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Invited Review

OR for entrepreneurial ecosystems: A problem-oriented review and agenda

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ABSTRACT

Innovation-driven entrepreneurship has become a focus for economic development and received increasing attention from policy makers and academics over the last decades. While consensus has been reached that context matters for innovation and entrepreneurship, little evidence and decision support exists for policy makers to effectively shape the environment for growth-oriented companies. We present the entrepreneurial ecosystem concept as a complex systems-based approach to the study of innovation-driven entrepreneurial economies. The concept, in combination with novel data sources, offers new opportunities for research and policy, but also comes with new challenges. The aim of this paper is to take stock of the literature and build bridges for more transdisciplinary research. First, we review emergent trends in ecosystem research and provide a typology of four overarching problems based on current limitations. These problems connect operational research scholars to the context and represent focal points for their contributions. Second, we review the operational research literature and provide an overview of how these problems have been addressed and outline opportunities for future research, both for the specific problems as well as cross-cutting themes. Operational research has been invaluable in supporting decision-makers facing complex problems in several fields. This paper provides a conceptual and methodological agenda to increase its contribution to the study and governance of entrepreneurial ecosystems.

1. Introduction

Innovation-driven entrepreneurship has become a focus for economic development and received increasing attention from policy makers over the last decades. More recently, attention has shifted from the quantity to the quality of entrepreneurship, i.e., those businesses that have the opportunity to scale and make a significant impact (Stam, 2015). While consensus has been reached that context matters in entrepreneurship, little evidence and decision support exists for policy makers to effectively shape the environment for productive entrepreneurship (Autio, Kenney, Mustar, Siegel & Wright, 2014; Welter, 2011; Wurth, Stam & Spigel, 2021). In response to these developments, the entrepreneurial ecosystem (EE) concept has been introduced as complex systems-based approach to the study and governance of entrepreneurial economies. The concept has been widely adopted by academics and policy makers alike (e.g., Mason & Brown, 2014; World Economic Forum, 2014; Startup Genome, 2020).

There is no universally applied definition of EEs, although most studies adopt a view of EEs as an interdependent set of elements (based on Isenberg, 2010) or actors (entrepreneurs and other economic actors and stakeholders) that interact within a particular (regional) environment and its resources and institutions (based on Stam & Spigel, 2017). Similarly, Mason & Brown (2014, p. 5) define an EE as "a set of interconnected entrepreneurial actors (both potential and existing), entrepreneurial organizations (e.g., firms, venture capitalists, business angels, banks), institutions (e.g., universities, public sector agencies, financial bodies), and entrepreneurial processes (e.g., business birth rate, numbers of high growth firms, levels of 'blockbuster entrepreneurship', number of serial entrepreneurs, degree of sell-out mentality within firms, levels of entrepreneurial ambition) which formally and informally coalesce to connect, mediate and govern the performance within the local entrepreneurial environment." In a broader sense, EEs can be studied as (eco)systemic agglomerations of organizational and institutional entities or stakeholders with socio-technical, socio-economic, and socio-political conflicting, as well as con-

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verging (co-opetitive) goals, priorities, expectations, and behaviors that they pursue via entrepreneurial development, exploration, exploitation, and deployment (DEED) actions, reactions, and interactions (Carayannis, Grigoroudis, Campbell, Stamati & Meissner, 2018a).

In the absence of a central controlling unit and explicitly focusing on entrepreneurial agency, which differentiate EEs from, for example, cluster initiatives, EEs show self-organizing behavior and its actors coordinate themselves in order to produce entrepreneurial behavior as a systemic output, which contributes to socio-economic development as a higher-level outcome (Stam, 2015; Wurth et al., 2021). EEs, therefore, provide a new way of conceptualizing the context of innovation and entrepreneurship. While there is a growing consensus of who the relevant actors and factors in regional EEs are, there is still a lack of a comprehensive and consistent theory as well as a deep understanding of the mechanisms that give rise to the dynamics in EEs.

Operational research (OR) has been invaluable to support decision-makers (DMs) facing complex problems in fields such as health (Brailsford & Harper, 2008), disaster science (Farahani, Lotfi, Baghaian, Ruiz & Rezapour, 2020), supply chains (Barbosa-Póvoa, da Silva & Carvalho, 2018; Wang, Wallace, Shen & Choi, 2015a), or intermodal freight transportation (Crainic, Perboli & Rosano, 2018). The last field, for example, can be studied as "a multi-actor complex system involving a broad range of interacting stakeholders, decision makers, operations, and planning activities" (Crainic et al., 2018, p. 401), which bears many similarities in terms of the underlying system structure to EEs. With widespread links to these areas, OR has evolved into an established field of research on its own, a 'melting pot' for theoretical and methodological approaches from these other disciplines, "aligned with humanitarianism, improved living and working conditions, sustainability, safety and fairness […] whose ubiquity will only intensify further in the coming years".[1] This is particularly relevant due to the rising socio-economic complexity and the increasing availability of data that requires rigorous approaches for data cleaning, analysis, and interpretation.

Despite these trends and its track record of contributions to a variety of fields and the expertise in the OR community, OR has been overlooked in the study and practice of EEs for the most part (similar to developments in 'network science', see Alderson, 2008, or 'sustainable development', see White & Lee, 2009). Similar to these two exemplary areas of application, there is not one single OR tool or approach suitable to address all issues. Instead, methodological pluralism both across different questions or problems related to EEs and potentially within the realm of individual questions (e.g., mixed method or hybrid approaches) will lead to a better understanding of the dynamics of EEs. Only more recently has there been an increasing interest from OR scholars in topics related to innovation, entrepreneurship, and socio-economic development, although not necessarily referring to the EE concept. Inversely, OR tools and techniques are starting to gain traction and attention in other communities related to EE research. The adoption of OR approaches in EE studies appears, to have the following important characteristics:

a) The published research in this field is rather fragmented across the domains of management, engineering, and public policy, among others.
b) There is a wide range of OR methods and techniques that have been or could have been applied to EEs.
c) From an OR perspective, the studies published in this field refer to very different decision-making problems.

The aim of this paper is to take stock of the literature and build bridges for more transdisciplinary research. This goes beyond the application of particular methods and also involves a more problem oriented approach to studying the context and dynamics of entrepreneurship. To this end, we first review emergent trends in ecosystem research and provide a typology of four overarching 'problems' based on current limitations. These problems connect OR scholars to the context and represent focal points for their contributions.

Second, we review the OR literature and provide an overview of how these problems have been addressed to date and outline gaps for future research. Due to the lack of a comprehensive EE theory, we focus on these higher-level problems as opposed to either providing an overview of OR applications to the EE concept as a whole or structuring the review based on different (families of) methodologies. These problems also cut across the previously described heterogeneity in terms of outlets and conceptual bases (e.g., EEs, national/regional innovation system, innovation networks). While a more wide-spread application of OR methodologies and tools can support researching EEs and policy design, our review also highlights the need for further methodological innovation to address the complexity of EEs.

The remainder of this paper is structured as follows. In Section 2, we elaborate on the status quo of EEs, discuss the foundations and limitations, and derive the four problems. In Section 3, we review and synthesize the literature for each problem, followed by an aggregated agenda beyond the individual problems for future research and opportunities for OR scholars in Section 4. Concluding remarks in Section 5 will end this paper.

2. Background

Understanding why some countries, regions or even sub-regional areas are more innovative or entrepreneurial while others struggle has long been of interest to scholars and policy makers alike. For this reason, several studies focus on the regional level, as it is commonly the most appropriate scale to explain innovative behavior (Asheim & Coenen, 2005). Regional knowledge bases and the skills and qualifications of the regional workforce are crucial components that enable knowledge spillovers and allow value and supply chains to develop. A number of conceptualizations have been developed over the past decades, including national/regional/sub-regional systems of innovation, learning regions, clusters, and the early work on Marshallian innovation districts (Marshall, 1920). Entrepreneurial ecosystems have recently become a buzzword within academic and practitioner communities and while the concept appears novel, it follows this rich intellectual heritage (Acs, Stam, Audretsch & O'Connor, 2017; Wurth et al., 2021).

EEs share actors, factors and some mechanisms with previous territorial models of innovation and entrepreneurship. The ecosystem approach to entrepreneurship is based on studying the components, their interrelations and the resulting environment for innovative and entrepreneurial activity within particular boundaries. This focus on (productive) entrepreneurship as the output as opposed to competition and value capture distinguishes EEs from clusters (Acs et al., 2017). In contrast to, for example, the crucial role of established companies and other anchor organizations in regional innovation systems, EEs place more emphasis on the entrepreneur and entrepreneurial behavior. These actors still play an important role within EEs, but it shifts the focus and the nature of the enquiry.

[1] Recent call for papers in EJOR for "OR as an ubiquitous science":https://www.journals.elsevier.com/european-journal-of-operational-research/call-for-papers/or-as-an-ubiquitous-science

EEs further emphasize the social aspects that other concepts have neglected in favor of technical aspects (cf. White & Lee, 2009; Wurth et al., 2021). This leads to the role of 'communities'. The ecosystem approach has shed light on previously unrecognized stakeholders and the role of local communities. While previous models of innovation and entrepreneurship have focused predominantly on inter-organizational links, EEs recognize the importance of individuals as well as organizations that aim to foster connectiveness among ecosystem actors and stakeholders ('ecosystem builders'). Entrepreneurial communities are complex systems, where the 'whole' is more than the sum of its 'parts'. Developing these communities requires a mix of predominantly decentralized (bottom-up) interactions and limited central (top-down) interventions, where viability is the result of finding the right balance (Beer, 1969, and also Mingers, 2006, for a feedback perspective on these issues in social systems). The absence of a central controlling unit and increased emphasis on bottom-up dynamics provides another point of diversion from previous conceptualizations such as clusters.

Therefore, ecosystems are neither restricted to nor do they map perfectly onto the boundaries of cities or geo-political regions. The latter are particularly relevant for policy and practice, as government and civil service are both limited in their influence by these boundaries and use them as a frame of reference for policy implementation (e.g., the use of NUTS-1 and NUTS-2 for innovation policy in the EU). However, successful EEs benefit from proximity across many dimensions, not limited to geography, including technological (often global links via technological platforms and innovation ecosystems), organizational, social and cultural ('communities'), among others (Wurth et al., 2021). In this sense, regions and EEs are not synonyms as EEs represent regions in a multidimensional space across multiple dimensions of proximity.

This bears many similarities to biological/ecological ecosystems and this analogy may help to establish a structure and the relationships in the ecosystem. EEs can be considered as a dynamic network of interconnected organisms and inorganic resources (Auerswald, 2015) or a geographically bounded area with mutually dependent components (Napier & Hansen, 2011). Moreover, several ecological concepts like self-organization, diversity, selection, diversification, resilience or adaptation may be adopted when studying the dynamics of EEs (Auerswald & Dani, 2017; Boschma, 2015). An example of self-organization and adaptation is entrepreneurial recycling, where successful entrepreneurs re-invest their expertise and money within the ecosystem (Mason & Brown, 2014). These concepts are crucial in fostering our understanding of how productive entrepreneurship is generated as an emergent property of the system (i.e., a non-linear relationship between the actors and factors of an ecosystem and productive entrepreneurship as an output) and how this, in turn, supports the development of the ecosystem itself (e.g., cultural changes, increasing resources). As intriguing as the analogy to biological ecosystems appears, EEs are socio-economic constructs and not biological ecosystems (Autio & Levie, 2017; Stam, 2015).

Consequently, there are still limitations with regard to our understanding of the EE concept. These hinder effective interventions and policy making, as well as scientific progress. We have summarized them in the form of four 'problems', which provide umbrellas for more specific research questions and practical challenges. In the absence of a comprehensive theory of EEs, these problems cut across the open issues in the literature (e.g., Alvedalen & Boschma, 2017; Cao & Shi, 2020; Spigel, Kitagawa & Mason, 2020; Wurth et al., 2021) and provide a more focused framework for organizing the literature and identifying future research opportunities and challenges. This approach also aligns well with the 'problem-oriented' nature of OR (see also similar reviews in other areas of application, e.g., Barbosa-Póvoa et al., 2018; Crainic et al., 2018; Ernst, Jiang, Krishnamoorthy & Sier, 2004). Lastly, we ordered and aligned the four problems with general modeling practices and processes (e.g., Belton & Stewart, 2002; Pidd, 2009) as shown in Fig. 1:

1. We lack clarity as to who the relevant stakeholders, DMs and parts of an EE are as well as their role, relationship and impact, and, therefore, have a limited understanding of the boundaries of EEs ('the stakeholder and boundary problem').
2. We need a more systematic and dynamic set of perspectives of an EE compared to the more static 'snapshots' the current literature provides ('the dynamic system problem').
3. We need a more systematic and coherent comparative analytical approach embedded in the study of EEs as opposed to the current single region or cluster studies ('the comparability and evaluation problem').
4. We need a clearer analytical framework encompassing the varying levels and dynamic stakeholder relationships of EEs in order to support the design and implementation of sustainable interventions, policies, and efficient allocation of resources ('the policy and interventions problem').

While already challenging on their own, these problems usually overlap and DMs must consider a variety of interdependencies between them when designing interventions and policies. For example, devising a new funding scheme as a response to the policy and interventions problem is a complex endeavor, but its complexity and ramifications are amplified when considering possible issues regarding the connectedness of ecosystem actors and their access to resources (the dynamic system problem). We will elaborate on these four problems in the next section.

3. Addressing the core decision-making problems

We use the four problems identified above as a guide to review current contributions of OR to the study and practice of ecosystems. Before discussing the problems in depth, we need to consider two issues. First, these problems are not completely unique to EEs due to the overlap of certain actors, factors, and mechanisms with other conceptualizations. We incorporate applications of OR approaches and methods to other concepts where appropriate to more widely reflect the insights gained from an OR perspective. As a result, this review will be a helpful starting point for researching other systemic models of entrepreneurship and innovation. Second, problems of this nature are commonly addressed by OR scholars in other contexts. We incorporate the work by the OR community and outline how it can advance our understanding of ecosystems.

Methodologically, we follow the principles of a 'problematizing review', namely reflexivity, reading broad but selectively, problematizing instead accumulating, and 'less is more' (Alvesson & Sandberg, 2020). We are purposefully using a problematizing approach to our review with the aim of identifying new avenues for research, which is also in line with the focus on modeling problems rather than systems (Alvesson & Sandberg, 2011). The review for each problem is built around the following key research questions:

a) How has the decision-making context been defined by OR researchers?
b) Which OR methods and techniques have been applied?
c) What are the open issues and main challenges for OR researchers?

3.1. The stakeholder and boundary problem

3.1.1. Problem definition

Studies in the context of the stakeholder and boundary problem examine an EE either as a whole at different levels (e.g., national,

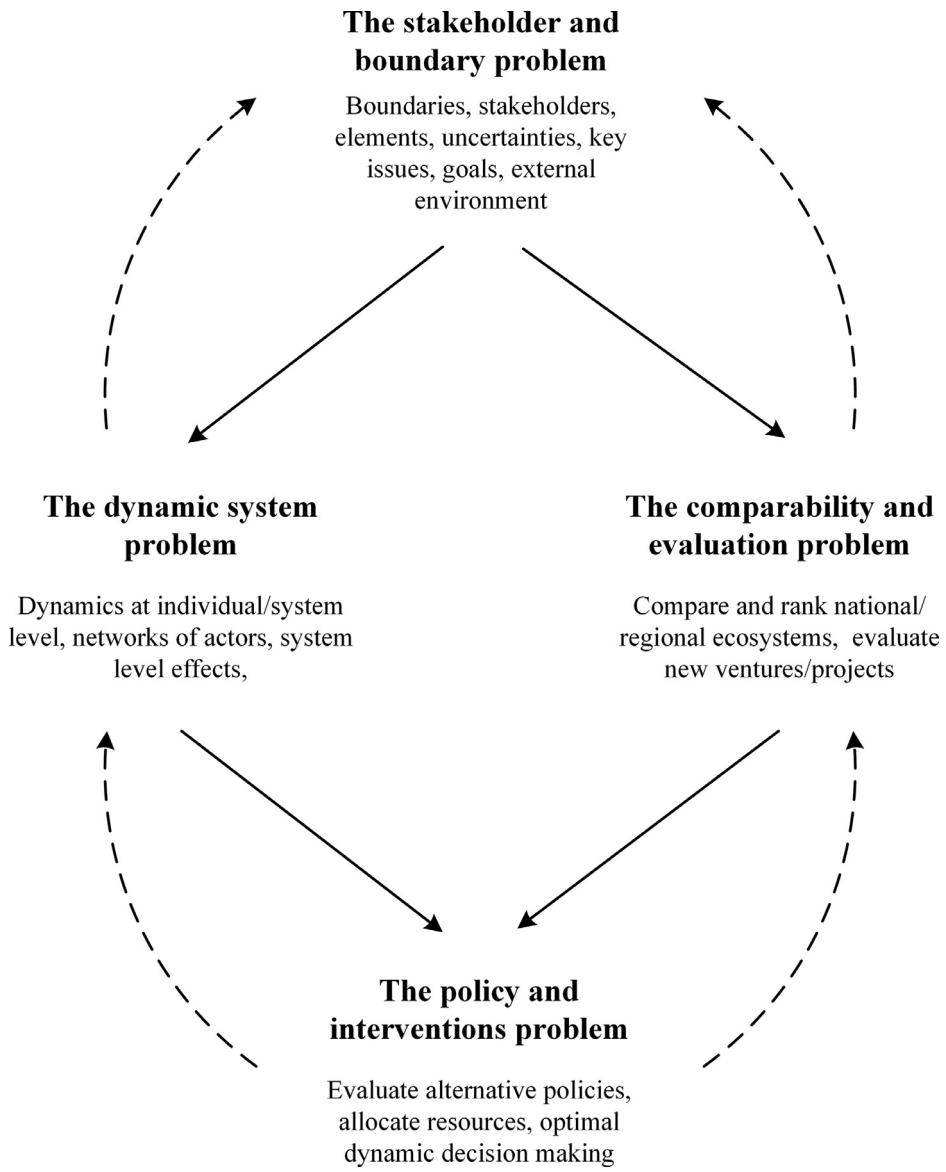

Fig. 1. A typology of problems in EE research.

regional) or in part, focusing on specific elements. These studies adopt, in general, an exploratory approach, trying to answer the following key questions:

- What are the boundaries of an ecosystem? How does 'place' affect the characteristics of an ecosystem?
- What are the elements of an EE and how can these be categorized?
- How do different elements influence the performance of an EE?
- What are the path dependencies, either between the elements or the outcomes of the ecosystems?
- Which behavioral decision models may be identified within the different processes of an ecosystem?

Some of these questions are also examined in the next sections, revealing that the stakeholder and boundary problem appears to have significant overlap with the other three key problems and the comparability and evaluation and the dynamic systems problems in particular. This is because defining the boundaries, identifying the relevant stakeholders and other elements of an EE is, in most cases, the first step when analyzing its dynamic behavior and evaluating its performance or efficiency.

In an OR context, this problem is closely related to the philosophy of problem structuring methods (PSMs). PSMs aim to structure complex decision-making problems (such as researching or developing interventions for EEs), having usually a participative and interactive character (Belton & Stewart, 2002; Mingers & Rosenhead, 2004; Rosenhead, 1996). Therefore, the study of the stakeholder and boundary problem should take into account the following important characteristics:

a) the subjective nature of modeling;
b) stakeholders with potentially conflicting views or goals;
c) collaborative decision-making; and
d) the boundaries of interventions.

A discussion of the previous issues in a general PSM context may be found, for example, in Ackermann (2012) and Velez-Castiblanco, Brocklesby & Midgley (2016). In any case, it should be noted that the framework adopted in ecosystem studies significantly affects how the previous questions are answered. For example, Flora & Flora (2012) argue that we should try to map types of capital (natural, cultural, human, social, and political) rather than just the organizations or institutions in entrepreneurial communi-

ties. This will not only help in analyzing ecosystems, but also identifying key boundary stakeholders.

3.1.2. OR methods and techniques

In the general context of the stakeholder and boundary problem, multivariate statistical analysis has been applied to identify the socio-economic factors that influence regional development (Jurun & Pivac, 2011; Soares, Marquês & Monteiro, 2003) or to classify regional entrepreneurship ecosystems based on their socio-economic characteristics (Del Campo, Monteiro & Soares, 2008). These studies aim to identify and analyze the key elements of an EE in order to improve national or regional policies.

Advanced techniques, such as data mining, can also be applied to identify other elements that may affect the performance (e.g., competitiveness) of an ecosystem (e.g., Zanakis & Becerra-Fernandez, 2005).

Studying how an ecosystem or the different elements of an ecosystem behave is also important. For example, Carayannis and Grigoroudis (2016), using Multi-Objective Mathematical Programming (MOMP) techniques, study how competitiveness, productivity, and innovation are linked in national entrepreneurship ecosystems. Simulation approaches can also suggest a framework for analyzing and evaluating entrepreneurship activities, such as knowledge and capital flows (Lee & von Tunzelmann, 2005; Walrave & Raven, 2016), examine the behavior of EE's elements (Backs, Günther & Stummer, 2019) or investigate the different type of innovation activities (e.g., product innovation and process innovation) (Samara et al., 2012). Similarly, Data Envelopment Analysis (DEA) models are used to identify the factors that may affect innovation capabilities (Song, Tao & Wang, 2015), analyze the different stages and hierarchies of innovation systems (Carayannis, Goletsis & Grigoroudis, 2015; 2016a), study the cooperation among industry-university-research and its effect on EE's efficiency (Fang & Chiu, 2017) or examine the efficiency gaps within an EE (Chen, 2017; Chen 2018; Lu & Lo, 2007).

Decision analysis, soft OR and similar approaches may also explore different aspects of an EE, such as the impact of technology transfer agreements (Grønhaug 1989), the evaluation of investment environment from the viewpoint of a host region or country (Gondal, 2004) or the impact of different EE policies (Herrera-Restrepo & Triantis, 2019). Focusing on alternative behavioral decision models, Khan (1986) and Khan, Macmillan & Manopichetwattana (1990) examine alternative approaches (linear, conjunctive, disjunctive and compensatory, noncompensatory) in order to analyze the characteristics of entrepreneurial ventures. Soft OR can provide further insight in this decision-making problem, including the application of cognitive maps for the behavioral analysis of DMs (Brännback & Carsrud, 2017).

The assessment and the analysis of the causal relationships among the elements of an EE (or among different EEs) is another important stream in the stakeholder and boundary problem. For example, using statistical approaches and structural equation modeling, Nasierowski & Arcelus (1999) and Cziráky, Sambt, Rovan & Puljiz (2006) study the interrelationships within national and regional ecosystems, while Lockett & Wright (2001) examine different rationales for the syndication of venture capital investments. Simulation approaches, such as system dynamics (SD), can also be applied in order to examine causal relationships in entrepreneurial activities, including the links between R&D investments, knowledge creation, and commercialization (e.g., Choi, Narasimhan & Kim, 2016) or analyze the how the relationships among the different elements may influence EE performance (Albino, Carbonara & Giannoccar, 2007). Similarly, Chapple, Lockett, Siegel & Wright (2005) focus on universities, as an important actor within an EE, to evaluate the efficiency of technology transfer activities. Finally, visualization techniques and conceptual models are used to understand venture behavior (Basole, Park & Chao, 2019) or opportunity identification and exploitation (Peiris, Akoorie & Sinha, 2015), while Exploratory Spatial Data Analysis (ESDA) may help to examine spatial variations in different national or regional EEs (Chocholatá & Furková, 2017).

Table 1 summarizes OR studies for the stakeholder and boundary problem, presenting alternative approaches and the orientation of different research efforts.

3.1.3. Open questions

Although several factors and elements that may enhance entrepreneurship and innovation have been identified in the literature, it is still not clear what is cause and effect in an EE (Alvarez, Carayannis, Dagnino & Faraci, 2018; Alvedalen & Boschma, 2017; Carayannis, Grigoroudis & Goletsis, 2016a; Carayannis 2018a). These elements include education and research, human capital, finance, customers, supporting organizations, infrastructures, regulatory frameworks, culture and leadership, among others. Assuming that all elements influence each other, it becomes almost impossible to analyze such a complex EE. Thus, existing studies focus on a particular perspective of EEs, but we need more holistic frameworks for how these elements are embedded and operating in such ecosystems.

Other important open research questions are related to the greater adoption of soft OR approaches, such as PSM and stakeholder theory. As noted in the previous sections, PSMs are participative methods that facilitate the engagement of stakeholders in decision-making problems in order to address complex organizational, social, environmental or technological issues (Marttunen et al., 2017). Therefore, approaches such as cognitive and causal maps, DPSIR (Drivers, Pressures, State, Impact, and Response), Scenario Planning, SSM (Soft Systems Methodology), Stakeholder Analysis, Strategic Choice Approach, SODA (Strategic Options Design and Analysis) and SWOT can examine this problem from different perspectives and facilitate the synthesis of information. On the other hand, stakeholder theory focuses on the assessment of stakeholders and their roles and influences, which is crucial within this problem. Most studies currently adopt an ad hoc and static approach, although "stakeholders" is a dynamic concept (Wang, Liu & Mingers, 2015c).

3.2. The dynamic systems problem

3.2.1. Problem definition

Our definition of EEs has highlighted the importance of different factors and stakeholders to support entrepreneurship. However, the majority of the EE literature has adopted a static framework without considering the evolution of the ecosystem (or its elements) over time (Alvedalen & Boschma, 2017; Wurth et al., 2021). It is not sufficient for regions to possess different types of capital or for entrepreneurs, innovative companies, and universities, among others, to be present but they need to be connected and interact with each other. Consequently, this problem looks at the dynamics at the individual and systemic level.

In particular, networks are crucial to our understanding of ecosystems - similar to any other socio-economic system (Hellmann & Staudigl, 2014). Current studies focus on the interactions between three components: individuals, organizations and institutions, They typically examine how networks of different actors are involved in entrepreneurial or innovation processes and how other factors may influence these interactions (Alvedalen & Boschma, 2017; Qian, Acs & Stough, 2013). Under these circumstances, system-level effects - including potential unintended consequences - of new entrepreneurship and innovation polices are difficult to predict (e.g., due to adaptation and learning among ecosystems actors). Unsuccessful policies may be costly and can

Table 1
Examples of alternative approaches for the stakeholder and boundary problem.

OR approaches	Scope of study		
	Identify, analyze and classify element	Influence of elements	Causal relations
Statistical approaches	Soares et al. (2003); Del Campo et al. (2008)	Soares et al. (2003)); Jurun and Pivac (2011)	Nasierowski and Arcelus (1999); Lockett and Wright (2001)
Decision analysis, MCDM[1]	Khan et al. (1990); Carayannis and Grigoroudis (2016)	Khan (1986); Gondal (2004)	Corrente et al. (2021)
Simulation[2]	Lee and von Tunzelmann (2005) Walrave and Raven (2016)	Backs et al. (2019); Samara et al. (2012)	Choi et al. (2016); Carayannis et al. (2016b); Albino et al. (2007)
DEA	Carayannis et al. (2015; 2016a); Chen (2017); Chen (2018)	Lu and Lo (2007); Fang and Chiu (2017); Song et al. (2015)	Chapple et al. (2005)
Soft OR	Grønhaug (1989); Brännback and Carsrud (2017)	Gondal (2004)	Basole et al. (2019); Peiris et al. (2015)
Other approaches[3]	Zanakis and Becerra-Fernandez (2005); Herrera-Restrepo and Triantis (2019)		Chocholatá and Furková (2017); Cziráky et al. (2006)

[1] Multicriteria Decision Aid (MCDA), including multiobjective linear and nonlinear programming.
[2] Including Monte Carlo simulation and system dynamics.
[3] E.g., Data Mining, Exploratory Spatial Data Analysis (ESDA), Structural Equation Modeling (SEM).

have long-term negative impacts. The dynamic systems problem will synthesize previous approaches and elaborate on future opportunities for improving policy-making and our understanding of dynamics of EEs in general. This is particularly relevant for policy makers and other stakeholders planning interventions.

3.2.2. OR methods and techniques

Given the inherent dynamic nature of an EE, several OR approaches can support modeling dynamic decision-making problems and better understanding the evolution of EEs. Simulation and network models are the most widely used approaches to address the questions within this particular problem. Simulation approaches (predominantly system dynamics, agent-based simulation) are widely used to examine causal relationships and their dynamics over time.

Applications of system dynamics, for example, date back to the original work by Jay Forrester on industrial (Forrester 1961) and urban dynamics (Forrester 1969). While the focus of system dynamics in the following decades shifted to other areas, there has been an increase in EE-related work over the past 20 years. Simulation approaches in general and system dynamics in particular have predominantly been used in evaluating the following major policy areas of EEs, which are further detailed in Table 2 (Uriona & Grobbelaar, 2019):

a) R&D policies,
b) innovation diffusion policies,
c) science and technology policies, and
d) regional agglomeration policies.

Choi et al. (2016) develop a system dynamics model for how R&D investments create new knowledge stocks and profits through the commercialization process. Using simulation results over a 10-year period, the authors examine how the trade-off relationships between product and process innovation change over time. System dynamics also provides the basis for a decision support system for strategic alignment of enterprises in ecosystems (Andres & Poler, 2016).

On a more strategic level, Samara et al. (2012) examine alternative innovation policies in national innovation ecosystems. The alternative innovation policies are evaluated as a series of what-if analysis scenarios in terms of the process and product innovation performance. Focusing on the integrated circuit industry, Lee & von Tunzelmann (2005) use system dynamics to evaluate policy alternatives for the Taiwanese government based on flows of knowledge and capital in the national system. A similar approach is used by Walrave & Raven (2016), who investigate sustainable transitions in technological innovation systems.

In contrast to the more strategic perspective of system dynamics, agent-based simulation models have the advantage of explicitly modeling the complex interactions of ecosystem actors. Such models can help in studying complex entrepreneurial processes, such as new venture formation, knowledge acquisition, alliances formation, interactions between entrepreneurs and institutions or cooperation among different actors (Albino et al., 2007; Carayannis et al., 2016b).

But agent-based models are not limited to micro-level models. A macro-level approach includes the development of an artificial labor market for experimentation, which allows for different levels of market segmentation with an online analytical processing (OLAP) interface to help DMs connect insights to the 'real world' (Chaturvedi, Mehta, Dolk & Ayer, 2005). Cellular automata, which can be categorized as a variation of agent-based simulations, can show how knowledge diffuses among collaborating actors (Su, Zhang, Yang & Qian, 2018). Agent-based simulation has also been applied to EEs and how incubators as intermediaries can help overcome 'weak network problems' (van Rijnsoever 2020). Combining an agent-based simulation with a network model, Backs et al. (2019) show how the ecosystem affects the patenting behavior of academics.

Similar to simulation approaches, social network analysis may be applied at a micro level (individuals or organizations within an EE) to investigate how the content, structure, and their interactions constitute the EE (Yasuyuki & Watkins, 2014). Social network approaches can be used to model the diffusion of knowledge, innovation, and information. In such an approach (Hupa, Rzadca, Wierzbicki & Datta, 2010):

a) The nodes of a knowledge network represent individuals, their aggregations and knowledge repositories.
b) The vertexes represent the dyadic relationships of individuals (e.g., strength of ties, effectiveness and impact of knowledge transfer).
c) The edges examine characteristics of the information transferred across different types of ties.

Social network analysis has also been combined with fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) to examine risks in R&D collaborations (Liu, Yang, Yang, Zhang & Li, 2020). This is linked to the next area, namely game theoretic models. Goyal & Joshi (2003), for example, model the incentives for firms to collaborate with other firms, including different costs for engaging and the nature of market competition, showing that most stable

Table 2
Examples of alternative approaches in the dynamic systems problem.

Approach	**Objective**	**Major actors**	**Major elements**	**Source**
System dynamics	Analyze the impact of innovation policies on the EEs' performance	Government, Enterprises, Research and technological organizations, Educational institutions	Knowledge and human resources, Research activities, Market conditions, Institutional conditions, Financial system, Innovation process, Technological performance	Samara et al. (2012)
	Analyze feedback causal relationships for R&D investments	Enterprise, Market	Product and process innovation, Revenue and profits, R&D investments, Labor and capital productivity	Choi et al. (2016)
	Selection of aligned strategies	Enterprises	Objectives of enterprises, Strategies of enterprises, Relations among enterprises	Andres and Poler (2016)
	Analyze the dynamic processes of the Taiwanese integrated circuit industry	Government, Industry (firms), Research institutes, Foreign companies, Universities	Financial (capital market), Human resources, Science and technology, Innovation commercialization, Product market	Tunzelmann (2005)
	Examine alternative transition pathways in technological innovation systems	Entrepreneurs, Consumers, Regime actors	Knowledge diffusion, Technology development, Market development, Technological and market legitimacy	Walrave and Raven (2016)
Agent-based simulation	Analyze cooperation among supply chain firms in industrial districts	Suppliers, Buyers	Actions of suppliers and buyers, Interactions between suppliers and buyers	Albino et al. (2007)
	Examine the influence of new ventures, entrepreneurs' social capital, and firms' performance	Knowledge standardizing institutions, Knowledge production-stimulating institutions, Knowledge variation-inducing institutions	New venture creation, New venture capability generation, Firm transition, Product innovation and adoption, Buyer requirement evolution, Institutional knowledge mediation	Carayannis et al. (2016b)
	Study the contribution of support mechanisms in EEs	Startups, Venture capital firms	Network development, Incubator support mechanisms	van Rijnsoever (2020)
	Evaluate technology transfer measures in academic patenting	Scientists, TTOs	Cognitive network, Spatial network, Social networks	Backs et al. (2019)
Social network analysis	investigate the content, structure, and interactions constituting an EE	Entrepreneurs, Support organizations	Connections among entrepreneurs and support organizations	Yasuyuki and Watkins (2014)
	Analyze risk interactions in R&D alliance	Members of R&D alliances	Risk identification, Risk assessment, Risk response	Liu et al. (2020)
Cellular automata	Study the process and rule of knowledge diffusion in knowledge collaboration organizations	knowledge collaboration organization	Knowledge dissemination, Knowledge diffusion, Knowledge availability	Su et al. (2018)

networks are asymmetric (group, stars, and inter-linked stars architectures). Although social network analysis is gaining increased attention, the number of studies is still limited in the EE literature (Alvedalen & Boschma, 2017).

More qualitative, approaches, including visual and conceptual, models may bring insight and further understanding of the interactions in an EE or the intersections between the different levels (e.g., meso and micro). Examples in this area are the studies by Basole et al. (2019) and Peiris et al. (2015), who examine the structure of several EEs and alternative conceptual models of opportunity identification, respectively.

A major advantage of simulation approaches is their flexibility to modify and experiment with the model structure, perform sensitivity analyses on key model parameters, and uncover potential performance patterns (see Crawford, 2009, for a further discussion). However, in some cases it can be difficult to build confidence or generalize results due to the underlying assumptions and necessary simplifications.

3.2.3. Open questions

Networks and connectedness form the basis of thriving EEs (e.g., Spigel, 2017) and play a vital role in entrepreneurship in general (Hoang & Antoncic, 2003). However, there is still a lack of network-based research and future work needs to address why networks develop (including the interaction with non-economic actors), what these networks look like within the wider EE configuration, and how these networks evolve over time - and the EE with it (Alderson, 2008; Slotte-Kock & Coviello, 2010; Sorenson, 2018). A key question that remains unanswered is how dynamic network processes affect the output and outcome of EEs (Hoang & Antoncic, 2003).

EEs are defined as complex systems that exhibit emergent behavior, meaning that a non-linear relationship exists between its components, mechanisms, and outcomes. From a network perspective, the implication is that an EE is not only the sum of the resources and activities of its actors but also builds resources at the systemic level (Musiolik, Markard & Hekkert, 2012). These processes are not well-researched. For example, individual entrepreneurs' motives to harvest the maximum benefit from their network and the EE might lead to adverse effects for the network the EE (Ibarra, Kilduff & Tsai, 2005). Further dynamics are path-dependent behavior in networks based on an entrepreneur's existing position in the network ('structural localism') and purpose-driven creation of new connections ('agentic network change'), the combination of which will ultimately explain the evolution of the network and the individual entrepreneurs' path (Hallen, Davis & Murray, 2020).

We can conclude that there is no 'one-fits-all' network design, but there might be an optimal design based on regional characteristics, the current state of the EE, and the objectives of its actors and stakeholders (Ahuja, 2000). In practice, policy makers would like to steer the EE to achieve a certain connectedness or network structure (Hellmann & Staudigl, 2014). However, we currently do not have the tools nor the required understanding of how this can be done through decentral, bottom-up interactions within the EE. Particularly the SD literature provides a rich collection of work on stakeholder involvement throughout the modeling process, which new research on EEs and networks should build on to address this issue.

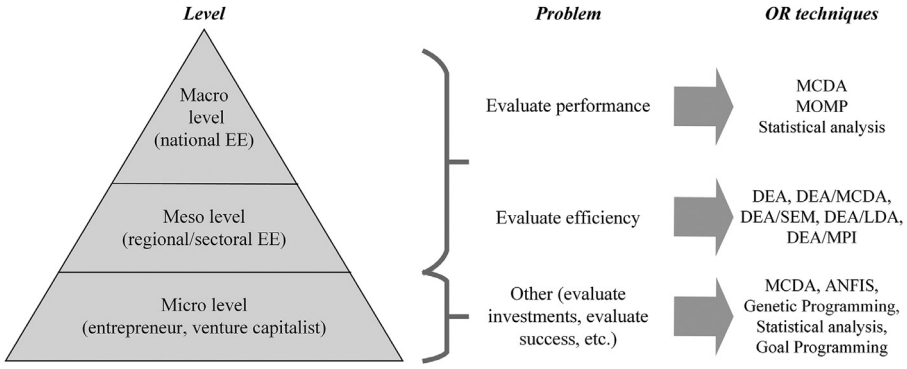

Fig. 2. Examples of alternative approaches for the comparability and evaluation problem.

Most simulation and network models that address research questions within the dynamic systems problem are calibrated to particular regions, phases in ecosystem development, or cases of particular technologies and innovations. While these studies do provide insights into the dynamics of these systems, synthesizing and generalizing how elements of ecosystems co-evolve is difficult but necessary. This requires understanding the interplay between top-down interventions and bottom-up (self-organizing) dynamics. Dynamic systems approaches already triangulate insights from case studies as well as qualitative and quantitative studies in general; but integrating findings from these approaches can support a deeper understanding of how EEs work.

For policy makers, a crucial outcome of studies addressing the dynamic systems problem is the identification of tipping points in systems and effective levers. There are two aspects that are crucial in this process, which are often cited as limitations in existing studies. The first aspect is the non-linearity both at the individual (process of venture creation and growth) and ecosystem level (increasing awareness of the importance of context and the regional environment and support for entrepreneurship). Second, the majority of existing studies are based on Gaussian distributions, whereas recent work has demonstrated that most entrepreneurial metrics (e.g., growth among firms, start-ups per region, funding attracted are highly skewed) and non-Gaussian (Crawford, Aguinis, Lichtenstein, Davidsson & McKelvey, 2015).

Long-term implications are almost impossible to predict a priori due to, for example adaptation and learning among EE actors. Adding to the problem is that policies are tested against current behavior of the EE and the involved individuals and organizations. However, the even bigger issue is that most policies are not tested at all because experimentation in the real world is expensive and can often have a long-term impact, if feasible and ethical at all. New approaches are required to support DMs, i.e. more research for policy as opposed to policy research.

3.3. The comparability and evaluation problem

3.3.1. Problem definition

The comparability and evaluation problem is one of the most widely studied problems in the EE literature. Measuring the performance of innovation systems remains a high priority on the political agenda, since politicians and policy makers want to see the effects of their decisions and, ideally, their EE or region rise in international rankings.

The majority of studies within this problem aim to evaluate and rank either a set of national/regional ecosystems or a set of new ventures or projects. Fig. 2 presents a typology of different sub-problems in this domain according to the level of analysis, i.e., macro level (national ecosystems), meso level (regional ecosystems), and micro level (entrepreneur, venture capitalist, project). The different levels of analysis highlight different perspectives within the comparability and evaluation problem.

The first problem is focused on the evaluation and comparison of ecosystem performance at the macro or meso level. Based on the need for international comparisons, indicator approaches (single, multiple or composite) have been widely followed. Given the myopic view of single indicator approaches, several composite innovation and entrepreneurship indices may be developed (e.g., Avanzini, 2011; EC, 2020). As noted by Carayannis, Goletsis & Grigoroudis (2018b, p.5), recent studies "have have been following the evolution of the innovation concept with the introduction of the idea of incremental innovations, the introduction of non-technological innovation, the focus on co-operation co-opetion, and recently on open innovation, as well as targeted open innovation…". Entrepreneurship barometers and innovation scoreboards (e.g., European Innovation Scoreboard, Regional Innovation Scoreboard, Global Entrepreneurship & Development Index, and the Global Entrepreneurship Index) are the most characteristic examples of composite indicators used in international and national policy making bodies.

The second problem refers to the efficiency evaluation of national and regional EEs. OR approaches in this context try to overcome the limitations of traditional analysis that focus only on the inputs (e.g., R&D expenditures) or only on the outputs (e.g., patents) of an EE. However, what is most important is the interaction (or joint evolution) of several factors that are responsible for the final outcome. These interactions give emphasis on knowledge produces with an EE, as well as the general environment for innovation and entrepreneurship in which these processes are embedded. The efficiency evaluation problem accounts for the complex nature of transforming knowledge to market outcomes, including the aforementioned interdependencies

At the micro level, the comparability and evaluation problem includes studies aiming to evaluate potential investment by venture capitalists, the success of new ventures or innovative projects or forecast EE performance. The main aim of these studies is to rank investments and projects or identify their critical success factors.

3.3.2. OR methods and techniques

The comparison and evaluation of different EEs should consider the multi-input/multi-output characteristics of entrepreneurial activities. Although developing composite indicators is a rather simple approach, they appear to have a number of critical issues or weaknesses, mainly the selection of the detailed indices and the aggregation procedure (see Greco, Ishizaka, Tasiou & Torrisi, 2019 for a discussion about the issues of weighting, aggregation, and robustness). Furthermore, these aggregated indicators are

based on a set of indices which are partial and indirect because the underlying phenomena are intangible or not directly observable (Grupp & Schubert, 2010).

Therefore, several Multicriteria Decision Aid (MCDA) approaches have been applied in order to rank national/regional EEs in terms of economic development, entrepreneurship activity or innovation performance. MCDA approaches are the dominant trend in this particular problem, including specific methods, including: Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Stochastic Multicriteria Acceptability Analysis (SMAA), UTASTAR, Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), Non-Linear Non-Weight Method (NLNW), Multi-Objective Optimization Method by Ratio Analysis (MOORA), Multiple-Criteria Hierarchy Process (MCHP) (Carayannis et al., 2018b; Corrente, Garcia-Bernabeu, Greco & Makkonen, 2021, 2019; Sepúlveda & Vasquez, 2014; Sitaridis & Kitsios, 2020; Su, Liang & Guo, 2020). The most important challenges regarding the application of MCDA methods are:

- defining the DM;
- assigning criteria and criteria weights; and
- choosing an aggregation approach.

In general, studies in the evaluation problem that adopt an MCDA approach should give particular attention to the decision-making context. As Cinelli, Kadziński, Gonzalez & Słowiński (2020, p.1) emphasize, MCDA "includes a series of steps that systematically help DM(s) and stakeholders in structuring a decision making problem, identifying their preferences, and building a decision recommendation consistent with those preferences". Thus, an MCDA process should include the following three main phases: (a) problem formulation, (b) construction of the decision recommendation, and (b) qualitative features and technical support (Cinelli et al., 2020).

Other approaches for the evaluation and comparison of ecosystem performance at the macro or meso level include Multi-Objective Mathematical Programming (MOLP) techniques (Carayannis & Grigoroudis, 2016), a combination of different MCDA methods (Tsai, Lee, Shen & Hwang, 2014), interactive linear programming Despontin (1982), and multivariate statistical techniques (Del Campo et al., 2008).

Several DEA approaches have also been applied in evaluating the efficiency of national and regional EEs (e.g., Fang & Chiu, 2017; Lu & Lo, 2007; Pan, Hung & Lu, 2010). Table 3 presents an overview of different DEA models for efficiency analysis of EEs with emphasis on the selected model variables.

Given the complexity of the examined ecosystems, studies examine multiple stages and levels of innovation and entrepreneurship (Carayannis et al., 2015, 2016a; Chen, 2017) or apply dynamic DEA models in order to analyze efficiency changes over time (Chen, 2018). DEA approaches are also applied to key actors in the EE. An example are universities, which are deeply embedded in most EEs and linked to other actors in multiple ways (Chapple et al., 2005). Stochastic frontier estimation, which aims to estimate the same efficiency values of a decision making unit as DEA but uses a parametric approach, has been applied in a study to identify the most critical factors for university-industry technology transfer (Siegel, Waldman & Link, 2003). DEA models may also be combined with MCDA methods (Lin, Lee & Ho, 2011), Structural Equation Modeling (SEM) (Kalapouti, Petridis, Malesios & Dey C, 2020), Linear Discriminant Analysis (LDA) (Martić & Savić, 2001), or Malmquist Productivity Index (MPI) (Lin et al., 2011).

Dynamic DEA approaches may be used in evaluating the performance of an EE in terms of efficiency (Chen, 2018). Using a slacks-based dynamic DEA, Teirlinck & Khoshnevis (2020) find a positive effect of within-cluster specialization and public funding on R&D output efficiency. Alternatively, multi-period DEA results may be used in a second stage for estimating a Malmquist Productivity Index (MPI) in order to perform a time-scale performance comparison of different ecosystems (Lin et al., 2011).

Furthermore, network DEA models can be used to model the different elements or processes and calculate not only the overall, but also the efficiencies of knowledge production and knowledge commercialization stages. This can help identify potential weaknesses and suggest improvement policies (e.g., Chen, 2018; Fang & Chiu, 2017; Lu & Lo, 2007). Kao (2004) provides a comprehensive review of network DEA models.

The evaluation of potential investments by venture capitalist is another important problem in this domain and the applied OR techniques may refer to MCDA methods (e.g., Siskos & Zopounidis, 1987; Zacharakis & Shepherd, 2005), goal programming models (Aouni, Colapinto & La Torre, 2013) or simple statistical tools (Dixon, 1991). The major OR challenges mentioned before can also be found here, however, the existence of a specific DM clarifies the decision-making process.

The analysis of successful and unsuccessful new ventures or innovative projects can also be considered as a comparability and evaluation problem. In this context, OR studies, using MCDA methods (Kitsios, Doumpos, Grigoroudis & Zopounidis, 2009), Adaptive Neuro Fuzzy Inference Systems (ANFIS) (Kiani Mavi, Mavi & Goh, 2017) or simple statistical techniques (Picot, Laub & Schneider, 1990), try to identify the most critical success factors. Finally, other studies at the meso and micro level, focus on the forecasting EE performance using semantic-based genetic programming (Hajek, Henriques, Castelli & Vanneschi, 2019) or the supplier/partner evaluation and selection problem.

3.3.3. Open questions

The multi-level evaluation of EEs is a critical issue. Previous studies usually focus on a specific level without considering the interactions among the macro, meso, and micro levels. For example, although national institutions and laws form the general framework where entrepreneurial activities within a country take place, specific regions may follow different regimes and exploit inputs in a different way. As noted by Sleuwaegen & Boiardi (2014, p. 1509) "each region has specific assets, unique capabilities and industrial policies that make it different from another region; still the regions are part of a country, therefore national contextual factors exist and affect the innovative performance".

The assessment of the DM in the evaluation problem remains an important challenge for OR scholars, since different DMs may have different perspectives, which affect the evaluation results. For example, Carayannis et al. (2018b), show that the four main actors of the Quadruple Innovation Helix (QIH) framework (i.e., government, university, industry, and civil society) assign different weightings to the evaluation criteria.

The set of appropriate evaluation criteria may heavily affect the results, regardless of the applied OR techniques. Although there is no consensus, several scholars emphasize that the assessed evaluation criteria should be of comparable importance to the measures of the concept under study; based on reliable statistics; hold their value over time; be relevant to medium and long-term policy issues; and be clear and transparent for reasons of public accountability (Grupp & Maital, 2001; Tijssen, 2003). The selection of evaluation criteria is restricted by the availability and validity of data. In several cases, innovation and entrepreneurship indices have been developed for different purposes and, thus, their inclusion in an evaluation framework should be treated with caution (Carayannis & Grigoroudis, 2016; Krammer, 2009). In any case, the properties of a consistent family of criteria (i.e., monotonicity, exhaustiveness, and non-redundancy) should be justified in MCDA studies (see Roy, 1985, for details).

Table 3
Examples of alternative DEA models in the efficiency evaluation of EEs.

Level	Inputs	Intermediates	Outputs	Source
National	Total public expenditure on education, Imports of goods and commercial services, Total expenditure on R&D, Direct investment stocks abroad, Total R&D personnel		Number of patents granted to residents, Number of partners secured abroad by residents, Scientific articles published	Pan et al. (2010)
	Imports of goods and commercial products, GDP expenditure on research, private business involvement in R&D, Employment in R&D, Expenses in education		External Patents by resident, Patents by residents, National productivity	Nasierowski & Arcelus (2003)
	GDP expenditure on research, Researchers per population, GDP per capita		Patents, Publications	Sharma & Thomas (2008)
	R&D expenditures by government, by business, by higher education, GDP expenditure in R&D, Researchers		Patents	Cullmann, Schmidt-Ehmcke & Zloczysti (2011)
	Total R&D manpower, R&D expenditure stocks		Patents, Scientific journal articles, Royalty and licensing fees	Chen, Hu & Yang (2011)
	New doctorate graduates, publications, Public R&D expenditures, Private R&D expenditures, Public-private co-publications, PCT patent applications, Community trademarks		Employment in knowledge intensive activities, Medium and high-tech exports, Knowledge intensive services exports	Matei & Aldea (2012)
	Number of full-time equivalent scientists and engineers, Incremental R&D expenditure funding innovation activities, Prior accumulated knowledge stock breeding upstream knowledge production, Consumed full-time equivalent labor for non-R&D activities	Number of patents granted	International scientific papers, Added value of industries, Export of new products in high-tech industries	Guan & Chen (2012)
	R&D personnel, R&D expenditure	R&D expenditures to research output institutions, R&D expenditures to higher education output	Sales revenue of new products, Invention patent applications	Fang & Chiu (2017)
	Science graduates in tertiary education, Participation in lifelong learning, Total R&D expenditure, R&D capital stock, Venture capital	Citable documents, Patent applications, Employment in knowledge intensive services/manufacturing, SMEs collaborating with others	High Tech Exports, Sales of new to market and new to firm innovation, License and patent revenues from abroad, Number of trademark applications in national offices	Carayannis et al. (2015))
Regional	Higher Education, Participation in lifelong learning, Medium-high tech employment in manufacturing, High/tech employment in services, Public R&D expenditure, Private R&D expenditure, High tech patent applications to EPO		Regional GDP per capita	Zabala-Iturriagagoitia et al. (2007)
	Capital stock, R&D expenditure, Employment	Patents	Gross output value, Exports	Li, Liu, Liu & Chiu (2017)
	R&D expenditure, R&D personnel	R&D capital stock	SCI papers, Domestic granted patents	Chen, Kou & Fu (2018)
	Internal R&D expenditure, Full-time equivalent of R&D activities by employees	Applied patent	Profits, Export, Sale revenue of new product, Value-added	Guan & Chen (2010)
	Population with tertiary education, R&D expenditures, Non-R&D innovation expenditures	SMEs innovating in-house, Innovative SMEs collaborating with others, Public-private co-publications, Patents	Technological (product or process) innovators, Non-technological (marketing or organizational) innovators, Employment in medium–high/high-tech manufacturing & knowledge intensive services, Sales of new-to-market and new-to firm products	Carayannis et al. (2015)); Carayannis et al. (2016a)

(*continued on next page*)

Table 3 (*continued*)

Level	Inputs	Intermediates	Outputs	Source
Sectoral	R&D employees, Internal R&D investment, External R&D investment	Process patent application, Product patent applications	Sales, Operating income	Chun, Chung & Bang (2015)
	Expenditure on science and technology, Number of science and technology personnel, Foreign direct investment, Expenditure on the import of technology, Expenditure on the purchase of domestic technology, Value of contractual inflows in domestic technical markets, Capital stock, Labor	Invention, Utility model, External design,	GDP, Sale of new products, Value of export, Annual income in urban residents per capita	Chen & Guan (2010)
	Employees, Manufacturing selling, R&D expense, Assets	Revenue, Profit	Stock price, Earnings per share in the market	Hung & Wang (2012)

Criteria weights are, in several cases, defined either by experts or statistical and data-driven methods (e.g., principal components analysis, entropy). Some scholars try to overcome this problem, using an equal weighting scheme or an unweighted approach. For example, Sitaridis & Kitsios (2020) apply TOPSIS (with equal criteria weights) and the unweighted MCDA method of Huang & Moh (2017) in order to rank national entrepreneurship ecosystems based on Global Entrepreneurship Monitor data. However, an unweighted approach, particularly under a linear aggregation formula, is equivalent to an equal weighting scheme. The choice of an appropriate aggregation procedure is also an important issue in MCDA studies, given that simple additive models are compensatory approaches, and this assumption cannot be easily justified in EE studies (see Bramanti & Tarantola, 2012, for a discussion on compensability in the Regional Innovation Index). For this reason, several scholars prefer to avoid aggregation, at least at the higher levels of criteria hierarchy (see examples in Carayannis et al., 2018b; Sitaridis & Kitsios, 2020).

The previous issues, weighting and aggregation, are strongly interrelated. For example, weights have the meaning of value tradeoffs in additive aggregation models (see Munda, 2008 for interpreting weights in social studies) and they do not indicate the "importance" of an indicator (see Billaut, Bouyssou & Vincke, 2010, and Bramanti & Tarantola, 2012, for examples). Given that there is a strong connection between evaluations and measurement scales, attention should be given to data normalization when developing aggregation procedures. If, for example, data are normalized each year, the weights should also change each year so to as to be consistent with the new normalization. As recommended by Billaut, Bouyssou and Vincke, (2010), if weights are not changed, results can be absurd. Finally, although the discussion around compensability is beyond the scope of this review, we should emphasize that the selection of a compensatory (e.g., linear aggregation) or non-compensatory (e.g., geometric aggregation) model may lead to the development of different policies in EEs: "the marginal utility from an increase in low absolute score would be much higher than in a high absolute score under geometric aggregation. Consequently, a country would have a greater incentive to address those sectors/activities/alternatives with low scores if the aggregation were geometric rather than linear, as this would give it a better chance of improving its position in the ranking" (OECD-JRC, 2008, p. 33).

The most critical issues regarding the development of DEA models in EE evaluation include the choice of the scale assumption (constant returns to scale-CRS, variable returns to scale-VRS), the assumption of the projection path (output-oriented or input-oriented), the selection of input and output variables, and the further analysis of DEA results (e.g., use DEA scores in Tobit regression, bootstrap analysis). More specifically, regarding the scale assumption, a recent empirical study by Barbero, Zabala-Iturriagagoitia & Zofío (2021) examined to what extent the size or scale of ecosystems is related to their performance and identified the existence of decreasing returns to scale in EEs. However, studies in this area are rather limited and it is not possible to generalize these findings. Additionally, an important open question for OR scholars is the appropriate number of examined stages (e.g., number of modeled innovation or entrepreneurship activities) in DEA modeling, since the examined underlying phenomena are intangible or not directly observable, and therefore the use of entrepreneurship indicators cannot always capture the dynamics of transforming inputs into outputs and the interrelations of EE components. Multi-stage DEA models can consider the different steps of innovation and entrepreneurship activities, from the initial knowledge production to the final commercialization and creation of financial outcome (Carayannis et al., 2015).

Besides the previous technical issues, it should be emphasized that measuring EE efficiency is different from evaluating EE performance, although these concepts are confused in several studies (see Edquist & Zabala-Iturriagagoitia, 2015 and Carayannis et al., 2016a; Zabala-Iturriagagoitia, Voigt, Gutiérrez-Gracia & Jiménez-Sáez, 2007 for comparisons, discussion and examples of innovation efficiency vs performance).

3.4. The policy and interventions problem

3.4.1. Problem definition

The problem of developing policies and interventions in an EE appears in several studies with different contexts and orientations. This problem may also refer to different actors within an EE. For example, from the entrepreneur's point of view, it can be related to the allocation of resources through the creation and operation of new ventures. Similarly, a major challenge for policy makers is to effectively allocate resources and balance the needs of innovative, usually high-tech start-ups and scale-ups and other start-ups. As noted by Johnson & Bock (2017), entrepreneurs face multiple sources and types of uncertainty during venturing activity, while studies in the resource allocation problem should consider the conflicting interests of ecosystem stakeholders.

The evaluation of alternative policies is a typical problem in this domain. The main aim of these studies is to identify the most important factors than can affect EE performance (Del Campo et al., 2008; Zanakis & Becerra-Fernandez, 2005) or to select which projects should be financed within an EE (Kutlaca, 1997; Parreiras et al., 2019; Yahya & Kingsman, 2002). The latter is a typical resource allocation problem where a large number of alternative interventions are evaluated in order to optimally allocate a limited amount of resources. This problem is typically found at the macro

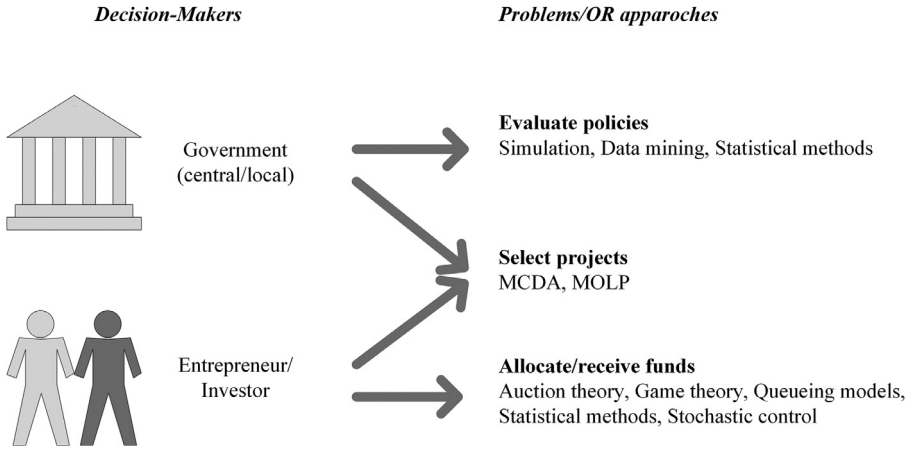

Fig. 3. Examples of alternative approaches for the policy and interventions problem.

and meso level (i.e., allocate resources in a national or regional EE) but also at the micro level (i.e., allocate resources by entrepreneurs or investors).

The policy and interventions problem appears to have some overlaps with the dynamic systems problem, since both include studies regarding the design, communication, and implementation of effective policies (Ghaffarzadegan, Lyneis & Richardson, 2011). For example, typical studies in this domain may evaluate alternative policy mechanisms (e.g., private or public R&D and non- R&D investments) in order to identify the best policy scheme. Uriona & Grobbelaar (2019) list several policy decisions that may be considered in this problem (e.g., inward foreign direct investments, government subsidies, degree of technological opportunities or knowledge cumulativeness, and skimming and penetration price strategies).

3.4.2. OR methods and techniques

The alternative OR approaches in the policy and interventions problem may be categorized based on who is the DM and what is the objective of the analysis. A typology of different problems in the EE literature is presented in Fig. 3, emphasizing the alternative problems faced by different DMs.

Based on this framework, governments may evaluate different policies in order to identify the important performance drivers of an EE, using data mining techniques (Zanakis & Becerra-Fernandez, 2005), statistical models (Del Campo et al., 2008), or other OR approaches. In a similar context, policy makers can also apply MOLP or MCDA models for the selection of projects within an EE, such as public financed R&D projects (Kutlaca, 1997), or government-sponsored entrepreneur development and R&D projects (Parreiras et al., 2019; Yahya & Kingsman, 2002).

Similarly, simulation (predominantly system dynamics, agent-based simulation) and network models have been used to model actors, activities and relationships within an EE and subsequently evaluate alternative policies (Andres & Poler, 2016; Choi et al., 2016; Lee & von Tunzelmann, 2005; Samara et al., 2012).

Optimization techniques, and particularly stochastic control, is another important category of OR techniques in the policy and interventions problem. These approaches try to model decisions faced by entrepreneurs during the product development of product commercialization process, for example:

- Decide when a new venture should enter the market (Lévesque & Shepherd, 2002).
- Decide whether to enter the market or continue product development (Armstrong & Lévesque, 2002).

These approaches are trying to account for the uncertainty in the evolution of an EE, using mainly an optimal stopping modeling approach. Other approaches included in the optimization domain may refer to multi-period game models, where, for example, entrepreneurs may compete in an auction-like setting for venture capital (Elitzur & Gavious, 2003), guarantee swaps have to be signed among a bank, an insurer, and an entrepreneur (Wang, Yang & Zhang, 2015b) or venture capitalists wish to optimize contracting in the context of venture capital financing (Lukas, Mölls & Welling, 2016).

Finally, a major domain refers to the allocation of investment funds, either from an entrepreneur's or investor's point of view. Considering this as a dynamic decision-making problem, queuing models, game theory, Markov chains or auction theory may be applied in order to optimize pre- and post-investment activities (Archibald & Possani, 2019; Elitzur & Gavious, 2011; Shepherd, Armstrong & Lévesque, 2005). Portfolio optimization techniques, including statistical approaches, may also be applied to this problem, when an investor wishes to target the right ventures and to determine the proper amount of investment (e.g., Zhong, Liu, Zhong & Xiong, 2018). Similarly, taking into account the time-varying value of a start-up, stochastic control can also help investors to determine the optimal dividend policy (Bayraktar & Egami, 2008). Despite the similarity with the general resource allocation problem, DEA models have not been applied here in the EE literature. This may be considered as an important research opportunity. For example, inverse DEA models may be used for allocating fixed EE resources based on their efficiency analysis.

3.4.3. Open questions

Uncertainty is a critical issue in evaluating EE policies and selecting innovation projects within an EE. Michnik (2013), for example, emphasizes that most MCDA models that deal with uncertainty are rather complicated and characterized by strong assumptions and suggest the integration of scenario planning and MCDA. MCDA approaches can contribute to solving R&D problems that involve multiple objectives under scarce or constrained resources, and, most importantly, provide an understanding of the decision-making context (Morcos, 2008).

Another critical issue in the policy and interventions problem is the modeling of entrepreneurial behavior. Entrepreneurs are motivated by both pecuniary and non-pecuniary factors, taking into account risk, uncertainty and profits. In this context, Kaiser (1990, p. 10) argues that "market forces drive an economy toward an efficient allocation of entrepreneurial resources" and analyzing the factors that influence the supply of and demand for en-

trepreneurial expenditures proposes a framework for the evaluation of entrepreneurial policy actions.

The evaluation and selection of partners (e.g., suppliers, collaborators) is one of the most common resource allocation problems faced by entrepreneurs. The problem itself is widely studied in the OR literature and can be related to the micro level of the policy and intervention problem. As noted by Ho, Xu & Dey (2010) in their extensive literature review on MCDA approaches in supplier selection and evaluation, the main challenges are the assessment of evaluation criteria and the pros/cons of alternative models. The same challenges may also appear in the EE literature; however, the distinctive characteristics of the entrepreneur should be considered (e.g., Kaiser, 1990; Yahya & Kingsman, 1999).

In general, entrepreneurial goals can affect the effective allocation of resources for both entrepreneurs and investors. An empirical study by Dunkelberg, Moore, Scott & Stull (2013) shows that new firm owners with non-monetary goals allocate their resources differently than owners with predominantly monetary goals, suggesting the need to better understand the entrepreneurial process when developing and promoting entrepreneurship policies.

In this context, understanding DMs behavior, effective modeling of uncertainty and determining an appropriate objective function, in addition to profit or revenue-related criteria, are the most important challenges for OR researchers in the context of these problems.

4. Critical issues and opportunities

The previous section has provided an overview of the application of OR methodologies and tools across the four overarching problems. Furthermore, we have outlined open questions for each problem. While some of them can be addressed with established approaches, methodological innovation is required from the OR community regarding not only new quantitative tools, but also new modeling efforts. We will present a discussion of particular cross-cutting challenges and opportunities for innovation in the following.

4.1. Systems, model boundaries and events

A major challenge across all four overarching problems is the sufficiently detailed and appropriate modeling of EEs. This includes the selection of model boundaries as well as the assessment of stakeholders. EEs are fractal, multi-level, multi-modal, multi-nodal, and multilateral configurations of dynamic tangible and intangible assets (Carayannis et al., 2018a). This is similar to many areas in which OR methods are widely used. EEs are a typical 'everything-affects-everything-else' case, like Brailsford, Desai & Viana (2010, p. 2293) describe the healthcare system and which resonates with the definition of intermodal freight transportation (Crainic et al., 2018). This requires identifying the relevant mechanisms to model a particular problem as opposed to attempting to create a model of the whole system that drowns in complexity. Based on this work, 'digital twins' of EEs can be developed to explore and test different scenarios and policy solutions, potentially in real time.

OR is a problem-based discipline and work is carried out to 'achieve something' for a particular client or stakeholder. For example, many network-based studies in the area of EEs on network visualization and 'graph-theoretic measures of system structure and dynamics' rather than analyses that take into account domain specific knowledge (cf. Alderson, 2008, p. 1047). Identifying gatekeepers (or 'connectors') is a crucial first step (Broekel & Mueller, 2018), but using other methodological approaches to find the optimal number of these 'connectors' for EE growth, minimizing the average distance between 'connectors' and entrepreneurs or other actors and using other multi-objective approaches to increasing connectivity given the constraints of a particular EE will lead to actionable insights.

Lastly, OR has dealt extensively with the implication of interventions and the role of 'events' within systemic problems. Halinen, Törnroos and Elo (2013) have emphasized the role of events in the formation of business networks. By extension, history has shown that events are also crucial for the development of EEs (e.g., Spilling, 1996). For example, studying networks as a process and not as a static artefact, as well as the impact of endogenous dynamics and events, provide challenges for OR researcher and a means to increase the relevance of OR in the area of EEs.

4.2. Decision-makers and stakeholders

Empirical studies show that different stakeholders may have different preferences and priorities (e.g., Carayannis et al., 2018b) and therefore, the assessment of the DM, and at which level of aggregation the DM operates, creates and captures value is a critical issue. This is particularly important in the comparability and evaluation problem, given that the majority of current studies are based on experts' opinions, who often do not represent an actual DM. Furthermore, from a practical perspective, this poses a challenge to engage EE stakeholders throughout the modeling process and the implementation of policy options.

Ecosystem research should not be seen as a purely academic exercise but focus on systemic interventions and policy design for societal impact (cf. the transdisciplinary research program proposed by Wurth et al., 2021). This builds on a rich tradition in OR – which is not as common in other academic disciplines. There is a widely-shared understanding that "OR practice involves intervening in a social process, as well as supporting decisions with quantitative methods, practitioners have developed their social and consultancy skills to improve their effectiveness, whilst academics have developed problem structuring approaches to enable OR to be applied more widely" (Ranyard, 1995, p. 474). This relationship has been further extended by including stakeholders more prominently and introducing the notions of 'engaged OR' and 'community OR' (Midgley, Johnson & Chichirau, 2018). This corresponds to the rise of the ecosystem concept and the increased acknowledgement of the importance of context for entrepreneurial activity (Autio et al., 2014; Welter, 2011) and bottom-up community development as opposed to purely top-down policy design – and OR is well suited to play a key role at this intersection.

4.3. Multi-level studies

There is a need for developing new models and approaches that capture the multi-level nature of EEs (e.g., interactions among macro, meso, and micro levels). First, EEs can be studied as multi-layer networks. Gathering data for each layer is a challenge in itself, particularly because many interactions in the EE are not formalized. Combining all layers and making sense of the network structure is an even bigger challenge. Exploring new secondary data sources, as well as applying problem structuring and other soft OR approaches is under-utilized but can lead to an improved and more nuanced understanding of the network. In line with this, there is often a delay until data become available (e.g., funding information or investment decisions). Even if information is available in real time, there is currently a lack of models and methods that can effectively and efficiently incorporate the data in the decision-making process in a meaningful way.

Second, and to some extent related, is the role of formal and informal institutions, which are co-created (informal) and created (formal) at different levels of aggregation and can influence both the structure and the performance of EEs. As noted by Alvedalen

& Boschma (2017), it is important to understand which agents are more successful when institutions change and why and if there are specific conditions or configurations within the EE that enable this change in the first place. New frameworks and mythological approaches are required to study both the adaption and co-evolution of existing as well as the design and implementation of new institutions within an EE.

4.4. 'Big data'

EEs are distinct from other territorial systems of innovation in multiple ways, one of them being their explicit inclusion of social aspects and community dynamics. While promising in theory, many of these social interactions are difficult to measure – despite the promise of digital data (Feldman & Lowe, 2015). An opportunity for researchers is the integration of 'big data' into OR models such as simulations (e.g., Tolk, 2015), DEA (Khezrimotlagh, Zhu, Cook & Toloo, 2019), real-time data combined with social network analysis (Rocha, Brown & Mawson, 2021) or combining networks with textual analysis (Hannigan, Briggs, Valadao, Seidel & Jennings, 2021). Particularly developing of novel data sets through advances in natural language processing allows studying the community aspects of EEs.

This represents a shift from supporting DMs with limited information to an abundance of potentially useful information in increasingly intertwined socio-technical and data-driven processes. It does, however, change the role of OR, requiring new "contextualized approaches to creating actionable insights" and "developing awareness of multiple courses of action, distinguishing how decision-making arises in socio-technical relations and clarifying who is empowered to make decisions and how" (Burger, White & Yearworth, 2019, p. 1147). In addition to exploring novel secondary data sources, primary data collection should be revisited as they often do not consider other modeling approaches beyond statistical analyses. As a consequence, modelers need to engage in interdisciplinary projects that include model development from the beginning. This allows the model to drive the data collection as opposed to modeling only trying to use existing data to the best possible extent (Pidd, 2009).

4.5. Multi-methodology and hybrid approaches

Another major opportunity for OR researchers is methodological pluralism and multi-methodology (e.g., Mingers & Brocklesby, 1997). Particularly a combination of qualitative and quantitative approaches in different forms are required to address the four problems. For example, in the dynamic systems problem, qualitative insights will help answer why (e.g., motivations of individuals) and how (e.g., individual behaviors and networking skills) networks develop, hereby addressing the current shortcomings of exploratory studies around network formation (Alderson, 2008). An example for this is the 'network ethnography' approach by Berthod, Grothe-Hammer and Sydow (2017).

Other opportunities include combinations of simulation models and MCDA or network science and game theoretic approaches to model co-evolutionary processes (Hellmann & Staudigl, 2014). In particular, these approaches can inform our understanding of network interdiction problems (Smith & Song, 2020) or dynamic competition of lobbying (Mandel & Venel, 2020), which represent important elements of EEs that have not yet been addressed. Other areas for methodological innovation include the dynamic modeling of networks (including the role of events). Ecosystems as multi-layered networks, which has been described conceptually but not yet been followed up with analytical and optimization approaches (Knippel & Lardeux, 2007). Entrepreneurial networks are not an isolated phenomenon but a means within the ecosystem to connect the right people and resources. Network characteristics and performance are, therefore, not just an outcome but also input to the development of the system. Further hybrid approaches and methods are required for connecting advances in network studies to the wider field of EE studies. For example, network aspects are only used as anecdotal evidence when comparing or evaluating ecosystems at the moment. New approaches need to be developed to link networks to other ecosystem indicators.

Complexity theory can also be combined with OR tools in order to understand the dynamic behavior of EEs and the interdependences between their elements. In this context, Roundy, Bradshaw & Brockman (2018) suggest the adoption of a complex adaptive system (CAS) approach that can help analyze the major characteristics of an EE (self-organization, open–but-distinct boundaries, complex components, nonlinearity, adaptability, and sensitivity to initial conditions). This is also related to the challenge of new multi-level studies, since in EEs, as complex systems, macro-level behaviors both emerge from and influence the micro-level interactions of the elements of the system (see also, Levin, 1998; Lissack & Letiche, 2002).

Another related and promising avenue are hybrid simulations (e.g., combinations of system dynamics and agent-based simulation) that address the interplay of individual decision-making and regional/institutional aspects is a major challenge for OR researchers in this domain (Brailsford, Eldabi, Kunc, Mustafee & Osorio, 2019). Another promising approach for future research is to use a combined resource-agent-based qualitative approach to managing complex systems (Kazakov, Howick & Morton, 2021).

4.6. Uncertainty and robustness

Entrepreneurship is, by nature, accompanied by uncertainty. This includes both the uncertainty in the entrepreneurial process and socio-economic processes in general as well as exogenous shocks such as pandemics, natural disasters, or even man-made crises like the financial crisis in 2008. Studying EEs in light of uncertainty may help us better understand stakeholders' behavior, which is particularly important in the policy and interventions problem. Insights into value-based network design, which links to the resource allocation problem, can support policy makers at different levels in making investment decisions for the EE, where investment is not driven by cost reduction but value creation for entrepreneurs and companies (Klibi, Martel & Guitouni, 2010).

Modeling uncertainty more explicitly and including it in the main mechanisms behind EEs is a first step towards more robust models, but there are further challenges and research opportunities. Robustness should not be considered as simple sensitivity analyse, where the change of one or more parameters is studied. Rather, it is necessary to consider Roy's general approach, where robustness is a tool of resistance of decision analysts against the phenomena of approximations and ignorance zones (Roy, 2010). Under this approach, it is possible to validate OR models by taking into account additional macro, meso, and micro entrepreneurship data.

5. Concluding remarks

Driven originally by practitioner work, the EE concept has emerged and is increasingly gaining momentum among practitioners, policy makers, and academics (Wurth et al., 2021). Research on ecosystems has remained fragmented without comprehensive support for decision-making. To overcome these limitations, we have defined four problems (stakeholder and boundaries, dynamic system, comparability and evaluation, and policy and interventions)

that serve as connection points between OR scholars and domain experts.

This review highlights that while OR approaches have been increasingly applied to EEs and related issues, these are still underrepresented and fragmented. We have provided a critical discussion about the applicability, assumptions, implementation, and limitations of alternative OR approaches as a response. Future work towards better tools for DMs is necessary as the complexity of the economy and social connectedness continue to rise and these four problems become even more interrelated.

For some problems and the more specific questions within them, current OR approaches and tools are sufficient. There are, however, different modeling approaches that have different assumptions and orientations (see, for example, alternative approaches in the dynamic systems problem in Table 2) that can complement each other. In other cases, although OR tools seem sufficient, these are not widely used (e.g., multi-level DEA models, which are able to study the hierarchical nature of EEs), and this offers an important opportunity for OR scholars to further contribute to the academic discourse and impact policy and practice. Other questions and, by extension, problems require methodological innovation such as new ways to capture dynamic, co-evolutionary relations within EEs or adopting approaches from other fields. For example, a system-of-systems approach may be used to study the fractal nature of EEs, while the QIH framework may be used to study the complexity of ecosystems (e.g., Carayannis & Campbell, 2009, 2011). In conclusion, this paper shows the existing contribution of the OR community to the study of EEs and hopefully paves the way for further inter- and transdisciplinary work.

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