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Structure and Evolution of Sensor Ecosystem to Forecast Emerging Scientific and Technological Directions

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Abstract: How do sensor research and technologies grow over time? This paper applies the network analysis with a new computational approach to map the structure and evolution of sensor research and technologies over a 30-year time frame (1990-2020).The goal of this study is to analyze the evolution of ecosystem in sensor research for forecasting emerging technological trajectories. Results show that the scientific interaction within ecosystem (represented with networks) of sensor generates a co-evolution of research fields supporting the accelerated growth of different technological trajectories, such as: wireless sensors, fiber optic and optical sensors, gas and biosensors. Results suggest main theoretical implications that explain the evolution of sensor research with critical aspects of innovation management to support R&D investments towards new technological trajectories having a high potential of growth.

Keywords: sensor technology; sensor research; network analysis; technological trajectories; technological change; scientific change; scientific development; wireless sensor networks; fiber optic sensors; biosensors

1. Introduction

The research field of sensor is undergoing a significant change to support the evolution of science and technologies in society (Andersen et al., 2004; Wilson, 2004). The goal of this study is to analyze the scientific ecosystems (interacting research fields) of sensor research and technologies to explain interactions supporting technological trajectories directed to fulfil human goals and needs, and solve problems in society. In particular, this paper investigates sensor research and technologies, from 1990 to 2020, to clarify major changes in the scientific structure over these 30 years (Coccia et al., 2021). In general, technological change driven by sensor research can lead to new technologies such as smart or intelligent sensors (Alharbi et al., 2021; Banerjee et al., 2021; Davoli et al., 2021; Yaqoob and Younis, 2021), and the Internet of Things (Pal et al., 2020; Seymour et al., 2021; Wang et al., 2021). New sensor technologies can develop and/or disrupt established technologies that support technological, economic and social change (Elsisi et al., 2021). In this context, this study endeavors to explain the evolution of research and technology in sensors with maps or networks considering dynamics of publications that are a main unit of analysis to show the organization and evolution of science (Boyack et al., 2009; Leydesdorff, 1987; Roshani et al., 2021). Leydesdorff (2007) has developed studies by generating a map of the whole set of journals, showing centrality measures to clarify local citation environments (small sets of journals where citing is above a certain threshold). Instead, Klavans and Boyack (2006) identify a new measure of relatedness for mapping science because the relatedness between bibliometric units (e.g., journals, words, etc.) provides critical aspects for structure and evolution of science. Relatedness measures have also a vital role in showing the relationship between data items (cf., Klavans and Boyack, 2006a). Small (1999) argues that the network of linkages from document to document and from discipline to discipline can show crossover fields and offer the possibility of exploring extended

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knowledge pathways and new technological trajectories. Boyack et al. (2005) maintain that science maps provide critical aspects to visually identify major areas of science and emerging technologies, their size and interconnectedness. Scholars also argue that emerging technology has basic characteristics, such as radical novelty, accelerated growth, and main socioeconomic impacts (Coccia, 2020). Manifold techniques have been developed in scientometrics and social study of innovation to detect and analyze emergence in science and technology domains (Leydesdorff, 1987; Coccia, 2019; Coccia, 2020, 2021, 2021a; Coccia and Finardi, 2013). These methods are based on large datasets and computational approaches that allow the computing of complex indicators for detecting new technological trajectories and patterns in science (Moya-Anegón, 2004). Quantitative approaches, based on bibliometric data of publications, are useful techniques to capture information earlier in the cycle of technology development, whereas patents, in contrast, trail behind (Cozzens et al., 2010). In this research stream, this study has the purpose of mapping the scientific ecosystem of sensor technologies over a 30-year time frame (in this case ecosystem is a community of research fields and technologies that interact, forming a complex network of interconnected elements that evolve over time). The idea here is to analyze the structure and evolution of sensor networks to detect new technological trajectories that are basic in science, technology and society. The discussion explains some characteristics of the structure and evolution of sensor networks with interesting theoretical and managerial implications for the scientific and technological development of sensors.

2. Materials and Methods

2.1. Data-processing resources

In this study, we used the Web of Science-WOS (2022) Core collection database to retrieve sensor research and technologies literature documentations. The term "sensor" was searched in the topics of articles. The results are refined by documents type = (Articles), Language = (English), Timespan = 1990-2020, and Indexes = (SCI-EXPANDED). The sample contains 362,362 papers split into three distinguished timespans, given by 1990-2000, 2001-2010, and 2011-2020.

2.2.. Data processing procedure and computational approach for network analysis

To address the main purpose of this study, we used articles original keywords (DEs) as the basis for building the keywords co-occurrence networks regarding sensor research and technologies. We also implemented this approach to visualize the interconnection between sensor technologies and conduct an analysis to interpret the evolving relationship between technologies in sensor network. We used the co-occurrence measurement to study the interconnection between different sensor sub-technologies (Rafols and Meyer 2010). The co-occurrences methodology is commonly used for identifying the underlying collaborative structure between terms. Two terms (keywords, journals, research disciplines, countries, authors, etc.) are considered co-occurred whenever they simultaneously appear in a single document (Delecroix and Epstein 2004). Many studies in various fields have widely used this approach to analyze the interconnection between different research fields (e.g., Li et al., 2018). In this study, we used the "Original Keywords" as the basis for representing the sensor technologies and creating the interconnection network between words. These words are known by the DE tag in the Web of Science bibliometric data, and they are separated by semicolon. To construct the co-occurrence networks between words, we apply the following data processing-procedures:

- bibliographic data were downloaded from the Web of Science (2022) database and split into three periods: 1990 to 2000, 2001 to 2010, and 2011 to 2020.
- all the combined phrases that lack "sensor", "sensing", and "sense" were removed and then removed the adjective clauses. This step focused only on words related to sensor technologies (for instance, biosensors, wireless sensor networks, gas sensors, etc.).
- We used Python programming language version 3.6.5 and Scikit-learn library version 0.23.2 for constructing the co-occurrence matrix (Pedregosa et al., 2011). In this

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step, we determined a threshold and removed the words with lower than ten times co-occurrences.

- Afterwards, we utilized Gephi software version 0.9.2 to visualize the co-occurrences matrix and calculate the network measures (Bastian et al., 2009). The node indicates the words related to sensor technologies, and a link makes a connection between two words whenever they appear in at least ten articles. In other terms, a link means two different words co-occurring on at least ten articles. The color of nodes also represents the community, meaning that when two nodes have a similar color, they are in the same community in the classification. The thickness of each edge represents the weight of co-occurrences. The more two terms appear in the same documents; the connected edge will be thicker.

After creating the word co-occurrences networks for each time frame, we employed network measures to identify and track the structure of the word co-occurrence networks to interpret the evolving patterns of sensor research and technologies over time (Coccia, 2018):

– Degree centrality (DC): Degree centrality is defined as the number of edges a node has (Sharma and Surolia, 2013). In the word co-occurrence networks, degree stands for the total number of words that appear with the node in the same documents.

– Betweenness centrality (BC): It shows how much a node is essential to create connections with other nodes in the shortest path. Betweenness Centrality is calculated by the following formula (Jia et al., 2012):

$$BC(v) = \sum_{s,t \in V} \frac{\sigma_{st} v}{\sigma_{st}}$$

Where BC(v) is the betweenness centrality value for node v, and σ-st is the total number of shortest paths between node s and node t.

– A node's Closeness Centrality (CC) is an indicator of a network centrality, defined as the number of links needed to connect each node in the network with all the other nodes in the network or the average number of links required to reach all other nodes in the network from a node in the network (Coccia et al., 2022).

– Finally, Community structure represents the categorization of technologies interconnection using the Louvain algorithm to distinguish the classifications (Blondel et al., 2008). The number of communities calculated by Blondel et al. (2008) is:

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{K_i K_j}{2m} \right] \delta(c_i, c_j)$$

Where, A_{ij} stands for the weight of the edge between i and j, $K_i = \sum j A_{ij}$ is the sum of the weights of the edges attached to vertex i, ci is the community to which vertex i is assigned, the δ function δ(u, v) is 1 if u=v and 0 otherwise and m=½ ∑ij A_{ij}. Co-occurrences networks generated by Gephi save in GraphMl format and imported into SCI2 software version 1.3 to implement the community detection algorithm (Börner, 2011).

We used degree centrality to demonstrate the evolution of nodes over time in the three periods and utilized community structuring to detect the classified technologies that have the highest interconnections to track the transition of linkages between sensor technologies over time. We used also Betweenness Centrality (BC) measures to indicate the nodes' role in facilitating the connection of sub-technologies at the heart of three under-studying networks. Nodes with the highest score of BC position as a bridge to make connections among the other network nodes (Kashani and Roshani, 2019).

3. Results and Discussions

3.1. The scientific ecosystem of sensor technologies in 1990-2000 period

The ecosystem of sensor technologies in the 1990-2000 period shows a network with 72 nodes concerning the words regarding sensor technologies (Figure 1, Map A). The total number of articles in this time frame dataset is 30,674 records. Figure 1 also shows the network of co-occurrences of these terms from 1990 to 2000 (map A 1990-2000). This network of map A (1990-2000) includes 72 nodes and 194 edges in total and 5 communities. Map A in figure 1 shows that "biosensor", "gas sensor", and "optical sensor" have the highest degree compared to other nodes: these three technologies have a higher interaction with other technologies at the highest level. Results of Table 1 suggest that the top five sensor technologies with the highest centrality degree are "biosensor", "gas sensor", "optical sensor", "fiber optic sensor", and "pressure sensor" among all the nodes in the network. We have also four communities, in which "biosensor" with a centrality degree score of 23 has a strong relationship (with "oxygen sensor", "ph. sensor", "immune sensor" and "capacitive sensor"), and it has the highest level of interconnection with diversified technologies. Based on their edge weight, these technologies have a high level of co-occurrence in documents leading to classify them as an interconnected community. Moreover, "gas sensor" with a centrality degree score of 21 is in the head of the community number 4, strongly connected to other sub-technologies, including "humidity sensor", "potentiometric sensor", and "amperometric sensor". In the second community, the "optical sensor" with a centrality degree score of 20 is highly connected to the "fiber optic sensor" (also with a 20-degree score), "temperature sensor", and "displacement sensor". The remaining sub-technologies are classified in a community called number 1, which has the highest number of nodes. In the community, the "pressure sensor" with a degree number of 18 is highly interconnected with "chemical sensor", "micro sensor", "smart sensor", "thermal sensor", and "integrated sensor".

3.2. The scientific ecosystem of sensor technologies in 2001-2010 period.

This period shows an ecosystem based on a network of interaction with a growing number of nodes (197) and edges (623). This time frame contains 83,512 records, 23 percent of total articles. This period has 9 communities. Figure 1 (Map B) shows that the leading technologies in the ecosystem of 2001-2010 period are "biosensor", "chemical sensor", "gas sensor", and "optical sensor". The most interconnected technologies considering the edge weight are "active pixel sensor" and "cmos image sensor", "biosensor" and "immunosensor", "strain sensor" with "temperature sensor" and "biosensor" and "chemical sensor". Table 1 shows that the top five sensor technologies on 2001-2010 period are "biosensor" with centrality degree of 53, included in community number 2 that is highly connected to "electrochemical sensor"; "chemical sensor" with centrality degree of 48 is included in the fourth community with "gas sensor" having centrality degree of 46 and "humidity sensor". "Optical sensor" with centrality degree 46 is highly connected with "oxygen sensor" and "glucose sensor" as community number 6. This result confirms the growing role of Optical sensors as forecasted by Andersen et al. (2004). Moreover, "fiber optic sensor" with centrality degree of 40 has the highest interconnection with "temperature sensor", "magnetic sensor", and "strain sensor" and is included in the fifth community. These nodes with the highest level of centrality degree score among all the nodes represent a high diversified interconnection with other sensor technologies compared to other nodes in this network. Interestingly, unlike previous period, the "fiber optic sensor" is separated as a new interconnected network from the "optical sensor" community. Our results show that during the second decade, the "wireless sensor network", "wireless sensor", and "remote sensor" co-occurrences in documents gained momentum with other technologies and emerged in the top 20 with the highest level of degree centrality.

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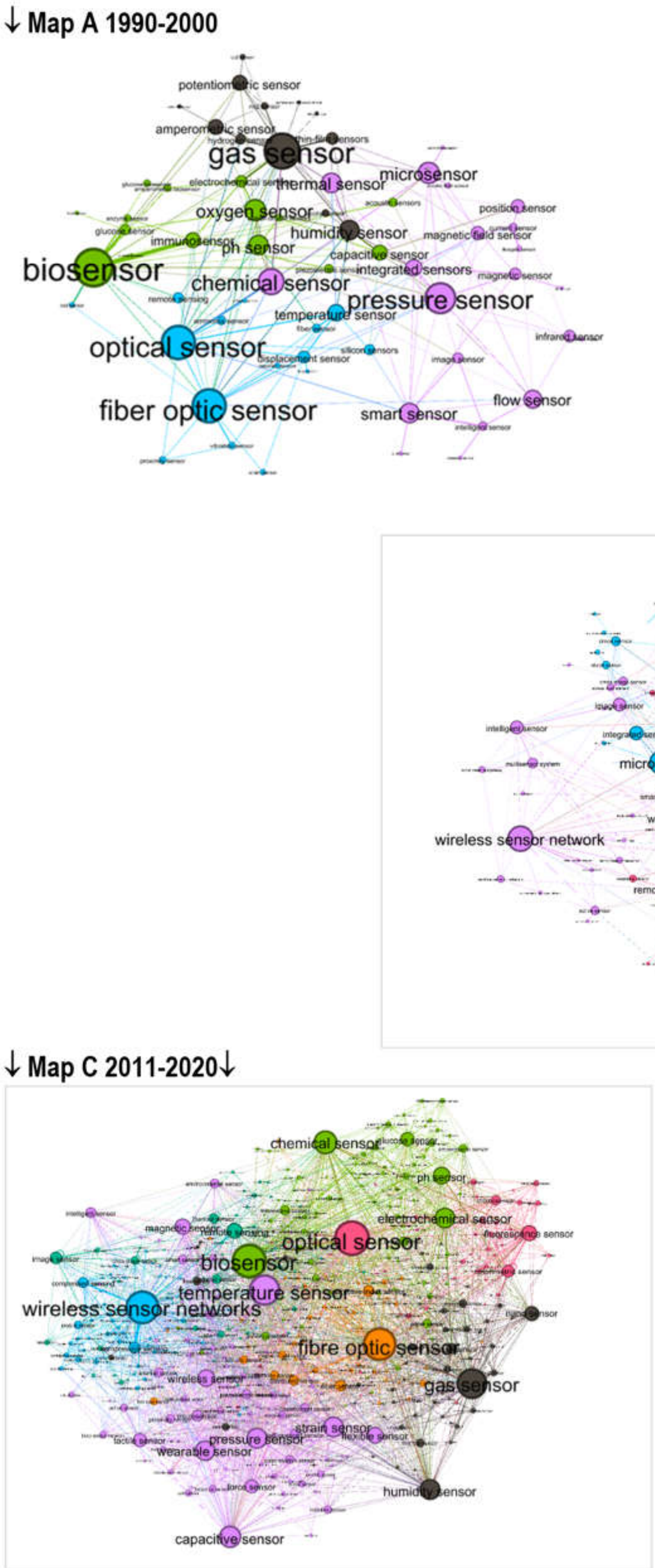

Figure 1. Structure and evolution of scientific and technological networks in sensor from 1990 to 2020**.**

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Table 1. Top 20 sensor technologies in networks with the highest centrality degree over 1990-2020 period.

1990-2000			2001-2010			2011-2020		
Word	Degree Centrality	Community	Word	Degree Centrality	Community	Word	Degree Centrality	Community
biosensor	**23**	**3**	biosensor	53	2	optical sensor	128	6
gas sensor	21	4	chemical sensor	48	4	biosensor	126	2
optical sensor	20	2	gas sensor	46	4	wireless sensor network	121	3
fiber optic sensor	20	2	optical sensor	46	6	fiber optic sensor	120	5
pressure sensor	18	1	fiber optic sensor	40	5	temperature sensor	111	1
chemical sensor	16	1	wireless sensor network	31	1	gas sensor	109	4
micro sensor	12	1	capacitive sensor	31	3	chemical sensor	83	2
oxygen sensor	12	3	temperature sensor	29	5	capacitive sensor	77	1
humidity sensor	11	4	micro sensor	28	3	pressure sensor	72	1
ph. sensor	11	3	electrochemical sensor	27	2	strain sensor	72	1
smart sensor	11	1	pressure sensor	25	3	humidity sensor	72	4
thermal sensor	11	1	ph. sensor	24	7	electrochemical sensor	71	2
flow sensor	10	1	oxygen sensor	22	6	wearable sensor	70	1
temperature sensor	10	2	wireless sensor	20	1	wireless sensor	59	1
integrated sensor	9	1	magnetic sensor	19	5	ph sensor	59	2
immunosensor	9	3	remote sensor	19	1	flexible sensor	55	1
capacitive sensor	8	3	strain sensor	18	5	magnetic sensor	53	1
potentiometric sensor	8	4	glucose sensor	17	6	fluorescent sensor	52	6
amperometric sensor	8	4	humidity sensor	17	4	remote sensor	52	7
displacement sensor	7	2	amperometric sensor	17	3	nano sensor	49	4

3.3. The scientific ecosystem of sensor technologies in 2011-2020 period

Finally, the scientific ecosystem based on interconnection between sensor technologies in 2011-2020 contains 249,492 records, 69 percent of all articles collected in this study (see Figure 1, Map C). The co-occurrence network of sensor technologies comprises 553 nodes and 2696 edges. "Strain sensor" with "temperature sensor", "compressed sensing" with "wireless sensor network", "biosensor" with "immunosensor", "rechargeable sensor networks" with "wireless sensor network", and "colorimetric chemo sensor" with "fluorescent chemo sensor" have strong relationships based on their edge weight score and are classified in 8 communities (cf., Bravo-Arrabal et al., 2021; Grasso et al., 2021; Kanoun et al., 2021). Figure 1 (Map C) shows that the size of nodes and network linkage have been growing and creating an ecosystem based on complex interconnection communities between manifold sensor technologies. The leading technologies in this period are, "optical sensor" with a centrality degree of 128, "biosensor" with a centrality degree score of 126, "wireless sensor network" with a centrality degree score of 121, "fiber optic sensor" with a centrality degree of 120, "temperature sensor" with a centrality degree of 111. Table 1 also shows the top 20 technologies considering centrality degree values: the top five sensor technologies are "optical sensor" with a centrality degree score of 128 included in

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community number 6 that has high interaction with "fluorescent sensor"; "biosensor" with a centrality degree of 126 is strongly associated with "chemical sensor" and "electrochemical sensor ". Surprisingly, these two technologies with the highest centrality degree in the previous decade had their separated interconnection in two different communities with other technologies. In this decade, although the "chemical sensor" rank, based on the degree of centrality decreased, it started a process of merging with "biosensor" in the same community. The growing role of biosensor in scientific ecosystem is a main confirmation of the preliminary study by Andersen et al. (2004) when the evolution and potential aspects of this sensor are rather ambiguous. The "wireless sensor network" with a centrality degree of 121 expands its interconnection community and gets the third rank in a degree centrality scoring. A finding of scientific interest is that none of the other technologies of community number 3 is in the top 20, which suggest that although the "wireless sensor" technology increases its interconnection and diversification with other related technologies, it is an emerging technology that has not made a strong relationship with other top technologies. This evolutionary characteristic also is present for "fiber optic sensor", but in this case, even the "optical sensor", which was the head of the community in which "fiber optic sensor" was included, stopped its growth and is not in the top 20 having high degree centrality score. Instead, the "temperature sensor" that was included in the same community with "fiber optic sensor", emerged as a new community in this decade and started expanding its own technology interconnection community.

3.4. General discussion of the scientific ecosystem of sensor technologies in 1990—2020 period.

The evolution of scientific ecosystem in sensor technologies is represented with a change of network indicators indicating a growing technological interconnection. In general, sensor research shows that the network's average degree has been growing from 5.4 to 10.6 over 1990 – 2020 period, suggesting that the growth of the scientific ecosystem in size and complexity is due to growing interconnection between technologies. However, the density of interconnection structures has been decreasing from the first decade, meaning that the closeness of the centrality degree of network and the interconnection between sensor technologies based on their co-occurrence have deteriorated. Moreover, the decreasing magnitude of betweenness centrality demonstrates that there is a lower dependency on some nodes having a bridging role, such that most of the sensor technologies have made connections directly with other technologies instead of making connections through other intermediate technologies. Moreover, the increasing level of closeness centrality and the stable number of communities suggest that the independence level of degrees connecting other nodes has been elevating (cf., Wasserman and Faust, 1994): technological interconnection in sensor tends to be more centralized, and the differences between communities or degrees tend to gradually increase. Results also show that the top ten sensor technologies have a technological evolution from three perspectives: direct connection, interconnection, and diversified interconnection. The centrality degree of a single node in a network indicates the potential aspect that could facilitate the interaction within the network (Rafols and Meyer 2007). In addition, results show that optical sensor, biosensor, fiber optic sensor and wireless sensor networks are central technologies directly linked to other nodes in the network (Kanoun et al., 2021; Jderu et al., 2021; Leonardo et al., 2021; Santana Abril et al., 2021; Yang et al., 2021). The wearable sensor, which has emerged later than other technologies, tends to have a high potential of growth and interaction with other sensor technologies because of its fast degree of centrality improvement. Finally, in this ecosystem of sensor research based on interconnection network, technologies tend to have a greater capacity to interact with other technologies (cf., Choi et al., 2011).

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Table 2. Top 20 sensor technology and measures of the evolution of networks from 1990 to 2020. 1

1990-2000					2001-2010					2011-2020				
Label	DC	BC	CC	community	Label	Degree	BC	CC	community	Label	Degree	BC	CC	community
biosensor	23	0.149	0.563	2	biosensor	53	0.135	0.562	1	optical sensor	128	0.122	0.556	5
gas sensor	21	0.128	0.558	3	chemical sensor	48	0.080	0.555	3	biosensor	126	0.137	0.553	1
optical sensor	20	0.131	0.563	1	gas sensor	46	0.090	0.538	3	fibre optic sensor	120	0.126	0.544	4
fiber optic sensor	20	0.113	0.553	1	optical sensor	46	0.067	0.553	5	wireless sensor networks	118	0.146	0.532	2
pressure sensor	18	0.072	0.525	0	fibre optic sensor	40	0.072	0.525	4	temperature sensor	111	0.079	0.543	0
chemical sensor	15	0.042	0.534	0	wireless sensor network*	31	0.056	0.488	0	gas sensor	109	0.095	0.535	3
microsensor	12	0.063	0.488	0	capacitive sensor	31	0.045	0.487	2	chemical sensor	83	0.044	0.515	1
oxygen sensor	12	0.032	0.496	2	temperature sensor	29	0.017	0.491	4	capacitive sensor	75	0.035	0.507	0
humidity sensor	11	0.018	0.473	3	micro sensor	28	0.026	0.517	2	strain sensor	70	0.032	0.506	0
ph sensor	11	0.036	0.484	2	electrochemical sensor	27	0.028	0.482	1	pressure sensor	72	0.030	0.488	0
smart sensor	11	0.052	0.462	0	pressure sensor	25	0.013	0.472	2	humidity sensor	70	0.029	0.496	3
thermal sensor	11	0.014	0.469	0	ph sensor	24	0.021	0.486	6	wearable sensor	70	0.034	0.511	0
flow sensor	10	0.032	0.480	0	oxygen sensor	22	0.030	0.478	5	electrochemical sensor	69	0.049	0.501	1
integrated sensors	9	0.020	0.473	0	wireless sensor*	20	0.013	0.461	0	wireless sensor	59	0.025	0.484	0
temperature sensor	9	0.016	0.449	1	magnetic sensor	19	0.021	0.446	4	ph sensor	59	0.024	0.498	1
amperometric sensor	8	0.008	0.459	3	remote sensor	19	0.020	0.475	0	flexible sensor	55	0.020	0.471	0
capacitive sensor	8	0.013	0.439	2	strain sensor	18	0.014	0.469	4	remote sensor	52	0.038	0.487	6
immunosensor	8	0.010	0.442	2	glucose sensor	17	0.006	0.440	5	magnetic sensor	51	0.018	0.479	0
potentiometric sensor	8	0.012	0.427	3	humidity sensor	17	0.010	0.456	3	fluorescence sensor	50	0.032	0.458	5
position sensor	7	0.005	0.416	0	amperometric sensor	17	0.010	0.434	3	nanosensor	49	0.019	0.474	3

Note: highlight grey cells indicate emerging sensors after 2000. DC=Degree centrality; BC= Betweenness centrality; CC =closeness centrality. 2 3

The technologies with a higher closeness centrality score have a low distance from their community nodes and a high distance from other excluded nodes. The technologies with a high level of closeness centrality (CC), including "optical sensor", "biosensor", "fiber optic sensor", "gas sensor", and "wireless sensor networks", have more powerful evolution and create distinct communities. Aside from DC level and CC score, the top ten technologies with higher betweenness centrality have a higher diversification than technologies with the highest level of closeness centrality.

Table 3. Top 20 emerging sensor technologies in networks from 2001 to 2020.

Top 20 emerging sensor technologies				
	2001-2010		**2011-2020**	
Rank	Label	Degree	Label	Degree
1	wireless sensor network	31	self-powered sensor	30
2	wireless sensor	20	environmental sensor	28
3	nano sensor	15	biomedical sensor	22
4	conductometric sensor	11	inductive sensor	21
5	distributed sensor	9	paper sensor	26
6	cmos sensor	9	low-cost sensor	21
7	cmos image sensor	9	liquid sensor	19
8	electrochemical biosensor	8	printed sensor	19
9	mass sensor	8	textile sensor	19
10	fiber bragg grating sensor	8	body sensor network	20
11	refractive index sensor	8	light sensor	18
12	fluorescence sensor	8	mechanical sensor	19
13	active sensor	8	aptasensor	16
14	light-addressable potentiometric sensor	6	dual sensor	16
15	active pixel sensor	6	ratiometric sensor	14
16	colorimetric sensor	6	biomimetic sensor	15
17	flexible sensor	6	chemiresistive sensor	17
18	wearable sensor	6	multifunctional sensor	17
19	dna sensor	6	visual sensor	13
20	biomimetic sensor	6	copper sensor	13

The evolution of interconnection between sensor technologies in the top 20 sensor technologies from 1990 to 2020 is in table 2 that shows how sensors with the highest centrality degree scores in 1990-2000 (biosensor, gas sensor, optical sensor, fiber optical sensor, pressure sensor, and chemical sensor) have been expanding over time. Some technologies, such as "strain sensor" had a low centrality degree score in the first period but it has increased to centrality degree of 18 and ranked 17 in the second period, reaching consequently a centrality degree score of 70 and rank 10 in the last period (2011-2020). Moreover, the "temperature sensor" rank improved from 15 with an initial degree of 9 to rank 8 and a degree score of 29 in the second period and finally rank 5 with a degree score of 118 in the last period under study. Moreover, "capacitive sensor" ranked 18 with an initial degree score of 8, elevated ultimately to 8 in the last period, and "electrochemical sensor" with a degree of 6 and rank 23 that improved to rank 13 with a degree score of 69 in the last period. These results show that technologies' positions just mentioned have evolutionary phases of transition in the network and converge towards vital nodes with the highest number of interconnections over time.

Table 3 shows emerging technologies: terms that came up in the network after 1990-2000 period and started and evolutionary growth. Finally, the emerging technologies have increased from 137 in 2001-2010 to 374 in the last period (2011-2020). This finding reveals that sensor research and technologies have a significant and continuous evolution in science and society.

3.5. Principal theoretical implications from innovation processing on sensor research

These results suggest some properties of the scientific change of the ecosystem of sensor technologies that can support general principles for the evolution of science and technology (cf., Coccia, 2018a, 2020a, 2022; Coccia and Wang, 2016):

Firstly, sensor technologies co-evolve with the overall growth of the scientific and technological ecosystem based on complex interaction of different technologies. In fact, the level of interconnections between sensor-related technologies is increasing over time dramatically.

Secondly, some sensor technologies achieve a critical position in the scientific and technological ecosystem, playing a connective role of master for other technologies. For instance, based on the results of betweenness centrality, wireless sensor networks increased exponentially in the network and got the bridging and supporting role compared to other technologies.

Thirdly, sensor technologies are generating new technological trajectories of specialization during their co-evolutionary pathways in the ecosystem.

This study suggests that the evolution of sensor research and technology and in general science proceeds with the following typologies (Figure 2):

- *Total fusion* of research fields is when two or more research fields (e.g., A and B) merge and create a new one (i.e., AB) that evolves as a whole. For instance, in sensor research: Nano-Bio Sensor is a fusion of Nanosensor and Biosensor. In this set, the combination of these two technologies and research fields created a new potential field-dependent from its initial principles.
- *Partial fusion* is, during the scientific change, the incorporation of a smaller research field (e.g., B) into a large research field (e.g., A), generating a super research field A' (that embodies B). For instance, in sensor research, the "chemical sensor" is also including parts of materials science (e.g., graphene) with the goal to generate ion/molecule sensors applied in pharmaceutical, and food production.
- *Evolution by total splitting (total fission)* is when research field A (including a research field B) splits up in research fields A and B that have autonomous evolutionary trajectories. For instance, in sensor research: Polymer sensor is a technology born in the Chemical sensor community, afterwards grew up independently and created its own realm of study.
- *Evolution by partial splitting (partial fission)* is when research field A (containing research fields B and C) develops by splitting in a research field A'' also containing B and a research field C that splits off from the original set A; both research fields have autonomous evolutionary trajectories. For instance, in sensor research: both gas sensors and liquid sensors dawned in the chemical sensors field; after a while, gas sensors started their evolution independently from chemical sensors and created their own domain; however, liquid sensors cannot still be considered as a dependent province, and its expansion is intertwined with chemical sensors growth.
- *Master technologies* increase exponentially in scientific ecosystem of sensor research. These technologies have a connective role for other technologies with an integrated-based structure by bridging and supporting the development of other inter-related technologies, such as wireless sensor network, biosensor, and fiber optic sensor. They play a vital role in integrating networks and connecting other sensor technologies to create new paths through evolution.

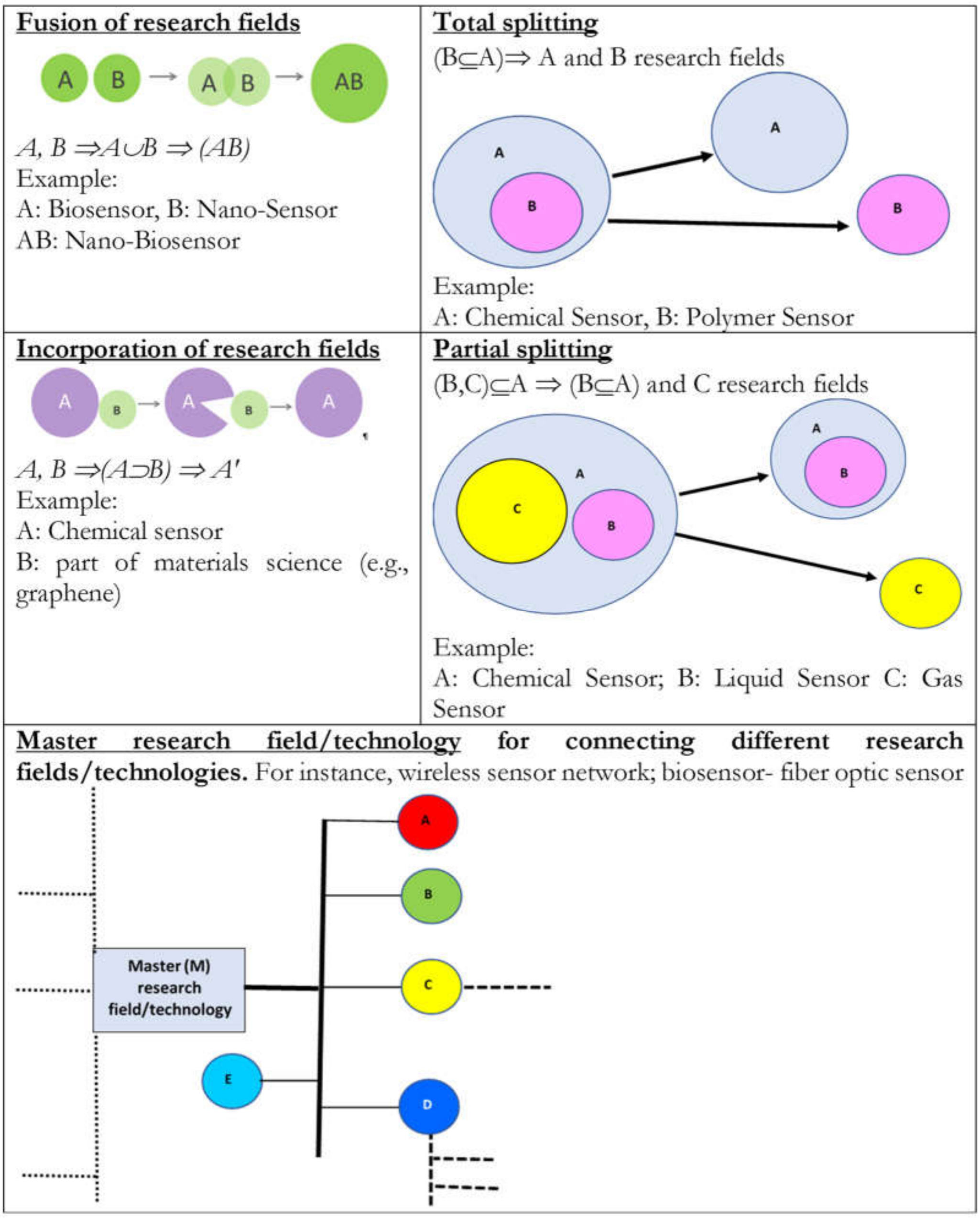

Figure 2. Patterns of evolution of science and technology based on characteristics of networks.

3.6. Innovation management implications from information processing on sensor research

Policymakers, managers and scholars know that financial resources can be an accelerator factor of progress and diffusion of science and technology to support the scientific development (Coccia and Bellitto, 2018; Roshani et al., 2021; Mosleh et al., 2022). This study provides critical innovation management implications to allocate resources with efficiency towards research fields and emerging technologies that have over time a growing degree centrality and levels of closeness and betweenness (e.g., wireless sensor networks) to foster the scientific and technological development for positive societal impact. In fact, these findings can support policymakers and funding agencies in making efficient decisions regarding sponsoring specific research fields and technological trajectories in sensors that can accelerate the development of science and technology with fruitful effects for the current and future wellbeing of people in society.

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4. Conclusions, limitations and prospects

The evolution of the scientific ecosystem of sensor over the last few decades is unparalleled (Andersen et al., 2004). Sensor technology is co-evolving with growing interactions of technological systems directed to fulfil human goals, needs and solve problems in society. In fact, the evolution of smart sensors is associated with the integration of the Internet of Things, through which it is possible to connect devices and exchange information among people, systems, and devices (Farias da Costa et al., 2021). The characteristics of evolutionary pathways in sensor research can improve the allocation of R&D investments in private and public organizations for beneficial social impact (cf., Coccia and Rolfo, 2000). Results show that the scientific ecosystem of sensor research is based on a network of interconnection, which is rapidly growing from 2011 to 2020 (cf., Choi et al., 2011; Lee and Kim, 2018). In this period, more than 300 technologies emerged, developed and connected to others, such as "biosensor", "fiber optic sensor", "wireless sensor network", "gas sensor" and "optical sensor. Moreover, results suggest that in the last decade, sensor technologies are moving towards pathways of specialization with scientific splitting from large research fields. For example, gas sensors are becoming more focused on "metal oxide gas sensor", "optical gas sensor", "electrochemical gas sensor", "calorimetric gas sensor", "acoustic based gas sensor". Consequently, their applications in industrial and manufacturing systems will be more and more directed to specialized applications. Moreover, "smoke sensor", "LPG sensor", "carbon monoxide sensor", "hydrogen sensor", "ammonia sensor" etc., are also the results of the development and specialization of gas sensor technologies. As a matter of fact, the stabilizing number of communities and the increasing level of closeness centrality in the network indicate that the interaction of sensor technologies in the ecosystem has been evolving through patterns of technological specialization.

These results confirm that the scientific dynamics of sensor research evolves with a process of interaction with other technologies that increase the size and complexity of the ecosystem (Coccia and Watts, 2020; Lee and Kim, 2018) through processes of splitting and merging in science in which splitting generates specialization, while merging process captures complementary aspects of different technologies and research fields (Sun et al., 2013). This study suggests that the research fields of sensors are in continuous evolution because of recent advances in information and communication technologies, artificial intelligence, internet of things, nanoscience, etc. that enable the interaction of different technologies directed to the expansion of human life-interests.

These conclusions are, of course, tentative. Although this study has provided some interesting, albeit preliminary results, it has several limitations. First, a limitation of this study is that sources understudy may only capture certain aspects of the ongoing dynamics of sensor research and technology. Second, there are multiple confounding factors that could have an important role in the evolution of sensor research to be further investigated, such discoveries or scientific breakthroughs, high R&D investments, collaboration intensity, openness, intellectual property rights, etc. Third, the computational and statistical analyses in this study focus on a specific period that can be extended in future studies. Forth, sensor research associated with new technology change their borders during the evolution of science, such that the identification of stable technological trajectories and new patterns in the evolution of sensors is a non-trivial exercise.

To conclude, future research should consider new data when available and apply new approaches to reinforce proposed results. The future development of this study is also directed to design indices of technometrics based on measures of betweenness, closeness, degree centrality of networks over time to assess and predict the evolution of new technological trajectories in sensors and other technologies, as well as to support implications of innovation management. Despite these limitations, the results presented here clearly illustrate the evolutionary paths of sensor research that are more and more based on interactions between research fields and technologies that need a detailed examination for supporting technological forecasting and appropriate strategies of management of technology.

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