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Dynamics of scientific knowledge bases as proxies for discerning technological emergence — The case of MEMS/NEMS technologies

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ABSTRACT

Emerging technologies embrace the very early stages of socio-technological evolution. Despite their appealing nature, they have been loosely defined and operationalized. In particular, operationalization approaches based on bibliometric methods have often tended to emphasize the exponential growth and the potential impacts of emerging technologies while overlooking their inherent uncertainty and 'fluidity'. The purpose of this paper is to contribute to the operationalization of emerging technologies by presenting an approach for quantitatively interpreting technologies of an emerging nature along both dimensions. We do so by looking into the dynamic properties of scientific knowledge bases in terms of their rates and directions of change. Our approach integrates bibliometric indicators, social network analysis and multivariate statistical methods on scientific publications, and their citing and cited references. The empirical case of micro/nanoelectromechanical systems technologies (MEMS/NEMS), which embrace micro- and nano-sensors and actuators, is used. A total of thirteen MEMS/NEMS technologies are evaluated. Overall, our results provide a quantitative framework for discerning technological emergence through the evaluation of the dynamics of scientific knowledge bases. These results highlight the coupled intense patterns of growth and cognitive fluidity characterizing emerging technologies. We also provide a glimpse into the difficulties encountered by specific nanotechnology fields in bringing forward nano-enabled devices.

1. Introduction

The study of technological change of a drastic nature, i.e. change with a potential to defy or even overthrow the status-quo, is not new. Earliest contributions are those of Kondratieff's 'long waves of technological change' and most prominently Schumpeter's 'perennial gales of creative destruction' of the early 1930s. Research interest on drastic technological change has been fuelled by its crucial role in the future viability of technology-intensive firms [1], its potential to create entirely new industries [2], and the continuously recurring and ever increasing intensity of the current waves of technological change [3], among others. Over the years, literature has proposed a number of terminologies and labels to study the newness and severity of drastic technological change; examples are radical, disruptive, discontinuous, breakthrough, nascent, and emerging technologies and innovations, just to name a few. As these terminologies and labels entail different perspectives to visualize a similar phenomenon, they are highly interrelated; their meanings partially overlap. Nevertheless, they are also conceptually unique for they are shaped by particular cognitive and intellectual influences.

This paper focuses on emerging technologies which deal with the understanding of the very early stages of technological evolution [4]. Emerging technologies are characterized by embracing: fast recent growth rates, transitions into something new, market or economic potentials, and a significant science-driven nature [5]. Yet, such growth and potential of change come with

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a price, namely the uncertainty and fluidity surrounding those technologies [4,6]. Despite their appealing nature, emerging technologies have been loosely defined and operationalized [5]. In particular, operationalization approaches based on bibliometric methods have often tended to emphasize the exponential growth and the potential impacts of emerging technologies while overlooking their inherent uncertainty and fluidity. Hence, in this paper we set our sights on enhancing the operationalization of emerging technologies by describing a bibliometric-based approach for quantitatively interpreting technologies of an emerging nature along both dimensions. To do so, we look into the properties of the knowledge bases underlying technologies.

Over the years, knowledge bases have been often used as 'differentiators' of the nature of technology and innovation across systems, sectors, and industries [7–9]. Given the heavy science-driven nature and the still early technological development of emerging technologies [5,6], scientific knowledge bases, expressed in scientific publications, have been regarded as appropriate proxies for the analysis and measurement of technologies of an emerging nature, provided their inherent limitations are considered [10]. In this paper, we center our attention on the dynamics of scientific knowledge bases in terms of their rates and directions of change. The former provides insights into the patterns of growth experienced by technologies, while the latter hints at their degree of cognitive fluidity. In particular, we relate the directions of change of the knowledge bases to the *problems* encountered by technologies throughout their evolution. Here, literature has highlighted the ability of problems to reflect the directions along which scientific knowledge bases are oriented [11,12]. As problems demand knowledge for their solution, we argue that the nature of the knowledge underlying technologies depicts a sort of a 'cognitive imprint' reflecting the types of problems confronted by technologies over time. This provides insights into the directional dynamics of knowledge bases, and, in turn, into the cognitive fluidity of technologies.

Our research approach integrates bibliometric, social network analysis and multivariate statistical methods on scientific publications indexed in the Thomson Reuters/ISI Science Citation Index Expanded database (hereafter ISI/SCI), and their citing and cited references. We focus on the empirical case of micro/nanoelectromechanical systems (MEMS/NEMS), which embrace micro- and nano-sensors and actuators. In total, thirteen different MEMS/NEMS technologies are included in this study. Two main methods of analysis are defined. First, the rates of change experienced by MEMS/NEMS knowledge bases are explored through the conduction of correlation and hierarchical cluster analyses on a series of bibliometric indicators. These analyses are used as proxies for discerning the patterns of technological growth. Second, co-citation networks are constructed and analyzed to study the directions of change along which knowledge bases are channeled. In particular, those co-citation networks are endowed with directionality through the allocation of a particular 'problem area', drawn from a pre-defined 'problem space' for MEMS/NEMS devices, to each of the network nodes. In turn, the cognitive compositions and the cognitive sub-fields underlying the problem-attached knowledge structures are used for assessing the degree of cognitive fluidity of technologies.

This paper is structured as follows. Section 2 provides an overview of the previous literature. Next, Section 3 describes briefly the framework of analysis used. Subsequently, Section 4 defines the research methods. Following, Sections 5 and 6 summarize the results of the analyses on the rates and directions of change of the MEMS/NEMS knowledge bases, respectively. Finally, a series of conclusions and discussions are presented in Section 7.

2. Theoretical background

2.1. Emerging technologies

Emerging technologies entail those technologies at the very early stages of technological development [4]. Although emerging technologies have gained ground within the TIM field particularly after the 1990s, they have been loosely defined and operationalized [5]. Despite that, literature has agreed on the "unmistakable connotations of revolutionary potential" they convey [13]. Day et al. [6] regarded emerging technologies as those technologies whose knowledge bases are expanding, existing markets are under strong innovative pressures, and new markets are created or exploited. For them, they include discontinuous technologies as well as more evolutionary technologies formed by convergence. Based on a literature review, Cozzens et al. [5] have enumerated a series of major concepts entailed by emerging technologies: fast recent growth, transition to something new, market or economic potential, and increasing science-driven nature.

Emerging technologies bring with them a rapid development of ideas, fast changes of knowledge, and a continuous increment in the population of organizations active in the field, among others [14,15]. As defined by van Merkerk and Robinson [16] such growth is coupled with the formation of linkages, sparse and porous at first, among a small number of heterogeneous actors and organizations. Jacobsson and Johnson [17] describe that such early linkage formation depicts embryonic structures around which formative technological innovation systems are being built. Technological emergence is also highly associated with the formation, change and transformation of knowledge bases [5,6]. Hung and Chu [18] visualize emerging technologies as potential catalyzers of change which, if properly fostered, may lead to the formation of new or transformed industries. Going far beyond, emerging technologies have also been defined as essential to successful growth, employment, competition, and sustainability [18]. Their impact goes beyond economic aspects to embrace disruptive changes directly impinging on society [19,20].

Yet, emerging technologies come with great levels of uncertainty, ambiguity, and fluidity [4,6]. On the one hand, they are characterized by high market and technical uncertainty as suggested by their unknown or unarticulated demand as products are new or about to be developed [4,11,14,21]. Moreover, market knowledge may be absent, and usage patterns and behavior may still be in formation [17]. As such, emerging technologies involve significant levels of unpredictability which make it difficult for actors to assess what the technology will bring [4]. On the other hand, emerging technologies are characterized by a fluidic nature as reflected in the absence of transparent and structured relations among actors, formative institutional frameworks, the existence of multiple paths, as well as the inexistence or emergence of dominant designs, architectures, and standards [4,6,22,23].

2.2. Bibliometric approaches on emerging technologies

Different methods have been used for evaluating emerging technologies. This section focuses on bibliometric approaches. Porter and Detampel [24] define bibliometrics as the use of publications, patents and/or their citations targeting the measurement and interpretation of scientific and technological advances. Recently, Cozzens et al. [5] highlighted the significant potential of bibliometric approaches, provided their limitations are considered, for the identification and measurement of emerging technologies. For the particular case of bibliometric approaches on emerging technologies, three main streams of research were discerned from the literature.

Given the uncertainty surrounding emerging technologies it is not surprising that a large amount of research efforts have been devoted to technological forecasting and related areas. Bengisu [25] relied on the statistical evaluation of publication and patent data for forecasting the technological growth of a series of materials and manufacturing technologies through the use of 's-curves'. Daim et al. [26] combined the use of publications and patents with tools such as scenario planning, growth curves and analogies to forecast emerging technologies in the fuel cell, food safety and optical storage technological fields. More recently, Robinson et al. [27] proposed an integrated framework for analyzing emerging technologies based on the future-oriented technology analyses (FTA) for the cases of bionanosensor and deep-brain stimulation technologies. Moreover, relying on patent data Chen et al. [28] identified and visualized the future technological evolution of the field of smart grid technology.

A second broader research stream has aimed at the understanding of the properties of emerging technologies. In particular, significant research efforts have been devoted to the newly emerging field of nanoscience and nanotechnology (N&N). Takeda et al. [29] made use of scientific publications to reveal the structure and research domains in the field of nanobiotechnology. Similarly, Lee and Su [30] studied the scientific knowledge structure of the electrical-conducting polymer nano-composites. Bonaccorsi and Thoma [31] and Bonaccorsi and Vargas [32] made use of a co-word analysis on publication and patent data to analyze the performance of N&N inventors and to evaluate the dynamics of knowledge of the N&N field, respectively. Relying on publication data, Islam and Miyazaki [33,34] have focused on the dynamics of nanoscience fusion trajectories and conflation phenomena, as well as on the definition of nanotechnology research domains [35].

Finally, a third stream of research has focused on quantitatively identifying emerging technologies. Upham and Small [36] made use of co-citation clusters of scientific publications combined with qualitative data to identify emerging research fronts. Shibata et al. [37] described the detection of emerging technologies in the fields of Gallium Nitride and regenerative medicine through the use of a co-citation network clustering approach. Lee [38] and Schiebel et al. [39] relied on the construction and analysis of 'co-word' networks for the identification of emerging research fields for the cases of information security technologies and optoelectronic devices, respectively. Chang et al. [40] analyzed patents through network approaches to monitor technological trends in the field of carbon nanotube-based field emission displays.

A method that can be found across the three research streams is bibliometric mapping which defines the attempt "to find representations of intellectual connections within the dynamically changing system of scientific knowledge" [41]. Most of bibliometric mapping approaches rely on co-occurrence information, i.e. the number of times two elements appear together in a publication, be it words (co-word), authors (co-authorships), source articles (bibliographic coupling), and cited references (co-citation analysis) [42]. Provided the inherent limitations of co-citation data [43], since the pioneering efforts by Small [44] and Marshakova [45] co-citation analysis has been regarded as a way to discern the intellectual structure or knowledge base underlying a field. In particular, the study of cited references has been closely related to 'socio-cognitive' aspects [19].

2.3. Technology in focus — MEMS/NEMS technologies

MEMS is an acronym for 'micro-electro-mechanical systems', also known as micromachines or microsystems technologies. MEMS defines both an interdisciplinary portfolio of downscaling techniques and process, as well as the parts, devices, and subsystems, typically sensors and actuators, with feature sizes down to the micro/nano-scale[1] enabled by those technologies. This paper focuses on the latter definition. Accelerated progresses in nanotechnology have gradually extended the field of MEMS into NEMS (nano-electro-mechanical systems). As key technologies within the field of sensors, MEMS/NEMS are expected to play a major role in the future as they span all sectors of industry and often lead to innovative products resulting in competitive advantage [46]. For the case of MEMS/NEMS, the latter has crystallized into different markets and application domains. In this study, thirteen different MEMS/NEMS technologies are included (Table 1). Such diversity provides a rich test ground on which to base our analyses.

Without aiming at providing an exhaustive list, a series of studies on sensor technologies in general and MEMS/NEMS in particular have been conducted over the years. Andersen et al. [46] conducted a technological foresight study on sensor technology. Recently, Juanola-Feliu et al. [47] reported on the research and development activities of an implantable

[1] 1 μm = 1×10^{-6} m; 1 nm = 1×10^{-9} m.

Table 1
Overview of MEMS/NEMS technologies included in this analysis.

Technology	Brief description and potential application domains
Accelerometers	Inertial device measuring acceleration forces
Bio-MEMS	Biological and medical applications of MEMS. Broad encompassing field: surgical instruments, drug delivery systems, bio-sensors, pressure sensors, among others
Gyroscopes	Sensors for measuring angular velocity. Uses in automobiles, consumer electronics, among others
Microfluidics	Handling of fluids in MEMS. It includes: micro total analysis systems, labs on a chip, and their components such as micro-pumps, micro-valves, etc.
MOEMS displays	Micro-mirror arrays, micro-gratings, etc. for display projectors, bar code readers, etc.
MOEMS telecomm	Devices for optical communications, such as optical switching units, variable optical attenuators, tunable filters, among many others
Micro-tips (AFM)	Probes and tips for measuring the properties of surfaces with atomic force microscopes
Power-MEMS	Includes energy-related applications for MEMS devices, such as energy scavengers, microturbines, microthrusters, microgenerators, micromotors, among others
Pressure sensors	Main applications in automotive, industrial automation, medical, and aerospace
Printheads	Heads for inkjet printing applications
RF-MEMS	High-frequency circuits (radio frequency, micro- and millimeter waves), such as high-Q inductors, phase shifters, antennas, tunable capacitors and resonators, among others.
ZnO nanosensors	Use of zinc oxide nanostructures for sensing and actuation applications
Carbon nanotube nanosensors	Use of carbon nanotubes for sensing and actuation applications

bionanosensor. Similarly, for the case of biosensors, Wang [48] defined a framework for exploring potential R&D collaborators. Kautt et al. [49] explored the similarities and differences of major international Micro and Nano Technology Centers. Walsh [50] and Linton [51] proposed roadmapping approaches for the fields of microsystems.

3. Overview of the framework of analysis

Over the years knowledge bases have been regarded as 'differentiators' of the nature of technology and innovation across sectors, industries, systems, etc. [7–9]. Knowledge bases are defined as those cognitive and physical structures from which actors draw upon to innovate [8,52]. As such, they embrace aspects such as knowledge, skills, capabilities, etc. of a diverse nature [7,8]. In particular, we are interested in the dynamic nature of knowledge bases; they grow, change, and transform [53]. Those dynamics are highly path-dependent and cumulative [52]; also, they are highly coupled to the actors, networks and institutions active in innovation processes [8,9,53,54].

From what has been discussed so far, we regard the dynamic properties of scientific knowledge bases in terms of their rates and directions of change as useful proxies for the understanding of technological emergence. On the one hand, the rates of change of knowledge bases provide insights into the patterns of growth of technologies. In this regard, knowledge bases underlying emerging technologies are expected to be broadening, expanding, and diversifying [6,55], which appears to be closely related to the interconnection of different scientific and technological domains [22,56]. On the other hand, the directions of change hint at the degree of fluidity, particularly in cognitive terms, of technologies. In this regard, literature has highlighted the ability of problem sequences to reflect the directions along which scientific knowledge bases are oriented [12]. By problem sequences, it is meant the recurrent patterns of problem search and solution tackled by the innovation systems building around technologies [11,12,53]. As problems demand knowledge for their solution, we posit that the nature of the knowledge underlying technologies is expected to leave a sort of a 'cognitive imprint' *reflecting* the problems encountered at particular stages of technological evolution. Hence, such 'cognitive imprint' may be used to infer about the directional dynamics of knowledge bases, which, in turn, relate to the cognitive fluidity of technologies. Bibliometrically, those 'cognitive imprints' can be expressed through the construction of co-citation networks. In this paper, those co-citation networks are endowed with directionality by associating them with problems through the allocation of a particular type of problem area to each of their nodes (please refer to Section 6.1 for the description of the problem areas). As a variety of efforts are conducted to advance a particular technology [57], it is clear that different problems are tackled concurrently. Those problems are highly interrelated; feedback loops are present among all problem phases. Despite that, given the cumulative nature of knowledge we expect the different problem areas to be cognitively dependent in the sense that the earliest phases of problem search should be partly cleared out and a certain amount of knowledge accumulated before attempts into subsequent phases are conducted [52,58,59]. It follows that the different problem areas may be visualized, from a macro perspective, as a loosely defined chain composed of upstream and downstream stages. We would expect emerging technologies to direct their cognitive efforts at different locations along the problem chain compared to those of mature technologies.

4. Research methods

The dataset comprised scientific publications and citations – including articles, reviews and proceedings – indexed in the ISI/SCI database, published in English and up to the year 2009. A keyword-based analysis was used to collect the publication data. The definition of the appropriate set of keywords for each MEMS/NEMS technology relied on mapping techniques in the form of 'technological trees'. The search queries consisted of both field-encompassing and artifact-specific keywords. For this search, the titles, abstracts, and keywords of scientific publications were reviewed. A total of 13,393 publications were collected, from which 89,901 citing references were drawn. Those citing references were restricted to articles, proceedings and reviews in any language, and published up to the year 2009; self-citations were excluded. Moreover, cited references were retrieved for some MEMS/NEMS technologies. The software VantagePoint was used for data cleaning, sorting, and analysis. Based on the collected data, the rates and directions of change of the scientific knowledge bases underpinning MEMS/NEMS technologies were evaluated.

For the case of the rates of change of MEMS/NEMS knowledge bases, bibliometric parameters such as publication outputs, publication years, countries of publications, and journal subject categories (SC), among others, were extracted from the source publications and their citing papers. Those parameters were further processed into eleven bibliometric indicators embracing aspects as different as the dynamism, variety, diffusion, complexity and age of scientific knowledge bases (see Section 5.1). For the particular case of the evaluation of the scientific variety of knowledge bases, we used the informational entropy of the shares of journal subject categories allocated by the ISI/SCI database to publications. Here, entropy is defined as follows [60]:

$$S = \sum_{\mathrm{i}} p_i \ln p_i$$

where p_i defines the share of proportions of SCs across a scientific field. Entropy is defined in terms of the number of scientific fields a knowledge base embeds and how intense they are [60]. In order to make the study of SCs practicable, SCs were grouped according to Porter and Rafols' classification into 21 macro-disciplines [61]. Subsequently, correlation and hierarchical cluster analyses were conducted on the bibliometric indicators to discern the general and specific rates of growth of MEMS/NEMS knowledge bases, respectively. For both analyses the statistical package SPSS was used.

For the case of the directions of change of MEMS/NEMS knowledge bases, co-citation networks were constructed and evaluated. For that purpose, cited references were collected, and subsequently cleaned and sorted by manually grouping together similar references and correcting input errors in their bibliographic information. To prevent the inclusion of random errors and size-related biases a normalized citation count of 0.6 was defined. Following, the software VantagePoint was used to construct co-occurrence matrices which depict pairwise relations between cited references. Those co-occurrence matrices were normalized with the Salton's cosine similarity measure in order to provide a better visualization of the similarity structures across the data and to control for size effects. The Salton's cosine measure as applied to co-citation data is defined as follows [62]:

$$S_s(i,j) = \frac{coc(i,j)}{\sqrt{cit(i) * cit(j)}}$$

where $S_s(i,j)$ stands for the cosine-normalized co-citation strength between cited references i and j, $coc(i,j)$ entails the number of co-citations between cited references i and j, and $cit(i)$ and $cit\ (j)$ depict the number of citations for the cited references i and j, respectively. A predetermined co-citation threshold greater or equal to 0.18, within the range of values typically used in the literature, was chosen in order to center our attention on those predominant co-citation relationships. The cosine-normalized matrices were visualized as co-citation networks with the software UCINET and NetDraw [63].

In a subsequent step, problems were allocated to the nodes of the co-citation networks. Those problem-attached co-citation networks were evaluated through a series of network indicators in order to assess the significance and predominance of the different problem areas within knowledge structures. This is referred in this paper as 'cognitive compositions'. For that purpose, the shares of nodes and citations, and normalized centrality values were estimated. Three common measures of network centrality were used [64]:

- Degree centrality, which defines the number of edges incident on a node in a network. As such, it indicates the degree to which a particular problem area exists in the network,
- Betweenness centrality, which depicts the extent to which a node lies on the shortest path between pairs of nodes in the network. This centrality value determines the locational quality of the problem areas; usually, those with high betweenness centrality tend to be located closer to the center of the network, and
- Closeness centrality, which entails the inverse of the average shortest path between a node and all other nodes in the network. Thus, high closeness centrality values depict those problem areas with a high influence on other problem areas.

The network centrality values were calculated with the software UCINET/NetDraw. Subsequently, the cognitive sub-fields, i.e. those agglomerations of highly cognitive-related nodes, underlying the MEMS/NEMS knowledge structures were discerned. This was done through the conduction of a hierarchical cluster analysis on the cosine-normalized co-citation networks. For this analysis, the software SPSS was used.

5. Rates of change of scientific knowledge bases

Within this section, the general and specific rates of change experienced by the scientific knowledge bases underpinning MEMS/NEMS technologies are described. This, in turn, provides insights into the patterns of growth of technologies. The results of this section rely on a series of bibliometric indicators to be described next.

5.1. Description of the bibliometric indicators

A total of eleven bibliometric indicators were defined:

- Dynamism of the generated knowledge *[DYN_PUB]* and the diffused knowledge *[DYN_CIT]* — These proxies define the median of the slopes of the curve of the accumulated proportions of publications and citations, respectively, for the period 2006–2009. They provide a measure of the recent speeds of growth of the generated knowledge *[DYN_PUB]* and the diffused knowledge *[DYN_CIT]*. The higher their values, the faster the speeds of growth experienced by the knowledge bases.
- Relative dynamism *[RATIO_DYNCP]* — This proxy describes the ratio of the dynamism of the diffused knowledge *[DYN_CIT]* over that of the generated knowledge *[DYN_PUB]*. Ratios higher than one imply higher relative speeds of knowledge diffusion vis-à-vis those of knowledge generation.
- Acceleration of the generated knowledge *[CHDYN_PUB]* and the diffused knowledge *[CHDYN_CIT]* — These indicators estimate the average of the 'slopes of the slopes' of the cumulative proportion curve of publications and citations, respectively, for the period 2006–2009. Higher acceleration values point to more sustained recent growth for the generated *[CHDYN_PUB]* and the diffused knowledge *[CHDYN_CIT]*.
- Rate of growth of countries active in the field *[RATE_COUNTRY]* — It indicates the rates of growth in the number of countries active in the field between the periods 2002–2005 and 2006–2009. By active, we mean those countries with at least five publications in those periods. As such, higher *[RATE_COUNTRY]* implies a growing interest and participation of countries in a particular field.
- Collaboration at the country level *[COLL_MACRO]* — This indicator estimates the proportion of papers – publications and proceedings articles – co-authored by authors from two or more different countries as a proxy for the collaboration at the country level. The higher the *[COLL_MACRO]* values, the higher degrees of collaboration in the knowledge generation.
- Collaboration at the author level *[COLL_MICRO]* — This proxy defines the proportion of papers – publications and proceeding articles – co-authored by three or more authors. It attempts to capture the degree of collaboration in the knowledge generation at the author level. Higher values point to higher levels of collaboration.
- Year of emergence *[YEAR_EMER]* — It describes the year in which more than ten publications are accumulated for a particular field. The latter provides a proxy for the 'chronological newness' of the knowledge base. Higher years of emergence suggest 'younger' knowledge bases.

The rest of the indicators relied on the journal subject categories (SC) for both publications and their citing references.

- Scientific variety of the generated knowledge *[S_PUB]* and the diffused knowledge *[S_CIT]* — These indicators define the entropy values of the shares of subject categories of publications and citations, respectively, for the period 2006–2009. As such, they depict the variety of the generated knowledge *[S_PUB]* and the diffused knowledge *[S_CIT]*. Higher values imply higher levels of variety.
- Relative variety *[RATIO_SCP]* — Ratio of the variety of the diffused knowledge *[S_CIT]* over that of the generated knowledge *[S_PUB]*. Ratios above one denote higher degrees of variation in the diffused knowledge relative to those of the generated knowledge.
- Potential scientific complexity *[POT_COMPL]* — It indicates the average number of journal subject categories per publication, as resulting from the ISI/SCI database, for the period 2006–2009. As such, *[POT_COMPL]* provides a rough indication of the potential complexity of a scientific field.

5.2. General rates of change of MEMS/NEMS scientific knowledge bases

In this section we discuss the general patterns of relationship among the above-mentioned bibliometric indicators through the conduction of a correlation analysis. Table 2 illustrates the resulting correlation matrix.

An examination of the correlation matrix in Table 2 reveals the following results. The variety of the generated knowledge base appears to be inversely correlated at significant levels with the year of emergence. This suggests that 'younger' scientific knowledge bases embrace lower levels of variety. Despite that, they show greater levels of collaboration. Formative knowledge bases in terms of their levels of diffusion are associated with higher levels of dynamism, collaboration, and potential complexity. It appears that rapid rates of growth of knowledge bases tend to be paralleled by a sustained, accelerated growth. Such significant levels of dynamism bring with it the building up of a 'critical mass' of actors as reflected in the greater engagement of countries and the larger degrees of collaboration. Moreover, the dynamics of the generated and diffused knowledge are highly coupled. This may be partly attributable to the high correlation typically observed between publications and citations [65]. Finally, these results demonstrate that newer and potentially more complex knowledge bases are associated with greater levels of dynamism; what is more, newly emerging knowledge bases entail higher levels of collaboration.

These results suggest that the patterns of growth of emerging technologies, as reflected in the scientific knowledge bases, cannot be explained by chronological newness alone. Instead, it is suggested that newness, high dynamism in terms of the speeds and acceleration of growth, high levels of collaboration, potential complexity, and early knowledge diffusion go hand in hand. This is also accompanied by a narrow scientific variety.

Table 2
Correlation matrix.

	Proxies	Correlations										
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	S_PUB	1										
(2)	RATIO_SCP	−0.11	1									
(3)	DYN_PUB	−0.26	−0.72**	1								
(4)	RATIO_DYNCP	−0.19	0.56*	−0.74**	1							
(5)	CHDYN_PUB	−0.33	−0.58*	0.84**	−0.55	1						
(6)	CHDYN_CIT	−0.28	−0.75**	0.93**	−0.57*	0.84**	1					
(7)	RATE_CNTRY	−0.03	−0.49	0.72**	−0.88**	0.51	0.50	1				
(8)	COLL_MACRO	−0.58*	−0.04	0.35	0.07	0.10	0.29	0.15	1			
(9)	COLL_MICRO	−0.23	−0.76**	0.69**	−0.35	0.46	0.69**	0.44	0.62*	1		
(10)	POT_COMPL	−0.13	−0.56*	0.56*	−0.20	0.64*	0.66*	0.12	0.00	0.30	1	
(11)	YEAR_EMER	−0.61*	−0.38	0.79**	−0.43	0.69**	0.74**	0.47	0.67*	0.66*	0.42	1

NOTES: S_PUB: variety in the generated knowledge; RATIO_SCP: ratio of the variety of the diffused over the generated knowledge; DYN_PUB: speed of growth of the generated knowledge; RATIO_DYNCP: ratio of the speeds of growth of the diffused over the generated knowledge; CHDYN_PUB: acceleration of growth of the generated knowledge; CHDYN_CIT: acceleration of growth of the diffused knowledge; RATE_CNTRY: rate of growth in the number of countries active in knowledge generation; COLL_MACRO: degree of collaboration at the country level; COLL_MICRO: degree of collaboration at the author level; POT_COMPL: potential scientific complexity; YEAR_EMER: year of emergence.

* Statistically significant at the 0.05 level.

** Statistically significant at the 0.01 level.

5.3. Specific rates of change of MEMS/NEMS scientific knowledge bases

The dynamics of the scientific knowledge bases underpinning MEMS/NEMS technologies are unique; yet, they share some similarities. This section attempts to discern the groupings of similar MEMS/NEMS knowledge bases. For that purpose, a hierarchical cluster analysis based on the Ward's clustering method/squared Euclidean distances was conducted. Z-score standardized values were used to reduce the effects of the different ranges of value across the indicators. Fig. 1 left presents the dendrogram resulting from the cluster analysis.

Four main clusters of MEMS/NEMS scientific knowledge bases were identified. Table 3 presents a schematic comparison of these clusters across five groupings: variety, diffusion, dynamism, complexity, and age. The bibliometric indicators described in Section 5.1 were allocated to each of those groupings. Different symbols are allocated to Table 3 according to the quartile values of the cluster means.

In terms of performance, the data in Table 3 shows two extreme clusters, namely Cluster I and Cluster IV. Between those clusters, Cluster II and Cluster III fall. Following, the properties of those clusters are described. We begin with the description of the extreme clusters:

- Cluster I — This cluster shows moderately high levels of variety in the generated and the diffused knowledge. It is characterized by fast, yet decelerating, rates of knowledge diffusion relative to those of their knowledge generation. Its dynamism is low. It is also characterized by low levels of collaboration, as well as by low degrees of potential complexity. This cluster includes the most mature knowledge bases. From those, 'pressure sensors' stand out as the most mature and the least dynamic MEMS/NEMS scientific knowledge base. Despite their relative maturity, 'inkjet printing-head' technologies display a higher dynamism particularly driven by novel application domains in the fields of biotechnology and nanotechnology.
- Cluster IV — Compared to Cluster I, this cluster depicts 'the other side of the coin'. It shows the lowest levels of variety, as well as the lowest, yet the most highly accelerating, rates of knowledge diffusion. This cluster also displays the highest dynamism

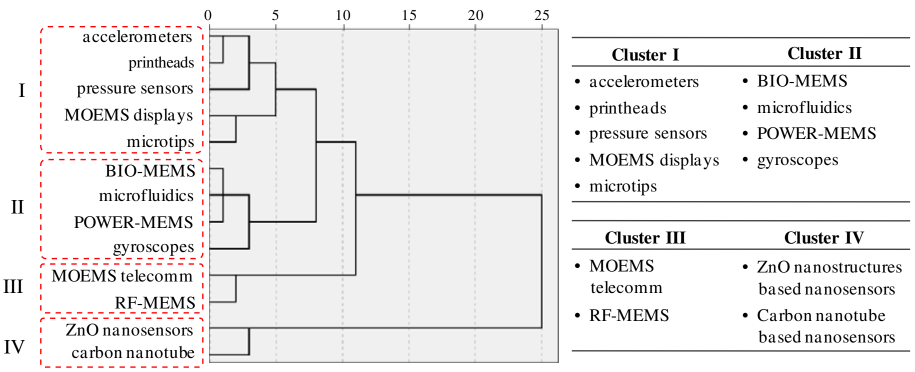

Fig. 1. Dendrogram and description of the clusters.

Table 3
Characterization of clusters across the indicator groupings.

Clusters	Groupings of indicators							
	Variety		Diffusion		Dynamism	Complexity		Age
	Absolute	Relative	Rel. speed	Rel. accel.		Collab	Pot. compl.	
Cluster I	+	+	+	− −	−	− −	−	− −
Cluster II	+ +	−	−	+	+	−	+	−
Cluster III	− −	+ +	+ +	−	− −	+	−	+
Cluster IV	− −	− −	− −	+ +	+ +	+ +	+ +	+ +

Notes:
rel.: relative; accel.: acceleration; collab.: collaboration; pot. compl.: potential complexity.
x<1st quartile → − ; 1st quartile<=x<2nd quartile → − − ; 2nd quartile<=x<3rd quartile → + ; x>3rd quartile → + +.

and potential complexity levels, and the chronologically newest knowledge bases. It includes the nanotechnology-related scientific knowledge bases ‘carbon nanotube sensors’ and ‘ZnO nanostructured sensors’.

- Cluster II — In terms of their generated knowledge, this cluster displays the highest variety and relatively high speeds of growth and acceleration rates. The dynamics of the diffused knowledge are still lagging behind but about to grow given their high rates of acceleration. Despite its high variety and potential complexity, this cluster shows moderately low degrees of collaboration. Relative to the rest of MEMS/NEMS technologies, this cluster embraces slightly aged technologies. In particular, this cluster includes broad-encompassing technological domains rather than punctual technologies. Some examples are BIO-MEMS, POWER-MEMS, and microfluidics.
- Cluster III — This cluster shows a performance mostly opposite to that of Cluster II. Despite its moderate chronological newness, this cluster displays the lowest average levels of dynamism. It shows high levels of collaboration yet low levels of potential complexity. Their relative newness coupled with their sluggish dynamism makes the knowledge bases of this cluster to be ‘stuck in the middle’. This cluster includes technologies such as ‘RF-MEMS’ and ‘MOEMS telecommunications’ which are closely related to the telecommunications ‘bubble burst’ of the early 2000s.

These results highlighted the ‘commonalities’ and differences in the patterns of growth among the different MEMS/NEMS knowledge bases. In this regard, Cluster IV appears to be in line with the patterns of growth of emerging technologies described in the previous section: newness, dynamism, complexity, scientific narrowness, and formative diffusion. As mentioned above, this cluster includes the nanotechnology-related scientific knowledge bases ‘carbon nanotube sensors’ and ‘ZnO nanostructured sensors’.

6. Directions of change of scientific knowledge bases

We now look into the directions of change of the scientific knowledge bases underpinning MEMS/NEMS technologies at different levels of emergence/maturity. As previously noted, the directional dynamics of knowledge bases are closely related to the degree of cognitive fluidity inherent in technologies. Quantitatively, this section relies on the construction and evaluation of co-citation networks drawn from the cited references of scientific publications. Here, a crucial step consists in the allocation of problem areas to the nodes of those co-citation networks. Before explaining the results of this section, the ‘problem space’ defined for MEMS/NEMS technologies is described next.

6.1. ‘Problem space’ for MEMS/NEMS technologies

The ‘problem space’ entails the set of general problem areas confronted by the field of MEMS/NEMS technologies in terms of micro- and nano-sensors and actuators. As such, it includes applied, theoretical and technical knowledge and know-how of different natures: scientific, technological, and organizational, among others. The definition of the ‘problem space’ relied on the evaluation of large amounts of technical literature coupled with the advice of an expert. From a scientific perspective, six general problem areas were defined:

- Material fabrication technologies — This problem area deals with the development and understanding of process technologies aimed at the bulk fabrication of materials.
- Micro/nanostructure fabrication technologies — It entails research efforts dealing with the understanding, development and improvement of technologies aimed at the processing of micro/nanostructures, which are defined as those arrangements or structures with physical dimensions in the micro/nanoscale.
- Characterization technologies — It embraces the exploration and understanding of the fundamental properties of materials and micro/nanostructures. Examples of those properties are: optical, electrical, mechanical, and magnetic, among others.
- Fabrication and analysis of components — This problem area deals with the development, evaluation, and improvement of single components for micro/nanosensors and actuators. It includes components such as the circuitry, actuation parts, etc.

- Fabrication and analysis of devices or systems — This problem area deals with the development, evaluation, and improvement of devices or systems.
- Design and optimization approaches — It includes those areas entailing approaches aimed at the design or optimization of micro/nanosensors and actuator technologies.

Two additional categories were defined for some nodes: 'general knowledge' which includes publications describing topics of interest for the field of micro/nanosensors and actuators as a whole, and 'literature review' that embraces those publications assessing relevant literature in the field of MEMS/NEMS technologies.

As indicated in Section 3, despite their high levels of interrelationship and feedbacks, the problem areas may be visualized, from a macro perspective, as a loosely defined chain composed of upstream and downstream problem areas. For the case of MEMS/NEMS technologies, such a cognitive chain may be depicted as follows. The rest of this paragraph is based on Lieber and

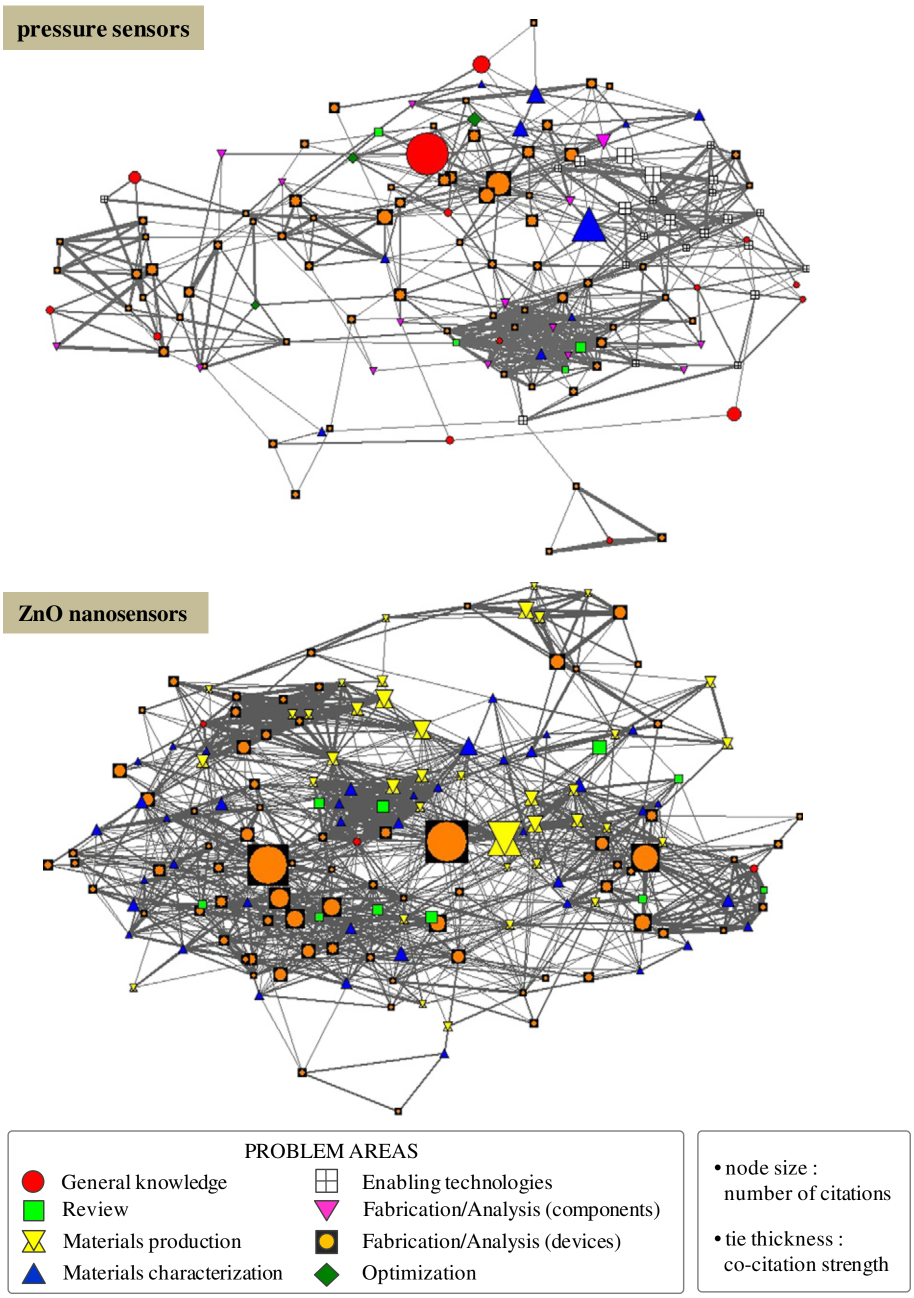

Fig. 2. Knowledge structures for 'pressure sensors' and 'ZnO nanosensors' (cosine ≥ 0.18).

Wang [66]. First, materials and micro/nanostructures with controlled and tunable chemical composition, structure, size, and morphology are required; they embrace the building blocks on which potential devices build upon. This, in turn, calls for the development of appropriate fabrication technologies. At the same time, efforts should be aimed at understanding the fundamental properties of the fabricated materials and micro/nanostructures through characterization approaches. The interplay between material fabrication and fundamental characterization does not only expand the basic understanding, but may also be helpful for defining potential device concepts. Subsequently, devices and their components should be developed and fabricated targeting particular application domains. Deeper understanding gives way to the conduction of approaches aiming at the optimization of devices and components.

6.2. Cognitive analyses of the knowledge structures

In the remainder of this section, we focus on 'ZnO nanosensors' and 'pressure sensors' which according to the results of the previous section were characterized by the most emerging and the most mature knowledge bases in the field of MEMS/NEMS technologies, respectively. Fig. 2 presents the knowledge structures for both technologies as reflected in their co-citation networks.

A series of attributes were allocated to both networks. The size of the nodes denotes the number of citations. The thickness of the ties depicts the co-citation strength between nodes. The color and the shape of the nodes indicate the type of problem assigned to a particular node. Here, a single 'problem area' was allocated to each node according to the farthest stage reached along the cognitive problem chain described in Section 6.1. For that purpose, each cited reference was evaluated. Moreover, the networks were arranged through the 'spring-embedding' algorithm which tends to locate similarly connected nodes closer together. For the sake of clarity, node labels and single-tie nodes were removed from the networks.

6.2.1. Cognitive compositions

Cognitive compositions evaluate the significance and predominance of the different problem areas in a knowledge structure. For that purpose, the distribution of the shares of nodes [%No] and citations [%CIT], and the average normalized network centrality values [nDEG, nBET, nCLOS] across the different problem areas were estimated, as shown in Table 4. Here, normalized centrality values were used in order to prevent the inclusion of any size-related bias. Following, the differences in the cognitive compositions between both MEMS/NEMS technologies are explained.

For the case of pressure sensors, the influence of 'material production technologies' is nonexistent as these MEMS devices rely mostly on silicon and its compounds which have already been intensively researched for decades in the development of semiconductor devices. As MEMS fabrication methods differ slightly from those of the microelectronics industry, technologies for the fabrication of microstructures account for a sixth of the shares of nodes and citations. Also, they show a moderate predominance according to their normalized centrality values. Despite their low significance in terms of the shares of nodes and citations, characterization technologies appear to take predominant positions. Particularly, one node stands out, namely a paper by KE Petersen from IBM Research Laboratory in 1982 highlighting the suitability of the mechanical properties of silicon for the development of miniaturized, reliable and low-cost mechanical components and devices. The bulk of the knowledge structure revolves around the development and analysis of components and devices. They account for about three-fifths of the nodes and citations, as well as take relatively high predominant positions within the knowledge structure. Those problem areas appear not to be solely focused on the development of new designs or application domains for pressure sensors (telemetric linkages, integrated electronics on sensors, etc.) and their components (compensation circuitry, actuation parts, etc.), but also on the improvement and optimization of their performance (noise, pressure variations and offsets, etc.), as well as the use of design and simulation approaches.

The emerging knowledge structure 'ZnO nanosensors' shows a different picture. As it embraces a newly emerging material, the influence of the understanding and development of reliable fabrication processes for ZnO nanomaterials and nanostructures is still high. They account for a quarter of the shares of nodes and citations; in particular, ZnO nanostructures take the most predominant

Table 4
Cognitive compositions (cosine>=0.18).

Problem area	Pressure sensors					ZnO nanosensors				
	%No	%CIT	nDEG	nBET	nCLOS	%No	%CIT	nDEG	nBET	nCLOS
Gnal. knowledge	14.5%	10.0%	3.4	0.8	8.0	1.7%	2.2%	9.2	0.3	39.8
Review	2.4%	2.9%	9.4	1.2	8.4	6.2%	6.6%	7.7	0.4	41.3
Mat. production	–	–	–	–	–	10.8%	10.9%	10.8	1.1	43.2
Fabrication tech.	14.2%	16.4%	5.8	1.6	8.3	13.3%	13.1%	8.8	1.0	40.0
Characterization tech.	11.5%	7.1%	6.9	2.4	8.3	19.8%	23.5%	8.7	0.6	41.9
Analysis of comp.	7.4%	10.7%	5.4	1.1	8.2	–	–	–	–	–
Analysis of devices	47.5%	50.0%	5.6	1.8	8.2	27.9%	26.4%	10.2	1.0	41.9
Other nanomaterials	–	–	–	–	–	8.2%	7.6%	9.5	0.5	41.5
Conventional ZnO	–	–	–	–	–	7.7%	8.4%	8.7	0.6	41.3
Design and optimization	2.4%	2.9%	3.3	1.1	8.1	–	–	–	–	–

Notes:
Gnal. knowledge: general knowledge; Mat. production: material production technologies; Fabrication tech.: fabrication technologies for micro/nanostructures; Characterization tech.: characterization technologies for materials and micro/nanostructures; Analysis of comp.: development and evaluation of components.

positions within the knowledge structure across all centrality values. Similarly, the characterization of fabricated ZnO nanomaterials and ZnO-based nanostructures takes around a fourth of the shares of nodes and citations, yet it shows lower predominance levels. The influence of the development, fabrication and analysis of 'ZnO nanosensors' is still lagging behind; it accounts for more than a quarter of the shares of nodes and citations. Yet, their high centrality values suggest their imminent role in this knowledge structure. The majority of device-related publications embrace early demonstrations or 'proofs of concept'; still far from potentially commercial devices. Moreover, the influence of devices made from other nanomaterials and conventional 'macro' ZnO materials, each with about a tenth of the nodes and citations yet slightly predominant, suggests the partly path-dependent nature of this nanotechnology field.

In terms of the cognitive compositions, the cognitive fluidity in knowledge structures is denoted by two aspects. First, the cognitive 'center of gravity' of the knowledge structure appears to be heavily tilted toward getting to grips with the earliest phases of problem search and solution, i.e. problem areas upstream. Second, the variety generated in their knowledge structures is significantly lower than that of their mature counterparts.

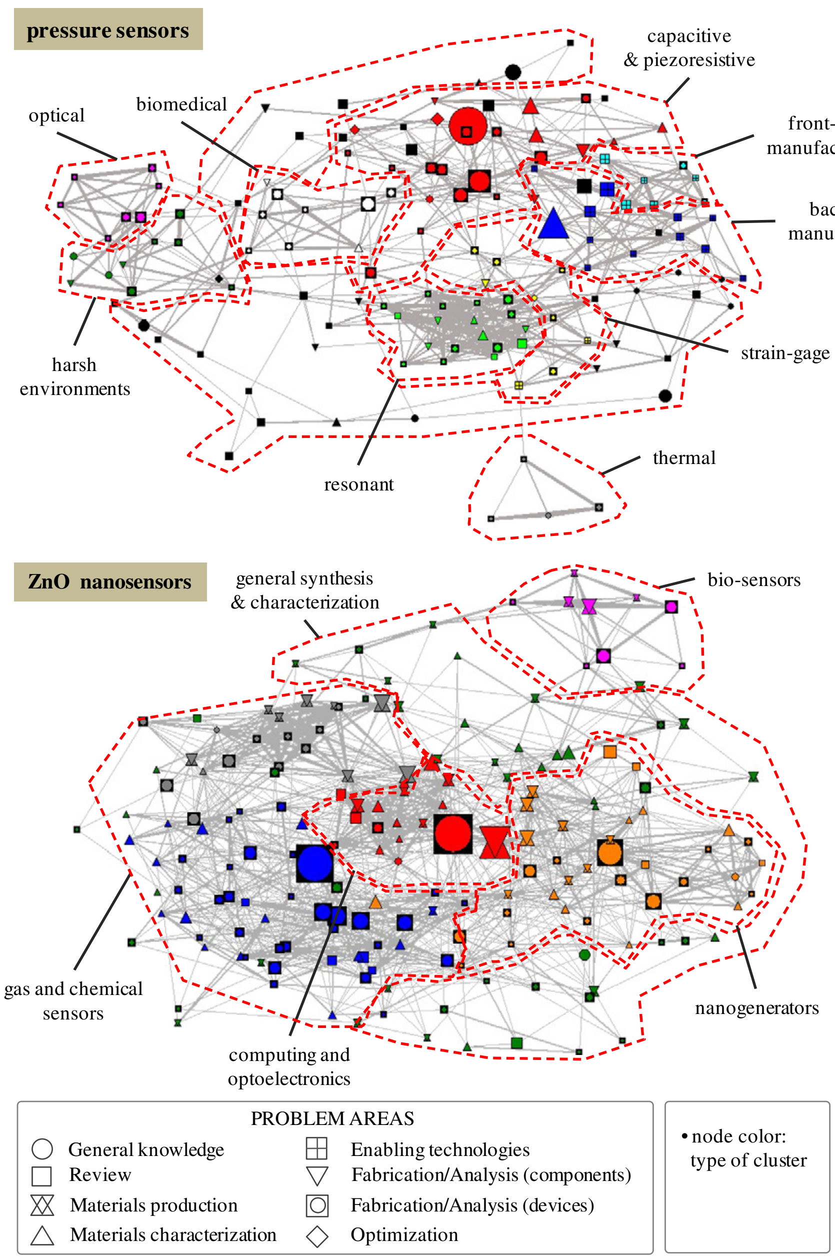

Fig. 3. Cluster for 'pressure sensors' and 'ZnO nanosensors' (cosine ≥ 0.18).

6.2.2. Cognitive sub-fields

Another way to visualize the cognitive nature of the knowledge structures is by discerning the cognitive sub-fields – the agglomerations of highly cognitive-related nodes – underlying knowledge structures. For that purpose, a hierarchical cluster analysis was conducted on the cosine-normalized co-occurrence matrices of 'pressure sensors' and 'ZnO nanosensors'. Following Rafols and Meyer's approach [67], the Ward's clustering method and squared Euclidean distances were used in this analysis. Fig. 3 presents the knowledge structures of both technologies with their clusters displayed in thick dotted lines.

The definition of those clusters was based on the evaluation of the resulting dendrograms. Moreover, the clusters were named according to the contents they embrace. The rest of this section explains the differences in the clusterings of both technologies.

First, the number of clusters of both knowledge structures differs. Whereas the knowledge structure of pressure sensors shows a more fragmented and diverse nature embracing a total of ten clusters, that of ZnO nanosensors displays a compact network structure composed of fewer clusters of larger size. Second, as suggested by their cognitive sub-fields, both knowledge structures appear to be driven by applications. This is not surprising, as devices depict fields of applied science. Nevertheless, the nature of their cognitive sub-fields differs. On the one hand, the knowledge structure of pressure sensors is divided into the different design principles that have been developed over the years for micro-pressure sensing, such as optical, piezoresistive, and resonant, among others, as well as special application domains, such as their use in the biomedical field or harsh environments. On the other hand, although the knowledge structure of ZnO nanosensors embraces potential application domains such as biosensors, gas and chemical sensors, and nanogenerators, it seems that those applications have not fragmented into more specific sub-domains yet, i.e. they still remain as single homogeneous groups. Third, differences can be discerned in the cluster interconnectivity for the knowledge structures. This is mostly sparse for pressure sensors, while that of ZnO nanosensors is significantly denser. Here, higher levels of cluster interconnectivity point to a greater cognitive dependence among clusters. Overall, these differences highlight the still formative nature of emerging knowledge structures.

7. Conclusions and discussions

In this paper, we have sought to contribute to the operationalization of emerging technologies by providing an approach for quantitatively interpreting technologies of an emerging nature along their patterns of growth and cognitive fluidity. To do so, we looked into the properties of the knowledge bases underlying technologies. In particular, we centered our attention on the dynamic properties of scientific knowledge bases in terms of their rates and directions of change. Our approach integrated bibliometric, social network analysis and multivariate statistical methods on scientific publications drawn from the ISI/SCI database, as well as their citations and cited references. The empirical case of MEMS/NEMS technologies was used.

In summary, our results showed that the patterns of growth of emerging technologies are reflected in chronologically new, highly dynamic, collaborative, and complex, yet 'narrow' and lowly diffused scientific knowledge bases. Those intense patterns of growth were seen to be coupled with cognitive fluidity. This is reflected in the strong focus of emerging knowledge structures on the upstream stages of problem search and solution. Furthermore, emerging knowledge structures appear to be more compact and less diverse. They also seem to be composed of fewer, larger, and more highly interconnected cognitive sub-fields. This suggests the formative nature of emerging knowledge structures. In this regard, it appears that fluidity calls for an ever intense experimentation and active construction aimed at better defining the newly emerging technological field [4,11,13]. We believe that the integration of the patterns of growth and cognitive fluidity allowed to gain a deeper insight into the properties of emerging technologies.

These results also provide a glimpse into the difficulties encountered by specific nanotechnology fields in bringing forward nano-enabled devices. Despite the significant opportunities and interests surrounding specific nanotechnology fields such as nano-sensors and actuators, their knowledge structures appear to be heavily influenced by the earliest phases of problem search and solution; application-related problem areas still play a secondary role. This may be attributable to their disruptive nature, which is mainly reflected in the redefinition of their ways of manufacture; although, as it was shown for the case of ZnO nanosensors, other nanomaterials and conventional 'macro' ZnO materials appear to be influential. In some cases, as in the case of nanogenerators – power generation by means of piezoelectric ZnO nanostructures – they may lead to the creation of new technology/product paradigms. Within this context, processes of knowledge accumulation appear to play a crucial role in the sense that a 'critical mass' of knowledge should be available before attempts into more complex areas. This is in line with Nightingale et al. [68] who highlighted the importance of requisite knowledge in N&N to generate products addressing a particular demand; for them, "when this knowledge is not in place, innovation simply does not occur, even when there is a clear demand". Unfortunately, knowledge accumulation is not automatic but entails, by associating it with competence building, "a painstaking and long process, entailing uncertainty and trial and error" [59]. Within this context, we believe that variety generation within the knowledge structure is a crucial aspect for the evolution of emerging technologies [69,70]. This is reflected in the diversity, in breadth and depth, of the problems tackled by and the solutions embraced in the knowledge structures.

We acknowledge that the use of bibliometric data is not exempted from limitations. In particular, the use of a single source – in our case scientific publications – reveals only 'part of the whole story', albeit a critical one for evaluating emerging technologies as they are characterized by being heavily science-driven. Hence, future work should be aimed at complementing the present study with additional sources of information, e.g. patents. Another interesting stream for future research entails the unraveling the *hows* behind emerging technologies, i.e. the 'emergence' of emerging technologies, which may complement the *whats* analyzed in this paper.

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