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Innovation Capability Maturity Model as a Mean for Data Policy Standardisation in Smart Specialisation Cycle

Saule Maciukaite-Zviniene
Professor
Head of Entrepreneurship and Innovation
Business School
Vilnius University
Vilnius, Lithuania
Email: saule.maciukaite-zviniene@vm.vu.lt
Lithuania

ABSTRACT

A major component of the Smart Specialisation (SS) agenda is the monitoring of progress towards the achievement of the goals and development of tools to support the activities of stakeholders in entrepreneurial discovery. However, there are capacity and management challenges for many countries in measuring the progress of SS. High-quality data is crucial for transforming SS indicators into useful tools for developing national mission-oriented innovation policies as well as facilitating a European level monitoring of SS progress. The paper explores potential interventions to improve the implementation of data policy for SS and indicates that Innovation Capability Maturity Model can not only ensure high-quality data, but also standardise the key processes of public management around SS. The adoption and mainstreaming of ICMM may aid in mission-oriented assessments and articulate pathways towards the maturity of SS data for improving SS cycle.

KEYWORDS: smart specialisation, innovation capability maturity model, data, management

Introduction

Achieving Smart Specialisation (SS) goals requires the effective development of big data transformations the integration of new and traditional data to produce high-quality indicators that are comprehensive, timely, and actionable for collaboration, decision making, and dynamic interactions between stakeholders. The quality of these indicators, defined in terms of completeness, uniqueness, validity, accuracy, and consistency(Höchtl et al.2016; Kemp,2014; Qiao et al.,2018; Stancova et al.,2018) is crucial for their use at national level planning, monitoring, and evaluation, as well as for facilitating European monitoring of SS progress and enablement of comparative evaluations between countries using big data approaches. The use of various instruments, including models, frameworks, and standards (Capello et al.,2018; Cohen,2019; Foray,2014; Markowska et al.2016; Rusua,2013; Fuster2020) facilitates multi- operations of SS processes for national decision making.

A major component of the SS agenda is monitoring the progress towards the achievement of innovation policy goals, as well as enabling the development of suitable tools to support the entrepreneurial activities of various public and private stakeholders. However, many countries have public management challenges within the data ecosystem in measuring the progress of SS. The collaboration platform of government, academia, business, and even individuals need to be enhanced in order to enable the delivery of high-quality data. It is consequently imperative to ensure that all countries participating in SS have dynamic national statistics systems that are in line with SS standards and benchmarks. High-quality data is crucial for transforming SS indicators into useful tools for developing national mission-oriented innovation policies as well as facilitating a European level monitoring of SS progress.

The sustainable development of monitoring systems and measurement of progress towards the achievement of defined targets, as well as the development of suitable tools and platforms to support the activities of different stakeholders is hence crucial for effective public management. The SS will demand further development to produce comparative and reliable data that is widely applicable, and which can ensure the ‘leave no one behind’ principle of the national statistics institutions (NSIs). The hypothesis underlying this paper proposes that the more mature an NSI is, the quality of the data it can produce will also be higher and consequently, this will result in better decision making in SS processes. Data indicators that accurately reflect progress, monitor resource allocation, inform policymaking and assess the impacts of SS related policies are essential for accountability. The use of indicators at a European decision level making necessitates

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coordination, integration, and interoperation between the various stakeholders within the data policy standardization. One of the key aspects of SS undertaken at the international level is to perform comparative ranking and clustering of different countries based on various aspects associated with their progress and achievement towards SS goals (SSG).

This paper is organized as follows It discusses the unfolding data evolution in evidence-based innovation policy and presents an extensive review of the current initiatives on improving the quality of data and it explores the possible integration of Capability Maturity Models (CMMs) within the SS framework for improved quality of SS data indicators. This is followed by establishing an innovative multidimensional prescriptive of Innovation Capability Maturity Model(ICMM) for SS data policy standardization and finally a provision of recommendations and conclusions.

By referencing the increasing complexity of big data, this paper explores the potential interventions towards improving the production of high-quality data. This research indicates that CMMs can be an instrument towards not only ensuring high-quality data but also for standardizing key processes concerning the production of SS data indicators and advancing interoperation. It also presents the preliminary formulation of a multidimensional perspective ICMM to assess and articulate pathways towards maturation of national data ecosystems, and consequently the effective monitoring of the progress of SSG through the production of high- quality data indicators.

At this level, there is a need for *coordinating* the processing of indicators between countries, a requirement to *integrate* data for indicators from various actors and sources, and finally to *interoperate* the diverse and heterogeneous elements for the data policy standardization. These complex interactions and data dependencies can be harnessed through standardization processes towards ensuring more effective and efficient use of data for effective policymaking.

The Data Evolution Approach

The volume of data in research and innovation policy has increased tremendously since 2001. Applying a data evolution perspective to SS consequently involves the integration of new data indicators (ex. most cited publications, enterprises providing ICT training, public-private co-publications, etc.) with "traditional" data (ex. gross domestic expenditure on R&D, population with tertiary education; R&D expenditure in the business sector; patent applications, etc.) to produce high-quality information that is more detailed and relevant for different users in innovation policy sector. It is especially relevant in SS to focus on competitive strengths and realistic rates of growth and to monitor entrepreneurial resources. Statistical institutions in different countries consequently engage with new sources and customer expectations as well as technologies and analytical tools. NSIs remain central actors for government's efforts to enhance the data transformation for SS. NSIs need to be able to adapt to the constant technological changes and increased involvement of different stakeholders, whilst lacking insufficient capacity and being vulnerable to political influences and European funding priorities. The data policy has experienced a technological and conceptual evolution where NSIs are now seen as shapers and integrators of the various elements of data indicators (UN, 2018). One of the key challenges and risks in data management processes is the gap between those having access to data and its provision and those who do not.

The performed analysis of consolidated reports (see Table 1) on SS implementation in different countries shows that paradox in research and innovation data production remains similar to those of other sectors, in the sense that those countries which require high-quality data production, (for example larger countries like Poland or non-EU countries like Serbia or Ukraine), might be less able to deliver high-quality data. The earlier research reported that the increased coordination among different stakeholders at both national and international levels has reported the following challenges: new technology and science knowledge face gaps from outdated or incomplete data (Marcovecchio et al.,2018). Consequently, mobilization of data and technological capacities are crucial for achieving SSG and transforming these into the public domain to maintain quality data for producers and consumers in innovation policy. Therefore, the efforts to match data cycles with policy cycles within SS should be seen as a priority for international organizations like the European Commission or the OECD (see Figure 1). The distinctive feature of data in policy cycles enables the evolution of a well- defined policy-making process (Höchtl et al.,2016). However, the failure of big data filters within the process of machine learning intended to separate "noise" from relevant information, may also prolong the decision-making process. It should be noted that different official documents identify SS as a key instrument for policy conception. Recent research by Forey D. (2014) shows that SS has evolved towards the vertical policy. "A vertical policy is a policy that selects projects according to preferred fields, sectors or technologies while a horizontal policy is only responding to demands that arise spontaneously from industry" (Forey, 2014).

Table 1. Number of Documents Included in the Review

Type of Document	Number of Documents	Years
Technical Reports	25	2018-2020
Fact-Sheets	5	2018-2020
Websites of Official Statistics	42	2019

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The analysis of documents on SS implementation-defined that the key issue for the potential of SS is consequently to identify high-quality indicators that will grasp the entrepreneurial discovery process within the policy cycle. It shows that governance processes and aims fall into the same field for SS potential, with the difference being that at this level the focus is on the interoperability and coordination of the data production. Entrepreneurial discovery in SS refers to the description of the priorities in the policy cycle that are supposed to be taken in the implementation phase. Once the SS cycle moves from the priorities phase to the policy mix phase, governments can adopt or shape indicators of dynamic data according to consumer and provider needs. The constructed SS data cycle (see Figure 1) shows that credibility and traceability remain essential, hence the use of technological solutions of data production to investigate the acceptance of specific means among NSIs and external stakeholders is useful. Similarly, to a policy mix phase, decisions on how to most efficiently provide human, technological and financial resources for the implementation of an effective data monitoring in SS processes may be improved if previous experiences are analyzed in detail, for example in case of Lithuania, Estonia, Poland.

Additionally, to the experience of countries, which performed the midterm evaluation, the paper leads to the assumption that big data also may have the potential to enable the testing of new areas of SS policy. The ability of NSIs and external stakeholders to pinpoint challenged areas in a targeted way and the possible discovery of a value addition resulting from potential sectors could make it easier to gather support for certain priorities while making the rejection of others more likely. This is especially evident from how different countries have been using big data for budgeting of specializations as this can increase entrepreneurial discovery in smart sectors and even reduce public costs.

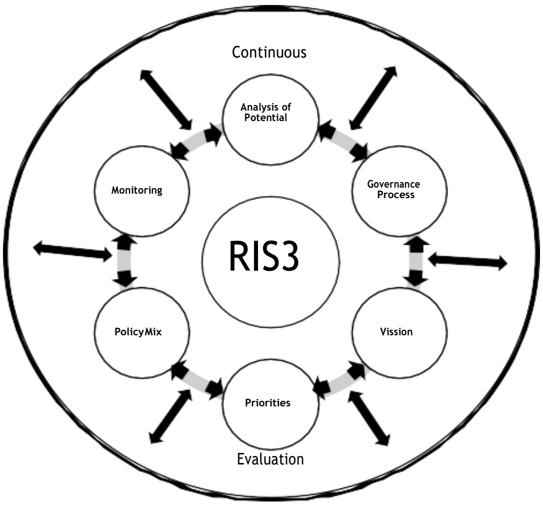

Figure 1. E-Smart Circle

The results in this paper emanating from one of the latest RIS3 reports on implementation on smart specialization (Cohen,2019) covering the EU countries: Austria, Belgium, Finland, France, Greece, Italy, Lithuania, the Netherlands, Poland, Portugal, Slovenia, and Spain also defined new measures for developing a data eco-system. For example, an open public data platform (Lithuania), free access to toolkit (Italy), open collaborative databases (France), and big data partnerships (Spain, Greece). It is defined as well from RIS3 country reports, that the availability of more data in the SS cycle facilitates a shift toward outcome-orientated support and the improvement of evaluation frameworks that could funnel resources to the most promising entrepreneurial discoveries which not necessarily align with the priorities to which the allocation occurred in previous periods. It is determined that the production of data in the policy mix phase of SS during application of measures, rather than after, can also create unprecedented flexibility when it comes to the transformation of policy ideas into actually executable policy. Furthermore, the inputs necessary for the aims and priorities in the policy mix phase can be increased inaccuracy by the use of SS data as there is otherwise always a risk that the data used in the definition of priorities and aims in the policy mix phase is outdated. Consequently, combining several databases can facilitate the timely delivery of census data and improve the cross-checking of data in SS with increased validity and traceability.

From the experience of countries, which implement SS, it is assumed that the speed needed for data adaptation is generally not fast enough to justify different trajectories from the SS cycle. In the future, the distinctive feature of SS is the availability of real-time big data processing during the implementation which leads to opportunities for continuous monitoring and evaluation. This enables a new view on the SS cycle and big data which enables evaluation to happen at any stage for external stakeholders. This paper proposes to shape a

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policy cycle in which evaluation consists of a continuous process of open possibilities, reassessments, and considerations. This approach may also change the understanding of general data analytics and it is proposed to be named as the "e-smart cycle".

The findings and challenges of various previous SS studies already demonstrate that SS is measurable and that aggregated statistics can be produced(David et al,2012). Consequently, in this paper, it is claimed that to produce a sustainable production of SS data indicators statistics must be high-quality, reliable, and easily accessible. One of the research results used for the improvement of SS data production is an integrated triangle view of big data (velocity, volume, and variety) by Lee (Lee,2017). This paper improves the triangle view and proposes a square view elaborated with the need for dynamic data for SS implementation which should be qualified with the availability and insurance of traceability to meet the requirements and expectations of users. Furthermore, the square shows that SS data should facilitate multidimensional levels to enable operational decision making, to enhance continuity, accuracy, and timeliness across multiple dimensions of SS (see Figure 2).

Different studies have highlighted six managerial and technical challenges about big data practices: data quality, data security, privacy, investment justification, data management, and shortage of qualified data scientists (Lee et al., 2015). Even though the paper applies that SS process data is collected from a wider array of sources, for example, research institutions, businesses, individual scientists, think tanks, etc., the data quality may decline in the absence of standardized quality metrics. SS processes also require the growing collection of personal data which raises concerns, especially in non-EU countries, like for example Ukraine, Serbia, and Albania a strong security protocol is consequently required.

The exploration of the recent country reports on SS implementation practices showed that the actual use of big data analytics has been limited and there has been no sense of obligation to move towards big data plans. The current architecture of data policies at the national level remains traditional and problems occur when trying to integrate big data applications to work across different databases. It should be also acknowledged that NSIs, especially in non-Eu countries, experience a shortage of skilled professionals for big-data services. Big data, assessment tools, and application of SS big data integrated views of big data (Figure-2) will help different organizations to realize the benefits of big data integration and to position themselves globally within the wider data production shift in public management.

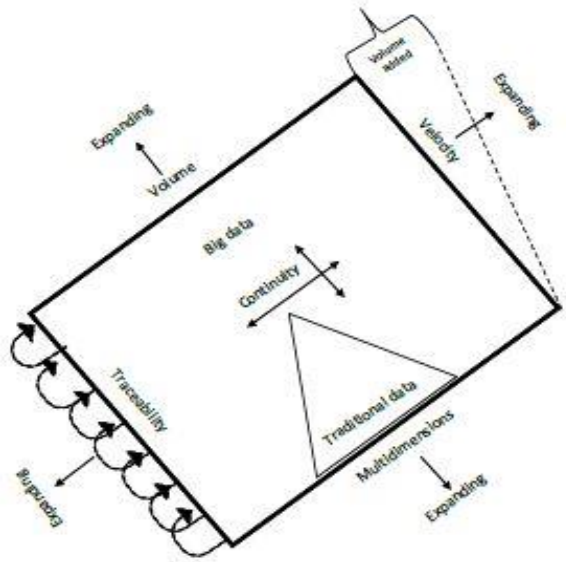

Figure 2. Square of Smart Specialisation Big Data

The process of SS implies a selective intervention logic and the level at which information and coordination externalities typically materialize is a specific economic activity such as a good or service, or a technology application (Capello, Kroll, 2018). Consequently, assuring traceability in an integrated model of SS big data as a precondition not only for research and industrial applications but also for providing high-quality indicators is closely associated with a sustainable dynamic data eco-system, technological solutions, and the European Commission open data repository, Eye@RIS3. In view of evaluating the development of a SS data ecosystem, the next part of this paper continues the analysis of SS country reports and focuses on assessing three complementary aspects: (1) how data indicators are defined, (2) how data production is improved, (3) how data is differentiated according to priorities. It is worth stressing that the paper does not explore the whole

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process of big data production, but it sheds some light on important aspects of this, like ‘ensuring high-quality data’, ‘standardizing the key processes’ and ‘advancing interoperation within the big data ecosystem’.

In view of evaluating the effects of big data measures applied in a SS context, it is important to realize to what extent and how data information is translated into the principles of SS in the indeterminate zone of CMMs. An effective benchmark for data policy standardization is the supply of information which can enable internal and external stakeholders with the possibility to drill out evidence through all phases of the “e-smart cycle”, in order to provide opportunities for politicians and other stakeholders to draw conclusions and improve policy process by generally accessible dynamic data.

Standardization of Data Policy for Smart Specialisation

The paper acknowledges and encourages to improve the quality of indicators, the collective approach of big data, whilst making the policy process more inclusive. Compared to a traditional industry policy or innovation policy, smart specialization exhibits a few characteristics: (1) public interventions must be selective and focused on particular economic activities; (2) selection of the intervention areas should be based on exploration and intervention of opportunities (Foray, 2015). Successful adoption of a selective intervention logic implies standardization of data policy; however, volume, traceability, and velocity of data substantially differ not only across countries or industries and technologies, but also vary in relation to the *coordination* of the processing of indicators between countries and within a country, *integration* indicators of data from various actors and sources, and *interoperability* with diverse and heterogeneous elements of the data ecosystem.

Standardization of data policy is the critical process for bringing data into a common format that allows for large-scale analytics, sharing of sophisticated methodologies, and the support of collaborative research and innovation activities. R. Kemp (2014) introduced the common legal framework for big data and conceptualized it in a legal analytical model which was explored in this paper and adopted referring SSG. From the beginning of the introduction of SS, it has been necessary to indicate the feasibility of big data measurements, though there had only been a few studies conducted (Markowska et al.,2016; David et al, 2009) on how to establish how SS could be presented in a measurable manner. In Figure 3 a complex picture of an innovative standardization is presented while merging both Kemp’s legal framework of big data with two areas of SS crucial for data processes: ‘the discovery process’ and ‘the tracking progress’.

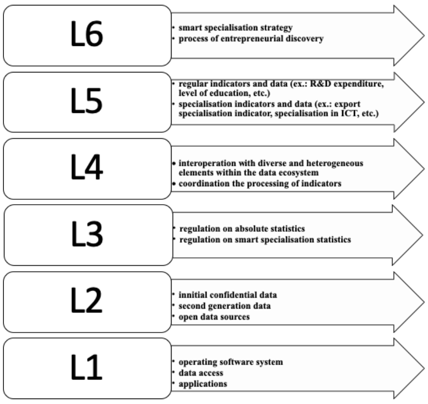

Figure 3. Standardisation of Smart Specialisation Data Ecosystem (adopted by the author from Kemp, 2014)
L1 – platform infrastructure; L2 – information architecture; L3 – IP rights in relation to data; L4 – contracting for data; L5 – data regulation; L6 – information management and security

One of the SS characteristics is the growing importance of a particular sector as the background of the remaining ones (Markowska et al.,2016). Therefore, in this paper, the big data is defined as the source of comparative advantages among regional economic actors and its emergence has hence not remained isolated to the technology, health, or bank sectors. Big data has also a potential to be broadly applied across SS specializations in the future. In the light of growing SS and regional cooperation, governments should pursue the quality of big data capabilities as a necessity for ground-level development for regions, which in turn can facilitate entrepreneurial discovery. The paper proposes a conceptual model for standardization of data processes based on research studies and best practices from country reports (Figure 4).

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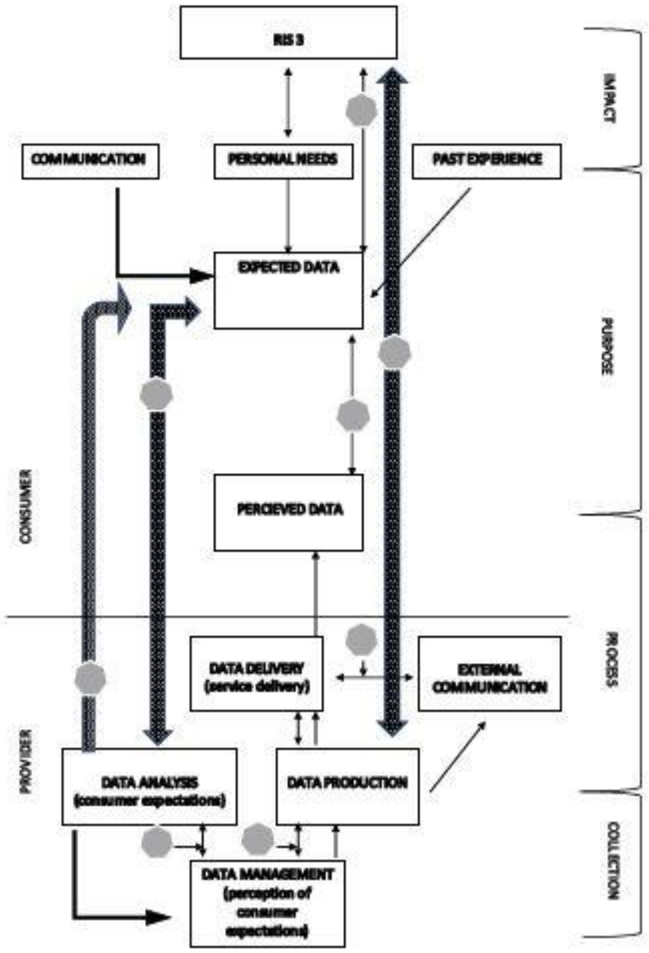

Figure 4. A Conceptual Model of Data Production Quality (indication of gap)

Applying tools to analyze big data (Figure 2) combined with an understanding of how big data can enhance implementation of SSG (Figure 3) will help organizations to realize the benefits of big data in entrepreneurial discovery as well as enable governments to realize the benefits of big data integration into the policy cycle (Figure 1). Furthermore, it will position the regions within wider innovation waves as big data becomes a part of competitive practices globally. However, the paper addresses mainly a need for an innovative model that can imply the challenges faced by NSIs and external stakeholders, as well as the need to implement cultural changes that can encourage cross-regional research and business cooperation. This paper will further develop ICMM for the standardization of data policy for SS.

Capability Maturity Model for Smart Specialisation Indicators

Because of the inherent and increasing complexity of big data, this paper will further adopt an approach that will explore potential interventions towards improving the capacity of organizations. The paper refers to the importance of coordination and interoperability of SS indicators, and a standardization approach is considered to both identify the capability of NSIs as well as providing a pathway towards more mature operations. Monitoring of progress in SS, especially transregional, advanced development of data production as well, for example, France, Lithuania, Spain. Consequently, having mature institutions that can fulfill the rapidly growing demands for high-quality information and adopting the best practices from data products are essential. Maturity models remain an acknowledged tool for the assessment of quality and effectiveness of institutional performance as well as it is applied as a tool for benchmarking (Judgev &Thomas, 2002).

The data quality initiatives of the European Commission (ESS Quality Declaration, EFQM model, the Code of Practice, and the legislative recommendations concerning quality, etc.) improved the quality of innovation data produced by NSIs. However, the improvement of SS monitoring remains a challenge combined with the assessment of the NSI's capability and procedural abilities to produce data for SS indicators. The analyzed countries' reports on the implementation of SS show that the distinctive features of big data in performance-based

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policymaking are not yet fully considered. The rapidly changing environment in the innovation sector, different natures of research and business organizations, numerous dimensions of SS have all influenced the development of the organizational context of NSIs. The demand for high-quality decisions based on growing unstructured data requires new forms of participation to obtain data, new ways to process data, and the redesign of processes to include more stakeholders ((Höchtl, Parycek &Schöllhammer, 2016).

The CMMs include a self-assessment that presents the organization's best practices in key process areas (e.g. capabilities) and then shows how the organization can redefine its capabilities as it evolves into a more mature state (Paulk, 2009; Paulk, Curtis& Chrissis, & Weber, 1993). To the best of the existing knowledge, very few studies have analyzed the CMMs within research and innovation (Yeh et al., 2017; Carroll et al., 2015). No existing works have provided an integrated view of data processes for SS that are consistent with the theoretical foundations of CMMs. According to the observations, the underlying concepts behind big data in research and innovation policy are not disruptively new, instead, the paper repacks the decision support, which becomes a part of the data policy. There are multiple ways of how big data can support the SS cycle and the evaluation of results is not an isolated step. It is a part of CMMs, which reduces the inefficiency of data production and enables alternatives identified by data analytics. However, at the same time, the paper shows that innovative tools are part of a bureaucratic environment within organizational cultures where each data producer or external user will likely be bent on turning new tools to their advantage, possibly at a cost for everyone (Gianelle et al., 2019). The ICMM developed in this paper is based on both empirical data from countries' SS reports and scientific literature. The ICMM is multidimensional and focuses on big data production to enforce the quality of SS indicators as well as it encompasses the technological advancements that require further development. To understand the content and the application options, the design and application of technological solutions and relevant tools for big data ICMM should consequently be integrated into a sectoral structure of SS (Knoke, 2013; Essman et al. 2009, Marcovecchio et al., 2018; Paulk, 2009; Perez, 2015).

Dimensions

For decades organizations, industry sectors and even policy areas have been described broadly in terms of golden triangle: people, processes, and technology (Poopelbuss et al., 2011; Jugdev,2002). Due to rapidly changing environments, political culture, and technological developments, numerous dimensions have been adopted to provide a specific description of the context of sectors, for example, data, strategy, exchange, etc. The paper concentrates on the data for SS indicators because reliable evidence-based policy enables successful entrepreneurial discovery and proper allocation of resources through all phases SS cycle (Figure 1). However, SS requires a set of key-principles for qualitative data (Figure 2) and consequently, the accomplishment of SSG demands more specific dimensions. Table 2 provides the ICMM dimensions (value chain, stakeholders, discovery, innovation narratives) which are determined after analysis of RIS3 reports and leads to the improvement of public management. According to Marcovecchio et al. (2018), these dimensions also cover the major principles of the acknowledged key data and nature of SS (Figure 5).

Table 2. ICMM Dimensions Defined for SS in Actions

Dimensions	Description*
Value chain	the provision of a compatible and supportive environment; the upgrading of innovation system; development of human capital; supporting collaboration among stakeholders; engagement in upgrading industry; anticipating and targeting of areas of growth within industry (for example, Pharmaceutical Industry in Ireland; Life Science Industry in Lithuania)
Stakeholders	academics, business, industry, policy-makers
Discovery	a real degree of involvement of companies (for example, biotechnology, health, information technology, advanced materials, optics)
Innovation narratives	EU Framework programme, smart specialisation strategies, legislation related to innovation policies

** Description is based on the practices of countries. Analysis is based on documents provided in S3 platform*

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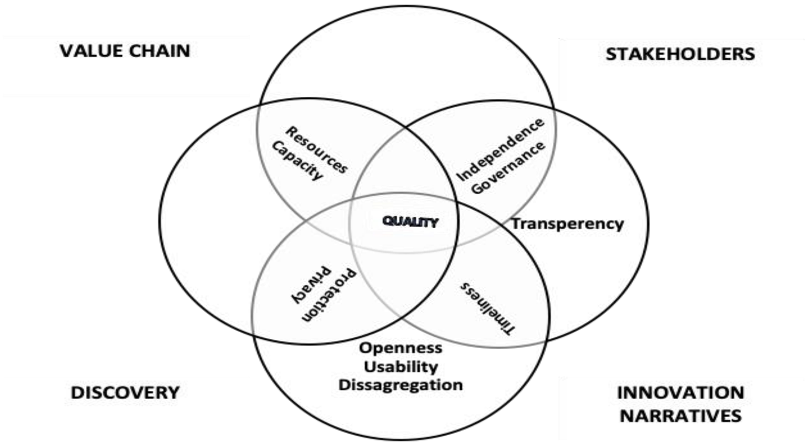

Figure 5. ICMM Dimensions and Data Key Principles (adopted by the Author from Marcovecchio et el., 2018)

Levels

In general maturity models include a sequence of levels that define a path from the lowest (initial) to the highest (ultimate) state of maturity (Pöppelbuß, Röglinger 2011), however, the maturity levels may differ depending on the statistical domain, part of the organization or sector. The model presented in this paper focuses mainly on one domain for improving public management, i.e. the production of big data to inform SS indicators. Aiming to identify the maturity level of NSIs (Table 3) in general, the further analysis applies five ICMM maturity levels of innovative approaches based on Esmann's capability maturity approach to innovation management: ad hoc, defined, supported, aligned, synergized (Knoke, 2013).

Table 3. Maturity level of NSIs in SS countries (registered in S3 Platform)

Country	Maturity level
EU member states	Aligned/Synergized
EFTA member states	Aligned/Synergized
Albania	Supported
Australia	Aligned
Bosnia and Herzegovina	Ad hoc/Defined
Kosovo	Defined
North Macedonia	Ad hoc/Defined
Moldova	Defined
Montenegro	Defined
Serbia	Supported
Thailand	Ad hoc/Defined
Turkey	Defined
Ukraine	Supported
United Kingdom	Synergized

In ICMM the levels define the innovative maturity of statistical organizations to produce qualitative data in different phases, however, the SS data production is a complex process. Although there is no single determining process for NSIs and this paper has no intention to produce a universal model for SS big data production, the general phases are defined (Figure 3).

Phases

There are different tools to support the production of data needed for SSG. Marcovecchio et al. (2018) in their research described the tools which are used by many different NSIs, however, they cover the limitations associated with demands from SSG and the evolving role of NSIs within big data ecosystems. *The responsiveness* of NSIs includes monitoring and reporting of indicators for SSG. It varies in different countries and depends on the SS strategy as well as different policy procedures. NSIs are mainly a coordinator of reporting and share responsibility for the production, development, and even dissemination of data with other line organizations. *Completeness* focuses on the production of data, but do not consider the full cycle of data, including the impact of the data. In a SS process, it is important to have continuous feedback from external stakeholders. *Specificity* may differ in NSIs where applied instruments cover the production of official statistics in general, but which does not necessarily cover the

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peculiarities of SS, for example, the focus on intellectual capital or entrepreneurially added value. *Updates* need to evolve rapidly, because sources, volume, and even types of data do not match with traditional processes. Although such countries like United Kingdom, France, Australia, Sweden, Czech Republic, Germany, Spain, Ireland, Italy, Greece are acknowledged as leading data economy countries (HBR, 2019), at this stage it is too early to evaluate the type of role of NSIs in big data production for SSG. The opportunities arising from big data could maximize the impact of SSG and the discussion in this paper leads to standardization of data policy for SSG.

This paper addresses the value chain of the data ecosystem through four major phases that are proposed to be applied in SS: collection, process, purpose, and impact (Figure 3). The construction of phases is based on the strengths and limitations identified. The *Collection* phase includes the activities to collect, manage as well as design SS analytical tools. The *Process* phase comprises the activities needed to identify and deliver data as well as the activities related to the initial communication to scientific communities, industry, and public sectors. The *Purpose* phase encompasses the activities needed to consume the results of data,

connecting the different stakeholders and incorporating data into the e-smart cycle and general communication of the data. The *Impact* phase contains the activities performed to use data to impact entrepreneurial discovery, to recycle data for further knowledge-gathering, and to define new SS specializations. The resulting ICMM for SS big data production is seen as the outcome of cross-cutting phases of the dimensions and segmenting them with the levels of innovative maturity. In Figure 6 each box represents the intersection of the elements of ICMM and describes the level of maturity of a NIS to produce and apply tools to big data for SS indicators.

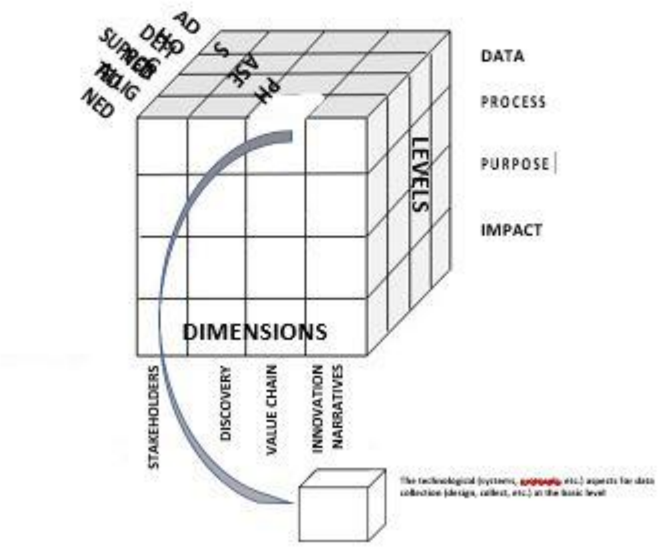

Figure 6. View of the ICMM for Smart Specialisation Data

It is acknowledged that the external dimensions that motivate intervention according to the SS logic can differ in countries substantially depending on the industries and technologies involved and the underlying societal challenges. Although, the types of intervention also vary across priorities the levels of maturity for data productions remain unique.

Recommendations

The EC and OECD play an important role in supporting NSIs in being able to produce high- quality data for SS indicators and providing them with the necessary tools. There is a clear need for reliable data within the NSIs community and the big data reality in which NSIs find themselves is comprehensive. However, there is a need for a more practical examination and targeting of the challenges of the big data within the SS cycle.

The paper shows that every country applying a SS strategy, regardless of the level of advancement, can benefit from ICMM targeted towards SSG and also entrepreneurial discovery. While countries have different resources for improvement and innovation, the achievement of SSG is not a competition between countries, therefore solutions from the business have to be analyzed for further research and might be adapted for later practice in improving data policy.

This paper does not come without limitations as it lacks quantitative data. Furthermore, it does not provide a thorough evaluation of stakeholders' behavior to determine the side effects of big data in the SS cycle. While businesses use big data to improve their intellectual capital investments, governments should use big data to provide better services for entrepreneurial discovery. Although investments to improve monitoring of data at an international level has been conducted

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over several decades, examples of this concern like human rights and global innovation, efforts such as these have to be evaluated to identify synergies and further standardize data policy and improve "e-smart cycle" with reference to the ICMM proposed in this paper.

Conclusions

This paper suggests a new analytical approach to assess the levels of data development changes in a SS cycle and to improve it. The analysis made provisions for a singular identification of standardizing big data for the S3 Platform to avoid the problems associated with selecting a multidimensional approach.

The paper also underlines the achievements of SS through interventions targeted towards improving capacities of NSIs. The analysis performed encourages the adoption of ICMM within a SS process at the national level. According to the observations, the underlying concept of big data is not relatively new, however, the paper showed multiple ways in which big data can apply in the SS process. Moreover, continual evaluation enabled by technological developments may increase the level of maturity of NSIs, through such innovations will still take place in a bureaucratic environment, because not all countries have applied the European regulation on the quality of data.

The challenges of ICMM stems from the diversity of NSIs and national legislation, however, an important assumption identified in this paper is that upgrading capabilities are highly dependent not only on cooperation between national stakeholders but also on integrating SS networks to improve data policy management.

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