

CHAPTER 10

Social Impact Assessment: Measurability and Data Management

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10.1 Introduction

In the last 4 years more data have been generated, analysed and managed than have ever been considered in the rest of human history. The data economy today represents one of the most interesting fields of study, policy and business at a global level because, with the combination of collection technologies and analysis technologies, it is possible to aim at the continuous improvement of every decision-making process. This phenomenon, however, is being more and more considered in all its complexity and shows scenarios full of opportunities when the purpose with which data are approached is extended to the concept of value, understood in its widest form of shared value (social value, environmental value and economic value). Although, on the one hand, the economic-financial value has its intrinsic measurability in the monetary

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metric, and, on the other hand, the environmental value has benefited from the identification of precise and shared standards on a global scale (for instance: footprint), the social value and its methods of definition and representation are the subject of debate at national and international level.

Until now, research in this field has almost never led to shared solutions and this finds a direct demonstration in the plurality of models adopted for the measurement and evaluation of social impact—76 models mapped in literature, see Grieco et al. (2015)—representative of strongly differentiated approaches and tools. Another research carried out by the authors (Corvo et al. 2020 in press) has examined this topic in depth trying to understand what are the characteristics of the most empirically used Social Impact Assessment (SIA) models and what are the leading approaches to the social impact assessment in practice. It is important to mention that the initial purpose of that research was to investigate which of the 76 models mapped by Grieco et al. (2015) were used by practitioners both in academic or grey literature. Apart from very few models that present clear methodology and characteristics, for instance Social Return on investment—SROI (see Then et al. 2017), the results of this analysis were inconsistent. This is due to the fragmentation of taxonomy and semantics of these models that might be named in different ways or using different methodologies under the same name/label. Since it was impossible to verify which were the most used SIA models by practitioners it was decided to assess the characteristics of those models (the sample is of 176 actual case studies of SIA both from academic and grey literature).

This variety certainly has the virtue of covering a broader range of dimensions to assess social value and of better adapting to the biodiversity of corporate subjects to which the social impact refers (from for-profit companies to social enterprises, from benefit companies to nonprofit companies), but, at the same time, it has the limitation of making the scalability of the assessments much more difficult and, therefore, the information that can be drawn from them is particularly subjective. The fuzziness of the SIA models also affects the impact finance that is supposed to be the system where these news metrics are taken into account (Spiess-Knafl and Scheck 2017).

This research aims to verify the possibility of using big data to meet the challenge of measuring and evaluating the social value generated by decision-making processes, activities (projects, programs, policies) and organisations (mainly social enterprises). The chapter is divided into several paragraphs: a literature review that presents the two streams of literature of this research (big data and also social innovation); a theoretical framework that problematises the issue of social impact assessment; a methodological section that explains the source of the data and the analysis; a paragraph that presents the main results and a conclusion section that highlights the implications for researchers and practitioners. This research addresses two main questions:

RQ1—Is it possible to reduce the measurability gap typical of social impact using big data analysis?

RQ2—Can the information processed with big data analysis improve social innovation processes in terms of scalability?

The authors attempt to answer these questions by creating an impact database that imports both the variables of the impact chain (Clark et al. 2004) and the SROI ones (Then et al. 2017) producing an impact benchmarking using only certified data (for instance from Social Value international). The research is an ongoing project that has become a research spin-off called Open Impact. This chapter might be considered a picture of the Open Impact research project updated to October 2020, since the database is constantly expanding

10.2 LITERATURE REVIEW

The literature examined refers to two fields of research that academics are focusing on all around the world:

- The field of research on social innovation, with specific analysis of studies on social impact;
- The field of research on big data, with specific analysis of studies on the potential of big data in social innovation processes.

Social innovation has drawn the attention of several scholars since the years immediately following the 2007–2008 crisis, and this cannot be considered an accident. On the basis of political initiatives undertaken by the British and US governments (the Big Society and the White House Office of Social Innovation and Civic Participation), social innovation is more and more considered as a paradigm that allows us to rethink the

social and economic relations in order to respond to social needs with new ideas, processes, products and services able to balance 3 essential characteristics:

- 1. Greater efficiency compared to traditional solutions
- 2. Greater effectiveness compared to traditional solutions
- 3. The creation of new social relationships enabling the actors to take part in collaborative processes of value creation.

The European Commission (2017), with an institutional definition, has focused its attention on the need for effectiveness of social innovation processes, while Murray (Murray et al. 2010) stresses the dual social meaning of this innovation (social for the challenges it addresses, social due to the typology of relationships that are triggered by the processes). Phills, changing point of view, shifts the attention from the processes to the generated value, believing that the peculiar characteristic of social innovation initiatives is the primarily social, rather than individual, destination of the generated value (Phills et al. 2008). Herrera emphasises the consequences on the organization' behaviour and the opportunity for these processes to meet the CSR strategies. When this hybridisation becomes institutionalised there are corporate social innovation' strategies (Herrera 2015). From another point of view, Nicholls and Murdock (2012) lead social innovation back to the need to recontextualise the public function to pursue public value, justice and equity objectives.

Westeley and Antadze (2010) claim that in order to structurally change the routines and constructions of previous authorities, the processes of social innovation require durability and impact. This aspect, particularly peculiar for our analysis, is declined in social impact and, understood in this sense, can be seen as something broader than a mere completion of the instances of accountability: it represents the signal that enables the interaction between multiple social actors with the aim of transforming the previous relationships towards new collaborative forms that generate impact and therefore can last over time, as Westeley and Antadze suggest. There are several contributions that try to draw the boundaries of social impact assessment and impact finance as the arena where those metrics are taken into account (Spiess-Knafl and Scheck 2017).

The field of research on big data has seen a growing scientific production since 2011, the year in which the most important global consulting

companies have devoted attention to the topic through reports, international conferences and the reorganisation of business strategies. Big data can be defined as the massive data collections showing 3 peculiar characteristics, called the "3 Vs" of big data (Davis 2014):

- 1. Large Volumes, in terms of quantitative consistency of the data stock:
- 2. High Velocity, as regards the fluidity of data collection and renewal;
- 3. Great Variety, with reference to the spectrum of information that can be derived from the data.

Akter introduces 2 additional aspects (bringing the Davies model from 3 to 5Vs), which are truthfulness and value, underlining the importance of verifying both the reliability and the possible usability of the data (Akter et al. 2016). Desouza and Smith, in reference to the actual usability of data, introduce the element of processability, attributing to big data the characteristic of being too complex to be processed with traditional database management tools and thus linking them to machine learning technologies and artificial intelligence (Desouza and Smith 2014).

An important step in the direction of our analysis is taken by the study by Opresnik and Taisch, which links the big data phenomenon to the different types of source-contexts from which they derive, distinguishing:

- Data generated by traditional companies
- Machine-generated data, that is data obtained thanks to sensors and other internet of things devices
- Social data, particularly relevant for this research (Opresnik and Taisch 2015).

The most interesting theoretical perspective for us, however, originates from the intersection of the two research fields just described and we could call it "big data for social good". In this field, on the contrary, there is still an insufficient presence of studies and elaborations. Although big data have been put at the service of the resolution of complexities related to the technical and economic sphere (Chen et al. 2012), no analysis has been carried out in detail with respect to the social value of big data (Agarwal and Dhar 2014).

10.3 THEORETICAL FRAMEWORK

The main reference of the research is the stream of studies on social impact assessment. This represents one of the areas of investigation of the social innovation paradigm and aims to identify precise metrics for assessing the capacity of social innovation initiatives to respond to social needs more effectively and efficiently than traditional solutions, generating new relations between stakeholders.

This topic is experiencing a moment of extraordinary interest, based on requests made by different actors:

- The UN requires robust metrics to be able to link information flows related to territorial projects to information cascades that support Sustainable Development Goals (SDGs);
- Banks and financial actors need simplified and consistent metrics to make allocation decisions in response to the growing propensity of savers/investors to place resources on impact securities;
- The PA, also due to the scarcity of resources, but even more because of the increasingly complicated relationship between institutions and citizens, intends to provide evidence of the social value generated by public programs;
- For-profit companies and social enterprises. For-profit companies try to be increasingly identified as subjects that aim not only at maximising profit but also at creating conditions of greater social and environmental sustainability (at least from a narrative point of view). Social enterprises are driven both by regulatory reforms (for example in Italy with the reform of the Third Sector Code) and by new financial policies (impact funds) to provide evidence of the social impact that they are able to generate.

This stream of literature can be integrated with the field of big data studies, where a specific focus on social big data has been present for some years. Social big data are understood as those data that arise from social interactions and behaviours able to leave traces in the web context (or out of it but that can be integrated through internet of things systems).

Since 2011, the year in which McKinsey published the report "Big data: The next frontier for innovation, competition, and productivity", a growing interest has been activated with respect to the potential use of data to improve productivity and competitiveness of organisations.

In this research, however, we intend to focus on a different potential, referring to the ability of big data to support decision-making processes aimed at responding to complex social challenges. More specifically, the present work attempts to investigate the possibilities of using big data to meet the challenge of measuring and assessing social impact on a large scale and with a multi-stakeholder perspective.

As already mentioned in the introduction, the research questions that the chapter attempts to answer are:

RQ1—Is it possible to reduce the measurability gap typical of social impact using big data analysis?

RQ2—Can the information processed with big data analysis improve social innovation processes in terms of scalability?

10.4 Methods

The methodology used can be schematically represented in 4 essential steps: mapping of data sources, data collection, data analysis and systematisation. The first two describe the sample of the research and its characteristics while the other two describe the method of analysis.

1. Mapping of data sources and construction of the collection database.

We have taken into account the most accredited repositories of projects with certified social impact assessments. These repositories are: Social Value, Social Finance UK, Issuelab, New Economic Foundation. Approximately 1000 reports containing data consistent with our needs have been identified and, among these, we have chosen to give priority to those that have passed a review or external validation process led by independent bodies. At the same time, a data import framework was built, using the support of experts in digital environments. This involved the construction of an entity-relationship matrix to link each imported variable to the others with which there is a sense relation based on the model adopted for the impact assessment. The model considered is that of the Theory of Change (ToC).

2. Data collection through document analysis.

Three independent analysts have analysed the reports identified as priorities based on the reliability of the data contained and have categorised the values reported in the variable fields set with the database framework. The analysed reports are 333. The authors took part in the analysis only if the analysts expressed an explicit request or the need to settle divergent interpretations.

3. Data analysis using business intelligence tools.

The collected data were analysed through Power BI, a software that integrates systems. Power BI is able to connect data and make them interact in order to transform data into information consistent with the built entity-relationship matrix. It is one of the most widely used systems for data management and use, produced by Microsoft, and available in a cloud version.

4. Systematisation and representation of preliminary results.

The data have been systematised into macro-variables to make them easier to represent. The macro-variables identified are consistent with the model of evaluation and measurement of social impact chosen (ToC) and are:

- stakeholders, classified as public, private and financial actors;
- input (financial and nonfinancial data);
- lenders, classified as public, private and financial actors;
- governance, classified as public, private or mixed projects;
- processes, with data on specific activities relating to social innovation projects;
- output, with both quantitative and qualitative data;
- outcome, specifically distinguishing hard (quantitative), cashable (with objective financial implications), and soft (qualitative) outcomes;
- indicators, with logical connection to the relative outcome;
- financial proxies, to allow the translation of outcome units into monetary value.

All this is summarised by SROI (social return on investment), which is obtained by dividing the social value generated by the outcomes (and measured through financial proxies) by the value of the inputs.

10.5 RESULTS

As anticipated, the first phase of analysis involved the analysis of reports (until 06/10/2020~333 reports have been imported in the database. This number keeps growing every day) relating to as many social innovation projects conducted at an international level as possible.

These correspond to an invested capital (input) of approximately 37 billion euros. The beneficiaries of these projects are 2 billion people and the organisations (companies, social enterprises, PA, other organisations) involved.

The areas of the projects are addiction, business, construction, CSR, culture, education, elderly, empowerment, environment, food, health, housing, justice, migration, sport, technology, volunteering and wellbeing.

A particularly relevant aspect concerns the wealth of the imported outcome areas, both from the quantitative point of view (they are 3045) and from the qualitative point of view (they are all surveyed with reference to the sources). They are linked to 3405 indicators that make the same outcome areas measurable and 3155 financial proxies that allow their translation into monetary value. Figure 10.1 summarises the results that emerged.

As the figure shows, it was possible to construct an average SROI of all the analysed projects, and it is equal to 6.38 (it indicates that, on average, 1 euro invested has generated 6 euros of social value). This shows that the integration of all the social impact data provides useful information to significantly increase the level of knowledge with respect to the generative potential of social innovation projects in terms of social added value.

However, the potential use of big data in this area is much greater: with digital interfaces it is possible to move around in the dashboard and get more and more detailed information. Each of the represented infographics, in fact, is dynamic and can be interrogated, and being logically connected with all the others on the basis of the ToC framework, allows it to represent the data according to multiple interrogation drivers. A further possible analysis concerns the comparison between clusters of projects grouped according to the geographical context in which they



Fig. 10.1 Data representation dashboard through Power BI



Fig. 10.2 Geographical distribution of the analysed projects

are realised. In fact, as the number of analysed reports increases, the tendency will be towards a greater homogenisation of the territorial representativeness of the projects and this offers the opportunity to produce differentiated analyses according to exogenous variables (political context, social context, economic context, technological context). Figure 10.2

shows a geographical representation of the projects analysed.

The availability of an interoperable system accentuates the usability of data and allows for increasingly granular units of information. The organisation of the database according to an entity-relationship matrix, in fact, allows also a disarticulated use of the data: each outcome area, which in the logical import scheme has a relationship structure with other variables, can also be interrogated individually. This aspect, in response to the first research question, exponentially increases the use of this data for subsequent measurement and evaluation activities and for impact forecasting activities. Figure 10.3 shows an example.

As shown in Fig. 10.3, the data can be queried by describing the needed information, by using the name of the project, or directly by using the outcome areas. These, therefore, will automatically connect to the indicators and financial proxies connected to enable not only cross use but also vertical use of the information available. This function marks the passage from the concept of data to the concept of information that can be derived from it. Thanks to the disarticulated and transversal nature of the information analysed, knowledge can be created on a specific domain that can be extended to coherent domains.

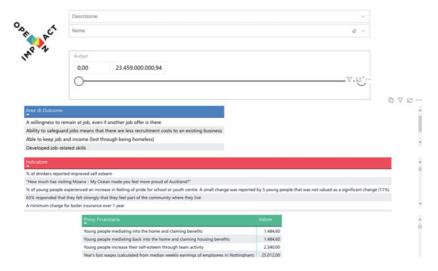


Fig. 10.3 Usability of measurement data and assessment of social impact

The next steps of this research project concern the extension of the analysis to cover the entire population of data available at the global level and the fertilisation of related fields, such as, for example, the measurement of the degree of marginal achievement of the SDGs.

By linking the outcome areas to one or more coherent SDGs, in fact, it is possible to verify how each project, program and policy is achieving results in line with the 2030 Strategy. This will favour a flow of bottom-up data to substantiate the transition to a more sustainable society. Figure 10.4 shows a preliminary result.

Each project, through the outcome areas, will impact one or more SDGs (for example, 416 outcome areas are linked to Goal 3). Through the data on the social value generated for each outcome area it will be possible to verify how much social value is generated by each project, or by a cluster of projects, by a program or by a policy with respect to each SDG.

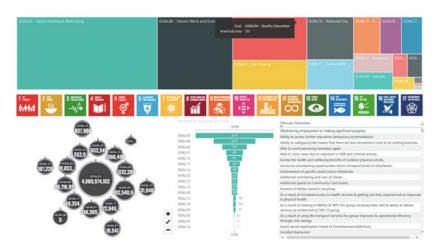


Fig. 10.4 Preliminary result of connection between the social impact data and the SDGs

10.6 Conclusion

The main conclusion reached, referring to the first research question, is that the use of systems for the collection, management and representation of big data in the field of social innovation has a very significant potential. This potential has the ability to generate cross-fertilisation on related research fields, such as, for example, the one of sustainability and the development of the 2030 Agenda (SDGs).

This can be declined in at least 3 ways:

- Potential for future activities to measure and assess the social impact of social innovation projects: with the collection, analysis and processing of big data, in fact, the measurement and evaluation processes can benefit from robust baselines that allow comparisons and create a valuable benchmark bank to verify the consistency of the social impact results.
- Potential in terms of predictive analysis with respect to the impact that can be generated by social innovation projects. Big data enable the strategic adoption of impact information, well beyond the measurement and evaluation phases. The usefulness of consolidated data can allow the design of future strategies and processes for policies, programs and projects aimed at generating impact. The aim is to be able to represent the expected impact ex ante and to proceed, ex post, to check the deviations from the measured impact.
- Potential in terms of creating shared knowledge useful for supporting complex decision-making processes. If these data are managed with open source logic and with a process of continuous validation of information (wiki approach), the community of researchers and practitioners who work on social impact will be able to continuously enrich the data collected and favour the qualitative and quantitative growth of information inferable from the data.

To answer the second research question, therefore, we need to consider the potential use of this data to improve the scalability of social innovation initiatives. This is possible where the results of the project demonstrate an adequate integration between social sustainability and the economic sustainability that can be generated from the results of the project. Social sustainability is achieved when the social value deriving from the application of proxies to the outcome areas is at least equal to the value of the invested budget. Economic sustainability occurs when the value of cashable outcomes, or those outcomes that have an immediate financial translatability, is at least equal to the value of the budget invested. The data collected, thus responding to the second research question, allows to identify sustainable projects, discern the determinants of sustainability and point out the most consistent scalability strategies.

This research project led to the creation of a spin-off of the University of Rome "Tor Vergata" (www.openimpact.it). Open Impact is interacting with different types of organisations that are adopting this logic to introduce the social impact life cycle as a strategic driver of change towards sustainability. The usage of Open Impact database has been tested with different market clusters:

- policy makers that can design policy using the data benchmark and forecasting results of the expected impacts (a test has been held with an Italian local government and with a central administration of urban regeneration policies);
- social enterprises and impact-oriented organisations that can design, monitor and evaluate the impact of their projects without the effort of starting every time from the identification of the variables of their ToC but adjusting their project to international benchmarks. Open Impact has developed a function that allows organisations to implement the impact value chain with their outcome areas, indicators and proxies.
- impact finance actors, such as funds, banks and foundations that can refer to a set of data to assess their investments. One of the future researches aim of the Open Impact project is to link each outcome area to other international standards such as EGSs and GRI standards to improve the reliability for this cluster of actors interested in impact assessment.

Open Impact is an open research project therefore the main limitations lie in its incompleteness. This chapter contains the early results that still lack the following:

- The incorporation of the whole SIA report population (until October 2020, 333 reports have been mapped in a population of

- an estimated 1000 open access reports, but this number might vary in time);
- An inferential analysis of variables. This is the next research step.
 The authors have stated to invest in domains such as urban regeneration and education to understand and decide what type of statistical analysis might be more interesting;
- The machine learning results are not exposed and analysed in detail;
- The link with other standards (like ESG, GRI) is mentioned only in connection with SDGs.

The attempt of this chapter is to present the early findings and to explain the theoretical background of the research project with a descriptive analysis of the variables involved. The future development of this project is symmetrical to the limitations enlisted here.

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