INCEPTUM

DOI: https://doi.org/10.33110/inceptum.v16i31.410

Fecha de recibido: 05/08/2021
Fecha de aceptado: 12/10/2021

A framework for research assessment in social sciences through Big Data

Un marco para la evaluación de la investigación en ciencias sociales a través de Big Data

Guadalupe Palacios-Núñez [1]
Miguel Ángel Pérez-Angón [2]
Pedro Simón Quiroz Armada [3]

Abstract

The scarce public policy funds demand cost-effective outputs and more innovative forms to inform decision-making. During the last years, there has been increasing use of Big Data for research and policymaking by international development institutions. For this reason, the main objective of the present work is to propose a framework to apply Big Data in a high-relevance program for science policy in Mexico, which assesses the researchers' performance. Social sciences are considered the most difficult area to assess, since there is no theoretical-methodological consensus and the academic impact is difficult to determine because social sciences do not exhibit long-term development. Instead, there are a plurality of paradigms or changing topics that do not have consensus among the academic community. In this regard, this work outlines a framework, which includes indicators of the social contribution of science since computational tools should have an orientation.

Keywords: Social Sciences; Research Assessment; Science Policy; Big Data; Blockchain.

1. Introduction

The fast growth of data produced from different sources poses great challenges to collect, analyze, store, and visualize a vast amount of data. During the last decade, technical approaches known as Big Data have emerged to deal with the massiveness, complexity, and dynamism of data. The term Big Data refers to the process of collecting and handling high-volume, high-velocity, and high-variety of complex data. These qualities indicate that a large size of different data can be high speed extracted from multiple sources and analyzed to generate knowledge, which adds veracity and value as attributes of Big Data (Addo-Tenkorang and Helo, 2016; Chen et al., 2015; George et al., 2016; Landers et al., 2016;

[1] Programa de Doctorado Transdisciplinario en Desarrollo Científico y Tecnológico para la Sociedad, Centro de Investigación y de Estudios Avanzados del Instituto Politécnico Nacional (CINVESTAV). E-mail: guadalupe.palacios@cinvestav.mx
[2] Departamento de Física, Centro de Investigación y de Estudios Avanzados del Instituto Politécnico Nacional (CINVESTAV).
[3] Cantera Digital S.A. de C.V.

Yaqoob et al., 2106). Big Data consists of extracting, storing, processing, and analyzing a large quantity of data to get useful information, make predictions, identify trends, reveal hidden patterns, and find unknown correlations to make efficient decisions (Marjani, 2017). The continuous development of Big Data is the result of research across scientific disciplines, such as social, behavioral, economic, and data sciences. This interdisciplinary field generates insights and prediction models from structured and unstructured data combining statistics, data mining, machine learning, and analytics. The capacity that offers Big Data to understand and explain phenomena has gained the attention of scholars and governments (George et al., 2016; White and Breckenridge, 2014). During the last years, there has been increasing use of Big Data for research and policymaking by international development institutions such as the United Nations (UN) and the Organization for Economic Co-operation and Development (OECD). This has to do with the fact that Big Data makes it possible to get information about the advance of end-goals to improve performance and make informed strategic decisions (Addo-Tenkorang and Helo, 2016; Landers et al., 2016; Taylor and Schroeder, 2015).

The scarce public policy funds demand cost-effective outputs and more innovative forms to inform decision making. Big Data analytics uses advanced technologies to visualize information, reduce uncertainty, and develop capabilities for strategic decision making. Big Data allows generating value from data. This value can be measured through parameters of operational efficiency and reduction of costs (Chen et al., 2015). For this reason, the main objective of the present work is to propose a framework to apply Big Data in a high relevance program of science policy in Mexico, which assesses the researchers' performance. This program, which was implemented in 1984 by the National Council for Science and Technology (CONACyT), is the National System of Researchers (NSR). The NSR has as the main goal to enhance the quality of the research through evaluations and to stimulate its development via meritocratic monetary transferences to researchers (Contreras-Gómez et al., 2020).

The amount of the stipend depends on the category in which the researcher is classified. These increasing categories are candidate, levels 1, 2, 3, and emeritus. The designation has a term during which researchers receive the monthly economic stimulus. The permanence and promotion to higher levels are determined by a process of evaluation of the performance. Therefore, this system is associated with prestige and merit in research. The evaluation criteria are nearly the same in all the areas of knowledge in which the NSR is divided: I. Physico-mathematics and Earth science, II. Biology and chemistry, III. Medicine and health sciences, IV. Humanities and behavioral sciences, V. Social sciences, VI. Biotechnology and agricultural sciences, VII. Engineering.[4]

[4] In 2020, S&T´s law was reformed and the areas of knowledge were divided into nine. Since our data cover until 2018 we based our analysis on the former law. It Is worth mentioning that the assessment´s criteria barely changed in the new law

In Latin America, there are similar systems in Brazil, Chile, Venezuela, and Argentina. The Brazilian and Chilean systems are considered the most robust, while some biases have been detected in the Mexican, Argentine, and Venezuelan systems, especially in the Social Sciences area (Andrade et al., 2011; Bekerman, 2018; Ezeiza Pohl, 2018; Marcano and Phélan, 2009; Vessuri et al., 1997; Reyes and Suriñach, 2015). The NSR´s process to assess researchers is based on double peer-review who determines the access, permanence, or promotion of each research in the system. These reviewers that belong to the evaluation committee could be supported by other experts if the multidisciplinary profile of the applicant required it. There are general quantitative and qualitative criteria to guide the process of evaluation, but there are no specific quantitative indicators. This has caused some studies have pointed out the lack of objectivity and transparency of the process, which is centralized (Sánchez Gudiño, 2010; Reyes and Suriñach, 2015).

The NSR has barely been modified since its creations. Even though there is no explicit number about the outputs, the rules state that the evaluation is based on the scientific articles published in journals with high impact factors, the number of citations received, and the training of human resources (Frixione et al., 2016). These homogeneous indicators are applied for all areas of knowledge despite the differences among them causing that social scientists try to emulate the expected behavior in natural and exact sciences (Gil-Antón and Contreras-Gómez, 2017). For instance, social sciences scholars are required to publish articles in journals with high impact factors indexed to the Web of Science (WoS) or Scopus. This implies that they must write articles about international issues and in English. Nevertheless, they mainly write about local problems in books, chapter books, and articles for national journals written in Spanish. The efforts to set up specific criteria for each area are meager and unsuitable (Vasen and Vilchis, 2017).

In-depth interviews with the members of the committee of evaluation have revealed that there are not explicit numbers because there is a qualitative examination of the manuscripts to weigh the value. Nonetheless, this has caused the applicants to state that the evaluations are unfair and proceed to sue, which is a waste of resources and time. The NSR is considered the most important program in the Mexican science policy since it is a reference to assess and reward academics in the entire country, even when they do not belong to the system. Undeniably, the program should be upgraded and enhanced according to the vertiginous technological change. In this context, it is crucial to review and redesign the system to develop more accurate indicators profiting new technologies. This is more imperative for the social sciences area that has been criticized for its lack of objectivity in the evaluation processes and for that reason this work focus on it.

In the last decade emerged studies about Big Data applied to social sciences and policymaking, presenting its advantages and drawbacks. These works show that Big Data is transforming research and impacting the policy cycle positively (Addo-Tenkorang and Helo, 2016; Bertot and Choi, 2013; Crosas et al., 2015; De Mauro et al., 2016; George et al., 2014; Höchtl et al., 2016; among others). This work aims to contribute with a proposal in the domain of policymaking 2.0 that employ Big Data to retrieve and analyze a large amount of data from different sources for problem-solving. In the digital era, governance use e-policy that evaluates all along the policy cycle, instead of doing it as a separate step at the end of the policy cycle. The continuous evaluation reduces the time of redesigns, which is important in public administrations that demand decrements in budget and, at the same time, more efficiency (Höchtl et al., 2016).

Social sciences are considered the most difficult area to assess, due to it has different dynamics of production and diffusion of knowledge, the space-time specificity inherently to social research difficult finding universal patterns, there is a lack of clear boundaries between disciplines and an absence of unambiguous differences with the rest of the sciences, and there is disagreement about what is considered valuable research outputs, quality standard, and legitimate activities (Becerril García et al., 2018; Englander and Uzuner-Smith, 2013; Hammersley, 2014; Reale et al., 2017; Williams and Morrone, 2018). In peripheral countries, there is no theoretical-methodological consensus in social sciences since the research agendas are fragmented in contextualized/ local studies and internationally relevant issues. This has to do with the fact that national science and technology councils in Latin America tend to evaluate based on the use of the WoS and the Scopus databases, which do not cover most of the publications of this area in the region (Vasen and Vilchis, 2017).

At the international level, there is a search for more accurate indicators of the scientific, social and political impact of the social sciences that overpass the limitations of the traditional bibliometric indicators (Archambault and Larivière, 2011; Reale et al., 2017). Nevertheless, even the academic impact is difficult to determine because social sciences does not exhibit long term development. Instead, there are a plurality of paradigms or changing topics that do not have consensus among the academic community (Buquet, 2013; Hammersley, 2014). In this context, this work also intends to outline indicators of the contribution of science to transform the environment since computational tools should have an orientation. It is important to highlight that this is not a prescriptive and an exhaustive proposal.

The next section explains the data and methods used to diagnose the process of access and permanence to the NSR. Section three present the results of the diagnosis as well as an overview of the functioning of the NSR focusing on social sciences. In part four, we review the concepts of the social, political, and academic impact in social sciences to set the theoretical bases of the proposal. Finally, section five outlines the framework to evaluate social sciences research based on Big Data and Blockchain. It is important to mention that this proposal does not contain technical details, which are out of the scope of the present work. The proposal outlines a general scheme to upgrade and enhance the system.

2. Data and Methods

The diagnosis of the process of evaluation of the NSR was based on an analysis of the entrance and permanence of the members from 2002 to 2018. To obtain the indicators of permanence and promotion we identified the active members in the databases of 2002, 2006, 2010, 2014, and 2018. These years were selected due to candidates are assessed three years after entering the system or four years if they were categorized in the same level. Since the number of identification of the members is not publicly available, to detect the members that remained through the years we applied the TextDistance library for python to identify the names in each year. The percentages of the permanence in each year were utilized to apply a linear regression to determine the probability of permanence in 2022.

Since the general criteria of evaluation that are publicly available do not contain quantitative specifications, we performed in-depth interviews with former evaluators of each area of knowledge. This allowed us to know the not explicit parameters, identify the differences in assessment of each area, and determine the specific criteria used in social sciences. The general proposal to enhance the system through the application of Big Data and Blockchain was outlined by conducting documentary research. This was done from an interdisciplinary approach that combined data science, social sciences assessment, scientometrics, and science, technology, and innovation policy. Some parts of the present proposal were developed based on previous experience in computational social sciences applied in Latin America (LATAM).

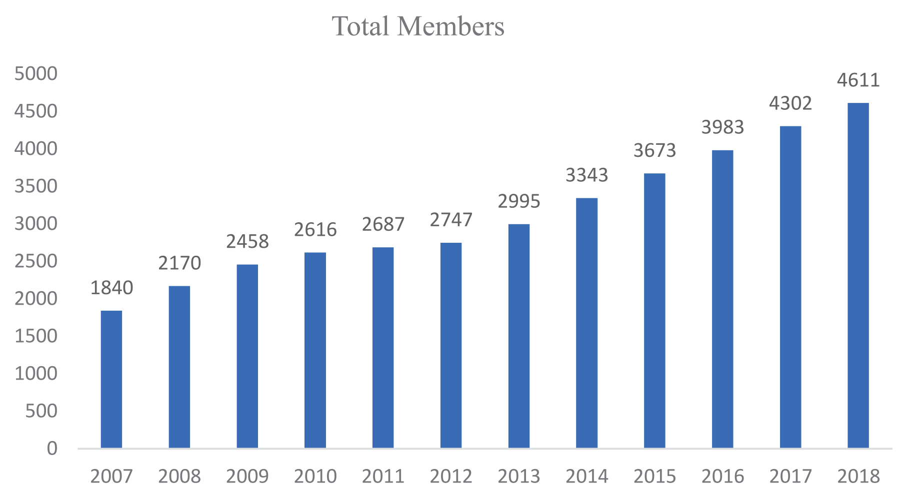
3. Results

The analysis of the permanence of scholars in the NRS, after 36 years of existence, may determine if this program has achieved one of its main objectives: attracting and retaining researchers with a true commitment to generate scientific and technological knowledge of the highest level. As we mentioned above, the NSR´s evaluation committees apply homogenous criteria among the different areas of knowledge to assess researchers. The lowest level must prove the ability to perform research presenting at least one scientific article or one book chapter. The candidate is required to appear as a single author or as the first author in the manuscript. It is also acceptable to present two works as a co-author within the same line of research. After three years, candidates are assessed with an expectation of promotion to a higher level. They cannot remain at the same level, if they are not promoted they get an extension of one year to submit five articles or they lose the membership (CONACyT, 2020).

Researchers of level 1 ought to have a defined line of research, have published an original book or a minimum of five scientific articles, and have trained human resources, this means supervised postgraduate theses. The relevant criteria for researchers of levels 2 and 3 include those mentioned for level 1. Furthermore, it is assessed the originality of the outputs and if they solve S&T or social problems. Besides, members of level 3 must have an academic prestige that grants them national and international awards. They should have made a remarkable contribution to knowledge, have published transcendental manuscripts in their lines of research, and have been cited by internationally recognized authors, as well as have had reviews of their work in journals of international circulation (CONACyT, 2020).

A study about the access and permanence to the NSR from 1997 to 2002 showed a decreasing tendency in both dimensions. The analysis displayed that the probability of entering the system went from 79% in 1997 to 70.1% in 2002. The average permanence of the new members was 70% in all areas of knowledge. The new members who remained in the NSR did not get a promotion to level 2 or 3, they just reached level 1. The authors pointed out that this was the result of the lack of quantitative specific parameters, thus the evaluators´ judgment or subjectivity was determinant (Reyes and Suriñach, 2012).

Figura 1 Total number of the NSR´s members in social sciences

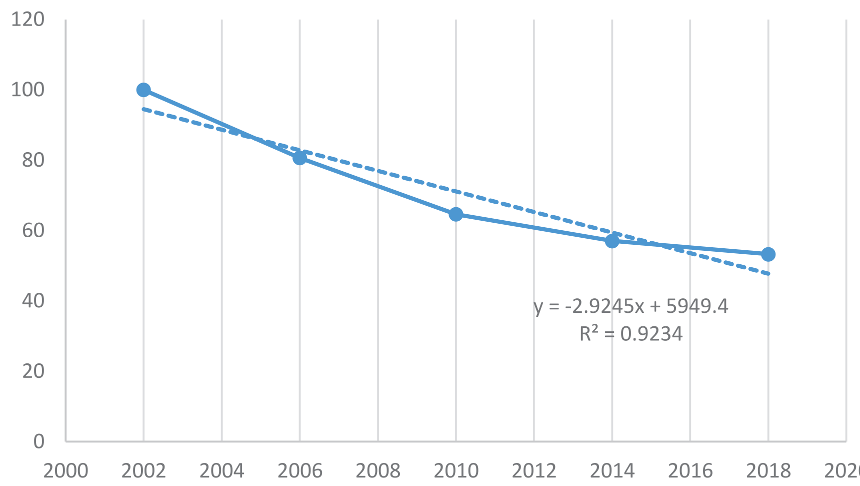


Source: own elaboration

Regarding the access, we found that in social sciences the tendency changed since 2008, as can be appreciated in Figure 1, which shows an increasing number of new members in that area. Concerning permanence, we started the analysis in 2002 to observe the effects of the new S&T´s law adopted in 1999. In this year, the areas of knowledge were reclassified and social sciences split from humanities. Since the evolution of the NSR depends on the profile and performance of the new members, it is important to examine if the system retained talented researchers (Reyes Ruiz and Suriñach, 2010). Figure 2 depicts the percentage of new members of social sciences in 2002 that remained until 2018. By 2006, from 212 new members, 80.66% remained. In 2010, 64.62% of these researchers still were in the system, and in 2014 only 57.07% persisted. In 2018, this number decreased to 53.30% and by 2022 it is expected that just remain 36.06% of them.

The new members in 2006 were 646, but by 2018 just 52.16% of them were in the system. In 2010, entered 1,386 new members and by 2018 there were left 52.59%. In 2014 were accepted 900 researchers and just remained 57.33% by 2018. Even when there has been a growth of new members, these data and Figure 2 exhibits a downward trend in permanence, which could indicate that the criteria used to evaluate the membership are not suitable. Reyes and Suriñach (2010) stated that the low permanence was the result of not attracting real talents to the NSR since the performance of members and nonmembers was quite similar. On the other hand, every year there are sues against the NSR by researchers suggesting the influence of subjectivity or aversions of their peers in the process of evaluation.

Figura 2 Percentage of permanence in social sciences



Source: own elaboration

The in-deep interviews revealed that the reviewers´ judgment indeed is crucial to determine the entrance, permanence, or promotion in the system. They pointed out that there are no explicit quantitative criteria since quality is assessed with qualitative standards. Nevertheless, it is expected a certain number of outputs mainly about the number of articles, citations, supervised theses, and the impact factor (IF) of the journals where the manuscripts are published. In humanities and social sciences, the reviewers mentioned that they weigh books, and some of them do not consider IF as an indicator. They also said to be aware that the research outputs and the time required for developing them are different in each area of knowledge as well as the profile of the researchers. Nonetheless, the permanence rate and the public virtual forums of the NRS members, where they complain about the unfair evaluations, seem to show that the process could be improved and updated.

The downward trend in the permanence of new members could be due to more heteronomous evaluations of the Science Citation Index (SCI) and SCImago Journal Rank (SJR). The evaluation committees extrapolate the quality of an article with the quality of the journal where it is published. Notwithstanding, academics of social sciences in LATAM conduct 80% of their research to solve national or regional problems, they write in their native language and publish in national journals that are not indexed in the SCI or SJR. This generates a low international citation rate or the predominance of domestic citations because the number of citations is determined by the geographical scope of the research, the language of publication, the co-authorship, and the journals where it is published (Borrego and Urbano, 2006; Buquet, 2013; Chinchilla-Rodríguez et al., 2015).

In the specific case of the NSR, having an article published in a journal indexed to the SCI or the SJR is enough to be categorized as a candidate, regardless of the number of citations. The higher levels must publish 4 articles indexed to the SCI or the SJR in a period of 3 years. Nevertheless, this hyper-productivity does not translate into quality, but researcher haves to decide if they "publish globally and perish locally or vice versa" (Aguado-López and Becerril-García, 2016). These demands have led researchers to modify their research topics to adapt them to a global agenda. This also prevents them from addressing local problems and discourages links with the social sectors of the territory. The fact that sole authorship and the author's place in the article is weighed, penalizing those who do not top the list, is a clear indication that collaborative science is not rewarded in the NSR (Vasen and Vilchis, 2017).

The NSR´s process of evaluation is not attracting, retaining, or promoting research talents. Previous studies on similar systems in the region pointed out that a redesign is needed since these types of evaluations have not caused any academic or social impact but misrepresentation and simulation in research´s activity (Andrade et al., 2011; Bekerman, 2018; Ezeiza Pohl, 2018; Marcano and Phélan, 2009; Vessuri et al., 1997). Furthermore, validating science from publishing in journals indexed to the SCI or SJR has strengthened the production of knowledge aimed at commercial purposes in detriment of open science that benefits academic and social impacts. Therefore, it is crucial to develop responsible metrics to evaluate the research outputs in a more contextualized way (Becerril García et al., 2018).

4. Discussion

S&T policy studies neither have homogeneous concepts nor robust methodologies, but all of them have in common that focus their analysis on production, dissemination, transfer, and exploitation or application of knowledge to solve political, social, economic, and environmental problems (Martin, 2012). Bibliometrics has been extensively used in LATAM to evaluate scientific activity, despite its limitations (Yunta and Peña, 2010). Measuring impact is imperative to justify the investment of public resources in S&T. Nonetheless, scientific evaluation is a matter far from reaching a consensus in the region. The approaches in this regard are divided into the uncritical adoption of the standards of the developed world and the substantive evaluations to consider the peculiarities of LATAM contexts and needs. There is also a wide range of intermediate positions (Buquet, 2013).

Productivity, which is measured by the number of publications, occupies a privileged place in the scientific evaluation. Notwithstanding that productivity is not positively correlated with the impact factor or the number of citations, researchers are requested to have published many articles despite the low academic value (Bornmann and Tekles, 2019; Villaseñor et al., 2017). The quality of manuscripts is difficult to determine in social sciences since there is no "dominant paradigm". Furthermore, the lack of consensus on the meaning of quality makes it challenging to find suitable criteria to evaluate it (Reale et al., 2017). With the lack of criteria to assess quality, the committees of evaluation use the JCR and SJR impact factors of the journals as a reference (Becerril García et al., 2018).

For instance, the NSR favors the manuscripts published in the journals that appear in the four quartiles of the Science Citation Index (SCI). The rest of the journals are classified into four lower groups: international competition, national competition, consolidation, and in development. This implies that the researchers are encouraged to publish in subscription-based journals to detriment of regional open access journals (Vasen and Vilchis, 2017). This is paradoxical since the Mexican government has implemented laws to make compulsory the release of scientific manuscripts funded with public resources to favor non-commercial open access (OA) and contribute to reducing social inequality. There are 362 institutional repositories in the region, containing 1.3 million documents, however, LATAM´s OA is fragmented between the so-called mainstream science and the alternative movement to validate regional research, which demands more responsible metrics (Becerril García et al., 2018).

In this regard, at the international level, there is an increasing demand to assess not just the scientific impact of research outputs but the economic, political, and social impact. Scientific impact refers to the contribution to create new knowledge. Social impacts are generated once the results of the research have been published, disseminated, and transferred to produce improvements or changes in society. Political impacts are related to the influence of research on the development of the macro and micro scale policy cycle (motivation, rationale, design, implementation, and evaluation). Nonetheless, there are no instruments in social sciences to measure these changes or determine how much research has contributed (Daraio et al., 2016; Reale et al., 2017).

To improve the academic quality of research it is necessary to broaden its goals to socioeconomic "impact". This implies promoting and evaluating the social, cultural, environmental, and economic benefits of research. Thus, research assessment could be based on its contribution to the production of new knowledge, capacity building, policy-making, development of new products or services, and broader socio-economic benefits (Donovan, 2011). The idea of stimulating researchers to solve specific problems, innovate, and contribute to sustainable development is not new in the region. In 2011, Venezuela replaced a similar system to the NSR for a new program based on funds for specific projects of decolonial endogenous development (Andrade et al., 2011).

Similar systems to the NSR in LATAM have shown that these instruments of science policy can exhibit growth in the number of researchers, publications, and citations without any real academic impact (Andrade et al., 2011; Bekerman, 2018; Ezeiza Pohl, 2018; Marcano and Phélan, 2009; Vessuri et al., 1997; Reyes and Suriñach, 2015). A decade ago, it was not possible to set a more ambitious assessment of impact. Nowadays, the technological advance allows using a large amount of data from heterogeneous sources available on online platforms. Therefore, it is feasible to assess the researchers' performance based on facts instead of interpretations (Marres and Weltevrede, 2013). Big Data can make more efficient the evaluation allowing the construction of multiple measures based on voluminous quantities of data (George et al., 2014).

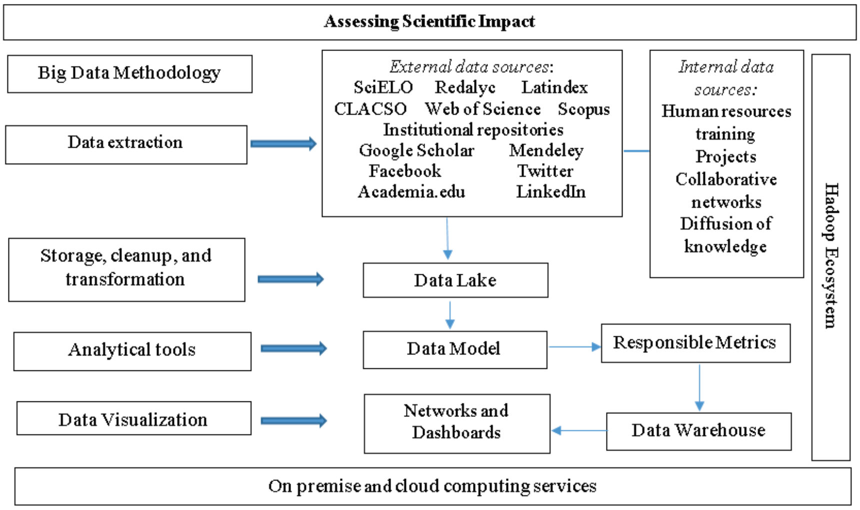
The framework that we will present below proposes a multidimensional assessment. We analyzed each dimension separated, starting with the scientific impact, which is the most relevant for the NSR. Since the number of manuscripts and cites are the main outputs to assess researchers´ performance it is crucial to enhance these indicators. Current bibliometric indicators are heteronomous of the SCI or SJR. Nevertheless, WoS and Scopus databases have low coverage of the regional journals where social scientists of LATAM publish. The contextualized nature of this field demands the development of plural indicators that include the databases of the region such as SciELO, Redalyc, Latindex, and CLACSO. These platforms do not allow harvest data, but the use of Big Data applications can solve this shortcoming.

Big Data methods such as web scraping can solve this problem by extracting and aggregating a large amount of structured or unstructured data from diverse sources. This permits to pass from samples to complete populations. Having a higher data scope overpass the limitation of the current analysis that generates biases as a result of the limited coverage of the databases. Web scraping makes it possible to collect data with a high scope and granularity, which refers to the direct measurement of the attributes (George et al., 2016). This provides the resources to pose new questions or develop a new framework based on 'next-generation metrics'. Apart from citation and publication counts, collaborations based on co-authorship can be measured to reward working in networks, as well as usage metrics that measure views or downloads of an item. This is relevant since many users read publications or use data without publishing (Wilsdon et al., 2017).

Usage metrics can be scraped from Google Scholar, Mendeley, Facebook, Twitter, Academia.edu, and LinkedIn, among others. Regarding collaborations, besides national and international co-authorship, research networks can be promoted. This implies that funding will also go to institutionalized research groups rather than just focusing on individuals (Cancino et al., 2014). Since academic impact does not imply societal contributions indicators mission-oriented based on different data sources beyond bibliographic databases can be used. Co-word frequency or mentions in policy documents or news items can be used for mapping societal engagement and different dimensions of science-society interactions. These are examples of responsible metrics currently in development (Noyons and Ràfols, 2018). Figure 3 shows all mentioned above and a process based on Big Data for this purpose. We propose to use Infrastructure as a Service (IaaS) that manages a mixed information and technology environment combining public, private, and on-premises cloud services. This is affordable since Mexican public universities hold enough infrastructure to implement a hybrid architecture combining "on-premise" and "cloud computing services". The data, applications, and processes could be physically placed in them. Universities also have plenty of human resources to design, implement, and operate the entire Big Data process. The suitable framework to process large data is a Hadoop-like ecosystem, which has open-source components to data storage, data processing, data access, and data management.

Figure 3 also shows how the process begins with data extraction through web scraping. Due to there are some disciplines and research groups oriented to study the national context and others to the international context both levels of knowledge production can be integrated. The high degree of scope and granularity of the data offered by web scraping allows developing more mathematically robust bibliometric indicators that include international journals, as well as regional repositories. Therefore, contextual indicators based on regional databases can be developed, instead of universal or homogeneous indicators. The implicit logic is to learn how to improve research (Marcano and Phélan, 2009) avoiding bibliometric criteria that lead to 'goal displacement' or drive researchers away from activities attuned to societal needs and local development (Noyons and Ràfols, 2018).

Figura 3 Dimension 1: Big Data process to assess scientific impact



Source: own elaboration

The data of regional and institutional repositories are not used commercially and can be scraped without charges obtaining the explicit consent of the institutions. Just the URLs related to the 20% of the publication of social sciences in WoS or Scopus must be paid (Becerril García et al., 2018). The private and public repositories are external data sources, but to develop responsible metrics it is important to collect internal data from the universities. Until now, the NSR´s members and applicants individually submit the information to a CONACyT´s platform. This platform demand proves of the supervised thesis and scientific articles. The rest of the outputs are just reported and it is not necessary to provide evidence. Nonetheless, the NSR and the universities should share goals to align efforts.

The internal data sources showed in Figure 3 must be part of a strategy of knowledge management to solve national problems and local needs. Therefore, it important that universities register, store, share, and validate this information along with the NSR. Besides, to enhance the socio-economic impacts should be added metrics about projects and collaborative networks. Currently, the NSR does not encourage collaborative work since appearing as a single-authored or the first author in the manuscripts is highly weighted.

Figure 3 shows that the Extraction, Transformation, and Loading (ETL) or data integration process consists of collecting all the data from the different data sources and executing the following actions: validate the data, clean the data, transform the data, add the data, and load them in the data lake where they will be exploited (Chaulagain et al., 2017). The purpose of this phase is to order all the information and give it a suitable format to apply algorithms and build models to extract knowledge. Analytical tools and data models must be oriented to build responsible metrics. The CVU of the members of the NSR, which is a number that is currently used to identify them in the system, must be assigned as the unique identifier to each element of the data lake. The CVU will serve as the primary key and will be part of the rules to integrate the information. However, data extraction has to be based on the authors' names (De Mauro et al., 2016).

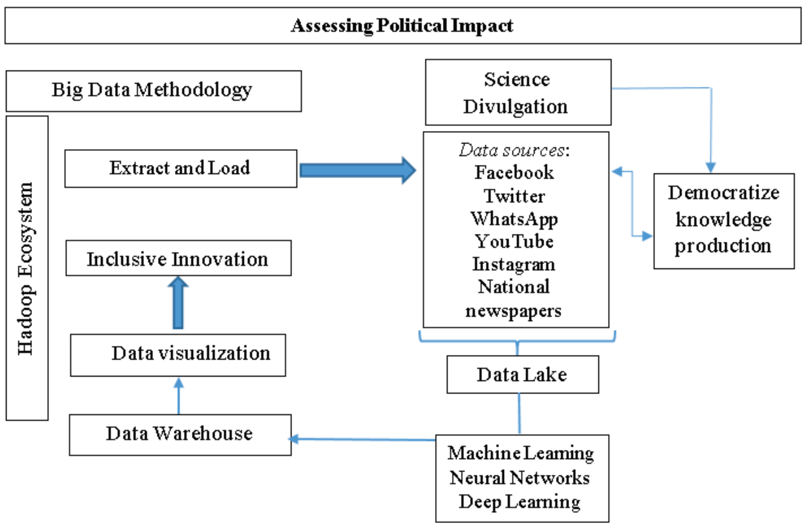
The data warehouse will be used to store the data that has been modeled or structured to display responsible metrics to make the decision-making process more efficient. The data warehouse will be hosted on an institutional server and will be designed to generate reports, present results, graphs, interactive infographics, and dashboards. The data warehouse will serve the evaluation committee to review the performance indicators of the current applicants or members. The idea is to transit to a smart government that aims to be open and transparent, relying on technology to achieve the quality and efficiency of services.

Big data analytics is used to discover trends, patterns, correlations, or other parameters applying statistics, mathematics, econometrics, simulations, and optimizations, among other techniques to gain insight from data and make better decisions. Big data analytics can be classified into three main categories: descriptive, predictive, and prescriptive. Descriptive analytics focuses on diagnosing the current state of the system and identify problems and opportunities under the existing processes and functions. Predictive analytics has to do with explanatory and predictive patterns through mathematical algorithms. Prescriptive analytics also uses mathematical algorithms and simulation to handle a high volume of complex data to make multi-criteria decision-making to improve system performance (Wang et al. 2016). Until now, the NSR bases the evaluation on descriptive analysis. The implementation of Big Data would allow the system to predict and prescript to implement a continual improvement process.

The evaluation of political and socio-economic impact implies reconsider the S&T policy. The NSR, like the rest of the world, has been based on two S&T policy framings that evolved alongside socioeconomic changes since World War II. The first one was "innovation for growth" that applied S&T to reach mass production and consumption. The second framing, "national systems of innovation", which emerged in the 80s, considered that the competitiveness of Nation-States depends on their institutions, policies, and coordination among the actors (government, industry, and university) to produce and apply knowledge. Both frames persist, but they do not consider negative externalities of the socio-technical system to economic growth. Therefore, in 2015 a third framing called "transformative change" emerged to generate a socio-technical system change. This is crucial to eliminate poverty, reduce inequality, face climate change, and promote inclusive sustainable consumption and production systems. This framing does not intend to replace previous ones but integrates social and environmental issues to innovation objectives (Schot and Steinmueller, 2018).

Grants stimulate and affect the kind of research outputs as well as their quantity and quality (Benavente et al., 2012). Therefore, to social sciences research cause a political impact, it is imperative that the indices of LATAM are equally valued than international ones. To reward research focused on solving national and regional problems might influence policymaking (Vasen and Vilchis, 2017). As can be appreciated in Figure 4, this implies also weight science divulgation as a responsibility of social researchers to illustrate policymakers and social sectors (Vessuri et al. 1997). In this duty, Big Data can be used to extract social media data on this matter.

Figura 4 Dimension 2: Big Data process to assess political impact



Source: own elaboration

Social media trends can reveal how political processes and activities affect public opinion and policymakers. To identify where do ideas or innovations come from, semantic networks can be used to see cumulativeness, evolution, and the emergence of ideas and knowledge (George et al., 2016). To transit toward the third framing S&T policy (transformative change) science divulgation is required for innovation from the bottom and for inclusive innovation. These aim to identify alternatives regarding all possible options and democratize knowledge production (Schot and Steinmueller, 2018). To explore meaningful or hidden patterns in large amounts of data, machine learning algorithms can be applied. This implies transform unstructured data into structures through cleaning, processing, and formatting them. A subarea of machine learning is neural networks where deep learning can be utilized to work with images, videos, and texts. These analytical tools can reveal unexpected relationships (Landers et al., 2016; Marjani, 2017; Yaqoob et al., 2106).

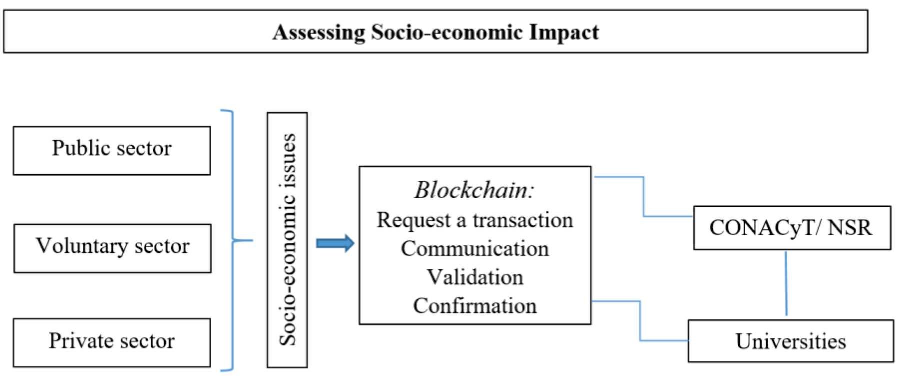
The legal, practical, and ethical implications of web scraping must be taken into account. Intellectual property laws and cybersecurity vary with local jurisdictions. It is better to scrape publicly available and unencrypted data sources or set Data Sharing Agreements (Landers et al., 2016). Previous studies on the social contribution of research pointed out that policy engagement implied training or direct personal interaction between academics and policy-makers. Therefore, social media data can be used to find patterns in research areas (Noyons and Ràfols, 2018) and Blockchain can be applied to trace training and personal interactions, as we will see below.

Regarding the assessment of the socio-economic impact, the NSR does not promote that the members contribute to the solution of issues through projects that link the university with social sectors. Creating the stimulus for cooperative innovation projects, whose results could be published in national or regional journals may contribute to change this unlinking. This implies developing an S&T policy based on governance that broadens the boundaries of the State and creates synergies among public, private, and voluntary sectors (Höchtl et al., 2016).

A useful emerging technology for managing research projects aimed at solving intersectoral problems is Blockchain, which is based on a decentralized distributed software system and is made up of blocks. Each block contains sequential data records by network participants or nodes in a precise and irreversible way. The application of Blockchain requires that the entire process be traced, from the demand for a product by some social sector to the evaluation of the evidence that the product had a real social or economic impact (see Figure 5). This involves defining who will have permission to access the system, determining which joining conditions they must satisfy, as well as verifying the transaction requirements before validation. This is governed by a consensus algorithm, which means that a record cannot be modified or deleted by a single actor, as there is data redundancy (each node has a copy of the Blockchain (Zīle and Strazdiņa, 2018).

Traceability involves identifying the organizations, interactions, communications, and transactions that will take place between them. With each transaction, a block is created facilitating the management and verification of the supply chain under governance protocols. Every transaction along a Blockchain supply chain is fully auditable. The data in a Blockchain can include property, location, resources, product specifications, quality, and dates, among others. The technical specifications must facilitate the traceability, authenticity, and legitimacy of the product. In this way, the Blockchain provides visibility, extended traceability, digitization, improved data security, smart contracts, authenticity and legitimacy of the product, and disintermediation of the supply chain, since no part controls the data. This Blockchain system would operate in a private environment, that is, it requires permission to join. A private modular platform option is Hyperledger Fabric, which is led by the Linux Foundation and is backed by service providers like IBM, Cisco, and SAP. Besides, time-stamping could be used to provide a temporal order between sets of events. This system reduces transaction costs by eliminating intermediaries, provides transparency, prevents fraud, and increases efficiency (Wang et al., 2019).

Figura 5 Dimension 3: Blockchain to assess the socio-economic impact



Source: own elaboration

This kind of technology for this purpose has been used under the name of "Researchain", which is a scientific research project management system. This has proven to solve problems related to academic misconduct like forgery, manipulation, repeated publications, false information, and plagiarism in the application of the project. The scientific research management platform built offers a clear production process and precise measurement of the outputs. Besides, it establishes mechanisms of credibility, responsibility, and contribution of each actor optimizing the scientific research management. Researchain improved process management, evaluation, and incentives, which promoted scientific and technological innovation synergistically (Bai et al., 2018). The full proposal is feasible if the institutions involved finance and participate in the construction of a collaborative platform with the resources that they already have. Institutions can contribute to infrastructure, human capital, and information (Becerril García et al., 2018). Collaboration is prescriptive for budget reductions in S&T. This would increase the quality of production, save resources, and enhance capacities (Chinchilla-Rodríguez et al., 2015).

Concluding remarks

Since metrics play an important role in any research system, we presented a framework to develop societal contributions indicators profiting Big Data methods (Noyons and Ràfols, 2018; Schot and Steinmueller, 2018). These indicators that are helpful to generate evidence propose a change in the incentive structures of academic research, which has not recognized or rewarded efforts to societal impacts. Big Data broaden what can be measured, increasing the diversity of indicators and avoiding a "self-referential system" based on bibliometric parameters where societal relevance is undervalued. Creating incentives for science as a socio-economic driver is possible adapting reward and evaluation systems to measure research quality and social impact (Wilsdon et al., 2017).

We presented a framework to enhance the research assessment in social sciences that do not intend to be a methodology. Like in any other project of Big Data the outlines of this proposal must be refined during its implementation. The indicators that we sketched are just examples of what can be automatized to complement and make easier the peer review evaluation not to replace it (Wilsdon et al., 2017). Assessments conducted within this framework may be available online and the databases may be publicly accessible on the NSR website. This not only would provide quality controls, it would also help to promote transparency and accountability.

Acknowledgments

We appreciate the comments of Gabriel Vélez-Cuartas and the scholarly inputs received from José Luis Olivares Vázquez. We acknowledge the support from the National Council on Science and Technology (CONACYT) and the National System of Researchers (SNI) of Mexico.

Referencias

Addo-Tenkorang R., Helo P. T. (2016). Big data applications in operations/supply-chain management: A literature review. *Computers & Industrial Engineering,* 101, pp. 528-543.

Aguado-López E., Becerril-García A. (2016). ¿Publicar o perecer? El caso de las Ciencias Sociales y las Humanidades en Latinoamérica. *Revista Española de Documentación Científica,* 39/4, pp. 1-14.

Andrade J. A., Márquez Á., Requena J. et al. (2011). Programa de Estímulo a la Investigación. Enl@ce: *Revista Venezolana de Información, Tecnología y Conocimiento,* 8/2, pp. 97-117.

Archambault É., Larivière V. (2011). Los límites de la bibliometría en el análisis de la literatura en ciencias sociales y humanidades'. In: Laclette J.P., Zúñiga-Bello P., Puga Espinosa C., (ed.) *Informe sobre las ciencias sociales en el mundo. Las brechas del conocimiento*, pp. 263-267. UNESCO y Foro Consultivo.

Bai Y., Li Z., Wu K. et al. (2018). Researchain: Union Blockchain Based Scientific Research Project Management System. In 2018 *Chinese Automation Congress* (CAC), IEEE: 4206-4209.

Becerril García A., Aguado López E., Batthyány K. et al. (2018). *AmeliCA: Una estructura sostenible e impulsada por la comunidad para el Conocimiento Abierto en América Latina y el Sur Global.* Redalyc, UAEM, CLACSO, UNLP, UdeA.

Bekerman, F. A. (2018). El programa de incentivos a los docentes-investigadores puertas adentro. *Asociación Argentina de Sociología; Horizontes Sociológicos,* 10/ 6, pp. 12-2018.

Benavente J. M., Crespi G., Garone L. F., Maffioli A. (2012). The impact of national research funds: A regression discontinuity approach to the Chilean FONDECYT. *Research Policy,* 41/8, pp. 1461-1475.

Bertot J. C., Choi H. (2013). Big data and e-government: issues, policies, and recommendations. *In Proceedings of the 14th annual international conference on digital government research,* pp. 1-10.

Bornmann L., Tekles A. (2019). Productivity does not equal usefulness. *Scientometrics,* 118/2, pp. 705-707.

Borrego Á., Urbano C. (2006). La evaluación de revistas científicas en Ciencias Sociales y Humanidades. *Información, cultura y sociedad,* 14, pp. 11-27

Buquet, D. (2013). *Producción e impacto de las ciencias sociales en América Latina.* Consejo Latinoamericano de Ciencias Sociales (CLACSO).

Cancino R., Orozco L., Ruiz C., Coloma J., García M., Bonilla R. (2014). Formas de organización de la colaboración científica en América Latina: un análisis comparativo del sistema chileno de proyectos y el sistema colombiano de grupos de investigación'. *In Perspectivas latinoamericanas en el estudio social de la Ciencia, la Tecnología y la Sociedad.* Buenos Aires, Siglo XXI.

Chaulagain R. S., Pandey S., Basnet S. R., Shakya S. (2017). Cloud based web scraping for big data applications. *In 2017 IEEE International Conference on Smart Cloud (SmartCloud),* pp. 138-143.

Chen D. Q., Preston D. S., Swink M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems,* 32/4, pp. 4-39.

Chinchilla-Rodríguez Z., Miguel S., de Moya-Anegón F. (2015). What factors affect the visibility of Argentinean publications in humanities and social sciences in Scopus? Some evidence beyond the geographic realm of research. *Scientometrics,* 102/1, pp. 789-810.

CONACyT (2020). *Reglamento del sistema nacional de investigadores* <https://www.conacyt.gob.mx/index.php/el-conacyt/sistema-nacional-de-investigadores/marco-legal/reglamento-sni> accessed 17 July 2020.

Contreras-Gómez L. E., Olivares-Vázquez J. L., Palacios-Núñez G., Leyva R. et al. (2020). Desconcentración del Sistema Nacional de Investigadores (SNI): Geografía y estratificación. El caso de las ciencias sociales (2002-2018). *Revista de la Educación Superior,* 49/193, pp. 83-106.

Crosas M., King G., Honaker J., Sweeney L. (2015). Automating open science for big data. *The ANNALS of the American Academy of Political and Social Science,* 659/1, pp. 260-273.

Daraio C., Lenzerini M., Leporelli C., Moed H. F. et al. (2016) Data integration for research and innovation policy: an Ontology-Based Data Management approach. *Scientometrics,* 106/2, pp. 857-871.

De Mauro A., Greco M., Grimaldi M. (2016). A formal definition of Big Data based on its essential features. *Library Review,* 65/3, pp. 122-135.

Donovan, C. (2011). State of the art in assessing research impact: introduction to a special issue. *Research Evaluation,* 20/3, pp. 175–179.

Ezeiza Pohl, C. E. (2018). *El Programa de incentivos a docentes investigadores y su incidencia en la producción y difusión de conocimiento en una Universidad pública del conurbano bonaerense*. PhD Thesis, Universidad Católica Argentina.

Frixione E., Ruiz-Zamarripa L., Hernández G. (2016). Assessing Individual Intellectual Output in Scientific Research: Mexico's national system for evaluating scholars' performance in the humanities and the behavioral sciences. *PloS one,* 11/5: e0155732.

George G., Haas M. R., Pentland A. (2014). Big data and management: From the Editors. *Academy of Management Journal,* 57/2, pp. 321-326.

George G., Osinga E. C., Lavie D., Scott B. A. (2016). Big data and data science methods for management research. *Academy of Management Journal,* 59/5, pp. 1493-1507.

Gil-Antón M., Contreras-Gómez L. E. (2017). El Sistema Nacional de Investigadores: ¿espejo y modelo? *Revista de la educación superior,* 46/184, pp. 1-19.

Hammersley, M. (2014). The perils of 'impact' for academic social science, *Contemporary Social Science,* 9/3, pp. 345-355.

Höchtl J., Parycek P., Schöllhammer R. (2016). Big data in the policy cycle: Policy decision making in the digital era. *Journal of Organizational Computing and Electronic Commerce,* 26/1-2, pp. 147-169.

Landers R. N., Brusso R. C., Cavanaugh K. J., Collmus A. B. (2016). A primer on theory-driven web scraping: Automatic extraction of big data from the Internet for use in psychological research. *Psychological Methods,* 21/4, pp. 475–492.

Marcano D., Phélan M. (2009). Evolución y desarrollo del programa de promoción del investigador en Venezuela. *Interciencia,* 34/1, pp. 017-024.

Marjani M., Nasaruddin F., Gani A., Karim A. et al. (2017). Big IoT data analytics: architecture, opportunities, and open research challenges. *IEEE Access,* 5: 5247-5261.

Marres N., Weltevrede E. (2013). Scraping the social? Issues in live social research. *Journal of cultural economy,* 6/3, pp. 313-335.

Martin, B. (2012). The evolution of science policy and innovation studies. *Research Policy,* 41/7, pp. 1219-1239.

Noyons E., Ràfols I. (2018). Can bibliometrics help in assessing societal contributions of agricultural research? Exploring societal interactions across research areas. *In Proceedings of the science, technology, and innovation indicators in transition conference.*

Reale E., Avramov D., Canhial K., Donovan C. et al. (2017). A review of literature on evaluating the scientific, social and political impact of social sciences and humanities research. *Research Evaluation,* 27/ 4, pp. 298–308.

Reyes Ruiz G., Suriñach J. (2010). Los nuevos ingresos como candidato a investigador en el SNI, 1996-2003. *Perfiles educativos,* 32/127, pp. 8-37.

Reyes R., Suriñach J. (2012). Las evaluaciones internas del SNI: coherencias o coincidencias. *Secuencia,* 83, pp. 179-217.

Reyes Ruíz G. Suriñach, J. (2015). Análisis sobre la Evolución del Sistema Nacional de Investigadores (SNI) de México. *Investigación administrativa,* 44, pp.115.

Schot J., Steinmueller W. E. (2018). Three frames for innovation policy: R&D, systems of innovation and transformative change. *Research Policy*, 47/9, pp. 1554-1567.

Vasen F., Vilchis I. L. (2017). Sistemas nacionales de clasificación de revistas científicas en América Latina: tendencias recientes e implicaciones para la evaluación académica en ciencias sociales. *Revista mexicana de ciencias políticas y sociales,* 62/231, pp. 199-228.

Vessuri H., Larrechea E. M., Estévez B. (1997). Los científicos sociales en Venezuela. Perfil bibliográfico e implicaciones de política. *Cuadernos del CENDES,* 18/48, pp. 89-121.

Villaseñor E. A., Arencibia-Jorge R., Carrillo-Calvet H. (2017). Multiparametric characterization of scientometric performance profiles assisted by neural networks: a study of Mexican higher education institutions. *Scientometrics,* 110/1, pp. 77-104.

Wang G., Gunasekaran A., Ngai E. W., Papadopoulos T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics,* 176, pp. 98-110.

Wang Y., Han J. H., Beynon-Davies P. (2019). Understanding blockchain technology for future supply chains: a systematic literature review and research agenda. *Supply Chain Management: An International Journal,* 24/1, pp. 62-84.

Wilsdon J. R., Bar-Ilan J., Frodeman R., Lex E., Peters I., Wouters P. (2017). *Next-generation metrics: Responsible metrics and evaluation for open science.* Report of the European Commission.

White P., Breckenridge R. S. (2014). Trade-Offs, Limitations, and Promises of Big Data in Social Science Research. *Review of Policy Research,* 31/4, pp. 331-338.

Yaqoob I., Hashem I. A. T., Gani A., Mokhtar S. et al. (2016). Big data: From beginning to future', *International Journal of Information Management,* 36/6, pp. 1231-1247.

Yunta L. R., Peña T. A. (2010). El análisis bibliométrico de la producción española en Ciencias Sociales y Humanas. ¿Contamos con las fuentes necesarias?. *Revista Española de Documentación Científica,* 33/1, pp. 151-155.

Zīle K., Strazdiņa R. (2018). Blockchain use cases and their feasibility. *Applied Computer Systems,* 23/1, pp. 12-20.