweenness centrality) over time.

According to the degree centrality index ($Dc_{(i)}$), the three TAs within the technology network showing the highest degree centrality are “Macromolecular chemistry, polymers”, “Medical technology”, and “Other special machines”. The first refers to chemical properties of polymers, the second is associated with medical technology, and the latter is associated with patents referring to turning, drilling, grinding, soldering, or cutting not focused on metals. “Macromolecular chemistry, polymers” appears to have the highest degree centrality over all time subperiods, with the exception of the period 2001–2005, when “Medical technology” achieved an important position relative to all other TAs. Contrary, the timely development of “Medical technology” and “Other special machines” is characterized by high fluctuations over time.

According to the betweenness centrality index ($Bc_{(i)}$), the three TAs within the technology network showing the highest betweenness centrality are again “Macromolecular chemistry, polymers”, “Other special machines”, and “Medical technology”. “Macromolecular chemistry, polymers” and “Medical technology” seem to play a very crucial role as bridging over the time period 2001–2005, decreasing its importance after 2005. Contrary, “Other special machines” gained higher relevance as bridging technologies after 2006.

B. Visualization Approaches

1) Visualization of Interdisciplinarity Evolution: Visualizations of interdisciplinarity allow us to identify the most interdisciplinary TAs that are involved in the development of the

[5]From $\mathrm{TI}_{(i)\leq 2000} = 0.305$ to $\mathrm{TI}_{(i)2011-2015} = 0.946$

[6]From $\mathrm{TI}_{(i)\leq 2000} = 0.353$ to $\mathrm{TI}_{(i)2011-2015} = 0.722$

TABLE V

Total Interdisciplinarity Technological Area ($I_{(i)}$), *Total Interdisciplinarity Sector* ($Is_{(i)}$) and *Total Interdisciplinarity Index* ($TI_{(i)}$), Four Subperiods: ≤2000; 2001–2005; 2006–2010; 2011–2015; and Over All Time Span ≤2000–2015

Sector	Technology area	≤2000			2001-2005			2006-2010			2011-2015			All periods		
		$I_{(i)}$	$Is_{(i)}$	$TI_{(i)}$	$I_{(i)}$	$Is_{(i)}$	$TI_{(i)}$	$I_{(i)}$	$Is_{(i)}$	$TI_{(i)}$	$I_{(i)}$	$Is_{(i)}$	$TI_{(i)}$	$I_{(i)}$	$Is_{(i)}$	$TI_{(i)}$
Chemistry	Basic materials chemistry	-	-	-	0,603 (13)	1,000 (01)	0,603 (08)	0,786 (09)	1,000 (01)	0,786 (05)	0,733 (19)	1,000 (01)	0,733 (13)	0,656 (22)	1,000 (01)	0,656 (19)
	Biotechnology	0,527 (10)	0,400 (03)	0,211 (11)	0,799 (08)	0,80 (02)	0,639 (07)	0,670 (16)	1,000 (01)	0,670 (12)	0,575 (25)	1,000 (01)	0,575 (20)	0,606 (25)	1,000 (01)	0,606 (21)
	Chemical engineering	0,762 (05)	0,400 (03)	**0,305** (09)	0,818 (06)	0,400 (04)	**0,327** (16)	0,772 (11)	0,800 (02)	**0,618** (15)	0,946 (02)	1,000 (01)	**0,946** (01)	0,917 (04)	1,000 (01)	0,917 (02)
	Environmental technology	-	-	-	0,889 (03)	0,800 (02)	0,711 (05)	0,500 (22)	0,600 (03)	0,300 (25)	0,543 (26)	0,600 (03)	0,326 (24)	0,588 (26)	1,000 (01)	0,588 (23)
	Food chemistry	0,950 (02)	0,800 (01)	0,760 (02)	0,395 (17)	0,600 (03)	0,237 (18)	0,878 (04)	0,400 (04)	0,351 (24)	0,818 (06)	0,200 (05)	0,164 (26)	0,745 (16)	0,800 (02)	0,596 (22)
	Macromolecular chemistry, polymers	0,713 (06)	0,800 (01)	0,570 (04)	0,682 (12)	1,000 (01)	0,682 (06)	0,555 (21)	1,000 (01)	0,555 (17)	0,706 (20)	1,000 (01)	0,706 (15)	0,666 (21)	1,000 (01)	0,666 (18)
	Materials, metallurgy	-	-	-	0,840 (04)	0,400 (04)	0,336 (15)	0,877 (05)	1,000 (01)	0,877 (02)	0,742 (16)	0,800 (02)	0,594 (19)	0,849 (06)	1,000 (01)	0,849 (04)
	Micro-structural and nano-technology	-	-	-	-	-	-	1,000 (01)	0,400 (04)	**0,400** (21)	0,984 (01)	0,800 (02)	**0,788** (06)	0,987 (02)	0,800 (02)	0,789 (08)
	Organic fine chemistry	0,615 (09)	0,600 (02)	0,369 (07)	0,834 (05)	1,000 (01)	0,834 (01)	0,806 (08)	1,000 (01)	0,806 (03)	0,634 (23)	1,000 (01)	0,634 (17)	0,767 (14)	1,000 (01)	0,767 (11)
	Pharmaceuticals	0,884 (04)	0,400 (03)	0,353 (08)	1,000 (01)	0,400 (04)	0,400 (12)	0,906 (03)	1,000 (01)	0,906 (01)	0,903 (04)	0,800 (02)	0,722 (14)	0,904 (05)	1,000 (01)	0,904 (03)
	Surface technology, coating	1,000 (01)	0,800 (01)	0,800 (01)	0,778 (09)	1,000 (01)	0,778 (03)	0,771 (12)	1,000 (01)	0,771 (07)	0,808 (07)	1,000 (01)	0,808 (03)	0,793 (09)	1,000 (01)	0,793 (06)
Electrical engineering	**Audio-visual technology**	-	-	-	0,750 (11)	0,400 (04)	**0,300** (17)	1,000 (01)	0,800 (02)	**0,800** (04)	-	-	-	0,970 (03)	1,000 (01)	0,970 (01)
	Electrical machinery, apparatus, energy	-	-	-	-	-	-	0,846 (06)	0,800 (02)	**0,677** (11)	0,771 (12)	1,000 (01)	**0,771** (08)	0,788 (11)	1,000 (01)	0,788 (09)
	Semiconductors	-	-	-	-	-	-	0,650 (18)	0,800 (02)	**0,520** (18)	0,793 (08)	1,000 (01)	**0,793** (04)	0,790 (10)	1,000 (01)	0,790 (07)
	Telecommunications	-	-	-	1,000 (01)	0,400 (04)	0,400 (12)	-	-	-	-	-	-	1,000 (01)	0,400 (04)	0,400 (25)
Instruments	Control	-	-	-	-	-	-	1,000 (01)	0,400 (04)	0,400 (21)	-	-	-	1,000 (01)	0,400 (04)	0,400 (25)
	Measurement	0,400 (11)	0,600 (02)	0,240 (10)	0,935 (02)	0,800 (02)	0,748 (04)	0,689 (15)	1,000 (01)	0,689 (10)	0,750 (15)	0,600 (03)	0,450 (22)	0,726 (17)	1,000 (01)	0,726 (13)
	Medical technology	0,682 (08)	0,800 (01)	0,545 (06)	0,525 (14)	1,000 (01)	0,525 (09)	0,447 (23)	1,000 (01)	0,447 (20)	0,653 (21)	1,000 (01)	0,653 (16)	0,530 (27)	1,000 (01)	0,530 (24)
	Optics	-	-	-	-	-	-	0,600 (20)	0,600 (03)	**0,360** (23)	0,751 (14)	1,000 (01)	**0,751** (10)	0,712 (18)	1,000 (01)	0,712 (14)
Mechanical engineering	Handling	0,940 (03)	0,800 (01)	0,752 (03)	0,778 (09)	0,600 (03)	0,467 (10)	0,781 (10)	1,000 (01)	0,781 (06)	0,753 (13)	1,000 (01)	0,753 (09)	0,785 (12)	1,000 (01)	0,785 (10)
	Machine tools	-	-	-	-	-	-	1,000 (01)	0,400 (04)	0,400 (21)	0,643 (22)	0,400 (04)	0,257 (25)	0,783 (13)	0,400 (04)	0,313 (28)
	Mechanical elements	-	-	-	-	-	-	0,828 (07)	0,600 (03)	**0,497** (19)	0,889 (05)	0,600 (03)	**0,533** (21)	0,842 (07)	0,800 (02)	0,674 (17)
	Other special machines	0,710 (07)	0,800 (01)	0,568 (05)	0,818 (06)	1,000 (01)	0,818 (02)	0,762 (13)	1,000 (01)	0,762 (08)	0,739 (17)	1,000 (01)	0,739 (11)	0,747 (15)	1,000 (01)	0,747 (12)
	Textile and paper machines	-	-	-	0,486 (15)	0,800 (02)	**0,389** (14)	0,692 (14)	1,000 (01)	**0,692** (09)	0,734 (18)	1,000 (01)	**0,734** (12)	0,711 (19)	1,000 (01)	0,711 (15)
	Thermal processes and apparatus	-	-	-	-	-	-	0,944 (02)	0,600 (03)	**0,567** (16)	0,788 (09)	1,000 (01)	**0,788** (05)	0,829 (08)	1,000 (01)	0,829 (05)
	Transport	-	-	-	-	-	-	-	-	-	0,617 (24)	0,600 (03)	0,370 (23)	0,617 (24)	0,600 (03)	0,370 (26)
Other fields	**Civil engineering**	-	-	-	-	-	-	0,364 (24)	0,800 (02)	**0,291** (26)	0,778 (11)	0,800 (02)	**0,622** (18)	0,407 (28)	0,800 (02)	0,326 (27)
	Furniture, games	-	-	-	0,456 (16)	1,000 (01)	**0,456** (11)	0,623 (19)	1,000 (01)	**0,623** (14)	0,909 (03)	1,000 (01)	**0,909** (02)	0,705 (20)	1,000 (01)	0,705 (16)
	Other consumer goods	-	-	-	0,138 (18)	0,800 (02)	**0,110** (19)	0,667 (17)	1,000 (01)	**0,667** (13)	0,780 (10)	1,000 (01)	**0,780** (07)	0,646 (23)	1,000 (01)	0,646 (20)

Gray marked values indicate the top ten interdisciplinarity TAs based on the total interdisciplinarity TA and the total interdisciplinarity index in the particular time frame. Bold values represent the TAs that have become more interdisciplinary over time. Hyphen indicates there were no IPC codes in the patent sample associated to that technological area in the particular timeframe. Source: Authors.

technology network forming the emerging field of bioplastics as well as their evolution over time. The visualizations of the interdisciplinary evolution of the TAs over the four subperiods 1) ≤2000; 2) 2001–2005; 3) 2006–2010; 4) 2011–2015 are shown in Fig. 3. These *scatter plots* depict the number of citations stemming from outside the own TA ($I_{(i)}$) on the horizontal axis, and number of sectors that TAs draw upon ($Is_{(i)}$) on the vertical axis. The graph is split at the mean values for each scale, $I_{(i)} = 0.50$ and $Is_{(i)} = 0.60$, thus resulting in four quadrants.

Quadrant I (High degree of interdisciplinarity with high sector diversity) displays those TAs that have a low number of self-citations ($Cs_i \leq \frac{\sum_i C}{2}$) relative to total citations ($I_{(i)} \geq 0.50$) and that cite TAs from four of five different sectors ($Is_{(i)} > 0.60$). The TAs located in this quadrant are considered as more interdisciplinary than the TAs positioned on the other quadrants. Quadrant II (Low degree of interdisciplinarity with high sector diversity) shows the TAs that have high number of self-citations relative to total citations ($I_{(i)} \leq 0.50$) and that cite TAs from

TABLE VI
NORMALIZED DEGREE CENTRALITY, FOUR SUBPERIODS: ≤2000; 2001–2005; 2006–2010; 2011–2015; AND OVER ALL TIME SPAN ≤2000–2015

Sector	Technological area	≤2000	2001-2005	2006-2010	2011-2015	≤2000-2015
Chemistry	Basic materials chemistry	0.040 (06)	0.018 (03)	0.019 (09)	0.023 (08)	0.029 (07)
	Biotechnology	0.048 (05)	0.006 (07)	0.026 (06)	0.039 (03)	0.033 (05)
	Chemical engineering	0.061 (04)	0.004 (08)	0.013 (10)	0.014 (10)	0.015 (10)
	Environmental technology	0.001 (19)	0 (12)	0.002 (16)	0.002 (18)	0.002 (17)
	Food chemistry	0.032 (10)	0.002 (10)	0.006 (12)	0.009 (11)	0.008 (12)
	Macromolecular chemistry, polymers	0.161 (01)	0.021 (02)	0.088 (01)	0.064 (01)	0.074 (01)
	Materials, metallurgy	0.022 (13)	0.003 (09)	0.005 (13)	0.008 (12)	0.008 (12)
	Micro-structural and nano-technology	0.001 (19)	0 (12)	0.001 (17)	0.002 (18)	0.001 (18)
	Organic fine chemistry	0.067 (03)	0.013 (04)	0.033 (05)	0.027 (05)	0.032 (06)
	Pharmaceuticals	0.008 (16)	0.002 (10)	0.007 (11)	0.003 (17)	0.005 (14)
	Surface technology, coating	0.036 (09)	0.003 (09)	0.045 (04)	0.035 (04)	0.034 (04)
	Surface technology, coating	0.036 (09)	0.003 (09)	0.045 (04)	0.035 (04)	0.034 (04)
Electrical engineering	Audio-visual technology	0 (20)	0.001 (11)	0.003 (15)	0.003 (17)	0.003 (16)
	Computer technology	0.002 (18)	0 (12)	0.002 (16)	0.002 (18)	0.002 (17)
	Electrical machinery, apparatus, energy	0.002 (18)	0.001 (11)	0.003 (15)	0.004 (16)	0.004 (15)
	IT methods for management	0 (20)	0 (12)	0 (18)	0 (20)	0 (19)
	Semiconductors	0.002 (18)	0.001 (11)	0.002 (16)	0.006 (14)	0.004 (15)
	Telecommunications	0 (20)	0 (12)	0 (18)	0.001 (19)	0.001 (18)
Instruments	Control	0 (20)	0 (12)	0.001 (17)	0.001 (19)	0.001 (18)
	Measurement	0.031 (11)	0.002 (10)	0.005 (13)	0.006 (14)	0.006 (13)
	Medical technology	0.040 (06)	0.045 (01)	0.072 (02)	0.025 (06)	0.06 (02)
	Optics	0.004 (17)	0.001 (11)	0.004 (14)	0.005 (15)	0.005 (14)
Mechanical engineering	Engines, pumps, turbines	0 (20)	0 (12)	0 (18)	0 (20)	0 (19)
	Handling	0.029 (12)	0.001 (11)	0.021 (08)	0.017 (09)	0.016 (09)
	Machine tools	0.011 (15)	0 (12)	0.005 (13)	0.004 (16)	0.004 (15)
	Mechanical elements	0 (20)	0 (12)	0.002 (16)	0.001 (19)	0.001 (18)
	Other special machines	0.157 (02)	0.008 (05)	0.053 (03)	0.056 (02)	0.052 (03)
	Textile and paper machine	0.037 (08)	0.007 (06)	0.022 (07)	0.024 (07)	0.023 (08)
	Thermal processes and apparatus	0 (20)	0 (12)	0.002 (16)	0.001 (19)	0.001 (18)
	Transport	0 (20)	0 (12)	0.002 (16)	0.003 (17)	0.002 (17)
Other fields	Civil engineering	0.015 (14)	0.008 (05)	0.004 (14)	0.007 (13)	0.01 (11)
	Furniture, games	0 (20)	0.001 (11)	0.007 (11)	0.004 (16)	0.005 (14)
	Other consumer goods	0.004 (17)	0.002 (10)	0.007 (11)	0.004 (16)	0.005 (14)

Number between brackets refers to rank compared to all other TAs in the network in the particular timeframe. A gray mark-up indicates the top ten central TAs in the particular time frame. Source: Authors.

four or five different sectors ($Is_{(i)} > 0.60$). Quadrant III (Low degree of interdisciplinarity with low sector diversity) indicates TAs that have a high number of self-citations relative to total citations ($I_{(i)} \leq 0.50$) and their technological knowledge (citations) are concentrated in only one or two sectors ($Is_{(i)} < 0.60$). Quadrant IV (High degree of interdisciplinarity with low sector diversity) shows TAs that have a low share of self-citations relative to total citations ($I_{(i)} \geq 0.50$) and their technological knowledge (citations) are concentrated in only one or two sectors ($Is_{(i)} < 0.60$).

The TAs located in the "High degree of interdisciplinarity with high sector diversity" quadrant show the lowest shares of self-citations relative to the total number of citations and these draw upon technological knowledge from four or five different sectors (following the IPC-Technology Concordance Table). Thus, these TAs are highly interdisciplinary. Technological areas in Quadrant II ("Low degree of interdisciplinarity with high sector diversity") are characterized by having a high share of self-citations relative to the total number of citations and by drawing upon knowledge from four or five different sectors.

TABLE VII
NORMALIZED BETWEENNESS CENTRALITY, FOUR SUBPERIODS: ≤2000; 2001–2005; 2006–2010; 2011–2015; AND OVER ALL TIME SPAN ≤2000–2015

Sector	Technological area	≤2000	2001-2005	2006-2010	2011-2015	≤2000-2015
Chemistry	Basic materials chemistry	0 (10)	0.02 (07)	0.031 (06)	0.04 (02)	0.026 (06)
	Biotechnology	0.005 (08)	0.055 (03)	0.023 (08)	0.037 (03)	0.014 (09)
	Chemical engineering	0.006 (07)	0.007 (08)	0.012 (10)	0.025 (08)	0.013 (10)
	Environmental technology	0 (10)	0.004 (09)	0.004 (12)	0.001 (19)	0.003 (15)
	Food chemistry	0.040 (04)	0.002 (10)	0.002 (14)	0 (20)	0.001 (17)
	Macromolecular chemistry, polymers	0.026 (06)	0.144 (01)	0.050 (04)	0.035 (04)	0.061 (01)
	Materials, metallurgy	0 (10)	0.001 (11)	0.011 (11)	0.009 (14)	0.01 (12)
	Micro-structural and nano-technology	0 (10)	0 (12)	0.001 (15)	0.004 (17)	0.001 (17)
	Organic fine chemistry	0.076 (01)	0.045 (04)	0.079 (01)	0.014 (11)	0.03 (04)
	Pharmaceuticals	0 (10)	0.001 (11)	0.002 (14)	0.004 (17)	0.004 (14)
	Surface technology, coating	0.001 (09)	0.031 (05)	0.061 (03)	0.027 (07)	0.029 (05)
Electrical engineering	Audio-visual technology	0 (10)	0 (12)	0.001 (15)	0 (20)	0.002 (16)
	Computer technology	0 (10)	0 (12)	0 (16)	0 (20)	0 (18)
	Electrical machinery, apparatus, energy	0 (10)	0 (12)	0.001 (15)	0.006 (16)	0.003 (15)
	IT methods for management	0 (10)	0 (12)	0 (16)	0 (20)	0 (18)
	Semiconductors	0 (10)	0 (12)	0.001 (15)	0.018 (09)	0.01 (12)
	Telecommunications	0 (10)	0 (12)	0 (16)	0 (20)	0 (18)
Instruments	Control	0 (10)	0 (12)	0 (16)	0 (20)	0 (18)
	Measurement	0.037 (05)	0.004 (09)	0.011 (11)	0.011 (13)	0.009 (13)
	Medical technology	0.064 (02)	0.096 (02)	0.040 (05)	0.029 (06)	0.034 (03)
	Optics	0 (10)	0 (12)	0.001 (15)	0.007 (15)	0.003 (15)
Mechanical engineering	Engines, pumps, turbines	0 (10)	0 (12)	0 (16)	0 (20)	0 (18)
	Handling	0.006 (07)	0.004 (09)	0.011 (11)	0.017 (10)	0.021 (07)
	Machine tools	0 (10)	0 (12)	0.001 (15)	0.001 (19)	0.001 (17)
	Mechanical elements	0 (10)	0 (12)	0.002 (14)	0.001 (19)	0.003 (15)
	Other special machines	0.051 (03)	0.022 (06)	0.067 (02)	0.051 (01)	0.037 (02)
	Textile and paper machine	0 (10)	0.004 (09)	0.024 (07)	0.032 (05)	0.016 (08)
	Thermal processes and apparatus	0 (10)	0 (12)	0.001 (15)	0.012 (12)	0.004 (14)
	Transport	0 (10)	0 (12)	0 (16)	0.002 (18)	0.001 (17)
Other fields	Civil engineering	0 (10)	0 (12)	0.003 (13)	0.001 (19)	0.002 (16)
	Furniture, games	0 (10)	0.002 (10)	0.002 (14)	0.004 (17)	0.002 (16)
	Other consumer goods	0 (10)	0.001 (11)	0.013 (09)	0.009 (14)	0.011 (11)

Number between brackets refers to rank compared to all other TAs in the network in the particular timeframe. Gray marked values indicate the top ten bridging TAs in the particular time frame. Source: Authors.

Three TAs (Measurement in subperiod ≤2000, Food chemistry in 2001–2005, and Environmental technology in 2006–2011) are located at the intersection of "Low degree of interdisciplinarity with high sector diversity" (Quadrant II) and "Low degree of interdisciplinarity with low sector diversity" (Quadrant III). Thus, these three TAs are characterized by having a low share of self-citations relative to the total number of citations and by drawing upon knowledge from only two sectors. This might be caused due to the fact that we have a five-year accumulation of data.

Contrary, the TAs located in Quadrant IV ("High degree of interdisciplinarity with low sector diversity") display a low share of self-citations relative to the total number of citations and draw upon technological knowledge from only two different sectors (following the IPC-Technology Concordance Table). This indicates that these TAs appear to rely on knowledge generated in only two sectors, turning to be less interdisciplinary. Generally, it can be observed that across time subperiods, TAs have progressed to the "High degree of interdisciplinarity with high sector diversity" quadrant, implying that TAs in the

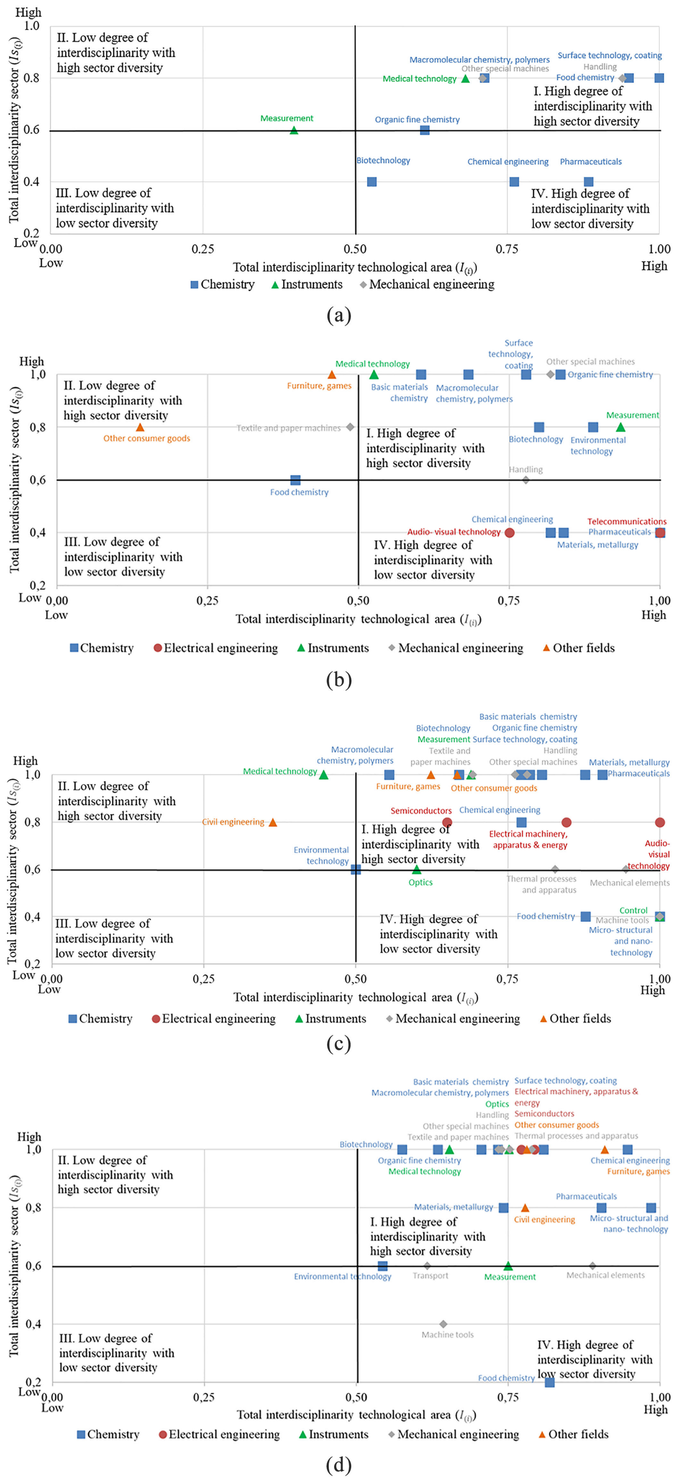

Fig. 3. Typology to visualize dynamics of IDR at technological level: *Total interdisciplinarity sector* versus *total interdisciplinarity technological area* for bioplastics, four subperiods: (a) ≤2000; (b) 2001–2005; (c) 2006–2010; (d) 2011–2015. The color and shape of the nodes represent sectors based on the IPC-Technology Concordance Table: Chemistry: blue and square; Electrical engineering: Red and Circle; Instruments: green and up triangle; Mechanical engineering: gray and diamond; Other fields: orange and up triangle. Source: authors.

technology network of bioplastics have become more interdisciplinary over time. For instance, the TAs characterized by a rapid increase of IDR based on the interdisciplinary indicators (chemical engineering and pharmaceutical) are located in Quadrant IV in the subperiod ≤2000 and in Quadrant I over the subperiod 2011–2015.

2) Visualization of Emerging Technology Networks: In addition to the visualizations of interdisciplinarity by TAs, technology network maps allow us to visualize relationships among the TAs that constitute the structure of the technological knowledge behind the emerging technology bioplastics, as well as the changes of these relationships over time. The visualization of the network analyses for the TAs over four subperiods: 1) ≤2000; 2) 2001–2005; 3) 2006–2010; 4) 2011–2015 and over all time span: 5) ≤2000–2015 is depicted in Fig. 4.

The first period of the analysis (≤2000) shows a relatively simple network visualization composed of 23 TAs and 5 sectors. The core nodes of the map (the most connected ones) correspond to "Macromolecular chemistry, polymers", "Other special machines", and "Organic fine chemistry". In the second period (2001–2005), the network visualization indicates a more complex structure due to the emergence of more nodes and relationships among them, containing 31 TAs and 5 sectors. The core nodes of the map are "Macromolecular chemistry, polymers", "Medical technology", and "Basic materials chemistry". However, "Organic fine chemistry" and "Other special machines" lose importance in the network with respect to the previous period.

The next period of analysis (2006–2010) shows a network, which is slightly more complex in terms of relationships among nodes, containing 32 TAs and 5 sectors. Specifically, the importance of "Macromolecular chemistry, polymers" and "Medical technology" persists. In addition, "Other special machines" gained relevance in this period, recovering the importance achieved in the first period of analysis. Furthermore, "Surface technology, coating" developed into one of the most strongly connected nodes for the first time. These four nodes can be considered as the central TAs in this period of analysis.

In the last period of the analysis (2011–2015), the technology network visualization contains 32 TAs and 5 sectors with more relationships among nodes. The core nodes of the map are "Macromolecular chemistry, polymers", "Other special machines", and "Biotechnology". Interestingly, "Biotechnology" emerged as a core node of the map although our patent sample shows a decreasing trend in the number of patents classified in this TA, indicating the strong role of "Biotechnology" as bridging TA. In addition, this might indicate that the patent sample draws upon technological knowledge from outside their own TAs.

Summing up all the years used for this analysis, the network visualization contains 32 TAs and 5 sectors. The five core nodes of the map are "Macromolecular chemistry, polymers", "Medical technology", "Other special machines", "Surface technology, coating", and "Biotechnology", which represent the central TAs in the technology network leading to the emerging technology of bioplastics.

VI. Discussion

In this article, we operationalize the assessment of IDR and emerging technologies by combining indicators with

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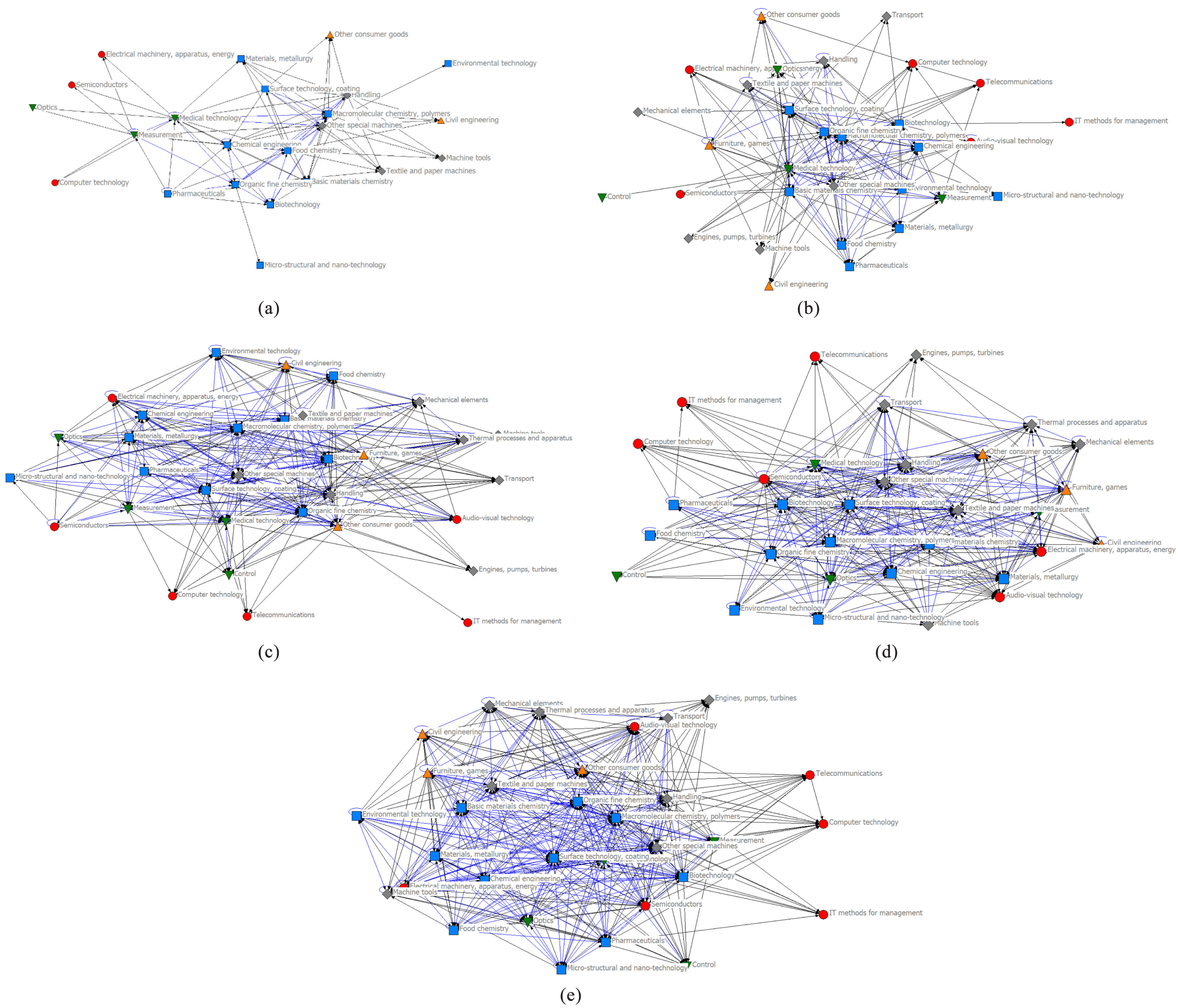

Fig. 4. Underlying technology network of bioplastic, four subperiods: (a) ≤2000; (b) 2001–2005; (c) 2006–2010; (d) 2011–2015; and over all time span: (e) ≤2000–2015. The color and shape of the nodes represent sectors based on the IPC-Technology Concordance Table. Chemistry: blue and square; Electrical engineering: red and circle; Instruments: green and down triangle; Mechanical engineering: gray and diamond; Other fields: orange and up triangle. The color of the lines represents directions of citations. Blue lines: reciprocal citations; black lines: one-way citations. Source: authors.

visualization approaches that enable to *assess, monitor,* and *visualize* a technology network. By drawing upon patents, patent citations, and patent classification codes as proxies for technological knowledge areas, this article develops a novel approach that alleviates the ambiguities associated with emerging technologies.

A. *Practical Implications for the Case of Bioplastics*

The combination of 32 different TAs from five different sectors forms the technology network of bioplastics. From a microperspective, the scatter plots indicate that across time subperiods, TAs have progressed to the "High degree of interdisciplinarity with high sector diversity" quadrant, implying that TAs in the technology network of bioplastics have become more interdisciplinary over time. The total interdisciplinary indicator can be used to quantify the degree of interdisciplinarity for each of the TAs forming the technology network of bioplastics. From a macroperspective, the network maps indicate that the technology network of bioplastics has become more complex over time. For instance, in the first period of analysis (≤2000), only 23 TAs form the technology network, whereas in the last period of the analysis (2011–2015), the technology network visualization contains 32 TAs with more relationships among TAs. The degree centrality and betweenness centrality indicators can be employed to identify and quantify the TAs that are central to the technology network of bioplastics resulting from interlinkages between TAs.

B. Contribution to the Foundations of Emerging Technologies

Emerging technologies formed by the integration and recombination of various scientific and technological knowledge fields within IDR [7], [11], [19], [20] are gaining importance for their ability to foster technological innovation and open up new areas of technology and science [8]–[10]. This potential has drawn interest from various actors, including scientific and industrial actors as well as (science) policy-makers [14], [18], [19]. As a result, research efforts have focused on developing a variety of indicators for the assessment of IDR that leads to emerging technologies, especially in the scientometric domain (e.g., [6], [39]).

Despite this broad interest, measures and indicators that can both evaluate diverse TAs and help to make sense of their emerging connections in the form of novel technology networks—the basis of emerging technologies—are still lacking in literature. The majority of extant studies attempting to assess IDR have focused on the level of integrating different scientific knowledge areas measured, inter alia, in terms of research publications [6], [14]. Given the aforementioned potential of emerging technologies for innovation, however, it seems evident that a mere assessment of interdisciplinarity at the level of scientific knowledge alone is unlikely to suffice. This underscores the relevancy of our article by developing a novel approach that enables to assess, monitor and visualize IDR and emerging technologies taking TAs as the unit of analysis.

This article extends the work of [6], who propose a conceptual framework for identifying IDR proposals, by developing a novel approach able to operationalize emerging technology networks formed by IDR. In contrast to [14], who define and detect emerging technologies and to [18], who examined the concept of technology emergence from the viewpoint of the philosophy of science and complexity, our article focuses on characterizing emerging technologies for their interlinkages between different TAs that, potentially, form a technology network. By combining [14], [18], our article is able understand the phenomenon of emerging technologies both from a micro and a macroperspective. More precisely, this article elucidates not only the degree of interdisciplinarity of the individual technological knowledge areas forming a technology network (microperspective), but also the dynamics of a technology network as a whole (macroperspective). Similar to [26], which indicate that research including more emerging technological ideas has a greater impact on its future citation impact, our article elucidates what TAs appear most relevant within a technology network based on citations patterns.

Our approach allows us to understand the phenomenon of emerging technologies by scrutinizing emerging technologies at the level of the emerging technology network formed by interlinkages of hitherto-unrelated TAs. Triggered by IDR, these different TAs are increasingly integrated and build technological networks, ultimately resulting in the formation of emerging technologies. Although scientific knowledge forms the basis of emerging technologies, it is ultimately the new combinations of technological knowledge, which potentially trigger the emergence of technology networks and resulting emerging technologies. This novel approach enables actors to assess IDR at the level of technological knowledge areas that are the basis for emerging technologies. As a consequence, this article contributes to mitigate the uncertainties, irregularities, and ambiguities associated with emerging technologies [14], [18].

C. Contribution to the Foundations of Knowledge Integration

As IDR is becoming more significant as a source for emerging technologies, there is growing appreciation of the need to manage and facilitate knowledge integration, especially between and among the diverse actors aiming to leverage the insights of IDR [9], [17], [19]. We see a particular challenge for the assessment (as well as monitoring and visualization) of emerging technologies resulting from IDR, as such a task requires the identification of the combined technological knowledge areas, i.e., the underlying technology network forming the bases of emerging technologies. Accordingly, this article seeks to complement existing approaches by focusing on the involved TAs that form a technology network. More precisely, such assessment supports the learning capacity of the involved actors by enabling them to better assess their current lack of knowledge and identify partners with complementary knowledge at an earlier stage [19].

This article contributes to the literature on knowledge integration by proposing a novel approach enabling to *assess*, *monitor,* and *visualize* emerging technologies by identifying relationships among different TAs. Such an approach has the potential to facilitate and direct learning processes for actors involved in the development of emerging technologies, notably, by identifying, which of the diverse knowledge areas are relevant and providing insight on how to manage knowledge integration across boundaries [19], [20].

Hence, this article extends the current understanding of knowledge integration from a technology perspective and develops an operationalization allowing to monitor the process of technology emergence [7], [11], [19], [20]. Furthermore, our novel approach explicitly characterizes emerging technologies by assessing not only interdisciplinarity at the level of TAs (microperspective) but also knowledge integration within a technology network (macroperspective) [7], [9], [18], [19], [36]. Here, we extend the work of [9] by applying the concept of knowledge integration and recombination to the context of an emerging technology network formed by IDR. This approach offers a means to extend the current indicators by enabling to assess and monitor the degree of interdisciplinarity of TAs within an emerging technology network in order to specifically facilitate knowledge integration [19], [36].

D. Contribution to Approaches to Assess, Monitor and Visualize IDR

This article develops, first, an *assessment* of the degree of interdisciplinarity of technological knowledge areas involved in the development of an emerging technology. In doing so, this article constructs three novel patent indicators, namely the *total interdisciplinarity technological area* $(I_{(i)})$, the *total interdisciplinarity sector* $(Is_{(i)})$, and the *total interdisciplinarity index* $(TI_{(i)})$. This is accompanied by measures of *degree centrality*

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$(Dc_{(i)})$ and *betweenness centrality* $(Bc_{(i)})$, which identify the most central and key bridging TAs, respectively, within a technology network. Second, this article elaborates a novel typology for *monitoring* the evolution of interdisciplinarity of TAs within an emerging technology network across time. Finally, this article develops a network-based approach to *visualize* the underlying emerging technology network.

a) Assessing and Monitoring Interdisciplinarity: According to our novel typology, technological knowledge areas can be classified into four categories on the basis of the three novel indicators. Applying this typology to the case of bioplastics, we were able to provide an initial demonstration of how these novel patent indicators could be applied to other emerging technologies resulting from IDR. Furthermore, by adopting technological knowledge areas as the unit of analysis, these novel patent indicators contribute to previous studies that have developed indicators to assess the degree of interdisciplinarity at the level of scientific knowledge, i.e., via publications [2], [28], [34], [39], [44], [56]. Specifically, the *total interdisciplinarity technological area* $(I_{(i)})$ builds on the study by [2], who construct an indicator that accounts for the number of different knowledge areas cited by a given scientific publication. Meanwhile, our novel indicator measures self-citations of a TA relative to the total number of citations. Also, the total interdisciplinarity sector $(Is_{(i)})$ extends previous studies [39], [46], [48] that have captured the scale breadth (i.e., number of categories) of the knowledge base of a publication, by measuring the number of sectors that are involved in the citations of a particular TA.

Furthermore, the typology developed in this article is able to further capture the degree of interdisciplinarity by combining $I_{(i)}$ and $Is_{(i)}$ over a certain time period to explore the dynamics that emerge from the interdisciplinarity of technological knowledge areas. In this way, we specifically extend the study by [39], who developed an indicator of interdisciplinary integration based on publications that accounts not only for the distribution of the cited references across different knowledge areas but also for the degree to which those knowledge areas are closely related.

b) Visualizing Emerging Technology Networks: In order to support the assessment and monitoring of IDR leading to emerging technologies, we provide two different visualizations. First, on the basis of the three novel indicators, TAs can be depicted by means of a scatter plot in order to provide an overview of the dynamics of interdisciplinarity over time. Second, the knowledge integration of different TAs forming a technology network can be visualized using technology network maps. This contributes to previous studies [55], [57] that also explored how to represent technological knowledge areas. Moreover, the *degree centrality* $(Dc_{(i)})$ demonstrates the TAs that have had the highest importance in the development of an emerging technology, while the *betweenness centrality* $(Bc_{(i)})$ reveals the TAs that have played a crucial role bridging and connecting technological knowledge within an emerging technology network that forms an emerging technology. Our article demonstrates that the combination of different visualization approaches (scatter plots and network maps) enables to understand the underlying technology networks formed by IDR from micro and macroperspectives. For instance, the scatter plots enable to understand the degree of interdisciplinary of TAs involved in a technology network (microperspective), whereas the technology network maps enable to understand relationships among TAs within a technology network as a whole (macroperspective). In addition, our article uses familiar approaches to visualize new indicators that support the interpretation of data.

VII. Conclusion

A. Theoretical Contribution

This article contributes to the foundations of emerging technologies [14], [18] by showing that knowledge integration within IDR leads to interlinkages between diverse knowledge areas which, as a result, link up to form a technology network, resulting in an emerging technology (as illustrated in Fig. 1). Hence, we consider knowledge integration as a crucial process within IDR in order for scientific and industrial actors as well as (science) policy-makers to benefit from the newly combined and subsequently integrated areas of hitherto distant areas of knowledge [7], [9], [19], [37]. This demonstrates the need to pay closer attention to developments at the integration of two or more knowledge areas. As illustrated in Fig. 1, knowledge integration across different TAs forms a technology network, potentially resulting in an emerging technology. Moreover, through the combination of indicators with visualization approaches, our article is able to provide proxies for operationalizing the assessment of IDR and emerging technologies based on technology networks.

B. Managerial and Policy Implications

Our operationalization of IDR makes use of a combination of indicators with visualization approaches to demonstrate that to conduct R&D in bioplastics, scientific, and industrial actors need to integrate knowledge from a diverse range of TAs. Thus, knowledge integration and collaboration with different partners are crucial in order for these actors to benefit from the knowledge of the different technological knowledge areas as well as the emerging technology network [7], [9], [19]. Consequently, effective management practices are key to the integration of knowledge across different technological knowledge areas [19]. In light of this, this article provides numerous practical implications for the diverse range of actors involved in IDR (e.g., scientific and industrial actors as well as (science) policy-makers).

First, the novel patent approach offers actors larger opportunities for understanding, accessing, discussing, combining, integrating, and managing technological knowledge in highly interdisciplinary knowledge areas. In particular, this article is useful for scientific and industrial actors as well as (science) policy-makers that wish to identify and monitor: 1) the interdisciplinary technological knowledge areas that are most relevant for the development of emerging technologies, and 2) the most central and key bridging technological knowledge areas within a technology network. On this basis, this article can help actors to

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explore the knowledge integration, networking, and collaboration possibilities between the different technological knowledge areas that are involved in the development of emerging technologies. For instance, an increasing range of bioplastics products is introduced in medicine ($Dc_{(\text{Medical technology}, \leq 2000-2015)} = 0.06$), or in manufacturing of machines to produce bioplastics (e.g., drilling, cutting) ($Dc_{(\text{Other special machines}, \leq 2000-2015)} = 0.052$). Hence, scientists and R&D managers might want to integrate in their teams or collaborate with experts from these disciplines to be at the fore front of inventions in bioplastics. Thus, such an approach to monitor knowledge integration is crucial for scientific and industrial actors, especially given the tendency to easily overlook opportunities that emerge from processes of knowledge recombination and the emergence of novel technology networks [8].

Second, as IDR is rather complex, as it combines knowledge from two or more scientific and/or technological knowledge areas, we, therefore, foresee a need for more empirically grounded approaches for science and technology management, as presented in this article. As a result, this article is especially useful as a way for scientific and industrial actors to identify potential experts with the required technological knowledge to conduct R&D, e.g., related to bioplastics (see, e.g., [7], [37]). For instance, consumer electronics technologies ($TI_{(\text{Audio-visual}, \leq 2000-2015)} = 0.970$) build upon a wide range of knowledge from different technological areas and sectors, thus, scientific and industrial actors might want to integrate or collaborate with experts from a wide range of backgrounds, including chemistry, medicine, or manufacturing of machines. Hence, these novel indicators can serve as a foresight approach with relevance for: 1) scientific and industrial actors seeking to improve their technological competencies by identifying opportunities for knowledge integration across technological knowledge areas [19], [65]; and 2) IDR institutions and funding agencies that wish to better understand, monitor and manage IDR and knowledge integration [30]. For example, the indicators developed in our article could be applied in long term monitoring studies such as the Bioeconomy Observatory, which aims at enhancing the knowledge base for policy-making in the bioeconomy by compiling and monitoring the process of the bioeconomy at European level [66].

Finally, this article provides relevant policy implications in light of the growing importance of IDR in science and innovation policy [12], [13]. Such practices involve the use of policy mechanisms to create opportunities for knowledge integration [19]. Therefore, (science) policy-makers can use our novel indicators and network maps to design and develop science and innovation policies in highly interdisciplinary and emerging knowledge areas. The *degree centrality* ($Dc_{(i)}$) indicator can help (science) policy-makers to identify technological knowledge areas in interdisciplinary settings where public funding may foster the underlying technology network of emerging technologies. Similarly, the novel interdisciplinary indicators and the *betweenness centrality* ($Bc_{(i)}$) are useful to identify technological knowledge areas that play a strong role connecting technological knowledge areas (i.e., key bridging technological knowledge areas) within a technology network. In this regard, the provision of our novel patent-based approach can avail (science) policy-makers to analyze how to foster IDR, for instance, by specifying, which technological knowledge areas should be made mandatorily integrated into research proposals. As such to foster R&D on bioplastics, based on $Dc_{(i)}$ and $Bc_{(i)}$, calls for funding might make mandatory collaborations from experts involved in relevant fields such as medicine or manufacturing.

C. Limitations and Future Research

The limitations of this article are primarily linked to the data used. First, we conducted this analysis using patent families and cited patent applications, therefore including patents from all patent authorities. However, there are differences between patent systems when it comes to citations. For example, in the US system, the patent applicant and his attorney are obliged to present the patent examiner with a complete list of relevant prior art for inclusion on the front page of the patent [67]. However, in the EPO system, the initial search for prior art is carried out by a designated searcher at the EPO, and should only include the most important patent references. This implies that US patents might be more interdisciplinary than the patents of other authorities, as they include a higher number of citations.

A second limitation of our article is that we draw upon the frequency of citations of prior patents as a proxy for technological linkages and, thus, for IDR as well as the importance of a technological knowledge area. However, a high degree of cross-citations might not necessarily reflect the extent to which ideas come from different knowledge areas [68]. Another limitation is that the IPC-Technology Concordance Table was used as a basis for our analysis in order to link IPC codes to technological knowledge areas and to derive the indicators. Therefore, some limitations may result from the use of this table, and more fine-grained indicators should be considered, e.g., by looking IPC groups and subgroups.

Future research might investigate the particular effect of patents that combine highly distant knowledge areas with respect to their citation patterns [68] or the approval process to which they are subject [10]. In addition, future research could benefit by extending the current approach, e.g., by considering company data or information on patent assignees to assess interdisciplinarity within emerging technologies. Future studies could also consider the application of our novel approach to not only other interdisciplinary and emerging technologies such as bioinformatics, nanobiotech, nutrigenomics, or artificial intelligence, but also to technology networks, which are characterized by a lower degree of interdisciplinarity (e.g., technology network based on established disciplines like biology).

Additionally, as an extension of our approach, a multilevel study could be highly desirable. Here, by combining the assessment based on scientific knowledge as well as technological knowledge, one could expect additional insights into the evolution of an interdisciplinary technology network (indeed, combining different data sources to access scientific and technological knowledge has already been done by, e.g., [69], [70]).

Furthermore, this article might benefit from making use of a wider range of proxies to assess interdisciplinarity (e.g., semantic analysis and cocitations) and thereby analyzing differences in their implications for emerging technology networks.

Finally, future studies might seek to elaborate on and extend our indicators by entertaining a more qualitative perspective. Indeed, if we compare our approach to that of [6], who used research proposals in order to assess IDR, we specifically envision the scope of IDR as an avenue of future research, e.g., to what extent the emerging technology is built upon narrow (related) versus broad (very unrelated) interdisciplinarity? However, this seems to be a challenging task, given the need to resolve the ambiguity around the notion of technological distance and the difficulty of assessing whether certain technological knowledge areas within a technology network are more related to one another than others [6]. Hence, future research could build on our patent approach by taking the broader context into account, e.g., funding schemes as political triggers for IDR and the commercial forces that spark the emergence of technology networks, or the relative impact of IDR featuring emerging technologies compared to emerging technologies in general.

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