The Ecosystem Knowledge Explorer: A Tool to Systematically Discover External Knowledge

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“Most organizations fail to manage performance effectively because they fail to look into the system holistically.”

Pearl Zhu
Author of Performance Master: Take a Holistic Approach to Unlock Digital Performance

It is crucial for any organization to discover knowledge from ecosystem-specific sources of knowledge that are considered external to the organization. Since knowledge exploration is a resource-intensive task for organizations, untimely or excessive knowledge exploration have detrimental impacts on the innovativeness and competitiveness of organizations. The benefits of performance measurement and management tools for knowledge management in organizations have been known for many years now. Therefore, the application of similar tools in ecosystems may enable actors to have access to valuable external knowledge. However, there is a paucity of such tools in management scholarship. The purpose of this study is to bridge this gap by proposing a conceptual tool – the Ecosystem Knowledge (EK) Explorer, which generates insightful knowledge for ecosystem actors using codified technical knowledge (e.g., scientific publications and patents). Not only does the EK Explorer reduce the uncertainty and fuzziness of the knowledge exploration phase for ecosystem actors, it also enables them to save resources and have access to strategic knowledge regarding competition, collaboration, technology management, and policy making in ecosystems. Bibliometric analysis, social network analysis, and text mining were used to conceptualize the constructs and measurable variables of the EK Explorer.

Introduction

In today’s global knowledge-based ecosystems (Järvi et al., 2018), having access to domain-specific knowledge from external knowledge sources is a matter of organizational life and death. Yet, exploring knowledge is resource-intensive, and requires organizations to have precise plans. Previous research has demonstrated that excessive knowledge exploration may have serious consequences for competitiveness and innovativeness of organizations. First, the timeliness of external knowledge exploration in ecosystems is paramount in the contexts of technology and innovation: being too late in knowledge exploration may endanger the future of organizations (Pellikka & Ali-Vehmas, 2016; Wubben et al., 2015). Second, if the search scope is too broad or too deep, the values appropriated through the explored knowledge might be less than the costs paid for knowledge exploration (Ahuja & Katila, 2004; Laursen & Salter, 2006; Li et al., 2013; Luo et al., 2018). To mitigate the impacts of excessive knowledge exploration, several moderators have been proposed (e.g., Laursen et al., 2012; Sidhu et al., 2007; Zhou & Li, 2012). However, despite previous efforts, there is no clear practical solution for organizations to systematically explore domain-specific knowledge from external knowledge sources, which in turn, may enable them to save resources and foster innovation.

Knowledge management comprises key success factors, strategies, and practices for knowledge creation, knowledge sharing, and knowledge sourcing, and it enables organizations to remain competitive and innovative (Alavi & Leidner, 2001; Lin, 2011). Knowledge management practices in intra-organizational processes (Alavi & Leidner, 2001; Durst & Runar Edvardsson, 2012) and enterprise-level performance measurement tools such as the Balanced Scorecard (Hoque, 2014; Kaplan & Norton, 1992) have been widely discussed in management scholarship (Alavi & Leidner, 2001; Durst & Runar Edvardsson, 2012). As they pertain to knowledge management in inter-organizational contexts, earlier theories and concepts extensively discussed how organizations must plan for knowledge management. These include, for instance, open innovation (Chesbrough, 2003), dynamic capabilities (Teece et al., 1997), absorptive capacity (Cohen & Levinthal, 1990), and integrative and dynamic knowledge management capacity (Lichtenthaler & Lichtenthaler, 2009). Disruptive technologies such as digital platforms (Korhonen et al., 2017; Steur, 2018), the Internet of Things (Ikävalko et al., 2018), and data analytics technologies (Kayser et al., 2018; Westerlund et al., 2018) are more recent phenomena, which have been of great value for knowledge management and knowledge exploration in both intra-organizational process management and inter-organizational information management. However, the application of intra-organizational knowledge management practices and solutions is not entirely applicable to ecosystems.

Notwithstanding a few contributions on performance indicators in inter-organizational processes such as in collaborative networks (Camarinha-Matos & Abreu, 2007; Camarinha-Matos & Afsarmanesh, 2007, 2008), supply chains (Chang et al., 2013; Gopal & Thakkar, 2012; Ramanathan, 2014; Ramanathan et al., 2011), and with limited applications in ecosystems (Battistella et al., 2013; Mäkinen & Dedehayir, 2013), efforts to measure and manage the performance of ecosystems remain rare (Aarikka-Stenroos & Ritala, 2017; Graça & Camarinha-Matos, 2017; Ritala & Almpanopoulou, 2017). This rarity may be due to a conceptual difference between the objectives of knowledge management practices in organizations versus in ecosystems. Ecosystems have ambiguous structures (Ritala & Gustafsson, 2018), and the interactions between ecosystem actors are complex (Ritala & Almpanopoulou, 2017). Competition is not the only strategy to create and capture value in ecosystems, and organizations collaborate, compete, and sometimes do both simultaneously (e.g., using co-optitive strategies) to survive. Furthermore, although organizations are responsible for appropriation of their own share from collectively created value in ecosystems, their captured value still depends on the ability of other actors in creating and capturing value (Chesbrough et al., 2018). To address the conceptual difference between knowledge management in an organization versus in an ecosystem, I use the term “ecosystem knowledge management”. Assimilation of ecosystem knowledge management is the prerequisite for conceptualizing knowledge management tools in ecosystems. Such tools may then enable to measure and manage the performance of ecosystems.

The objective of this study is developing a conceptual performance measurement and management tool called the Ecosystem Knowledge (EK) Explorer, or EK Explorer, which is designed to be used for systematic exploration of non-market types of external knowledge such as science, technology, actors, and geography from globally-operated and platform-based ecosystems. Bibliometric analysis, social network analysis, and text mining are used to conceptualize the tool. Not only may using such a tool save time and resources for organizations, it may be beneficial for managers in providing valuable knowledge that could not be explored otherwise. The generated knowledge may be used for making decisions regarding competition, collaboration, technology management, investments, and policy making in ecosystems.

Conceptualizing the Structure of the EK Explorer

According to Järvi and colleagues (2018), boundaries for (knowledge-based) ecosystems have become blurry and, nowadays, ecosystems must be analyzed from a global perspective. Therefore, I adopt *a* globally-operated ecosystems view – rather than one focused on spatially bounded ecosystems – to develop the EK Explorer tool. Integrating this view with Valkokari (2015), an ecosystem of a specific knowledge domain consists of *all* actors worldwide contributing to the production and flow of knowledge in that domain: scientific communities, inventors and innovators, technology entrepreneurs, innovation policy makers, innovation brokers, funding agencies, and intermediators.

Codified technical knowledge is referred to explicit technical knowledge that is stored and can be transferred from one person to another. It is the output of innovation in ecosystems, which is produced and exchanged by knowledge workers, inventors (R&D personnel or independent inventors), personnel of engineering departments, and worldwide researchers from research organizations and universities (scientific communities). Codified technical knowledge may stem from innovation in new product development, process optimization, or service-oriented projects. In technological innovation, the outputs of innovation may be stored and legally protected as copyrights (such as publications, technical drawings, databases, architectures, software, mobile applications, source codes, algorithms, databases, or mathematical concepts), patents, or industrial designs (WIPO, 2004).

The focus of this study is those platform-driven ecosystems where technical knowledge is peer-reviewed and examined for robustness and novelty before codification (i.e., scientific publications and patents). These data sources contain bibliographic and citation-related information. To develop the EK Explorer, I use the structure of stored data in patent and scientific publication databases. When analyzing bulk data for scientific publications and patents, not only does codified technical knowledge disclose information regarding the relevant knowledge domain and its growth over time, it also generates insights regarding contributors to the created knowledge. Therefore, using codified technical knowledge as input, the EK Explorer comprises two distinct units of analysis: codified technical knowledge and contributors to such knowledge.

Accordingly, based on different types of codified technical knowledge and different types of actors involved in ecosystems, the EK Explorer comprises four major components: Scientific Communities (1) and R&D Networks (2) for analyzing actors (i.e., contributors to codified technical knowledge), and Scientific Research Management (3) and Technology Management (4) for analyzing technical knowledge. To better understand the components, let us consider a wind energy ecosystem as an example. The codified technical knowledge of a wind energy ecosystem consists of all patents and scientific publications relevant to wind energy technologies, which are used for analyzing the components Technology Management and Scientific Research Management respectively. The direct contributors to codified technical knowledge in a wind energy ecosystem are inventors and public or private sector R&D units (R&D Networks), and researchers, research organizations, and universities (Scientific Communities). Although indirect contributors such as state-level and federal-level policy makers, governments, funding agencies, and investors are not immediately considered in the EK Explorer tool for performance measurement (because they do not directly create technical knowledge), they are considered as beneficiaries of the tool for *performance management.*

To define the main constructs and variables for the EK Explorer, different data analysis techniques in bibliometrics, social network analysis, and text mining are used. The techniques include local and global citation analyses (e.g., Facin et al., 2016; Gomes et al., 2018), co-citation analysis (e.g., Castriotta & Di Guardo, 2016; Egghe & Rousseau, 2002; Facin et al., 2016; Gomes et al., 2018; Loi et al., 2016; Randhawa et al., 2016), bibliographic coupling (e.g., Egghe & Rousseau, 2002; Park et al., 2015), undirected social networks (e.g., Chen et al., 2019; Cong & Shi, 2019; Taddeo et al., 2019), measures of centrality in social network analysis (Borgatti et al., 2018), and word/n-gram counting in text mining (Ignatow & Mihalcea, 2018).

Constructs and variables for Scientific Communities

For Scientific Communities, a node may represent a researcher, a research organization, a region, or a country. Accordingly, separate units of analysis must be taken into account. Table 1 lists the constructs, variables, and measuring system used for Scientific Communities.

Constructs and variables for R&D Networks

For R&D, a node may represent an inventor, an R&D unit, a region or a country. Accordingly, separate units of analysis are considered. Constructs, variables and measuring system for R&D Networks are explicated in Table 2.

Constructs and variables for Scientific Research Management

For Scientific Research Management, a node may represent a research paper, a knowledge domain or a knowledge sub-domain (unless the unit of analysis is stated otherwise in Table 3). Constructs, variables and measuring system for Scientific Research Management are described in Table 3.

Constructs and variables for Technology Management

For Technology Management, a node may represent a patent, class/sub-class of technology – classes and sub-classes of patents defined in International Patent Classification, commonly known as IPC (WIPO, 1971), or Cooperative Patent Classification, commonly known as CPC (USPTO & EPO, 2010) – knowledge domain or a knowledge sub-domain. Constructs, variables and measuring systems for Technology Management can be found in Table 4.

Table 1. Structure of the Scientific Communities component of the EK Explorer tool

No.	Construct	Variable	Measurement
1	Actor engagement	Degree of actor engagement	The degree to which a node contributes to scientific research in a specific knowledge domain. The variable is measured by the share of the number of publications (by the node) from all the publications in a specific knowledge domain/sub-domain.
2	Actor influence	Degree of influence	The degree to which a node plays the role of knowledge broker in the relevant scientific community. This variable is measured by betweenness centrality in the relevant directed network.
3	Actor impact	Degree of impact	The degree to which a node is popular (impactful) in their relevant directed network. This variable is measured by the indegree of nodes.
4	Actor activity	Degree of activity	The degree to which a node is active in their relevant directed network. This variable is measured by the outdegree of nodes.
5	Actors' similarity	Degree of similarity	The degree to which nodes have similar research outputs. This variable is measured by the frequency of co-cited publications.
6	Actor collaborativeness	Degree of collaboration	The degree to which nodes collaborate in their relevant network. This variable is measured by the number of co-authored publications.
7	Potentiality for collaborative research	Degree of potentiality for collaborative research	The degree to which nodes have similar research output (provided that no previous co-authored publications exist between the nodes). This variable is measured by the frequency of co-citing documents.

Table 2. Structure of the R&D Networks component of the EK Explorer tool

No.	Construct	Variable	Measurement
1	Productiveness	Degree of productiveness	The degree to which a node contributes to R&D output in a specific knowledge domain/sub-domain. The variable is measured through the share of published patents by the node from all the published patents in the knowledge domain/sub-domain.
2	Effectiveness	Degree of effectiveness	The degree to which a node contributes to R&D output in a specific knowledge domain/sub-domain. The variable is measured through the share of granted patents invented by the node from all the granted patents in that knowledge domain/sub-domain.
3	Actor influence	Degree of influence	The degree to which a node plays the role of knowledge broker in the relevant directed network. This variable is measured by betweenness centrality in the relevant network.
4	Actor impact	Degree of impact	The degree to which a node is popular (impactful) in their relevant directed network. This variable is measured by the indegree of nodes.
5	Actor activity	Degree of activity	The degree to which a node is active in their relevant directed network. This variable is measured by the outdegree of nodes.
6	R&D similarity	Degree of similarity	The degree to which nodes have similar granted patents. This variable is measured by the frequency of co-cited patents.
7	Technological competence	Degree of technological coreness	The degree to which nodes have technological coreness in their patent portfolio and cite their own work rather than imitating others. This variable is measured by the share of self-cited (backward citation) patent families from the total number of patent families granted to an organization.
8	R&D uniqueness	Degree of uniqueness	The degree to which nodes are cited by themselves rather than by others. This variable is measured by the share of self-cited (forward citation) patent families from the total number of patent families granted to an organization.
9	R&D collaborativeness	Degree of collaboration	The degree to which nodes collaborate in their relevant undirected network. This variable is measured by the number of co-patented technologies.
10	Potentiality for R&D collaboration	Degree of potentiality for joint R&D	The degree to which nodes have similar granted patents (provided there exist no co-patenting activities between the nodes). This variable is measured by the frequency of co-citing patents. Technological distance must be taken into account when considering this construct.

Table 3. Structure of the Scientific Research Management component of the EK Explorer tool

No.	Construct	Variable	Measurement
1	Sub-domain engagement	Degree of sub-domain engagement	The degree to which a sub-domain is involved in the evolution of research. The variable is measured by dividing the number of scientific publications in that sub-domain by all the papers published in the relevant knowledge domain.
2	Research impact	Degree of impact	The degree to which a node is considered impactful in their relevant network. This variable is measured by the number of indegrees of the node controlling for citation lags.
3	Research output similarity	Degree of similarity	The degree to which nodes are similar in terms of content (based on citations). This variable is measured by the number of times two documents are co-cited.
4	Research foundationality	Degree of foundationality (influence on new knowledge formation)	The degree to which sub-domains influence the formation of a new knowledge domain. The variable is measured through the share of cited documents of each of the sub-domains from all the cited documents.
5	Sub-domain independence	Modularity of sub-domains	The degree to which sub-domains in a knowledge domain are independent from each other. This variable is measured through the degree of modularity in co-citation analysis.
6	Research growth	Degree of research growth	The overall trend of evolution of a knowledge domain/sub-domain over time. This variable is measured through the overall growth in number of publications in a domain/sub-domain over a certain period of time.
7	Research growth pace	Research growth pace	The pace of growth of a knowledge domain/sub-domain. The variable is measured through the division of "degree of research growth" by the number of years of analysis.
8	Theme presence	Percentage of theme presence	The share of a theme/sub-theme from all the themes/sub-themes in a certain period of analysis. This variable is measured through the division of the count of words/n-grams relevant to a theme/sub-theme by the total number of words/n-grams relevant to all themes/sub-themes (after text pre-processing steps such as tokenization, stop word removal, stemming, and lemmatization) in a certain period of analysis.
9	Theme transition	Degree of theme transition	The degree to which evolution of a theme/sub-theme changes (or fluctuates) over time. This variable is measured through the change in "percentage of theme presence" from one period of analysis to another.
10	Theme strain	Theme strain	The overall growth of a theme in a certain knowledge domain/sub-domain over time. The term "strain" (same as strain in material deformation) is used for this variable to make judgements about the growth of themes over time more rigorous. This variable is measured through subtracting the count of words/n-grams in the last period of analysis from the count of those words/n-grams in the first period of analysis divided by the count of words/n-grams in the first period of analysis.
11	Rate of theme strain	Rate of theme strain	The growth rate of a theme in a certain knowledge domain/sub-domain. This variable is measured through the division of a theme strain by the number of years of analysis.

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Table 4. Structure of the Technology Management component of the EK Explorer tool

No.	Construct	Variable	Measurement
1	Sub-domain engagement	Degree of sub-domain engagement	The degree to which a sub-domain is present in the evolution of technology for a specific knowledge domain/sub-domain. The variable is measured through the share of granted patents in that sub-domain from all the patents granted in the relevant knowledge domain.
2	R&D impact	Degree of technology impact	The degree to which a node is considered impactful in their relevant network. This variable is measured by the number of indegrees of the node controlling for citation lags and patent renewal fees. Although there exist different constructs and measures for technology impact and patent value, this construct provides an instant overview of the R&D impact.
3	Technological similarity	Degree of technological similarity	The degree to which two nodes are similar in terms of content. This variable is measured by the number of times nodes are co-cited.
4	Technological foundationality	Degree of foundationality (influence on new knowledge formation)	The degree to which sub-domains influence the formation of a new knowledge domain. The variable is measured through the share of cited documents for each sub-domain from all the cited documents.
5	Technological sub-domain independence	Modularity of sub-domains	The degree to which sub-domains in a knowledge domain are independent from each other. This variable is measured through the degree of modularity in co-citation analysis.
6	Technology growth	Degree of research growth	The overall trend of evolution of a knowledge domain/sub-domain over time. This variable is measured through the overall growth in number of granted patents in a domain/sub-domain over a certain period of time.
7	Technology growth speed	Rate of technology growth	The rate of growth of a knowledge domain/sub-domain. The variable is measured through dividing “degree of technology growth” by the number of years of analysis.
8	Theme presence	Percentage of theme presence	The share of a theme/sub-theme in a certain period of analysis. This variable is measured through the division of the count of words/n-grams relevant to a theme/sub-theme by the total number of words/n-grams (after text processing) in a certain period of analysis.
9	Theme transition	Degree of theme transition	The degree to which evolution of a theme/sub-theme changes (fluctuates) over time. This variable is measured through the change in “percentage of theme presence” from one period of analysis to another.
10	Theme strain	Theme strain	The overall growth of a theme in a certain knowledge domain/sub-domain. This variable is measured through subtracting the count of words/n-grams in the last period of analysis from the count of those words/n-grams in the first period of analysis divided by the count of words/n-grams in the first period of analysis.
11	Rate of theme strain	Rate of theme strain	The growth rate of a theme in a certain knowledge domain/sub-domain. This variable is measured through the division of theme strain by the number of years of analysis.

Using the EK Explorer for Systematic Knowledge Exploration

So far, the need for performance measurement and management tools in ecosystems as well as the proposed conceptual EK Explorer tool for the above-mentioned purpose have been explicated. It might, however, still be unclear what questions can be systematically answered by applying the tool in practice, which will unlock the insights and value of the EK Explorer. To clarify this issue, I show what knowledge could potentially be explored using the EK Explorer by delineating the possible research questions that could be systematically formulated and answered in each of the four components. For the component Scientific Communities, Table 5 enables the user to systematically disentangle the scientific communities of an ecosystem, compare the performance of the actors, and identify potential opportunities for future collaborative research. Likewise, for the component R&D Networks, Table 6 allows the user to systematically disclose the assignees (patent holders) of an ecosystem, compare their performance, and identify potential opportunities for joint R&D projects. As it pertains to Scientific Research Management, the questions in Table 7 assist with systematically analyzing the evolution of scientific research in an ecosystem and identifying state-of-the-art research themes. Similarly, with respect to Technology Management, Table 8 helps the user to systematically explore technological trajectories in an ecosystem in addition to highlighting promising technologies and technological themes.

In practice, the EK Explorer can be used in ecosystems, where the codified technical knowledge is science-intense, patentable, or (ideally) both. One major benefit of using the EK Explorer is that it enables managers to access knowledge without a need for collecting primary data from ecosystems – at least in the preliminary phases of knowledge exploration. Accordingly, different organizations and managers in different locations of ecosystem structure may benefit from the EK Explorer. Strategy, R&D, and innovation managers may significantly benefit from using the tool in practice. This is regardless of the size of the firm as the EK Explorer can be used for different purposes that suit managers' goals (collaboration, competition, technology management, investment, policy making, etc). Research organizations and universities may use the tool to define new collaborative research partners and identify emerging research trends. Policy makers and government authorities may benefit from the outcome for more systematic intervention policies (more systematic funding of collaborative projects, etc). Investors can use the tool as a new source of information for their future investments. Outsiders with potential future research or technology ideas (e.g., entrepreneurs and SMEs with strong technical ideas or diversified large companies with prospective products relevant to the ecosystem) may use the tool as a new source of information for their next strategic decisions. Intellectual property (IP) consultants, patent attorneys, and in-house IP lawyers may use the tool to retrieve more relevant information about the state-of-the-art technologies to prevent their clients from infringing patents or to identify the cases of infringement.

Table 5. Knowledge discovery in the Scientific Communities component of the EK Explorer

Research Questions: Scientific Communities
1. Which actors have the highest/lowest degree of engagement?
2. Which actors have the highest/lowest degree of influence?
3. Which actors have the highest/lowest degree of popularity (impact)?
4. Which actors have the highest/lowest degree of activity?
5. Which actors have the highest degree of research similarity?
6. Which actors have the highest/lowest degree of collaboration?
7. Which actors are the most common potential candidates for collaborative research?

Table 6. Knowledge discovery in the R&D Networks component of the EK Explorer

Research Questions: R&D Networks
1. Which actors have the highest/lowest productivity?
2. Which actors have the highest/lowest degree of effective contribution?
3. Which actors have the highest/lowest degree of influence?
4. Which actors have the highest/lowest degree of popularity (impact)?
5. Which actors have the highest/lowest degree of activity?
6. Which actors have the highest degree of similarity?
7. Which actors have the highest degree of core technological competence?
8. Which actors have the highest degree of uniqueness?
9. Which actors have the highest/lowest degree of collaboration?
10. Which actors have potential for joint R&D projects?

Table 7. Knowledge discovery in the Scientific Research Management component of the EK Explorer

Research Questions: Scientific Research Management
1. What are the major sub-domains?
2. What are the most impactful research publications?
3. What are the most impactful research publications over the past five years?
4. What are the most/least impactful sub-domains in this area of research?
5. What are the most/least impactful sub-domains over the past five years?
6. What are the main clusters of research?
7. What are the most influential research papers (breakthroughs that build a new stream of literature) in the past 20 years?
8. What are the main theoretical foundations for the influential sub-domains in the past 20 years?
9. To what extent sub-domains are independent from each other?
10. What is the degree of research evolution?
11. What is the degree of research evolution for sub-domains?
12. Which sub-domains have the highest/lowest rate of evolution?
13. Which sub-domains have the highest/lowest rate of evolution over the past 5 years?
14. What are the most/least important themes discussed over the past 20 years?
15. How have the most important research themes transitioned over the past 20 years?
16. Which themes have the highest/lowest strain? (or, which themes have gained the most/least popularity?)
17. Which themes have the fastest/slowest rate of strain?
18. Which themes have got the fastest/slowest rate of strain over the past five years?

Table 8. Knowledge exploration in the Technology Management component of the EK Explorer

Research Questions: Technology Management
1. What are the major sub-domains of technology?
2. What are the most/least impactful patents in the past 20 years?
3. What are the most/least impactful patents in the past 5 years?
4. What are the major clusters of patents?
5. What are the main technological breakthroughs and sub-domains?
6. What are the main technological foundations for new sub-domains in the past 20 years?
7. To what extent sub-domains of technology are independent from each other?
8. What is the overall degree of evolution of technologies?
9. What is the degree of evolution for sub-domains?
10. Which sub-domains of technology have the fastest/slowest rate of evolution in the past 20 years?
11. Which sub-domains of technology have the fastest/slowest rate of evolution in the past 5 years?
12. What are the most/least important themes over the past 20 years?
13. How have the most/least important themes transitioned over the past 20 years?
14. Which themes have the highest/lowest strain? (in other words, which themes have gained the highest popularity?)
15. Which themes have the fastest/slowest rate of strain in the past 20 years?
16. Which themes have the fastest/slowest rate of strain over the past five years?

Conclusion

Excessive or untimely knowledge exploration may have detrimental impacts for innovativeness and competitiveness of organizations. Despite exploring several moderators to reduce those impacts, as identified by previous research, academic research has thus far failed to propose a conceptual performance measurement tool for ecosystems. The objective of this study was to propose a tool for systematic knowledge exploration in knowledge-based ecosystems. The conceptual tool I proposed here, the EK Explorer, consists of four major components and altogether 39 constructs and measurable variables, which can be used in knowledge-based ecosystems for collaboration, competition, technology management, investment, or policy making purposes.

My study contributes to the intersection of different streams of literature – those relating to ecosystems, knowledge management, and operations management – in two ways. First, I defined a new term "ecosystem knowledge management" to fill the gap between the existing understandings of knowledge management in organizations versus in ecosystems and developed the conceptual EK Explorer tool for systematic knowledge exploration in ecosystems with various new constructs. Second, while research approaches in ecosystem studies are mainly exploratory (Dedehayir et al., 2018) and using data-driven and network visualization approaches for analyzing ecosystems is quite common and popular among scholars (See e.g., Basole et al., 2015; Basole, 2009; Huhtamäki & Rubens, 2016; Russell et al., 2015; Still et al., 2014), using the EK Explorer tool may make the design phase of research less fuzzy.

The EK Explorer tool has two major limitations. First, as mentioned earlier, the only sources of codified technical knowledge for the inputs of the tool are peer-reviewed sources and, in particular, scientific publications and patents. In technological innovation, although scientific publications and patents may be applicable to the majority of knowledge domains and knowledge-based ecosystems, they are not entirely applicable to all. For example, technical knowledge that is created in software or service ecosystems may not be

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patentable and, thus, should be stored as source codes, algorithms, or as similar sources. To generate insights from sources other than patents and scientific publications, however, the EK Explorer lacks relevant constructs and thus, is not viable. Second, the EK Explorer is not capable of generating insights regarding technology market, commercialization of innovation, and customers.

Future research may focus on designing similar tools that can 1) apply data sources other than scientific publications and patents as inputs and 2) generate market-related knowledge to be used by and for ecosystem actors. In addition, the application of the proposed tool EK Explorer should be tested in empirical contexts to examine whether the tool can disclose similar patterns for individual (behavioural), organizational, regional, national or international strategies in ecosystems. This would then be of great value in formulating relevant hypotheses and building theory.

About the Author

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