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# A foresight toolkit for smart specialization and entrepreneurial discovery

Radu Gheorghiu<sup>a,b</sup>, Liviu Andreescu<sup>c,b,\*</sup>, Adrian Curaj<sup>d,b</sup>

- <sup>a</sup> The National School of Political Science and Public Administration, Romania
- <sup>b</sup> Institutul de Prospectiva, Romania
- <sup>c</sup> School of Business and Administration, University of Bucharest, Romania
- <sup>d</sup> Politehnica University, Bucharest, Romania

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#### ABSTRACT

Smart specialization strategies (RIS3) have exploded in number across Europe over the past couple of years, among others due to the European Commission's sustained effort – both conceptual and at the level of policy – to push this notion forward. What lies beneath the spate of recent RIS3s, in terms of specialization options as well as of the processes through which the latter were reached, is only now beginning to be examined in depth. Notably, the Commission did not offer a proper blueprint for RIS3-making, but opted instead to suggest a wide range of possible instruments. Based on our experience with the Romanian strategy-building process, in this article we outline a foresight-based toolkit for smart specialization and entrepreneurial discovery, though we too stop short of proposing a detailed full-fledged blueprint.

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#### 1. Introduction

'Smart specialization' is Europe's brand new policy template designed to bridge the three "mutually reinforcing priorities" of smart, sustainable, and inclusive growth that define the Union's development strategy (EC, 2010: 11). The smart specialization (S2) approach has been recently put to use by states and regions throughout Europe in the design of their research, development, and innovation (RDI) policies, among others in contemplation of the carrot of structural funds, for which RIS3 has served as an *ex ante* conditionality. Nevertheless, despite the wide deployment, "the first book on [this] new policy approach . . . widely adopted in Europe and beyond" was published as late as 2015 (Foray, 2015: 2). While this is not to say that there is a dearth of literature on the topic, the belated publication of this relatively concise work does signal that the smart specialization policy template was deployed rather in a hurry, if not altogether "rashly" (Kroll, 2015a). Furthermore, this has taken place at continental scale and without a clear blueprint instructing states and regions working on their "research & innovation smart specialization strategies" (RIS3) on how to achieve the prescribed "prioritization of knowledge investments" in a few select fields with future economic potential, a move which lies at the heart of the S2 concept.

The absence of clear procedural guidelines is remarkable, among others because the smart specialization template is rather bold. This is so, first, because the notion of prioritization runs contrary to the by now seemingly well-established consensus that RDI policy should be horizontal, instead of 'picking winners' (an idea which S2 literature tries hard to

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<sup>\*</sup> Corresponding author at: School of Business and Administration, University of Bucharest, Romania. E-mail address: andreescul@gmail.com (L. Andreescu).

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re-legitimize in the new context and under a new guise). Secondly, the S2 policy template is bold especially in states, such as those in the Central and Eastern Europe (CEE), where the established policy routines are not well-suited for the 'entrepreneurial discovery' (ED) process at the core of RIS3 strategy-making. Specifically, under this approach governments are supposed to assume an active role in discovering and then betting on economic niches that "are new, aim at experimenting and discovering technological and market opportunities and have the potential to provide learning spillovers to others in the economy" (Foray, 2013: 58). The process, as noted above, goes as far as selecting and promoting "technologies, fields, sub-systems, even firms" (Foray, 2013: 57). In this light, deploying a so-called 'place-based' approach, one which is suited to careful, persistent entrepreneurial exploration, suggests that the RIS3-making enterprise should be a regional-level pursuit. This has indeed been advocated by the proponents of S2, among which the European Commission (EC) itself. It should be noted here, as a possible illustration of the speed with which the theory of smart specialization and entrepreneurial discovery was rushed to implementation, that many if not most countries in the CEE remained committed to a national-level process, which has likely been more palatable under the existing policy routines (Karo & Kattel, 2015).

Our goal in this paper is neither to probe the theory of smart specialization in any depth, nor to explore the ups and downs of its implementation in the latest round of pan-European strategy-making on research and innovation (Kroll, 2015a; Paliokaitė, Martinaitis, & Reimeris, 2015). Rather, we highlighted the absence of an S2/ED blueprint because we intend to propose herein the outline of such a composite instrument. This 'toolkit for smart specialization and entrepreneurial discovery' stops short of a full-fledged blueprint, but advances a more consistent, if also more limited, set of instruments than the Commission or S2 supporters have offered so far. We believe that the toolkit, at least in the context of an entrepreneurial discovery process, provides the premise for a more iterative, semi-continuous foresight project. In the next section we discuss in additional detail the importance of foresight in the process of prioritization known as entrepreneurial discovery. We continue by outlining the toolkit and by describing our experience with designing and developing parts of it. Most of the latter, but not all, were used in the elaboration (during 2013–2014) of Romania's own national strategy for RDI for the programming period 2014–2020.

#### 2. Foresight for smart specialization

Undoubtedly the most important guidance to the making of RIS3s, alongside a series of conceptual papers whose substance was gathered in the recent book mentioned in the previous section (Foray, 2015), is the European Commission's own *Guide to Research and Innovation Strategies for Smart Specialisation* (EC, 2012). Yet, while this expansive document does a systematic job of explaining the policy concept, the desired outputs of the process, and the principles and criteria to evaluate the latter by, it falls somewhat short of providing a functional blueprint for the entrepreneurial discovery process supposedly underlying the selection of S2 priorities. The ED process represents a presumably complex, though also tentative procedure through which governmental or regional policy-makers "hold[ing] the knowledge about the local innovation systems" are supposed to mobilize economic and other actors "well positioned to develop a thorough understanding" of place-based opportunities, strengths, and challenges "towards a shared goal" (EC, 2012: 12). In lieu of such a blueprint, the *Guide* offers a broad survey of methods and instruments which might prove useful in designing an ED process. This set includes foresight and associated methods (such as Delphi, scenario building, cross-impact and morphological analysis, and others), but not a procedure. Indeed, the *Guide*'s six-step 'step-by-step approach to a RIS3 design' is limited to a rather generic participative strategy-making formula. Somewhat ironically, the 'prioritization step' seems to be the least developed of all.

It is understandable that the *Guide* shies away from methodological normativity, especially given the Commission's strong prescriptivism with respect to the goals of national and regional R&I strategies. However, this 'official' document, as well as most of the other literature published so far (implementation studies are only beginning to see the light of press), do leave a gap between theory and practice. Authors such as Kroll (2015b: 1) have lamented the fact that "policy practice . . . soon overt[ook] the ongoing conceptual development of the RIS3 approach so that it became increasingly difficult to disentangle what was core to the concept and what had evolved around it for practical policy-oriented reasons." Be that as it may, we feel that part of the problem resides precisely in the failure to provide a practical blueprint for entrepreneurial discovery capable of matching the 'core concept' of smart specialization. Admittedly, such a blueprint should only be offered as a model – ideally, one among others –, not as a standard procedure to be followed to the letter. However, a self-consistent toolbox may serve governments faced with the problem of designing an ED process better than a large assortment of methods and devices such as those identified in the *Guide*. The latter's mix-and-match six-step design, while a good summary of potentially relevant tools, is probably too eclectic to even approximately fit the square pegs of ED practice into the round holes of smart specialization theory.

The toolkit to be introduced in the following sections is built on foresight principles, which we find almost ideally suited for the entrepreneurial discovery process. The latter, and smart specialization as a whole, has an important 'self-discovery' rationale. As Foray (2015) himself clarifies, this notion is inspired by the developmental economics of Hausmann and Rodrik (2002). In their view, government intervention should be directed, among others, at helping both entrepreneurs and decision-makers discover new profitable products, not least by overcoming informational externalities which threaten low returns from innovation to the private entrepreneurs. As entrepreneurial knowledge is typically dispersed locally, Foray (2013: 61) argues that "[e]ntrepreneurs in the broadest sense (innovative firms, research leaders in higher education institutions, independent inventors and innovators) are in the best position to discover the domains of R&D and innovation in which a region is likely to excel given its existing capabilities and productive assets." This broad view of a more ambitious

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form of governmental intervention, made possible by an equally broad exploratory partnership with key actors, has become increasingly accepted in the EU against the backdrop of the recent drive towards the 're-industrialization of Europe' in the wake of the economic crisis (Westkämper, 2013).

That said, the national or regional government's twin roles of (co-)discoverer and priority-setter render it particularly vulnerable to questions of legitimacy. The dialogue with key actors and stakeholders who hold the 'place-based' and specialized knowledge needed to make self-discovery possible must (appear to) be impartial and embedded in a process that extends beyond the setting out of priorities. It should also secure actors' support for the prioritizing of investments which, at least on the short term, may be perceived by some as favoring their indirect competitors or privileging other subsectors. Under such a setup, a 'broad participatory' foresight process seems particularly well-suited to ensuring both dialogue and legitimization through consensus-seeking mechanisms.

#### 3. Outline of a toolkit for smart specialization and entrepreneurial discovery

Detailed presentations of the designs of national or regional foresight-based RIS3s are only now beginning to emerge. Paliokaitė et al. (2015, 2016), for instance, describe the complex, three-stage foresight carried out in Lithuania. Mieszkowski and Kardas (2015), to take another example, examine the more limited use of foresight as a stakeholder involvement tool in a rather broad range of recent Polish sectoral and regional priority-setting exercises. Our aim herein is different, the article's goal being primarily to outline a consistent set of tools and a generic procedure integrating them. Some of these tools have already been developed, and several of them were employed in the Romanian RIS3 exercise. The design of the latter process is presented elsewhere in detail (Gheorghiu, Andreescu, & Curaj, 2016), and will be used here occasionally to illustrate the use of (components of) the toolkit, but it will not be discussed systematically.

Briefly stated, for the purposes of an entrepreneurial discovery process design we understand smart specialization in the following way:

- as a process aimed, primarily, at constructing shared visions concerning future economic opportunities building on research, development, and innovation;
- with the exploratory and the prioritization components occurring mostly at the level of small innovation ecosystems; and
- with the state playing several roles, among which those of a co-discoverer, a facilitator, and a priority-setter.

As noted already, the exploratory nature of the entrepreneurial discovery process and the latter's priority-setting objective are potentially fraught with issues of legitimacy. Coming to terms with these issues is ripe terrain for a broadly participatory design, particularly where the strategy-making process involves an entire nation (as in various countries in the CEE primarily, but not exclusively). Since the state must eventually "empower[] those actors who are more capable of realizing [the country or region's economic] potential", a wide spectrum of actors – such as "innovative firms, research leaders in higher education institutions, independent inventors and innovators" – must be involved in a process seeking to build "external organizations of connections with universities, laboratories, suppliers, users" (Foray & Goenaga, 2013: 5). However, this raises inescapable dilemmas of stakeholder involvement, as well as of evidence gathering and presentation—a central topic in the literature on participation in foresight (van de Kerkhof & Wieczorek, 2005; van der Helm, 2007). The packaging of evidence is particularly important in this context, not least because it needs to empower participants both to apprehend the RDI ecosystem and its parts, and to better locate themselves in the ecosystem.

We submit that a foresight exercise for entrepreneurial discovery should meet at least three broad conditions, the first related to inputs, the second concerning the process, and the third respecting the outputs. Specifically, foresight for ED should:

- provide 'inclusive' evidence;
- enable argument-based exploration of prioritization options; and
- aim at consensus concerning the selection of priorities based on shared assumptions with respect to the research and innovation ecosystem.

From this perspective, evidence is 'inclusive' when it reaches beyond the typical bird's-eye-view of the RDI ecosystem consisting of standard indicators of innovation and/or research activity. Rather, the evidence should enable the *individual* actors (whether persons or organizations) involved in the process to locate their own position on the 'systemic map' relative to other similar actors or their activities. Not only does this provide participants with a better understanding of their niche; it also gives them a clearer sense of their niche's position within the wider ecosystem.

The argument-based exploration of prioritization options is particularly important if the foresight exercise is widely participatory, as should be the case with entrepreneurial discovery. It allows actors and stakeholders participating in consultations and other forms of interaction to support their proposals and assessments of potential priority fields with substantive arguments, rather than simple estimates derived from available indicators and other similar quantitative information.

To the extent to which it is achievable, the consensus on the selected priorities should reflect shared assumptions with respect to the RDI ecosystem. In fact, the process of reaching such assumptions should capitalize on the 'inclusive' evidence

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and the argument-based nature of the exploration. The latter are expected to provide the communal – in the sense of shared or mutually acknowledged – underlying premises of any consensus.

In the subsections below, we outline the entrepreneurial discovery toolkit and its main components as we see them. We then briefly present the Romanian experience so far in relation to those elements in the toolkit that were developed in this country in the RIS3-making process or in parallel with it. In a nutshell, the toolkit consists of the following main 'compartments':

- Ensuring ecosystemic transparency, where we see data analytics playing an increasingly leading role;
- Mapping emerging global trends, among others though horizon scanning mechanisms such as technological radars for weak signals;
- Entrepreneurial dialogue, through consensus-seeking consultation instruments involving broad participation; and
- Public policy alignment, for the achievement of which specific governance arrangements for entrepreneurial discovery may have to bet set in place.

#### 3.1. Ecosystemic transparency: data analytics and beyond

The main principle behind the idea of ecosystemic transparency is that of 'inclusive' evidence. As described above, this entails moving beyond descriptions of the RDI system in terms of "hard-boiled indicators" (Wolters, 2007), towards evidence enabling individual actors to locate their own position on the 'system map' relative to other similar actors and their activities.

The self-discovery/entrepreneurial discovery process depends on "fine-grained observation and detection capabilities on the part of the policy makers" (Foray, 2013: 72). The latter need analytical evidence for the prioritization process, both in its substantive dimension (the output, i.e., selected priorities *perse*), and in its procedural one (for legitimation purposes, among others). To this end, an extensive dialogue with members of the RDI ecosystem is essential, as usually emphasized in connection with national foresight practice (e.g., Gavigan & Scapolo, 1999). At this juncture, the decision-makers act not as planners, but as "humble" mediators, a point underscored in both the smart specialization (Foray, 2015: 73) and the foresight literature (Havas, Schartinger, & Weber, 2010: 95).

It is worth emphasizing here that not only does the decision-maker lack omniscience in this type of exploratory context; the organizational or individual actor itself frequently has somewhat limited information on its relevant environment, including the position of its more familiar niche within the larger, systemic context. While organizational actors have often been regarded in policy circles as the main locus or holders of 'distributed' information, this should not be taken to imply they are also necessarily well-informed (except, perhaps, if the central planner is taken as a yardstick). They may hold an advantage over the central decision-maker, which is precisely the reason why the latter is 'demoted' to the position of a mediator tasked with ensuring communication channels and incentives across the different actor categories (Aghion, David, & Foray, 2009). In truth, however, even in today's increasingly better and more widely networked RDI systems, actors have relatively limited information about the world outside their immediate environments. Indeed, the latter are, in fact, the product of highly individualized organizational histories (Schein, 2010) which may generate informational blind spots.

This is perhaps especially true of more fragmented RDI systems, where organizational and individual actors' 'field of vision' is frequently limited to their customary environment, but it is certainly the case in more integrated ecosystems as well. Hence the need to enable actors to 'see themselves' and in relation to the broader system—what we have dubbed above 'inclusive' evidence. Such evidence should enable RDI actors to spot shared or similar interests, as actually revealed in, for instance, publicly-funded projects, patents or publications; to visualize potential and real networks of collaborators extending beyond the typical organizational horizon; to appreciate the strength of inter-organizational relationships by comparing them with similar links between other research & innovation organizations (perhaps also in other fields); and to estimate the extent to which organizational interests, competences, and collaborative links overlap with those of other local or regional businesses. In a nutshell, 'inclusive' evidence enables actors to appreciate 'where they stand' in complex networks of actors and relationships.

The main challenge, besides acquiring such complex systemic data, is to package it in formats that are simultaneously informative, simple to communicate, easy to absorb, and comprehensive. We believe that data analytics tools, now relatively widely available, sometimes for free, are well suited to this task. They enable policy-makers acting as facilitators in processes of entrepreneurial discovery to design and present intuitive social network analyses (SNA) on organizational and individual actors. These can be translated into visually appealing, easily graspable graphs and maps.

#### 3.1.1. Our experience

For illustration purposes, below are a few 'snapshots' from a data analytic approach to providing 'inclusive' evidence in the process of designing Romania's national RIS3. The process took place in 2013 and early 2014 and, as noted above, is described in detail elsewhere (Gheorghiu et al., 2016). This source also provides details on how data analytics were embedded in the entrepreneurial discovery procedure, and we invite the reader to consult the details there. We will only note here that the data analytics fed into various key stages of the priority-setting process, including the sampling of actors and stakeholders for broad online consultations, as well as for numerically much more restricted panel work.

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The graphs below were built with a SNA package developed for, among others, the intelligence community; an open-source graph manipulation software; semantic analysis software; and (not included among the samples below) a well-known Geographic Information System (GIS) package for geographical data. The graphs are zoomable and searchable: for example, organizations and individuals looking for their projects and their organizations on the 'map' can effortlessly determine their position in the network; or they may simply explore in additional detail various agglomerations to locate the organizations or projects or publications serving as major nodes (Figs. 1–3).

Among the key advantages of using data analytics in the ways described above is that it may mitigate the so-called "translation problem", namely, bridge the gap between broad participatory processes and decisions at the level of individual organizations (Havas et al., 2010: 94). Specifically, the 'inclusive' evidence provided through such tools is designed not only to serve the broader, collective strategic processes but, as noted previously, also to impart new information to the participating organization or individual. Since the latter should now be enabled to understand themselves more clearly in a wider, interdependent context, one expects this information to be useful for decision-making at organizational or individual level as well. Ideally, this should connect the 'network' or systemic dimensions of the broader foresight process with the more 'local' policy-making levels.

This being said, the additional challenge remains that of moving beyond not only 'hard-boiled indicators', but also 'traditional' data sets such as those used in the analyses briefly introduced above (large databases of nationally funded competitive R&D projects, patents, research publications, and so on). Other types of data, for example that provided by research & innovation social networks, should arguably be able to provide a much richer view of the RDI landscape. Governments, regional and central, may play a key role in this respect too. In Romania, for example, a public agency for research and innovation funding (UEFISCDI) was responsible for a social network-like platform enabling public and private research organizations (ROs) to provide research infrastructure booking services. The platform (www.erris.gov.ro) has been online since summer 2015 and, as of this writing (roughly 9 months after launch), it boasts over 250 infrastructures. BrainRomania, a more ambitious social network portal for the 'global' Romanian R&I community, is in the making by the same agency.

It is too early to say whether and to what extent the initiatives above will work on the longer term; and to know how the data they yield will be leveraged. Some of the successful global social networks for academics or researchers (such as ResearchGate or Academia.edu) suggest there is, at least, some hope. The promise held by data analytics in the collection and structuring of 'inclusive' evidence and for increasing the transparency of R&I ecosystems is, we submit, considerable.

#### 3.2. Mapping global trends: horizon scanning with a technological radar for weak signals

The importance of awareness of emerging global trends hardly needs to be emphasized to a futures studies audience such as the readership of this journal. For the more specific purposes of smart specialization, horizon scanning can provide crucial information on decisive subjects such as short cycle technologies (Lee, 2013), peripheral trends (Day & Schoemaker, 2005; Haeckel 2004), or opportunities arising in connection with key enabling technologies.

As a second major source (besides social network analyses) of 'informational input' into a foresight-based ED toolkit, we envisage horizon scanning as an instrument whose primary output is data on so-called 'weak signals' (WS). The latter term is relatively familiar in the foresight community and we will not insist on it here beyond a brief description. In a pioneering

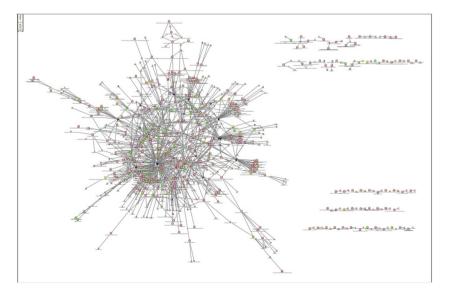


Fig. 1. A clustering of institutions and projects in the field of 'Energy'.

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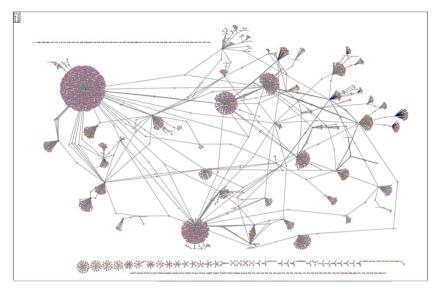


Fig. 2. A clustering of institutions and their projects, articles and patents in the field of 'Agro-food'.

article, Ansoff (1975) characterized weak signals as premature and somewhat vague information on discontinuities or surprising threats and opportunities for the organization. The strategic significance of weak signals was aptly defined by the same author in terms of the "apparent paradox" that if the firm "waits until information is adequate for strategic planning, it will be increasingly surprised by crises; if it accepts vague information, the content will not be specific enough for thorough strategic planning". He consequently recommended "graduated response through amplification and response to weak signals, in contrast to conventional strategic planning that responds to strong signals." (Ansoff, 1975: 23) Starting from this general treatment in relatively traditional management science approaches, research on weak signals quickly took off and gained particular popularity in the futures studies community (Hiltunen, 2006, 2008; Mendonca, Pina e Cunha, Kaivo-oja, &

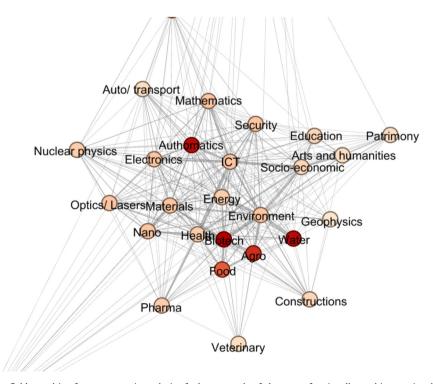


Fig. 3. Linkages among fields resulting from a semantic analysis of a large sample of abstracts of nationally- and internationally-funded projects.

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Ruff, 2004; Rossel, 2012; Schoemaker & Day, 2009), yielding increasingly sophisticated techniques of identification (e.g., Thorleuchter & Van den Poel, 2013).

#### 3.2.1. Our experience

A functional weak signal radar faces significant challenges. In broad terms, perhaps the three most important ones are the following:

- finding good inputs, i.e., a large and varied number of relevant sources of technological news and other information;
- designing a good signal-filtering system, i.e., keeping the feed of potential WS both relevant and numerically manageable, so as to prevent informational overflow; and
- generating useful categories of weak signals.

In response to these challenges, we piloted – in an experimental stream parallel to the 'official' RIS3-making exercise described by Gheorghiu et al. (2016) – a radar for technological weak signals. Its ultimate goal is to grow into a fully-automated procedure, among others with the assistance of artificial intelligence (specifically, machine learning AI based on natural language processing).

The main design idea of the pilot was to rely, in selecting and categorizing weak signals, not so much on pre-existing theoretical classifications (which in our experience proved practically cumbersome), but rather on a 'tacit knowledge' approach (Collins, 2010). To that end, the design of a technological WS radar relied on building a community of practice consisting of 'generic weak signal processors' (in our case, graduate students), rather than on experts. Improvement in the quality of filtering was achieved through structured game-like interaction, on the assumption that through many iterated negotiations participants will develop 'group intuition' with respect to weak signals. Ultimately, knowledge derived from group interaction can be codified into stable categories devised as part of the process, while the signals get sorted into weak-signal classes and non-WS.

The process outlined above was carried out via a platform dubbed *TAGy* (see Fig. 4). In the procedure, a flow of 'signals' (potentially weak and otherwise) is fed to randomly selected groups of two processors, who categorize them following a strict negotiation procedure. In very brief terms, if the processors (or taggers) agree on the first trial with respect to the

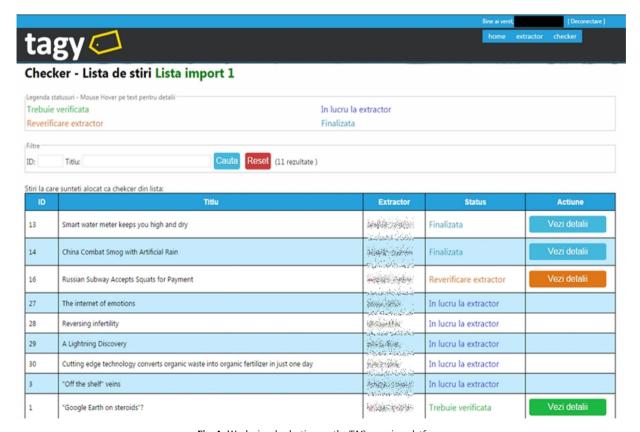


Fig. 4. Weak-signal selection on the TAGy gaming platform.

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classification – into weak signals or not, and, if the former, into the appropriate weak signal category –, the selection ends. Disagreement leads to a negotiation based on an argumentative procedure.

After a one-year piloting phase, the technological WS radar briefly described above has selected approximately 7200 weak signals out of some 152,000 candidates. Of over 400 initially pre-selected electronic sources of information, more than 200 are currently active, after an additional selection procedure tracking the flow of information and particularly duplication among the sources (via repurposed plagiarism software). The current repository consists of 740,000 pieces of information, of which more than fifty percent date from 2015. According to our experience in the pilot, it is possible to evaluate monthly some 15,000 distinct pieces of information (such as news, articles, etc.) with a pool of 16 (trained) individuals taking part in the *TAGy*. Pre-filtering the data with the AI instrument based on natural language processing (NLP) developed during the same project, we estimate that a monthly flow of 30,000 pieces of information can be categorized by 8 persons under the same conditions.

#### 3.3. Entrepreneurial dialogue

It is not within the scope of this paper to describe in detail the weak signal radar outlined above, but simply to suggest that it may prove a worthwhile instrument in foresight-based entrepreneurial discovery. Indeed, there are potentially many ways to design and put to use a 'strategic radar' system. Schoemaker, Day, and Snyder (2013: 816), for instance, recommend "a scenarios-based system for integrating the scanning as well as monitoring of external signals, the assessment of possible strategic responses, and any follow-up probes to amplify interesting signals". Many other options are possible. In our own effort to elaborate the Romanian RIS3, we tried out feeding information concerning the technological week signals into exploratory 'entrepreneurial workshops' bringing together a variety of actors and stakeholders to examine the future of research and innovation across economic sectors. In a couple of such experimental workshops organized in Romania in parallel with the RIS3 elaboration process, the radar-derived weak signals were employed to probe into future uses of ICT in agriculture. WS-based exploration was embedded in a World Café format and resulted in visions for the economic subsector in question. This or similar procedures may become an essential part of the entrepreneurial dialogue discussed in this subsection.

The entrepreneurial dialogue represents, in a sense, the centerpiece of the ED toolkit outlined here. We have already discussed the central or regional government's role as facilitator, as co-discoverer, and as priority-setter. There are potentially many ways to structure the dialogue, but a generic template would most likely include the following four stages (see also Gheorghiu et al., 2016):

- Initiation
- Exploration
- Consolidation
- Commitment

During the initiation phase, the preliminary evidence base is collected and structured (for example, the social network analyses and graphs presented in Section 3.1) and the participants in the various stages are selected, partly based on the information provided by said evidence (for example, the most connected researchers, the SMEs most reliant on R&I, and so on). The exploration stage relies on exposing participants to information derived from horizon scanning (e.g., the technology radar) and from social network analyses; this process is aimed at eliciting further information – and creativity – from the participants. This can be done in a variety of formats and through a spectrum of established consultation procedures. One option is the cross-sectoral, scenario-building 'entrepreneurial workshop' mentioned in the previous paragraph.

In an ED design specifically aimed at prioritization, the exploratory phase may consist of an initial collaborative selection of a large set of potential smart specialization fields, followed by a similarly participative narrowing down process. The latter would enable the argument-based exploration of prioritization options, one of the three aforementioned principles of a foresight-based ED design. The consolidation stage, on the other hand, entails the construction of a set of detailed scenarios for the shortlisted fields of smart specializations obtained after the narrowing down process in the exploratory phase. Participants in the consolidation process 'look over the horizon' in order to match the local ecosystem and the global emerging trends and other developments of interest. Finally, in the commitment phase, the final selection of S2 priorities is made.

#### 3.3.1. Our experience

The key to a successful entrepreneurial dialogue is basing the priority-selection agreement on shared assumptions with respect to the research and innovation ecosystem. Once again, this can be achieved in a variety of ways, depending on the specifics of the exploration and consolidation stages, where such consensus-seeking procedures play an essential role. This being said, it is arguably easier to achieve an argument-based consensus within small panels or facilitated workshops; the standard becomes harder to satisfy as the number of participants increases substantially. To do so with thousands of participants, we used in both the exploratory and the consolidation phases of the Romanian RIS3-making foresight a 'dynamic argumentative Delphi' (DAD) online consultation procedure (for details, see Gheorghiu, Andreescu, & Curaj, 2014) which expands on previous experiences with online roundless or multi-round Delphis (Gordon & Pease, 2006; Gnatzy, Warth, von der Gracht, & Darkow, 2011). The DAD served, firstly, in gathering proposals concerning promising R&I programs

inovare promitatoare?

quantitative

assessment

Va rugam evaluati

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Criteriul 2. Relevanta provocarilor pentru CD In ce masura considerati ca subdomeniul Mai jos gasiti o serie de arii de cercetare-inovare prin care alti experti si-au sustinut raspunsul la intrebarea din partea stanga propus cuprinde arii de cercetare-Va rugam sa justificati raspunsul dvs. selectand cel mult 3 afirmatii dintre cele de mai jos si/sau introducand o afirmatie noua. Nota: Cifra din paranteza care apare dupa fiece afirmatie indica numarul de experti participanti la consoltare care au selectat deja afirmatia respectiva Ohs Aceste arii nu se refera in Proiectarea si de voltarea de noi algoritmi de calcul paralel pentru: a) modelarea, simularea si analiza sistemelor complexe din domeniul fizicii, chimiei, stiintelor vietii, stiintelor spatiale, ingineriei, materialelor; b) modelarea si simularea pomerica a evolutiei sistemelor sociale; c) prognozare in meteorologe si hidrologie; d) analiza imaginilo exclusiv la cercetarea romaneasca.) e) proiectare industriala. (171) Cercetari in calcul de inalta performanta referitoare la algoritmi paraleli pentru diverse domenii aplicative (data g, calcul evolutionar, optimizarea microdispozitivelor, geometrie computationala, grafica pe calculator, cesarea imaginilor etc). (146) argumentative Dezvoltarea de metode numerice noi, concepute pentru programarea paralela pe noi arhitecturi hardware multicore. GPLJ. GPGPU). Paralelizarea pentru noile arhitecturi hardware a aplicatiilor secventiale si a bibliotecilor support ftware existente. Programarea si optimizarea codurilor de calcul paralel hibrid (MPI + memorie partajata). (100) Abordarea prin metode HPC a unor tematici de varf pe plan mondial (calcul evolutionar, simularea sistemelor cu enimente discrete, modelare neuro-fuzzy, calcul simbolic, etc.). (49) ezvoltarea noilor modele computationale și HPC nu este apanaiul doar al specialistilor din tehnologia informatiei și unicatiilor ci presupune o intensiva colaborare cu cercetatorii domeniilor tinta. (21) Domeniile: procesarii automate a semnalelor audio video sau a extragerii de cunostinte din text pot fi sprijinite de dezvoltarea tehnologiilor de calcul. (13) Intreg algenalul de cunostinte din ITC, teoretic si aplicat, atat din directia stiintei calculatoarelor precum si din cel a intreg arrenator de conostinte dir II.C., teoretic si aplicat, atact diri directa stimiter calculatoratero precum si diri cei a electronicini 2 telecomunication (inclusiv cu sprijin diri stimita materialelor) se suprapune pe urmatorarele traiectori spre 2020: I. Torcen computing (HPC economic dpdv energetic/un centru de calcul consuma in medie 10M/M/. 2. small scale suprecomputing (supercomputing acasa si la birou). 3. HPC BigData, procesarea si gestionarea rezultatelor de ordinul 2ctaoctetilor. (9)

Fig. 5. Quantitative assessment and dynamic ranking of arguments in a roundless online Delphi.

de date, bazate pe calcului de inalta performanta si noi modele computationale (8)

prelucrare de continut, definit de sine statator) (5)

Dezvoltarea de metode, tehnici si algoritmi de analiza si recunoasterea formelor, capabile sa proceseze volume mati

Se constata o suprapunere intre cum e definit subdomeniul si subdomeniul Big Data (subdomeniul tehnologiilor de

in potential priority fields (exploration stage); and, subsequently, assisted in the final shortlisting of smart specialization fields (consolidation phase).

As described in another paper (Gheorghiu et al., 2016), the consolidation-phase online consultation was particularly intensive. Participants were asked to evaluate scenarios for the shortlisted S2 subfields (R&I programs), with the emphasis placed on approaching an argument-based consensus. The latter entails not simply a quantitative evaluation of the scenarios in question, but also offering explicit justifications to support the quantitative assessment. These justifications or arguments become visible to all (subsequent) participants in the Delphi exercise, who are asked to consider them – either by selecting the most convincing ones, or by adducing new justifications - in supporting their own quantitative estimates (see Fig. 5).

More than 4000 RDI actors and stakeholders took part in the online consultation of the consolidation stage of the Romanian RIS-building process. A total of 90 R&I programs (scenarios) in 13 potential smart specializations were assessed by the participants (each of whom selected one or, at maximum, two fields of expertise). The average number of evaluators per scenario/survey sheet was 161, with the lowest number of responses for a sheet at 36 (only 8 sheets out of 90 had less than 50 respondents). As expected in light of previous DAD experience, the number of arguments per survey question remained, with a few exceptions, within limits easily manageable by a respondent. As can be gleaned from Fig. 6, the vast majority of

### Distribution of no. of new arguments

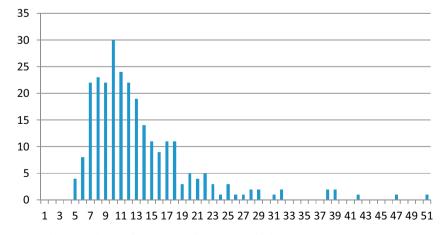


Fig. 6. Distribution of the number of participant-added arguments per survey question.

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the relevant scenario-evaluation questions had between 7 and 20 justifications. An in-depth discussion of the DAD method is available in Gheorghiu et al. (2014).

#### 3.4. Public policy alignment

We describe the final element of our proposed toolkit only in overly broad terms, perhaps because this part is also the least amenable to a clear procedural structure and depends considerably on the conditions on the ground, in the nations and regions where smart specialization is being pursued. The prioritization achieved through the process of entrepreneurial discovery signals a change of paradigm in industrial policy, where an agile government must now bet on promising economic activities – sometimes, arguably at the limit of competition regulations – by working intensively with small ecosystems of actors. In its early phases, entrepreneurial discovery may involve a partial decoupling from the general R&D policies. At least in some regions or nations, the smart specializations will initially be little more than a sandbox experiment, though one designed to increase gradually in scope and in importance relative to the rest of research and innovation policies.

This signals the need for of a clear mechanism to integrate the smart specializations in the policy space of research, development, and innovation. Depending on the national or regional context, this will in turn entail a specific governance system for the entrepreneurial discovery process. Recent studies show that, in some Nordic and Central European regions, existing policy practices in research and innovation were already suitable for smart specialization strategy building. As a result, given their "long experience and strong capacities in strategy building" these areas "did not gain substantially new insights through their RIS3 processes" (Kroll, 2015a: 2095). On the other hand, as suggested by the early studies on implementation in Central and Eastern Europe (Karo & Kattel, 2015; Paliokaitė, Martinaitis, & Sarpong, 2016), a distinct governance scheme may have to be put in place and permitted to function outside the usual policy routines.

#### 3.4.1. Our experience

To return now to our experience in Romania, the three main steps in policy alignment are, again in broad terms and at this early phase of implementation:

- the introduction of smart specializations in competitive project funding and in project-based structural funding;
- investments in research and in innovation infrastructures, in line with the priorities and with an infrastructure roadmap to be devised in the near future;
- correlation with regional development policies, for example through projects such as the 'Laser Valley', an urban development project which seeks to capitalize on the construction, close to Bucharest, of a pan-European research infrastructure (the ELI-NP laser).

As to the governance of this process, three organizations are 'under construction' at this point:

- an inter-ministerial Competitiveness Council, which will ensure, among others, coordination and the integration of smart specializations in policies across the relevant sectors;
- at the more operational level, an Innovation and Entrepreneurship Council; and
- a network of regional 'R&I scouts', who support the collection of quantitative and qualitative data and, more generally, participate directly in the regional entrepreneurial discovery exercises.

#### 4. Conclusions

Scholars of smart specialization have understood early on how risky the S2 proposition may appear in the eyes of European policy-makers. Great efforts were expended on justifying it conceptually. One of the claimed rationales of smart specialization is that of catalyzing 'distributed innovation' by ensuring knowledge sharing and spillovers within an RDI ecosystem whose actors often have competing interests. As Powell and Giannella observe (2010: 578), betting on a set of technologies can lead "firms and nonprofit organizations to contribute their efforts to a community endeavor that drives collective invention despite the lack of apparent economic gain to any particular organization". Indeed, as argued by one of the prominent representatives of new development economics, from "an efficiency standpoint, the only legitimate ground for promoting certain industries over others is that the promoted industries are a source of technological externalities—benefits from technological innovation that spill over from the innovating firm to other firms or sectors" (Rodrik, 1994: 32).

While this does lend theoretical support to the prioritization of knowledge investments at the heart of smart specialization, it remains equally true that the singling out of 'most favored' R&I niches is a politically sensitive task. Particularly when it comes to knowledge, the selection, premised as it is on the economic and social relevance of RDI, is sometimes viewed as unacceptable cherry-picking. It may also be seen as threatening blue-sky research, which – the typical argument goes – should be broadly supported for its unforeseeable benefits.

The dangers of (appearing to) 'pick winners' can be limited both by opening the prioritization process to broad participation and by deepening the evidence base, i.e., making it more transparent, more accessible, and more relevant to the individual participant. We suggest that one way of achieving this is by recourse to a 'foresight-based toolkit for

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Fig. 7. From serial to semi-continuous large-scale foresight.

entrepreneurial discovery', which may contribute eventually not only to greater acceptance of smart specializations, but also to better input from actors and stakeholders during the ED process. While foresight procedures have been called on to ensure that the selection of smart specializations is (self-)reflective and collaborative, wide consultations will also amplify the difficulty of reaching a consensus on a narrow set of favored R&I niches, particularly since potentially many innovators and researchers stand to lose individually. Legitimacy has to be built on the foundation of a rich evidence base rendering the R&I ecosystem transparent; and a procedure that enables an argument-based agreement on prioritization relying on communal assumptions about the R&I ecosystem.

As to the first point above, we submit that data analytics may help bridge evidence-based selection and argument-based consensus in several ways.

- First, by improving actors' and stakeholders' understanding of the system and of themselves in it by placing each of them in the picture, so to speak -, data analytics may assist them in participating more reflexively.
- Secondly, data analytics proves adept at generating shared evidence, that is, evidence that can easily be translated in a common language precisely because it provides participants with context, including their own, and the opportunity for comparative judgment.
- And thirdly, and as a result, in combination with large-scale consultation processes (such as online Delphi), data analytics tools may enhance the argumentative foundation of foresight exercises for smart specialization.

Thus, unlike the more traditional, serially organized large-scale foresight, foresight based on data analytics, horizon scanning, and argumentation has the necessary ingredients to become – as in Fig. 7 – iterative, perhaps even continuous. This has been long regarded as a (perhaps the) desirable format in the literature (e.g., Salo, Könnölä, & Hjelt, 2004), though most practitioners have also recognized it is a comparatively rare occurrence (Dufva & Ahlqvist, 2015). It also fits well the standards of an entrepreneurial discovery process, which Foray (2015: 31) describes as "a decentralised dynamic process that should ensure the continuous transformation of productive structures through research and innovation".

The prospect of an iterative foresight-based entrepreneurial discovery process deployed at regional or national scale may sound overly optimistic. Yet it may also be the case that smart specialization as an ex ante conditionality could instate just the right kind of incentives to turn foresight-inspired ED into a continuous practice. It should also be stressed, though, that the previous discussion barely scratches the surface of the broader implications of using data analytics tools in foresight. One can envisage a number of significant challenges. Some of the more obvious ones involve questions of access to and protection of information. A more serious dilemma involves the neutrality of information collected and processed through typical 'big data' procedures. The many options available to data analysts - and their public or private employers - could render such information easier to manipulate. This being said, if used as a facilitating mechanism rather than as a control tower, we believe the toolkit could be a game-changer for large-scale foresight for entrepreneurial discovery.

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