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Using acknowledgement data to characterize funding organizations by the types of research sponsored: the case of robotics research

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Abstract Funded research has been linked to academic production and performance. While the presence of funding acknowledgements may serve as an indicator of quality to some extent, we still lack tools to evaluate whether funding agencies allocate resources to novel and innovative research rather than mature fields. We address this issue in the present study by using bibliometrics. In particular, we exploit the citation network properties of academic articles to classify specific research fields into four categories: change maker, breakthrough, incremental, and matured. We then use funding acknowledgement information to identify the sponsors involved in each research type to characterize funding agencies. We focus our analysis on the robotics field in order to reveal international trends of financial acknowledgements. We find that the incremental and matured research areas show the highest counts of funding acknowledgements. Moreover, although research funded by some agencies is mostly recognized as incremental-type research, those in other categories may perform better in terms of the number of citations. Additionally, we analyze the interest of selected funding agencies in granular subject categories. The characterization of funding agencies in this study may help policymakers and funding organizations assess or adjust their strategies, benchmark with other key players, and obtain an overview of local and global acknowledgement trends.

Keywords Acknowledgement analysis · Funding analysis · Citation network · Emerging technology · Robotics

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Introduction

Researchers have called for funding agencies to target innovative research in order to encourage organizations to embrace risk (Berg 2008; Muller 1980). The challenge comes in the form of giving researchers the freedom to pursue curiosity-driven research on their own as well as society's demand for tangible outputs to ensure that the return on investment can be measurable. Thus, the funding strategies followed by organizations may determine the directions of innovation in the academic domain (Braun 1998; Lok 2010). However, the need for better tools to measure the impact of funding and thus encourage the emergence of new knowledge in the frontiers of science is a recognized gap (Lane 2009).

Bibliometricians have developed quantitative indicators that assess research impact, mainly in terms of the number of publications and citations received. However, as methodological tools become refined and data coverage broadens, new avenues of exploration have opened. In this research, we take a step forward from the evaluation of the academic impact of research funds to study the allocation of funds for innovative research. To explore the role of funding organizations in driving research in a more innovative and path-breaking direction, we use quantitative methods such as citation network analysis and research classification schema (Takano et al. 2017) as well as the funding information found in the Acknowledgements sections of academic articles. In particular, this study attempts to identify both the methods that help explain whether funding organizations are targeting new research fronts as well as the state of funding in specific knowledge fields.

Funding and acknowledgements

Linking funding to academic output is challenging. Some studies have used separate data sources to establish this connection (Hosotsubo and Nishii 2016). These works have tried to connect the grantee data from funding organizations' reports to the metadata in other bibliographic databases by author name or paper title matching. However, such a process has several shortcomings. For instance, the principal investigator is not always the person writing the paper, while the time it takes to generate the output varies across fields (Boyack and Börner 2003; Boyack and Jordan 2011). Other streams of research establish connections between grants and publications directly by looking at the funding information in the Acknowledgements sections of academic articles.

In early acknowledgement studies, funding data were extracted from the acknowledgement text manually. However, more recently, the refinement of machine-learning techniques for text mining has facilitated the task of entity recognition, and algorithms have been developed for this specific task (Giles and Councill 2004). Data providers such as Clarivate Analytics through the Web of Science have also started including such information in a cleaner and more curated format (Web of Science 2008). This advancement has provided richer data that span disciplines and countries and thereby allow comprehensive assessments.

The use of acknowledgements as a proxy of funding has been criticized. For example, authors may not mention all their sponsors for several reasons, varying from simply forgetting to cultural or political reasons, or just because different practices exist across academic fields (Cronin et al. 1992). Further, acknowledgements might be unsuitable for computing the actual funding received for the completion of the article (Rigby 2011). Notwithstanding these obstacles, the mere presence of acknowledgement data has proven to be a useful source to understand sponsorship trends (Cronin 2001) and assess research quality (Gök et al. 2016). Indeed, among the earliest applications of acknowledgement data for analyzing funding patterns were the studies by Lewison and Markusova (2010), a bibliometric analysis of cancer research in Russia, and Wang and Shapira (2011), which includes an overview of funding in nanotechnology.

Acknowledgements and academic impact

Previous research has studied the presence of funding data in the acknowledgements as an explanatory variable of high-quality outputs (Gillet 1991; Lewison and Dawson 1998). The dependent variable in these studies generally takes the form of citations received by funded papers versus non-funded papers. In the work by Gök et al. (2016), acknowledgement information was used to identify funding organizations and categorize them as governmental, non-governmental, and international funding for six European countries. These categories, among other features, were used as the independent variables in a regression model explaining the number of citations received by the articles. A high correlation was found between the citations received and the presence of financial acknowledgements, particularly from national sources, a correlation that also holds when academic articles are analyzed by topic instead of at the country level. Similarly, Shen et al. (2016) observed that highly cited computer science articles are also those that have funding acknowledgements. Academic articles that have received funding are also linked to being accepted by journals with relatively high-impact factors (Wang and Shapira 2015), having a greater number of co-authors (Yegros-Yegros and Costas 2013), and motivating interdisciplinary knowledge (Lyall et al. 2013). In summary, this stream of research includes funding acknowledgements as an explanatory factor of any of the dimensions of academic impact. Beyond this, few bibliometric studies have considered using acknowledgement data to explain the performance of funding organizations in targeting innovative research and shifting research trends.

Acknowledgements and research fronts

Research at the interface of detecting emerging technologies and using acknowledgement data is scarce. Wolcott et al. (2016) used the sponsor data found in the acknowledgements as an explanatory variable to predict the emergence of innovative research. However, they found only a low correlation with their definition of breakthroughs. Further, to address the issue of detecting emerging technologies during the peer review of grant applications, Hörlesberger et al. (2013) applied a logistic regression model to selected features of each proposal, showing that interdisciplinarity and similarity to previously identified emerging research are defining factors. Both these articles contribute significantly by linking funding to the concept of emergence; however, a research gap between the overall landscape of a specific research field and its funding sources still exists.

As discussed above, bibliometric research on funding and acknowledgements has focused on the evaluation of academic impact based on the number of publications and citation counts. However, while article production and citation count may suggest high-quality research, this is not necessarily true as an indicator of innovation. Therefore, the notion of whether funding agencies target cutting-edge research remains under-researched.

Parallel to studies of funding, an increasing number of bibliometrics studies address the issue of detecting emerging topics. For example, Rotolo et al. (2015) identified five attributes of emerging technologies: radical novelty, relatively fast growth, coherence, prominent impact, and uncertainty and ambiguity. The former three can be observed by adopting quantitative methods, and several bibliometric methodologies may be used to identify one or more of those attributes. For instance, radical novelty and coherence can be captured by citation network analysis (Shibata et al. 2009) by observing how new clusters appear in the network over time as well as by observing the close connections of the nodes. Purely text-based (Yan 2014) and hybrid methods (Glanzel and Thijs 2012) have been used in a similar manner. On the contrary, fast growth can be detected by comparing the document counts of a topic with a function, usually based on an S-shaped curve (Ho et al. 2014).

Moreover, by exploiting the features of a citation network alongside the phases of the technology lifecycle, Takano et al. (2017) built a classification schema that divides a corpus of literature into four categories: breakthrough, change maker, incremental, and matured. In particular, this framework distinguishes between truly radical emerging technologies based on relatively new knowledge (the change maker category) and emergence from well-understood research fields (the breakthrough category).

In the present research, we build upon those methodologies to characterize the funding organizations identified in the Acknowledgements section of articles based on their level of participation within the four above mentioned technology categories of breakthrough, change maker, incremental, and matured. We also use the properties of the citation networks of academic articles to infer those features related to the emergence of technology and then classify the articles accordingly. Therefore, our research incorporates a new layer of analysis of publication records and citation counts. Specifically, we explore the case of robotics research, a broad field discussed, applied, and investigated across disciplines. Robotics has drawn worldwide attention and is integrated into the technology development strategies of several countries (Ministry of Economy Trade and Industry of Japan 2015; National Science Foundation 2016; SPARC 2016), suggesting that it receives governmental support and warrants public agency involvement.

The intentions of funding organizations to target research focuses can be revealed by looking at the objectives posted in their guidelines, websites, and call-for-grants. However, the challenge is knowing whether the outputs achieved from receiving the funding have remained aligned with those original objectives. Studying this gap between outputs and objectives as well as the lack of tools for such an assessment is the main motivation of the present research. Our contribution is twofold. Firstly, we link acknowledgements to research categories. Secondly, funding organizations obtain an assessment tool with which to compare their research targeting as reported by sponsored authors.

Data and methods

In this study, we define a funding organization as any entity mentioned in the funding acknowledgements of academic articles. These may be ministries, agencies, NPOs, companies, projects, or programs. Table 1 lists the organizations that appear frequently in this study. We focus our study on two groups of funding organizations: (1) the leading international funding agencies according to the number of sponsored articles and citations received by them and (2) the five Japanese organizations most frequently found in the dataset. The latter are used to investigate how different agencies and programs that have different characteristics affect research direction and performance. The Ministry of Education, Culture, Sports, Science and Technology of Japan (MEXT), a ministry of the Japanese government, has two funding agencies, JSPS and JST. JSPS is responsible for pure and basic science, while JST is applied research. GCOE is a program of the MEXT

Table 1 Selected funding organizations in the field of robotics

Funding organization	Country	Acronym
863 State High-Tech Development Plan	China	863-CH
973 National Basic Research Program	China	973-CH
Defense Advanced Research Projects Agency	USA	DARPA
European Commission	EU	EC
European Union	EU	EU
The Fundamental Research Funds for the Central Universities	China	FRFCU-CH
Global Center of Excellence	Japan	GCOE
Japan Society for the Promotion of Science	Japan	JSPS
Japan Science and Technology Agency	Japan	JST
MEXT	Japan	MEXT
New Energy and Industrial Technology Development Organization	Japan	NEDO
National Institute of Health	USA	NIH
National Science Council	Taiwan	NSC-T
Natural Science and Engineering Research Council	Canada	NSERC
National Natural Science Foundation	China	NSF-CH
Swiss National Science Foundation	Switzerland	NSF-SZ
National Science Foundation	USA	NSF-US

that aims to develop research, education, and international partnerships. NEDO is a funding agency under another ministry, the Ministry of Economy, Trade and Industry, and this supports applied and industrial research.

To collect the data, we searched the Web of Science Core Collection for academic articles on the topic "robot*" published between 2009 and 2016 inclusive. This query retrieved 79,209 articles having either "robot," "robotic," or "robotics" in the title, abstract, or keywords. Web of Science includes funding information since 2008; however, the acknowledgement data were not complete for that year (Paul-Hus et al. 2016). Therefore, we selected our starting point as 2009. Other data providers such as Scopus also started to include acknowledgement information but in later years; thus, our database selection was also conditioned by the broader coverage.

Web of Science takes its funding information directly from the Acknowledgements sections of papers, reaching precision and recall rates above 90% when it comes to the entity recognition task (Grassano et al. 2017). It provides two fields, one having the raw text as written in the paper and the other a curated field showing only the names of organizations and when available, the funding code. In this research, we used the latter field. While this greatly facilitated the identification of funding agencies, a good deal of effort was still required for data cleaning and name disambiguation, particularly for funding entities with long names. We used programming to help identify similar instances; however, ultimately all names were manually checked and standardized.

The hierarchical relationships in the funding organizations were also observed as in the case of the MEXT as a parent of JSPS and JST. However, some papers may acknowledge both child and parent as funding organizations. Parent organizations may also simultaneously support the work of some researchers (Lepori 2011). Table 2 presents examples of multiple hierarchical levels, particularly in Europe. For instance, authors may acknowledge

Table 2 Examples of acknowledgements reporting different levels of an institutional hierarchy

Case	Acknowledgement
The EU and the EC as different entities	"This work was supported in part by the European Union. 'Operation part financed by the European Union, European Social Fund.' This work has been partially funded by the European Commission's Sixth Framework Programme as part of the projects SAPHARI under Grant No. 287513" (Povse et al. 2016)
Two projects from the same parent organization	"The work described in this paper was conducted within the EU Integrated Projects LIREC (LIving with Robots and intEractive Companions, funded by the European Commission under contract numbers FP7 215554, and partly funded by the ACCOMPANY project, a part of the European Union's Seventh Framework Programme (FP7/2007-2013) under grant agreement n287624" (Koay et al. 2014)
The EC as part of the EU	"This work was supported in part by the Seventh Framework Program of the European Commission under Grant 287728 through the framework of European Union Project STIFF-FLOP, in part by the National Institute for Health Research Biomedical Research Centre through the Guy's and St Thomas' NHS Foundation Trust and King's College London, in part by the Guy's and St. Thomas' Charity, in part by Vattikuti Foundation, in part by the National Institute for Health Research Biomedical Research Centre, and in part by the Medical Research Council Centre for Transplantation. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health. The associate editor coordinating the review of this paper and approving it for publication was Dr. Anupama Kaul" (Konstantinova et al. 2014)

the European Union and the European Commission as different entities, as can be seen in the first case in the table. This is also reflected in the curated field of the Web of Science showing the organizations and programs: "European Union; European Union, European Social Fund; European Commission's Sixth Framework Programme as part of the projects SAPHARI [287513]". It is worth noting that in this example, the funder is actually the same, but reported as a different. We did not always regard this as a redundant acknowledgement, thereby complicating the task of separating and counting the contributions of each entity. Therefore, in terms of institutional structure, we respected the entries as reported in the dataset with no further merging.

Once the data were cleaned, we proceeded to create the citation network. In a citation network, articles play the role of nodes, connected to each of their cited references also present in the dataset retrieved. While other citation methods exist (Kessler 1963; Small 1973), there is more evidence that direct citation networks are the best representation of the knowledge structure of a field (Klavans and Boyack 2017; Shibata et al. 2009). We focused only on the maximum component of the network, neglecting all papers not connected to any other paper. To finish this step, we applied a community detection algorithm (Newman and Girvan 2004) to extract highly intertwined groups of papers (i.e., clusters), which target concentrations of similar research topics or technologies.

While we could have created a citation network by using only the set of papers that reported funding, such an approach is biased against the detection of innovative technologies, because it is known that some highly cited papers, which are the constitutive blocks of clusters, may not have funding acknowledgements (Zhao 2010). Our approach classifies the technologies into categories by using all the available connected data. Thus, by classifying the clusters, we can see how different funding organizations participate within them, not necessarily sponsoring the core paper, but at least demonstrating their ability to allocate funds to promising new and emerging fields.

Clusters are the unit of measurement for the following step. We used a research classification schema (Takano et al. 2017) to label each cluster as change maker, breakthrough, incremental, or matured. This classification responds to two main features of the clusters: the average age of the cluster, which is the average of the publication years of all the papers within the cluster, and the age of the core paper, which is the paper having the maximum connections in the cluster. Table 3 provides an interpretation of these four categories. The research classification schema corresponds to the technology lifecycle, and it has served as a good representation of the state of research on the Internet of things and related technologies (Takano et al. 2016).

Finally, for funding organizations mentioned 10 times or more in the dataset, we computed the amount of papers they sponsored in each of these four categories. To investigate the funding patterns among funding agencies, the obtained distributions were standardized following Eq. (1), where μ is the average of the proportions of each category and σ their standard deviation:

$$x_{\text{new}} = \frac{x - \mu}{\sigma} \tag{1}$$

These standardized values were then used as an input into the principal component analysis and plotted as a biplot after multidimensional scaling, generating a map of funding organizations and their trends. This analysis was conducted for both the amount of papers and the number of citations received in those papers. We also computed the citation rates corresponding to the categories as follows:

$$r = \frac{\sum_n c}{n(2016 - \bar{y})} \tag{2}$$

where n is the number of articles acknowledging an organization in a single category, c is citations received by those articles, and $\bar{y}$ their average publication year. The average age is obtained taking 2016 as reference. Then r is the rate of citations per article per year.

Finally, to account for possible changes in acknowledgement patterns or other out-of-control variations such as improvements in the entity recognition algorithms of Web of Science, we conducted a robustness check by replicating the abovementioned methodology for 2011–2016 and 2014–2016.

Table 3 Research classification schema

Type of technology	Interpretation
Change maker	Research target is active, and its core literature is relatively new
Incremental	Research target is active, but its core literature is relatively old
Breakthrough	Research target is inactive, but its core literature is relatively new
Matured	Research target is inactive, and its core literature is relatively old

Additionally, we studied the funding strategies of the organizations by inspecting the subject categories on which they focus. Web of Science assigns to each article one or more specific scientific subject areas according to the journal it was published. Thus, the interests of a given organization may also be revealed by looking at the distribution of the categories into which its papers fall. In a similar process, in the previous step, we mapped the funding organizations by using the subject categories as variables for the principal component analysis. Figure 1 provides an overview of the research.

Results and discussion

Overall landscape of robotics research and funding

Of the 79,209 academic articles having the keyword "robot" in any of their text fields, 59,088 (75%) were connected by citation relationships. The rest were papers using the word "robot" that did not necessarily belong to the field. Approximately one-third (31.92%) of the articles in the network reported at least one funding organization in the acknowledgements, a proportion close to that reported for the entire Web of Science Core Collection database (Paul-Hus et al. 2016).

Altogether, 460 clusters were detected and classified as breakthrough, change maker, incremental, or matured. However, 157 were small clusters, in which none of their articles reported funding acknowledgements. Those small clusters accounted for only 1.22% of all nodes in the network and were removed from the analysis. Figure 2 shows the network of

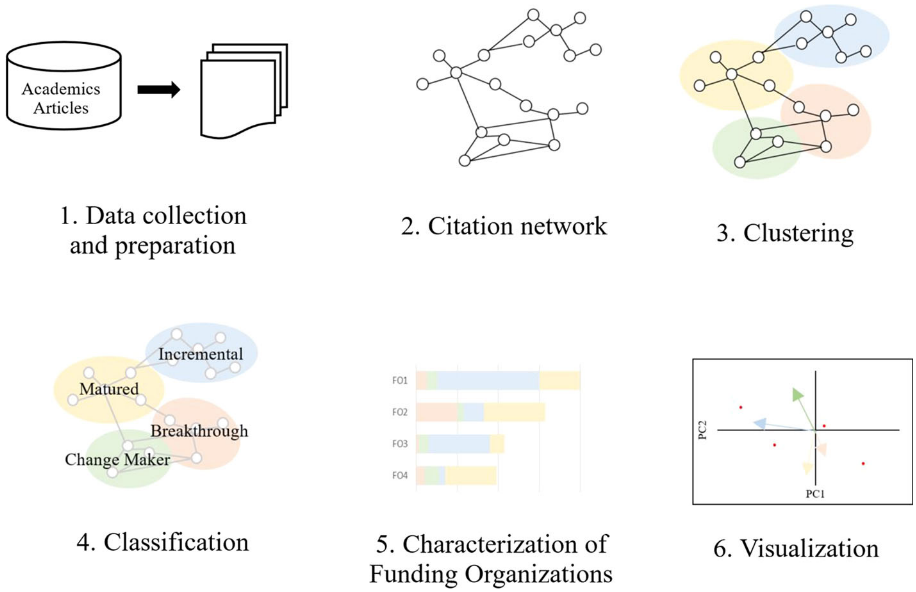


Fig. 1 Methodological overview of this research

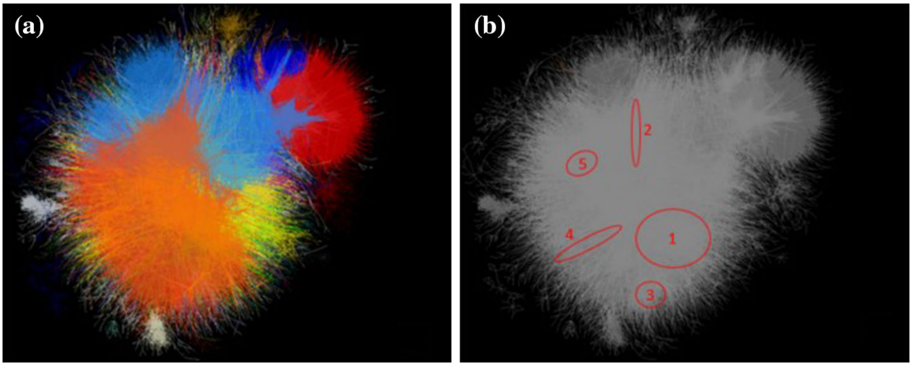


Fig. 2 **a** Citation network of robotics research; 460 clusters were found. Citations within the same cluster are shown in different colors in the figure. **b** Change maker clusters tend to be small and hidden behind the larger clusters. Five out of the 38 change maker clusters' positions are shown as an example. #1 Research on navigation for service robotics in agriculture; #2 Multi-legged robot walking; #3 Wireless technologies for sensing and charging; #4 Machine-learning algorithms for navigation; #5 Motion control for hanging robots. (Color figure online)

Table 4 Classification of articles on robotics research by type of technology

Type of technology	Articles	% of articles reporting funding
Breakthrough	1730	42.4
Change maker	1212	35.9
Incremental	41,112	33.9
Matured	14,311	26.4

robotics research along with the largest change maker clusters in terms of academic articles.

Table 4 shows the aggregated number of articles falling into the four categories. Academic articles on robotics were largely classified into incremental clusters. The breakthrough and change maker categories, without surprise, represented a small proportion of publications owing to the difficult nature of producing new cutting-edge knowledge with relatively large academic impact. We found that the breakthrough and change maker clusters were small, having an average size of 21 and 32 articles, respectively. On the contrary, clusters representing incremental and matured technologies comprised an average of 548 and 134 articles, respectively. This finding is explained on the basis that as more researchers join the topics, the incremental and matured clusters grow in size.

The largest number of clusters in the network were classified as incremental. These clusters have a new knowledge base, with the average year being 2014, but the core academic article is relatively old. Robot-assisted therapy was one of the many examples found. This domain includes the usage of robots for the rehabilitation of motor function after strokes (Lo et al. 2010). Further, in the medical field, we found research on robotic thyroid surgery and transoral surgery (Kang et al. 2009). Within the pure engineering spectrum, we found literature addressing issues such as motion systems for spherical robots (Joshi et al. 2010), among several others.

Next, we found that robotics research was focused on matured technologies, corresponding to those clusters at the older end of the dataset, published around 2012 on average. Among them, we found work on micro-robots (Nelson et al. 2010) and tele-operated robots (Sanders et al. 2011). Breakthrough clusters are those having a core paper that has received attention in recent years, but a relatively old knowledge base (around 2012 on average). The relevant literature includes attempts to solve the robot selection problem when robotics systems for a defined task are widely available (Parameshwaran et al. 2015). This cluster draws ideas from operations research and management concepts such as multiple criteria decision-making, which dates to 1974; however, its application in the context of robot system selection has received attention lately. Similarly, we found the concept of tensegrity, a structural principle broadly applied in architecture, but now used for the improvement of dynamics or locomotion by integrating the principle in a robotics structure (Caluwaerts et al. 2014). We found 83 breakthrough clusters having at least one funding organization engaged.

Finally, we found 38 change maker clusters (i.e., those having a relatively new knowledge base and core papers published around 2014). The technologies discussed in this category are primarily oriented to service robotics, with robots for agriculture the largest cluster. This includes robotics devices, or algorithms dealing with the automation of tasks in open and unstructured environments, and the handling of live produce that requires gentle and accurate treatment (Bechar and Vigneault 2016). Other research include progress in the speed and autonomy of legged robots (Tedeschi and Carbone 2015), and machine-learning algorithms for autonomous navigation (Fathinezhad et al. 2016).

Table 4 also shows the proportion of papers with funding acknowledgements; from this perspective, the breakthrough and change maker clusters performed better than the other two in the period of study, which is a positive overall indicator for funding organizations given that they may be expected to contribute more actively in these categories. However, even though breakthroughs are desirable outcomes, under our methodology, they refer to new technologies born from old, well-understood research topics. While there are several factors influencing research direction, from a funding perspective, organizations may be considered to be playing safe by allocating financial support to a well-understood knowledge base. More interesting is the case of change makers. Because both the core literature and the knowledge base are newer, the risk involved in the fund allocation decision may be perceived to be higher.

Characterization of funding organizations

More than 11,000 organizations were acknowledged in the network; of these, 8432 were acknowledged only once. Hence, we decided to focus on those organizations mentioned 10 times or more, obtaining 445 funding organizations. For each of those, we computed the number of papers they funded in each of the four categories such that the distribution obtained served as the characterization itself. Then, we analyze the 10 most mentioned funding organizations by number of articles. Table 5 presents their characterization. Notably, most of the acknowledgements came from incremental research. The funding organizations with a larger share of papers in the change maker clusters were the NSF-CH, NSF-US, EC, EU, and 863-CH. Such distributions can help reveal the underlying patterns across funding organizations, taking into account even small variances in the distribution. Further, we conducted principal component analysis with the same input data. After standardization and the multidimensional scaling of the principal components, we mapped the state of funding for the field of robotics, as depicted in Fig. 3.

The most acknowledged funding organizations are government agencies. The private sector seems to have little participation in funding research compared with public funding. The company with the most acknowledgements is the US company Intuitive Robotics Inc.,

Table 5 Characterization of funding organizations by the number of articles and type of technology they sponsor. The 10 most frequently mentioned organizations are shown

Rank	Organization	Articles	Breakthrough (%)	Change maker (%)	Incremental (%)	Matured (%)
1	NSF-CH	3420	5.2	2.1	79.3	13.3
2	NSF-US	1853	2.9	1.7	79.2	16.2
3	EC	802	1.4	3.7	84.3	10.6
4	EU	717	2.0	4.0	76.6	17.4
5	NIH	651	6.0	0.2	60.8	33.0
6	NSERC	522	3.3	1.5	81.2	14.0
7	863-CH	487	3.9	3.3	73.1	19.7
8	FRFCU-CH	460	5.0	2.8	80.4	11.7
9	NSC-T	407	1.2	0.5	85.5	12.8
10	973-CH	366	6.3	1.4	81.4	10.9

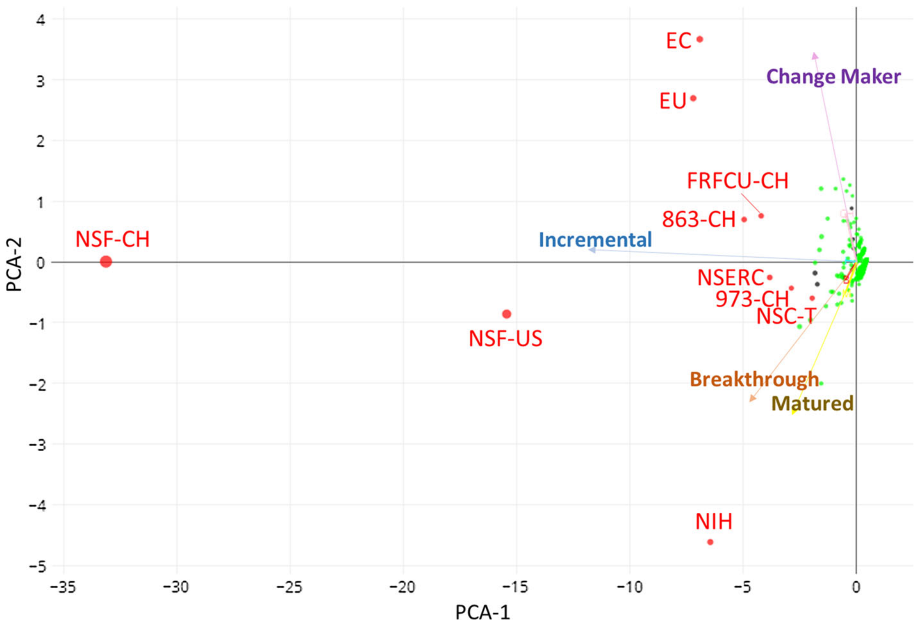


Fig. 3 Funding organizations by the number of papers sponsored in each category. The top 10 funding organizations are shown in red. (Color figure online)

which is responsible for the da Vinci Surgical System, a robotics system for minimally invasive complex surgeries. It ranked in position 26, being mentioned in 153 articles (22% incremental, 78% matured). The misrepresentation of the private sector in the Acknowledgements sections of academic articles may be explained by the greater interest in patenting than in academic research or a strategic preference for anonymity (Rigby 2011).

The axes in Fig. 3 represent the principal components and the dots refer to the relative distance among the funding organizations. The four variables are shown as arrows pointing from the origin. The direction of the arrows is interpreted as the intensity of that attribute. Finally, when two or more funding organizations appear close, this is an indication that they share a similar acknowledgement pattern. The 10 organizations marked in red clearly show their outlier nature. In particular, the NSF-CH plays a prolific role in terms of the number of publications, being mentioned mostly in the incremental category. Following the NSF-CH, the NSF-US also appears in the incremental category, but its funding in this category is lower than the former, given the larger participation of matured and breakthrough technologies in its distribution. Further below is the NIH, which is mainly recognized as a sponsor of incremental and matured categories and has almost null participation in change maker technologies, resulting in its existing position. Its conservative nature for fund allocation is well known in the academic community (Berg 2008; Rangel et al. 2002); therefore, this position is expected. The EC and EU are close each other; as discussed above, this may be due to redundant acknowledgement practices or merely the interchangeable use of the name. Further, as can be seen, their closeness serves as confirmation that they may allocate funds following the same strategy. Although they appear less in change maker articles in comparison with the NSF-CH, in terms of their own distribution, they are better at targeting change maker technologies. The remaining organizations follow different patterns as revealed in the chart. Among the two Chinese programs, 863-CH and 973-CH, the objective of the former is funding cutting-edge technology, while that of the latter is funding basic research. Their positions in the map represent these objectives.

Figure 4 illustrates the pattern of acknowledgements in terms of academic impact measured by the number of citations received by the sponsored papers. While the characteristics of the two maps are similar, this time the matured attribute is present over the horizontal axis close to the incremental arrow, implying a high correlation between the

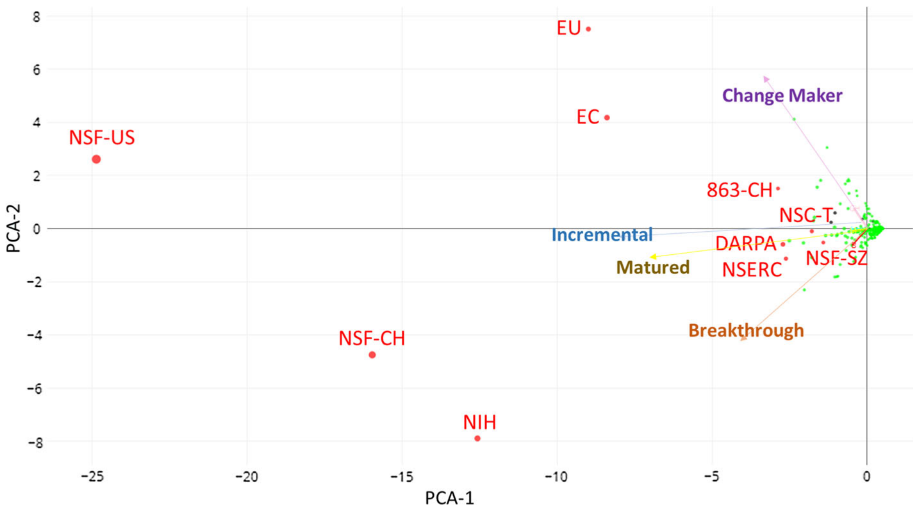


Fig. 4 Funding organizations in terms of citations received by their sponsored articles in each category. The top 10 funding organizations are shown in red. (Color figure online)

two. Therefore, the projections over the vertical axis are determined by the breakthrough and change maker attributes, which happen to be orthogonal.

Eight of the previously discussed organizations are also the ones which papers collect the most citations. Again, the NSF-CH and NSF-US dominate the map. However, the papers funded by the NSF-US have greater academic impact. Although this impact comes mainly from incremental papers, the organization's position is pulled up, showing that change maker technologies play a better role in capturing citations. The NIH, EC, EU, and 863-CH remain in similar positions to those based on the number of papers in Fig. 3. Citations received by papers funded by DARPA and the NSF-SZ were found to be higher than those funded by the 973-CH and FRFCU-CH, being in the 16th and 18th position respectively in terms of citations. The performance of Swiss funding in relation to other European countries has also been acknowledged before (Gök et al. 2016).

Finally, we tested the proposed method by replicating the experiment in other 2 periods of time; 2011–2016, and 2014–2016. In particular, we looked for changes in the proportion of articles reporting acknowledgements, or for external changes like improvements in the entity extraction method of the data provider that might have affected the results described in our case study. Table 6 provides a summary of the characteristics of the network and the amount of papers with funding information per each range. Articles need a span of time to collect citations, affecting the connectivity of the network. The shortest the range the more disconnected it is. Considering the shortest period of 3 years, most of the papers are disconnected. Conversely, there is a higher proportion of articles reporting funding. This increase in the proportion of articles with acknowledgement is a known fact for the Web of Science (Paul-Hus et al. 2016), which is reflected in our dataset of robotics.

Next, we checked how articles are distributed in each category as shown in Table 7. The proportions are consistent. Incremental and matured categories remain with the largest shares.

Nine of the organizations we have shown in the study remain the top regardless the time range. The other one is the National Research Foundation of Korea which displaces NSC-T for the periods 2011–2016 and 2014–2016. Therefore, we could verify that a short range of time affects the composition of the network, in exchange of an increase in the proportion of articles with acknowledgements. However, the most frequent funding organizations reported in this study remained consistent regardless of this variations.

Japanese funding agencies

We also developed a detailed view of Japanese funding organizations in robotics to contrast our methodology with the expected outputs from their actual guidelines and strategies. Figure 5 shows the funding maps by the number of papers and their citations of the five

Table 6 Summary of replication of experiment for different ranges of time

Range	2009–2016	2011–2016	2014–2016
Published articles	79,209	60,366	33,422
Connected articles	59,088	43,218	15,197
Connected articles %	74.60	71.59	45.47
Articles reporting funding	18,861	15,043	6147
Articles reporting funding %	31.92	34.81	40.44

Table 7 Articles reporting (R) and not reporting (NR) acknowledgments for each category

	2009–2016		2011–2016		2014–2016	
	R (%)	NR (%)	R (%)	NR (%)	R (%)	NR (%)
Breakthrough	1.3	1.7	1.5	2.6	1.1	1.9
Change maker	0.7	1.3	0.5	0.5	5.0	7.2
Incremental	23.8	46.6	23.1	38.9	18.7	23.9
Matured	6.5	18.1	10.0	22.8	15.7	26.4

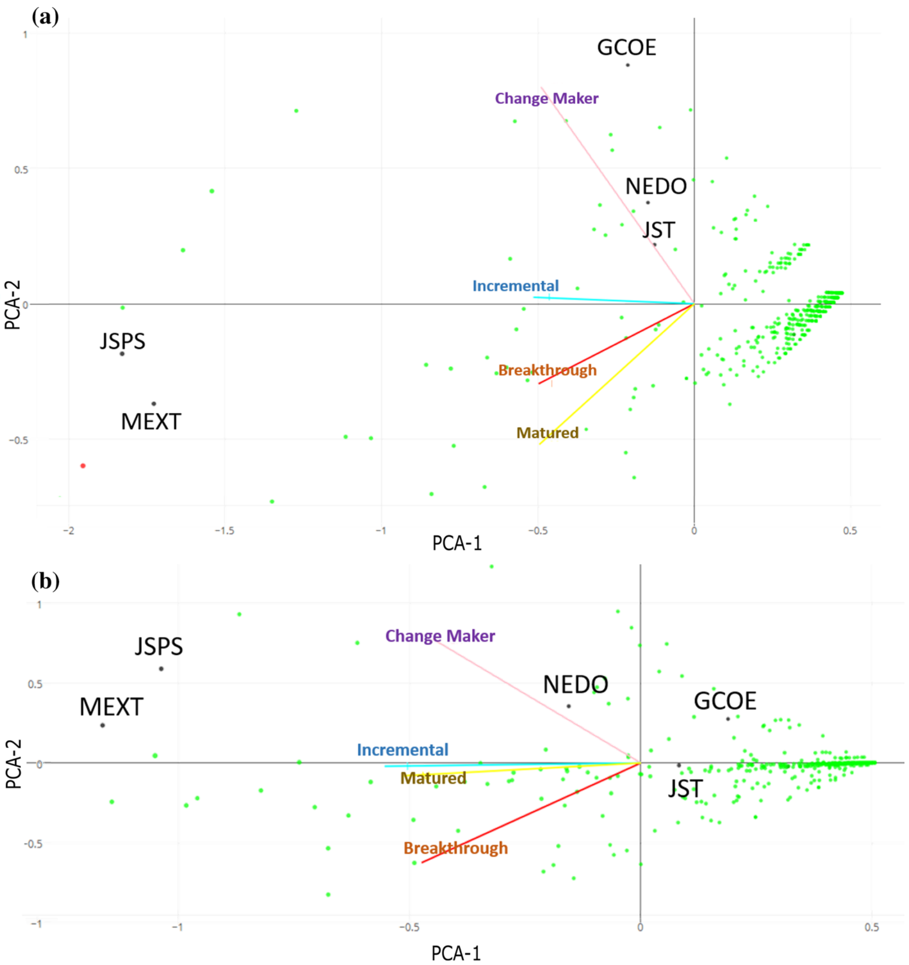


Fig. 5 Japanese funding organizations in relation to the four types of technologies: **a** by papers sponsored and **b** citations received by the sponsored papers

Table 8 Characterization of Japanese funding organizations by the number of articles and type of technology they sponsor. Five most frequently mentioned organizations are shown

Rank	Organization	Articles	Breakthrough (%)	Change maker (%)	Incremental (%)	Matured (%)
1	JSPS	305	2.3	1.3	82.0	14.4
2	MEXT	241	2.5	1.7	72.6	23.2
3	JST	78	1.3	2.6	84.6	11.5
4	NEDO	48	2.1	6.3	70.8	20.8
5	GCOE	39	2.6	12.8	82.1	2.6

most acknowledged Japanese organizations. Their characterization by the number of papers is shown in Table 8.

Funded papers from JSPS mostly belong to incremental-type technologies. JST, on the contrary, has better positioning in targeting change maker technologies. According to their respective objectives, JSPS supports curiosity-driven basic research, while JST supports mission-oriented applied research. The observed results might occur because basic research funded by JSPS takes a long time to develop and tends to focus on incremental research, whereas JST tends to focus on disruptive and cutting-edge research. Their position in Fig. 5a not only reflects that fact, but it also may be influenced by the application and examination process of grants. Applications to Grants-in-Aid for Scientific Research, the major funding program in JSPS, are submitted to specific academic categories and examined by peer review in those categories. Therefore, interdisciplinary research proposals usually face a difficulty in choosing the right category during the application. Moreover, during the examination process, the past achievements of applicants are taken into consideration in addition to the proposal. This leads to incremental research being accepted based on an applicant's past achievements and well-developed capabilities, thereby suppressing emerging and change maker research, which may diverge from previous achievements. On the contrary, JST allocates its funds through a project manager and committee from various backgrounds, implying more freedom when it comes to funding change maker research.

GCOE is a special program within JSPS oriented to "highly creative and vanguard research" wherein the proposal must embed a future concept. Along with the spirit of multidisciplinary and international collaboration, which are known indicators of better academic performance, it is not surprising that GCOE obtains a higher position for change maker technologies. NEDO, similar to the case of JST, supports applied research but is responsible for the development of industrial technologies and companies. Hence, it is examined by adopting a similar system to JST but policymakers also help decide the fund allocation. NEDO produces higher citation impact, which might be because of the applied characteristics of robotics technologies and superior capability of Japanese companies in this field. Finally, the MEXT is also acknowledged in the articles, although the core research funding allocation is decided by JSPS and JST, as mentioned earlier. The appearance of the MEXT may come from other types of funding such as scholarships, which may be administered directly by the ministry, or the natural practice of a researcher mentioning both the funding agency and the parent ministry. Given the proximity to JSPS, this may be true, especially for researchers funded by that agency.

Interestingly, both JSPS and JST seem to switch roles from the perspective of citations (Fig. 5b). Although the peer review system is conservative, curiosity-driven work by academics will lead to high-impact research. The position of JSPS suggests that the citations received from its change maker papers have better impact that in the case of JST. NEDO and GCOE remain in a position where change maker technologies play an important role. Finally, the MEXT continues to be close to JSPS, further evidence of this "double acknowledgement."

Citation rates of sponsored articles

We computed the average yearly rate of citations per paper for the most acknowledged organizations in each category and reported it in Table 9. For each of the them we marked in bold the category with the highest performance. Articles sponsored by some funding organizations may perform better in different categories, and no uniform pattern was found for the Japanese organizations, however the international organizations tends to have better rate in the incremental category.

From the totals of the international organizations we find that articles sponsored by NIH and NSF-US have the highest rate. However, our classification reveals that is heavily determined by the matured and incremental type of research they sponsor. Articles sponsored by any of the four Chinese funding organizations have a lower citation rate.

A closer look to the change maker category reveals that EU, NSF-US, and EC are the key players. As previously discussed, articles sponsored by NIH and identified as change maker do not get much citations in comparison with other papers funded by NIH in other categories.

Regarding Japanese agencies, JST has the highest rate, followed by NEDO. Being matured and breakthrough their respective higher categories. Articles having JSPS in the

Table 9 Average rate of citations per paper in each category

Rank	Organization	Breakthrough	Change maker	Incremental	Matured	Total
5	NIH	3.7	1.8	**5.5**	4.4	4.5
2	NSF-US	1.6	3.5	**4.8**	4.7	3.5
3	EC	1.4	2.5	3.4	**4.9**	3.1
4	EU	1.4	**3.9**	3.3	2.2	2.5
9	NSC-T	1.3	2.1	**3.0**	1.4	2.4
6	NSERC	1.2	0.5	**2.5**	1.3	1.9
7	863-CH	0.7	1.8	**2.0**	1.2	1.5
10	973-CH	0.5	1.2	**1.7**	0.7	1.4
1	NSF-CH	0.8	0.8	**1.9**	0.9	1.3
8	FRFCU-CH	1.2	1.3	**1.4**	0.7	1.1
3	JST	0.3	0.2	2.3	**4.1**	2.4
4	NEDO	**3.1**	2.0	2.9	1.5	2.3
2	MEXT	1.1	**2.0**	**2.0**	1.6	1.7
5	GCOE	0.8	0.9	**1.5**	0.7	1.3
1	JSPS	0.6	**2.6**	1.4	1.6	1.3

For each of the them we marked in bold the category with the highest performance acknowledgement collect the most citations in the change maker category. Therefore, the conservative peer-review system of JSPS tends to target a larger amount incremental research, as shown in Fig. 5. However, this selective process made possible for the comparatively small proportion of change maker articles sponsored to gather more citations.

Funding strategies by targeted subject area

Within the scope of robotics research, funding organizations also have more specific fields of interest. In particular, robotics is an interdisciplinary field that integrates diverse research areas including mathematics, physics, materials science, and mechanics. Applications are also diverse, such as instruments for the manufacturing industry and medical devices. Therefore, we examined those specific targets by mapping the distribution of subject fields assigned to the articles. This assignation is made by the Web of Science based on the subject categories of the journals the articles are published in. Given that the data under analysis concern robotics, we removed the four subject areas that were a direct representation of this field, namely robotics, engineering, computer science, and automation and control, and focused on the subsequent most frequent categories. Figure 6 shows the distribution of the top international and Japanese organizations. The categories vary from purely basic to medical research, with “instruments and instrumentation” and “surgery” being the most common. Top organizations seem to have a similar pattern of interest, especially for the most frequent categories. However, smaller categories may also play a significant role. Therefore, we repeated the multidimensional reduction of the principal components to bring the patterns to the fore.

Figure 7 shows the specific research fields targeted by the funding agencies. Similar to the previous figures, the axes represent relative distance. However, unlike the biplots based on the four technology-related categories, this time, the attributes span the chart owing to the different nature and skewness of the distributions, which are less sharp than those produced in the previous charts that featured a large representation of the incremental category. We find that medical research dominates the right-hand panel, while the basic and engineering fields represent the left-hand panel. Funding organizations in the same

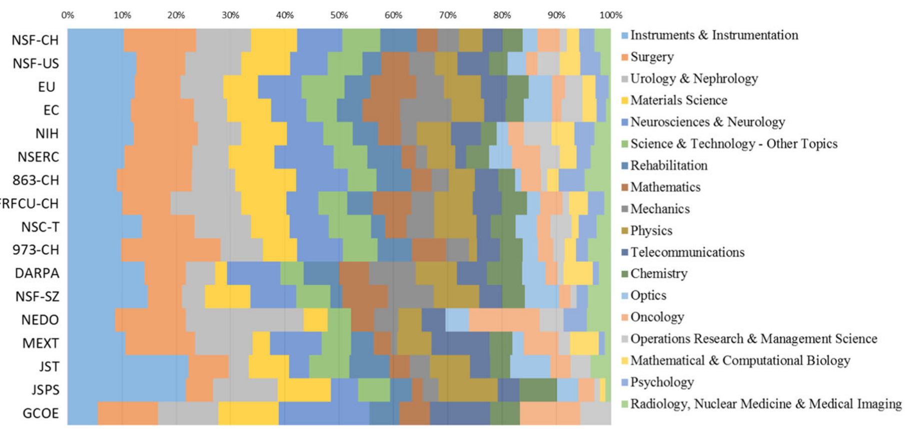
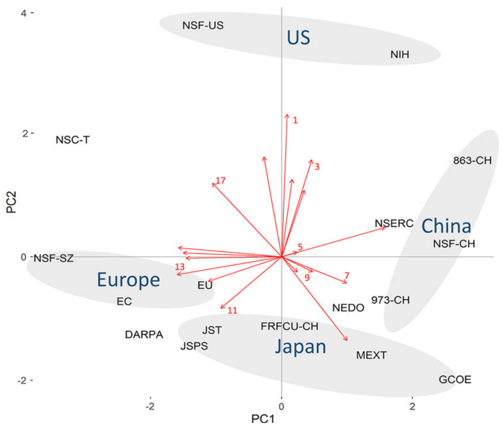


Fig. 6 Distribution of the most sponsored subject fields within robotics research for the selected funding organizations. (Color figure online)



Subject fields in clockwise order:

1. Psychology
2. Mathematical & Computational Biology
3. Materials Science
4. Radiology, Nuclear Medicine & Medical Imaging
5. Urology & Nephrology
6. Surgery
7. Rehabilitation
8. Neurosciences & Neurology
9. Telecommunications
10. Oncology
11. Chemistry
12. Mathematics
13. Optics
14. Physics
15. Mechanics
16. Instruments & Instrumentation
17. Science & Technology - Other Topics
18. Operations Research & Management Science.

Fig. 7 Patterns at the country level in relation to the subject fields within robotics

country seem to be grouped by region in the chart. This is not necessarily expected, because funding organizations may have different objectives. We can thus infer, to some extent, from the chart that robotics research follows funding policies set at the country level (or at the regional level for the EU). This finding may not hold for all agencies; for instance, DARPA seems to have a different strategy to the NSF-US and NIH. In addition, the FRFCU-CH is closer to targeting the interests of Japanese organizations rather than Chinese organizations.

Summary and conclusions

This research aimed to develop a methodology that can characterize funding agencies in relation to different technology types based on the information in the Acknowledgements sections of sponsored articles. In this regard, we offer an assessment tool to contrast the acknowledgement patterns of funded researchers with the actual objectives of the organizations. We characterized funding organizations based on their participation in sponsoring robotics research. Then, by means of citation network analysis, we extracted features to classify the research articles into four types of technologies: breakthrough, change maker, incremental, and matured. We found that most financial acknowledgements are of the incremental type followed by the matured, breakthrough, and change maker categories in that order. The NSF-CH and NSF-US are the two most recognized organizations promoting robotics research, while although also largely mentioned in the incremental category, European funds are among the most recognized sponsors of change maker technologies. Other funding agencies such as the NIH focus on both the incremental and the matured technology types.

We also investigated Japanese funding agencies to understand how their characteristics affect their research directions. We found that the conservative peer review-based funding allocation system of JSPS targets a larger amount of incremental research, but the small proportion of articles regarded as change maker may have a higher academic impact that the change maker articles of JST. Other organizations such as NEDO were positioned towards change maker research as expected.

Within robotics, funding agencies also target specific fields of knowledge, with medical research particularly relevant (surgery is one of the most frequent targets). By mapping the funding agencies to their corresponding fields of interest, we thus found that they tend to concentrate on the country level, a pattern easily explainable given that most are government-dependent agencies, but also suggesting similar guidelines within each country.

We started with the premise that research fronts can be observed from citation networks of academic articles. Among the methodologies for creating citation networks it has been found that direct citation networks work better. We also know, that novelty and coherence are two attributes of emergence, both applied to our framework, through clustering and a classification based on their age. We expect the academic landscape provided represent the state-of-research for the time range in study. We then measured the participation of funding organizations as reported in the acknowledgement section of the articles.

Researchers acknowledge financial sponsors voluntarily or because of grants requirements. In both cases this serves as a signal of the openness of funding organizations in being linked to the outputs brought by the sponsored researchers. Therefore, Acknowledgements can be used as an indication of that disclosure. Under the proposed method, only those organization openly engaged in academic production can be assessed. Moreover, given the shortcoming on how researchers acknowledge their sponsors, it can only be measured their participation, and not the amount of funding received. In fact the mere presence of Acknowledgments does not necessarily correlates with funding (Cronin and Shaw 1999).

The proposed methodology can be applied to assess whether the outputs sponsored by funding organizations correspond to their funding objectives, based on the number of academic outputs. When funding organizations are characterized in a manner that differs from their original intention, they receive feedback about a certain misdirected operation in the funding strategy. However, funding organizations may have different objectives of that of targeting revolutionary research, they may be even uninterested in scientific outputs, as was shown for private funding in our dataset. Thus, our method offers a limited view of the intention of funding organizations, circumscribed by the domain in analysis.

Using the Acknowledgements sections of academic articles to understand funding decisions presents some limitations. First, authors may willingly or unwillingly fail to mention a sponsor for cultural or political reasons (Rigby 2011), different practices across research fields, or secrecy (Wang and Shapira 2011). While the present methodology is unable to identify the causality of such mismatches, this serves as a signal for funding organizations to re-evaluate their strategies and operations. We also observed different acknowledgement patterns for differently structured funding organizations. Authors may mention only the project or program in question, thereby omitting higher organizational levels and thus making the process of harmonization challenging. For instance, is not infrequent that authors acknowledge EC and EU as different entities, or interchangeably, despite the projects they refer to are administered by the EC. Nonetheless, under our methodology we could observe that the two entities share a similar pattern, highlighting their intrinsic connection. Second, these studies rely on the precision of the data provider to identify the entities mentioned in the acknowledgement text accurately.

With respect to the data and methods, the classification model adopted in this research depends on relative bibliometric features. The refinement of bibliometric tools for classifying technologies into innovation categories is a field rich in opportunities. Given the presented results and their correspondence to known funding patterns, our case study nonetheless summarizes the suitability of such categories. It may be pertinent for future research to extend the methodology to map the innovative participation of institutions or authors, or even companies, by using citation network analysis related to patents. Another path for future research, is the study of causalities. It was found that European organizations tend to target change making research better than other organizations in this study. We also observed patterns at a country level when it comes to specific scientific subject targets. While the patterns were revealed, there is still space in speculating why this happens, and how such knowledge can be transferred to other organizations. In addition, studying the allocation strategies of funding organizations at the grant proposal and evaluation levels, by comparing those proposals accepted and rejected, is another future research direction. In this study, we analyzed the output of research projects. However, greater access to proposal data would have allowed us to clarify the funding strategies of each agency as well as the relationships between outputs and financial inputs. Indeed, the mapping of funding agencies by using the proposed method may help policymakers and funding organizations assess whether their proposed objectives are in line with actual outputs, set new directions, and establish benchmarks. Researchers may also benefit from the study of funding patterns to establish collaborative strategies or spot agencies that are more likely to sponsor their type of research.

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