# Network visualizations of knowledge assets: their value and user experiences for innovation development

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**Abstract:** This paper explores the value of network visualizations for presenting complex knowledge assets to executive decision makers in order to develop culturally-relevant insights for program development. The value is first addressed with an analysis of network visualization process called 'Ostinato', an operational context in relation to cognitive fit as a theoretical context. Then value is explored with an analysis using taxonomy of interactive dynamics for visual analytics. Further evaluating the usability of visualization is conducted in the context of the Parisian ecosystem, with board members using network visualizations to explore complex multi-layered knowledge about relationships among key executives, companies, and financing organizations. All findings support the argument that value of knowledge assets in problem-solving performance depends on both format of the data and nature of the task. Furthermore, the findings support the importance of continual involvement and interaction between data analysts and decision makers; they highlight the importance of considering knowledge assets as value drivers that can support knowledge-based innovation.

**Keywords –** network visualization, user experience, visual analysis tool, visual analytics, innovation development, ecosystem

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## 1 Introduction

Successful innovation toward economic gains remains the goal in many innovation development activities, in organizations and at policy levels. In an increasingly networked world, there is a growing urgency to find effective methods and techniques to understand and manage the complexity of business ecosystems (Adner, 2012) as well as the complexity of the innovation ecosystems at regional areas (Russell et al., 2015) and at cross-national levels (Still et al., 2014). In addition, "You can't manage what you don't measure" is a respected management approach (McAfee and Brynjohlfsson, 2012).

Recently, the idea of data-driven decisions being touted as better decisions has been supported by the availability of data, especially big data (McAfee and Brynjohlfsson, 2012). In the policy field, this has been addressed with call for evidence-based decision-making, which has been promoted as a means to reduce the risk of bad decisions (Burwell et al., 2013; Seelos and Mair, 2012).

A dynamic innovation ecosystem can be characterized by "a continual realignment of synergistic relationships that promote the growth of the system" (Russell et al., 2011), through which information, talent and financial resources flow. Hence, looking at these knowledge assets and their relationships becomes essential. Increasingly more data is now available for decision makers; however, much of this data is limited to traditional file formats (for example with Excel sheets).

According to cognitive fit theory (Vessey and Galletta, 1991), the fit between the presentation format and the decision-making task influences the person's problem-solving performance. We argue that visualizations of complex data in the form of network visualizations are advantageous to decision makers in their innovation development tasks (Still et al. 2014). Using the cognitive fit theory, we have explored the value of network visualizations for visual decision support in the context of business ecosystem analysis with individual problem-solving tasks with synthetic data (Basole et al., 2016). However, much of the decision making takes place in teams, oftentimes with the expectation of better decisions and better acceptance of the decision (Kocher et al., 2006). It has also been said that collaborative data analysis differs from single-user analysis in that a group of people share the data analysis experience and often have the goal to arrive at a joint conclusion of discovery (Lam et al., 2011).

Accordingly, in this paper, we analyse the usability of network visualizations with a theoretical framework as well as with an experiment in which participants, in dyads, applied interactive network visualizations (based on real data) as visual tools for insights and decision making about an ecosystem. We recognize that there is extant literature about evaluating usability of visualizations – for example already Lam et al. (2011) analysed 345 evaluation papers to provide a systematic overview of the diversity of evaluations and research questions that are relevant to information visualization research community. Furthermore, some literature specifically addresses network visualizations (for example Heer and Agrawala, 2008; Jianu et al., 2014). We have these to better understand the complexities related.

## 2 Supporting innovation development with visualizations

Companies capable of managing networks create more value, and subsequently profit (Libert et al., 2014). Subsequently, when collective gains are sought at the network level, change agents seek to orchestrate networks and manage their growth (Paquin and Howard-Grenville 2013; Ritala et al., 2013). Incubators and accelerators acquire and use knowledge to develop programs that orchestrate innovation networks. Using those knowledge assets to build shared vision of change has challenged many innovation leaders. Stories of the desired transformations are sometimes used to develop mental models of the change objectives in order to align expectations and actions of multiple stakeholders. The current contexts of ubiquitous data and outcome accountability, however, heighten the interest in evidence-based decision making. The challenge of effectively presenting such knowledge assets of relationships has created new opportunities for data visualization to improve the quality of decision making.Prior studies on financial decision-making (Frownfelter-Lohrke, 1998), requirements analysis (Moore, 1996), and complex managerial decisions (Speier and Morris, 2003) have applied and empirically validated the theory of cognitive fit. It has been developed to help understand how alignment between presentation format and decision-making task influences an individual's performance in problem solving (Vessey and Galletta, 1991). Cognitive fit theory further suggests that a preferable and more consistent mental consideration of the problem is realized when representation of the problem fits the problem-solving task.

We are aware of task-technology fit as another "theory of fit", which emphasizes that for an information technology to have a positive impact on individual performance, the technology must be utilized, and the technology must be a good fit with tasks it support (Goodhue and Thompson, 1995). However, based on our extensive analysis of prior work using cognitive fit theory, based on literature review from 1990 to 2015 (Basole et al, in press), we conclude that it is an appropriate theoretical lens for understanding the relationship between information format and ecosystem analysis tasks.

### 2.1. Nature of the task: knowledge assets for innovation development

The relevance of knowledge assets as fundamental strategic factors of business success has been widely recognized in today's competitive scenario; in fact, more and more organizations accredit their competitiveness to knowledge assets and consider knowledge as a differentiating factor in knowledge economy (Nonaka and Takeuchi,

1995). Indeed, innovation has been defined as "the embodiment, combination and/or synthesis of knowledge in novel, relevant, valued new products, processes, or services (Leonard and Swap, 1999). In light of this, the optimal development and deployment of an organization's knowledge assets has become a strategy for company's success.

### 2.1.1. Ecosystem context

The focal shift for innovation from a single firm toward an increasingly network-centric activity (Chesbrough, 2003) has added significant complexities to innovation management. Methodological approaches to analysing business innovation ecosystems has roots in in the idea of value networks (Clarysse et al., 2014), including both academic (Ahuja et al., 2011) and practical (Adner, 2012) approaches. Prior academic analyses in biotechnology knowledge ecosystems (Owen-Smith and Powell, 2004, Powell et al., 2010), software (Iyer et al., 2006) and information technology industries (Iansiti and Richards, 2006) have focused on events and activities at singular levels. Recent approaches include the financing infrastructure (Huhtamäki et al., 2011), relational capital (Still et al., 2015) and multi-level approaches (Russell et al., 2015; Basole et al., 2015).

Much confusion remains about the concepts of business, innovation and knowledge ecosystems coupled with concepts of platforms, especially innovation platforms. In this paper, our emphasis is not on the semantics, but on the understanding of the multiple-actor systems. Focusing the analysis on surviving and thriving within ecosystems (Valkokari, 2015), we acknowledge (1) that these multiple actors constantly produce new outcomes by combining artefacts, skills, and ideas, (2) that these different business, knowledge, and innovation outcomes distinguish the system from other systems, and (3) the system is inherently linked to time and space (both virtual and geographical).

### 2.1.2 Support for management

In rapidly changing business environments, regional innovation organizations have emerged to provide practical assistance to companies, investors and funding organizations seeking to aggregate their knowledge assets and synergize their participation in innovation ecosystems. In Austin Texas, the IC2 Institute has established data based services for networking and incubator programs at the local level (Gibson and Butler, 2014). In Finland, several organizations use knowledge assets to provide innovation development services (Huhtamäki et al., 2011; Huhtamäki et al., 2012) at the national level. Across several European countries, the EIT ICT Labs (currently operating as EIT Digital) program provides networking support for new knowledge workers and their potential employers (Still et al., 2014). New initiatives, such as those of CapDigital and similar change agents, increase the relational capital of growth and start-up companies by facilitating information sharing among small companies and enterprises by facilitating collaboration on national and European projects (Russell et al., 2015).

### 2.2 Format of the data: showing complex data as networks

In this research, we do not present data; we present visualizations of the analysis of data. According to Weber and Hine (2015), rather than focusing on ecosystems of platforms, a model should be explored in which ecosystems are viewed as structures of relationships between interacting actors. Ecosystems can be seen as networks of relationships: through these relationships actors are connected. The relationships are indicative of resource flows, especially those of knowledge assets to which the organization has potential access.

The introduction of the network perspective, and especially that of social structures, (Wasserman and Faust, 1994) can be seen as the defining characteristic of an innovation

ecosystem. It allows utilizing visual analysis of social networks to explore innovation ecosystems and clusters of their unique knowledge assets, unique actors and unique reciprocal links among them (Chandler and Vargo, 2011).

Visualizations of networks are based on network metrics, which explain the characteristics of the network structures. These metrics for understanding the dynamics of an ecosystem are categorized based on distinct but related levels of analysis: the network as the whole (ecosystem), such as network density, and the node level (firm/individual) such as degree and betweenness centrality (Basole et al., 2013). This differentiation is important because knowledge assets are not homogeneous, and network dynamics at each level, although related, are also distinct (Zaheer et al., 2010).

The benefits of network visualizations have been presented to include the fact that they enable researchers and other stakeholders to 'see' the structural context and the scalable influence of that context within the market structures (Freeman, 2000; Chandler and Vargo, 2011). At the same time, they are seen to show the connections of individual nodes, organizations or the network at large, for example in the ICT ecosystem (Basole et al., 2015).

## 2.3 Evaluating the value and usability of visualizations

It has long been acknowledged that an information presentation format, or visualization, enables decision makers to see patterns, spot trends, identify outliers and thereby improve comprehension, memory and decision making (Tufte and Graves-Morris, 1983). Visualizations leverage the human visual system to support cognition and the process of sense making, in which information is collected, organized, and analysed to generate knowledge and inform action (Heer and Agrawala, 2008). Visualizations provide a powerful means of making sense of data (Heer and Schneiderman, 2012).

The science of visual analytics seeks to find ways to support analytical reasoning with interactive visual interfaces (Thomas and Cook, 2006). The use of visualizations is advantageous for establishing a common ground for discussion and for helping individuals see their position in a larger context.

Usability describes the quality of use of applications by end-users, and has been seen to refer to three 'use' words that must all be true for a product to be successful: it must be (1) useful, accomplish what is required, (2) usable, do it easily and naturally, and (3) used, make people want to use it (Dix et al., 2004). Somewhat connected to the disappointment with usability and its utilitarian approach, terms of 'sociability' and 'user experience' have gained momentum. Though sociability the social interaction is emphasized, whereas user experience emphasizes the user's relationship to products and services, being ultimately personal and context-dependent (Still, 2010).

In the context of interfaces for information visualization users not only interact with widgets on the interface but also with data supporting decision-making, which could be affected by the way information is presented. Accordingly, the usability has been separated into the categories of i) visual representation usability, referring to the expressiveness and quality of the resulting image, ii) interface usability, related to the set of interaction mechanisms provided to users so they can interact with data through the visual representation, and iii) data usability, devoted mainly to the quality of data for supporting users' tasks (Freitas et al., 2002). Toward this, Freitas et al. (2002) have created a criteria for the evaluation of visual representation of information visualization

techniques, which includes cognitive complexity, spatial organization, information coding, and state transition.

The ultimate test of a product's usability has been seen to be based on measurements of the user's experience with it (Dix et al., 2004). Still, case studies of information visualization systems in realistic settings were found to be the least common type of studies (Plaisant, 2004). For example, using their evaluation criteria, Freitas et al. (2002) evaluated their bifocal browser- visualization with an inspection of interfaces by an expert who was able to recognize usability problems. It has been stated that usability of information visualization tools can be measured in a laboratory, however, to be convincing, utility needs to be demonstrated in a real setting, that is a given application domain and set of users (Plaisant, 2004). For example, four visualization methods for meshing group information and node link diagrams—essentially hence four different network visualizations—were at the core of a user study which used Amazon Mechanical Turk website as well as eye-tracking analysis (Jianu et al., 2014) and found that there were meaningful differences on how people perform tasks in these four visualizations.

Overall, evaluation is becoming increasingly important in the field of information visualization as visualizations are becoming more prevailing in our daily life. It has been encouraged for the information visualization community to reflect on evaluation goals and questions before choosing methods (Lam et al., 2011).

## 3   Analysis of network visualizations

In this paper, we are approaching the analysis of network visualizations with a specific network visualization process and its subsequent results. The process model developed toward visualizations of complex data for stakeholder involvement is called 'Ostinato process model for data-driven visual network analysis' (Huhtamäki et al., 2015). It is a visual analytics tool, which is semi-automatic as human insights are required for example for data curation, and is still in its minimum viable product phase (MVP).

The Ostinato process can be considered adaptable to a variety of data, metrics and explorations, with visualizations supporting specific decision goals. During its development process, it has been used in a number of academic endeavours and context for understanding the ecosystem (Russell et al., 2015). For example in the context of EIT Digital (previously EIT ICT Labs)—an initiative designed to drive European digital transformation— where toward the goal of understanding the existing relationships between the geographical locations, the participants affirmed the value of networks as geospatial representations, though the insights from the network metrics and their interpretation were considered challenging (Still et al., 2014).

Furthermore, the effectiveness of network visualizations resulting from the Ostinato process was addressed in our previous attempt to explore the value of them (Basole et al., in press). In the context of business ecosystem analysis, three visualization methods (list, matrix, network) and their impact for performance in individual tasks were studied. Network visualizations were found to support the wide lens perspective, and respondents considered the network representation as the view that could help accomplish business ecosystem analysis more quickly and easier.

Toward better understanding of the value of network visualizations, in this paper we use three approaches. The first one intends to present the Ostinato process in relation to the cognitive fit theory, which suggests that when the problem representation fits the

problem-solving task, a preferable and more consistent mental representation of the problem will be realized, facilitating the problem solving process, consequently resulting in preference for the representation (Vessey and Galletta, 1991). The second one analyses the Ostinato process as well as its resulting visualizations with a taxonomy of interactive dynamics for visual analytics by Heer and Scheiderman (2012). The third one follows our previous experiment (Basole et al., in press), hence going beyond the theoretical perspective of usability analysis, getting real user feedback about the usability and value of network visualizations. Accordingly, simultaneously addressing the call by Plaisant (2004) for integrating visualization tools into solutions for real problems as well as the fact that much of the decision making takes place in a team (Kocher et al., 2006), we conducted an experiment in which Parisian policy makers (in dyad setting) were presented with knowledge assets as interactive network visualizations (based on real Parisian ecosystem data) to support decision-making.

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### 3.1 Ostinato process and cognitive fit

The Ostinato process model is the operational context for the technical steps used to create the method and visualizations, and the cognitive fit is the theoretical context chosen to select the variables and to explain and to understand our findings. The Ostinato process model is built on a four-stage process for analysing a business ecosystem developed by Basole et al. (2013): (1) boundary specification for determining the primitives (nodes, relationships) of the networks as well as the analysis timeframe; (2) metrics identification for selecting the appropriate social network and graph theoretic metrics for understanding the dynamics of an ecosystem; (3) computation, analysis and visualization toward analysing and visualizing temporal, relational ecosystem data; and, finally, (4) sense-making and storytelling, describing the processes from data to understanding and visual narratives for telling the story.

The Ostinato process (Figure 1) leverages knowledge assets dynamically, and is usually mainly performed by a data analyst or someone with sufficient data analytics skills, though close collaboration with experts bringing the understanding of the context is imperative. For this study, it was implemented with custom batch-processing tools (Python and NetworkX) and an interactive network analysis platform (Gephi) that implements a core set of key functionalities for visual network analytics (Bastian et al, 2009), and for example, with its force-driven layout (Fource Atlas in Gephi), allows for lay-out of nodes in clusters, making the interconnecting tissue between them visible. For going beyond static visualizations, GEXF.js, a Web-technology based open source library for network visualizations was used.
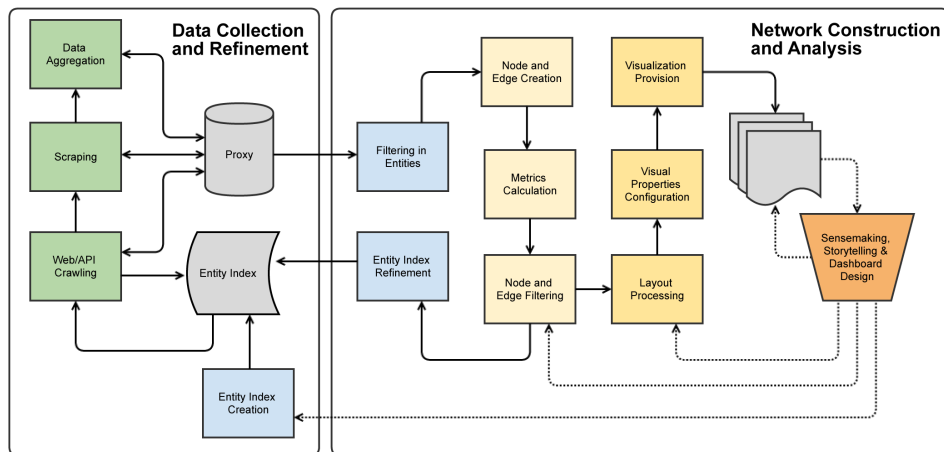
**Figure 1.** The Ostinato Process (Huhtamäki et al., 2015)

The Ostinato process decribes a system—in includes loops, cycles and several sybcucles. In contrast, cognitive fit theory can be seen as linear description, in which a series of factors lead to explaining an outcome (see Figure 2). For the Ostinato process model, the starting element is the task characteristic of network management or ecosystem management, which also has been addressed with network orchestration. The mental representation is seen to be supported by the prevalence of social networks in our lives, hence contributing to the understanding of the networks and their elements and their structures. In addition, the visual representations of networks – such as by LinkedIn InMaps which was created to "help to visualize and gain insights from your professional network" [1] – can be seen to have an impact toward the latter phases of the cognitive fit (the "fit" and the performance & preference).
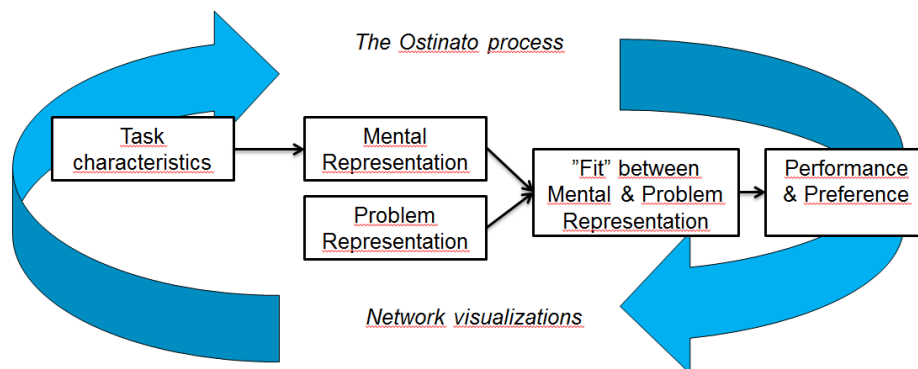


**Figure 2.** Ostinato process and cognitive fit.

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The Ostinato process model can be presented as a means of getting toward cognitive fit (Figure 1): it has several feedback loops that refine the cognitive fit. All four of these loops have the phase of "sense making, storytelling & dashboard design" at one side: on the other side is (1) network construction and analysis, (2) layout processing, (3) node and edge filtering, and (4) entity index creation. In practice, this is achieved with creation of the visualizations, their iterations and co-creation during the process. Hence, the analysis supports the importance of continual involvement and interaction between data analysts decision makers, who are the experts of the context and its challenges.

### 3.2 Analysis of visual analytics

Visualizations resulting from the Ostinato model can be analysed with the taxonomy of interactive dynamics for visual analytics by Heer and Schneiderman (2012). The taxonomy was created for supporting the fluent and flexible use of visualizations, in order for creating visualizations that "users must be able to make sense of it", hence addressing the usability and user experience and the value of the visualizations. It is intended also to support creating visual analysis tools.

**Table 1.** Analysis of interactive dynamics ( Heer and Schneiderman (2012).

| Taxonomy | In network visualizations |
|---|---|
| Data & View specifications | |
| Visualize data by choosing visual encodings | Colours for different types of actors |
| Filter our data to focus on relevant items | Showing certain types of relationships |
| Sort items to expose patterns | Patterns of relationships are visible |
| Derive values or models from source data | Depends on network metrics |
| View manipulation | |
| Select items to highlight, filter, or manipulate them | Items can be selected |
| Navigate to examine high-level patterns and low-level detail | Shows all the links/relationships of one selected entity |
| Coordinate views for linked, multi-dimensional exploration | Can see both the network and some details of the selected entity |
| Organize multiple windows and workspaces | Not addressed at this point |
| Process & Provenance | |
| Record analysis histories for revisitation, review and sharing | Not addressed at this point |
| Annotate patterns to document findings | Not at this point |
| Share views and annotations to enable collaboration | Not specifically |
| Guide users through analysis tasks or stories | |

The taxonomy consists of 12 task types grouped in the three high-level categories, as shown: data and view specification (visualize, filter, sort, and derive); view manipulation (select, navigate, coordinate, and organize), and analysis process and provenance (record, annotate, share, and guide). These categories incorporate the critical tasks that enable iterative visual analysis, including visualization creation, interactive querying, multiview coordination, history, and collaboration (Heer and Schneiderman,

2012, p.46). This wish-list of tasks can be seen to mostly include elements of 'interface usability' as defined in the context of interfaces for information visualization, explaining to the set of interaction mechanisms provided to users so that they can interact with data through the visual representation (Freitas et al., 2002). In addition, the list addresses much of the criteria for the evaluation of visual representations of information visualizations technologies (Freitas et al., 2002): the data & view specifications of Heer and Schneiderman can be seen to correspond to cognitive complexity and to information coding, view manipulation corresponds to spatial organization, process & provenance corresponds to state transition.

The analysis (Table 1) shows that many of the specification are present in the network visualizations. At the same time, the full spectrum of the taxonomy is not supported by the current minimum viable product of the tool, which is natural in this MVP phase of the tool. Overall, the Ostinato process provides visualizations that are intended for users to make sense of them.

### 3.3 Usability of network visualizations with user experiences

Our experiment focused specifically on the user experience and the subjective outcomes of the deployment; it was conducted in late 2013. The task of the participants was focused on network visualizations of knowledge assets as visual tools for decision making.

The experiment was conducted in Paris at the headquarters of CapDigital, the French Business Cluster for digital transformation. Since 2009, the cluster has been implementing the Paris Region's strategy for supporting innovative small and medium-sized companies (SMEs) in the digital content and media industry[1]. At the time of the experiment in 2013, CapDigital had about 700 members. In 2015, its membership increased to almost 1,000. In its quest to have "an information system that enables us to capitalize on knowledge within the ecosystem and related technological domains"[2], CapDigital has been collaborating with various organizations, one of which allowed the researchers to work with CapDigital on this experiment.

The selection of knowledge assets and data for analysis and visualization was made collaboratively between the research team and the leadership team of CapDigital. The analysis and visualization approach were framed by the objective of increasing the Board's awareness of the ecosystemic context of CapDigital's operations and impact, as well as the desire to more fully utilize available knowledge assets to inform the Board's decisions about program direction.

In the experiment setting, there also was an earlier task that included comparisons between list, matrix and network visualizations. Neither this task nor its results are reported in this paper as we concentrate on the value of network visualizations

### 3.3.1 Background information of the participants

The ten (10) participants came from business enterprises and from government, and their professional activities included business executive and management roles, investors and policy makers and their advisors. The participants were male and female board members of CapDigital. Hence, they were all experienced decision makers with deep knowledge of the CapDigital program, the companies that comprise its membership, and the technology development context of digital media in the Parisian metropolitan area.

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[1] http://www.capdigital.com/en/
[2] http://www.capdigital.com/en/capdigital/organization/

Some background information about the participants was gathered with a pre-study survey. Participants reported the complexity of their daily decision making environment, with an average score of 4.9 out of 7 (with a range of 4 to 6) and the complexity of their business decisions with an average score of 4.8 (with a range of 4 to 6). Business intelligence tools typically used by these participants included statistical analysis, Excel dashboards, CRM, mindmaps, black/white boards, google alert, and – for a few – data visualization tools such as Informatica. All participants reported using online information as a source of business intelligence, and 7 out of 10 said they rely heavily on personal contacts for business intelligence. Eight of the ten expressed a preference for working with others when making complex decisions; two said they prefer to make decisions by themselves.

### 3.3.2 Format of the data and network visualizations

Building on three prior collaborative iterations of the Ostinato process with CapDigital, the interactive visualizations for this experiment were constructed using data from three complementary knowledge assets: (a) private data about the relationships within Cap Digital projects and companies (managed and curated by CapDigital), (b) public data from two datasets that originated from public and third-party sources of data and are curated by Innovation Ecosystems Network (IEN) (Rubens et al., 2010), providing crowdsourced data about companies, their individuals and investors. Following the Ostinato process these steps were implemented:

1. Boundary specification: the CapDigital dataset was used in combination with an IEN dataset of growth companies and an IEN dataset of startup companies. In each case data were selected on the basis of: companies with headquarters or branches that were operating in the Parisian ecosystem, their investors, key individuals that were affiliated with them and financing organizations/business angels that had invested in them. In order to use the three datasets together and for referential integrity, we produced a set of unique identifiers for companies and other actors. For this experiment, we utilized CapDigital's expertise in the Parisian ecosystem, in a semi-manual process conducted by their data-curation specialist, using identifiers for companies and investors.

2. Metrics:  In the experiment, participants engaged with network views that focused on the node level, i.e. the level of individual actors – companies, investors, business angels, and individuals, as well as projects. Therefore, the emphasis was placed on understanding the roles of individual nodes (actors in the ecosystem) by using node-level metrics (degree, betweenness centrality). Betweenness centrality was selected as the key metric and was used in defining the size of individual nodes, as its value equals the number of times a given node appears in the shortest path from all nodes in the network to all others. It shows the importance of a node in bridging the different parts or components of the network together. During the experiment, for ease of use, betweenness centrality was referred to as the "linking factor."

3. Computation toward visualization: An interactive view for participants was constructed with a data-driven, semi-manual method. In a co-creation process before the exploration, CapDigital representatives took an active role in designing and implementing the views of the network analysis that highlighted key considerations for board-level decisions.

4. The experiment centered on the sense making and storytelling phase of the process, in which the value and use of the network visualizations were explored.

An example interactive visualization used in the experiment is presented in Figure 3. The visualization is a map of the relationships between entities of a specific ecosystem, displaying hence the roles and positions of individual nodes as well as density and patterns of relationships in the ecosystem as a whole. In this example, in the ecosystem of Paris, the entities shown in the visualization include organizations (in red), individuals (in blue) and financing organizations (in green). The lines between these entities describe a relationship between them: the lines between companies and individuals are based on employment relationships, the lines between companies and financing organizations are based on financing relationships; the lines from company to company are based on formal acquisition or alliance relationships. The size of the node is determined by the network metrics.

The interactive visualization allows for zooming in and out, as can be seen from the left-hand side of the screenshot. In the right, "a big picture" of the network visualization is shown so that user can easily see which part of the big picture is currently being looked at.
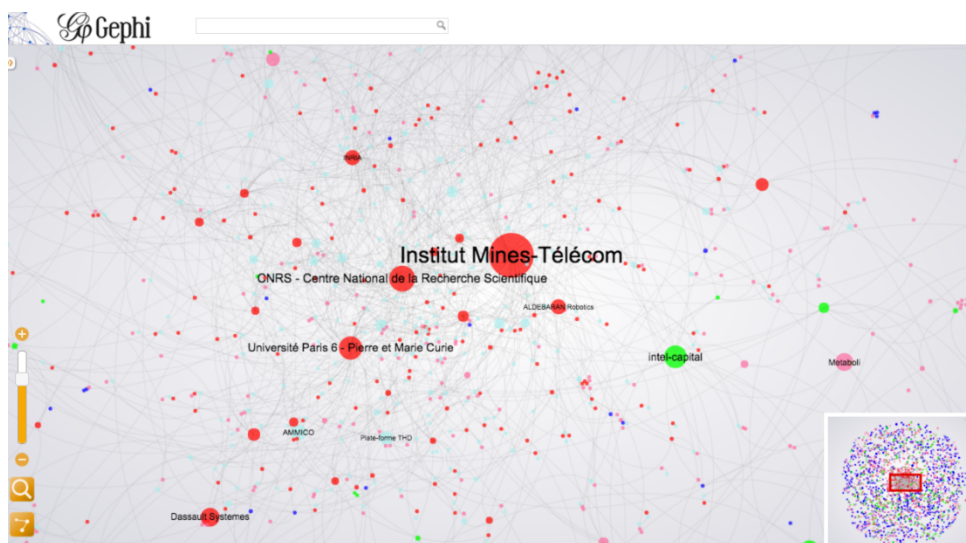


**Figure 3.** An example network visualization

### 3.3.3 Experiment's nature of the task

Following the introduction of the research team (consisting of 2 external researchers and 2 CapDigital representatives) and brief description of the experiment, the participants were presented in English (spoken) and in French (written) instructions for the task involving large quantities of data.

In assigned dyads (pairs), the participants were required to work together to find the selected company, and follow its links (going through 2-4 connections in the middle) so that they could reach the public or private funding organization. The specific task that participants had two parts: *focusing on a selected CapDigital company and, using [only] the interactive network visualization tool, collaboratively identify relationship pathways for acquiring financing and explain their choice:*

A. *Through which connections could the selected company establish a pathway of connections for private funding from an identified private funding source; and*

B. *Through which connections could the selected company establish a pathway of connections to a selected source of public funding.*

The dyads were given 15 minutes to complete the task. After this time, they were asked to verbally state their solutions to both questions. Hence, the dyad was expected to arrive at a joint conclusion of discovery, as stated by Lam et al. (2011) in their description of collaborative data analysis, including taskwork and teamwork.



**Figure 4.** Two participants getting ready to use interactive network visualizations



**Figure 5.** Two participants working as a dyad on a task.

### 3.3.4. Experiment survey for user experience

Following completion of this task, a post-task survey was administered. As we had three or four elements that competed as interesting variables in our complex study and wanted to focus on the study on the mode of data visualization relative to the tasks presented, we chose well-accepted task load measures. Hence, our post-task survey asked participants to rate the challenge of task 2 using the NASA Task Load Index (Hart and Staveland, 1968) about the level of difficulty, their self-perceptions of success and frustration. It asked them to rate the usefulness of the interactive network visualization and to comment on what they liked and did not like about using it.

The experimental protocol included also a possibility for an informal discussion after the completion of the tasks as well as the surveys. Researchers and CapDigital representatives documented these discussions.

### 3.3.5. Results

The experiment challenged experienced decision makers to make relevant decisions using real data. 10 participants, performing in 5 dyads, used the interactive network visualizations to complete a task of identifying relationship pathways. All of the participants were able to complete the two tasks within the allotted time frame of 15 minutes.

As reflected in ratings of the user experience with the NASA task load index (see Figure 6), the task was not perceived to be physically demanding; participants did not feel hurried, stressed or that they had to work very hard to complete it. For the most part, they felt the task was moderately demanding, and they felt successful in completing it.
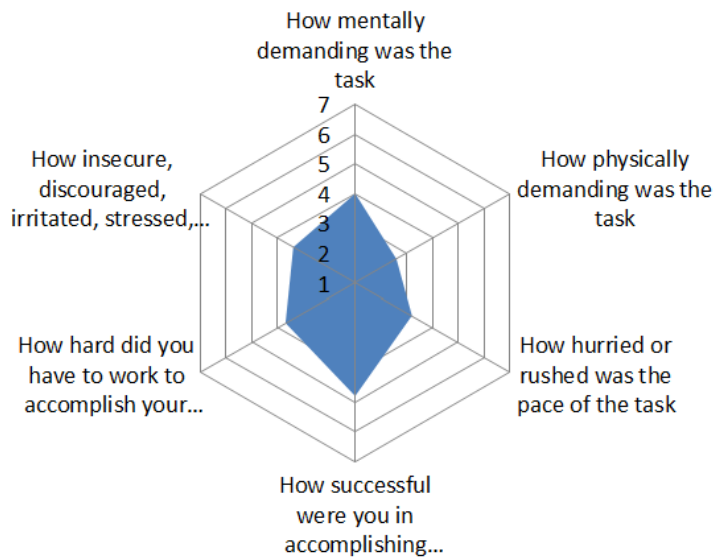
**Figure 6**. Average responses regarding user experience using NASA index, scale 1 to 7, 7=high rating; 10 participants

Participants perceived the interactive network visualization as useful (Figure 7). It was seen as most useful for finding info about direct connections as well as for finding info about the big picture. The emphasis in the task type on connections (relationships) may have contributed to this result.
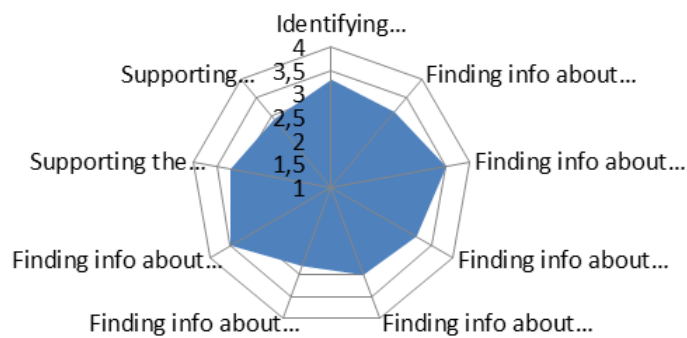


**Figure 7**. Usefulness ratings for the interactive network visualization following Task 2. 5-point rating scale; 5= extremely useful; 10 participants.

The participants described what they liked about the visualizations with words such as "fun," "easy to use," "seeing the connections" (see Table 2). They also noted that there was info missing, some links were unclear, and that understanding the "galaxy" or its construction was not easy.

Observations of the four members of the research team provided several insights about the value of the network visualizations. Overall, the approach of data-driven visual network analysis was well-received among the participants; the interactivity of the visualizations engaged participation from all. Among these organizational policy makers, all perceived benefits from using a combination of tools and data. Access to interactive visualizations stimulated their awareness of the importance that their organization's data could be accessible in usable formats.

**Table 2**. What the users liked, did not like and commented on about the interactive network visualizations

| What users liked | Simple |
| --- | --- |
| | Intuitive |
| | Easy to use |
| | Fun |
| | Easy to find big actors |
| | Visually efficient |
| | Zooming in and out |
| | Size of the view |
| | Seeing the connections, seeing links |
| | Complete |
| | Colors make it easier |
| What users did not like | Info missing? Need to have more precise data |
| | Too many types of data; Different types of links to get access not clear |
| | Size factor not explained |
| | Some links unclear |
| | Understanding the galaxy not clear |
| | Finding 1 item/company was not easy |
| | Data is "spread out" |
| | Suprises in the node sizes |
| | Understanding the "galaxy" geography |
| Other comments | There were data points missing |
| | Links disappear when the selected entity is out of screen |
| | I do not understand the difference between inbound and outbound links |
| | Nice work! |

Specifically regarding the network visualization format, the new term "linking factor" (used instead of betweenness centrality) was understood at a practical level and used in conversation by all participants. Participants saw value in the network view. As they explored the interactive network, they articulated suggestions on how it could be configured for easy use; they expressed a desire for more data but also – for some types of inquiries – less data, in order to focus on critical insights from the visualizations.

Participants were enthusiastic about the potential of crowd-sourced data to contribute value to the knowledge assets of the organization; they perceived major value in the insights that could be developed from such knowledge and directed toward organizational goals and program priorities. Several raised questions about the cost of procuring and using similar types of knowledge assets on an ongoing basis.

## 4    Discussion

Visualizations of knowledge assets held by organizations are advantageous for understanding complex issues, such as relationships and innovation, and help to create shared objects around which a mutual understanding of current state and desired change can be developed. Visualizations leverage the human visual system to support cognition and the process of sense making. They provide executive decision makers with data-driven analysis that can be backgrounded by context or which can serve to frame an issue for decision making.

All findings of this study (the theoretical as well as the practical from the Parisian ecosystem) support the argument that value of knowledge-assets in problem-solving performance depends on both format of the data and nature of the task, corresponding hence to our theoretical context of cognitive fit theory. This finding has also been presented in our earlier experiment of visual decision support for business ecosystem analysis (Basole et al., in press). Furthermore, the findings support the importance of continual involvement and interaction between data analysts and decision makers—which is why the Ostinato process, which provided the operational context for our study and accordingly was analysed in the study and includes collecting, selecting data, determining metrics for analysis, visualizing the results and making sense through storytelling is an iterative process. Hence, we echo the conclusion of another network visualization study (Jianu et al., 2014) that mapping visualizations to tasks that they address well can lead to more effective visualization deployment.

Our analysis of network visualizations bears significant limitations, which result from the specificity of the process and type of network visualizations as well as the experiment that was conducted. For example, we concentrated on the Ostinato process, and we used interactive network visualizations (produced with Gephi). Our experiment in Paris was based on cognitive fit theory, we used NASA Task Load Index for task load measurement as well as a specific survey certain questions to inquire about the usability of the visualization. Furthermore, while we ensured to involve real decision-makers, our sample size is small. Hence, there are many exciting possibilities for future research to address, for example to explore task load from alternative perspectives. Overall, while we recognize the need to improve the generalizability of our findings, we again state that with the experiment part of this study, we responded to the call by Plaisant (2004) of integration visualization tools into solutions for real problems, demonstrating the utility of network visualizations in a real setting. We then continue to present the contributions for evaluating network visualizations as well as the practical implications for supporting innovation development with network visualizations of knowledge assets of relationships.

### *4.1 Contributions for evaluating network visualizations*

The fit of the visualization to the mindset of the analyst is important, which was analysed with the cognitive fit theory, emphasizing the value of feedback loops in the Ostinato process toward interactive network visualizations. Hence, the main theoretical contribution of this study is that it extends the application of cognitive fit to the context of innovation development and to decision makers in ecosystems. The Ostinato model process was seen to support the cognitive fit, as network visualizations are seen to fit the task of managing and orchestrating complexities related to innovation.

In addition, with the taxonomy of interactive dynamics for visual analytics (Heer and Shneiderman, 2012), it was presented that resulting interactive network include elements for users to make sense of them. According to the name of the taxonomy, it was seen to mostly include elements of 'interface usability', which is one of the three types of usability in the context of interfaces for information visualization (Freitas et al., 2002).

In our paper, following the extensive analysis of Lam et al. (2011) and its resulting evaluation scenarios, we addressed the evaluation of deriving relevant knowledge in a given domain, evaluating collaborative data analysis, while concentrating on evaluating user experience. Accordingly, from the experiment in Parisian ecosystem, with 10 participants, we got positive user feedback, which supported the use of network visualizations in the complex context of innovation development. Analysis of results stresses the importance of taking knowledge assets into consideration as value drivers that can support decision process performance improvements. The participant's requests for additional refinements to the visualizations and questions about cost of providing such data on ongoing basis attests to the utility of the interactive network visualization for the types of issues they deliberate. Hence, the other two elements of usability of information visualizations —namely the visual representation usability and the data usability (Freitas et al., 2002) —did come up in the experiment, especially in the informal discussions after the experiment task. Decision-making tools that leverage the knowledge assets of an organization must be appropriate to the context of the decision, the mindset of the decision makers, and the data available to the organization. This study provides insights that can stimulate further research on visualization tools for data driven decisions by senior executives. Literacy and fluency with the tools and the metrics are essential for the full realization of benefits from implementing the Ostinato method, since the final stage – sense making and storytelling – depends on comprehension and a vision that can be shared. The Ostinato process addresses selection of data and metrics for network visualization; experiences in this study support the importance and the value of involving stakeholders in those steps. Feedback from participants informed an additional consideration about the iteration needed between crafting the visualization and selecting the data. Complexity in the visualizations fuelled exploration of potential pathways. When potential pathways had initially been identified, participants expressed a desire to have the complexity reduced – in order to focus on trade-offs among alternative options.

### 4.2 Practical implications for supporting innovation development

The findings from the three approaches to exploring network visualizations give preliminary positive indication that network visualizations can be effectively used to reveal patterns and insights in an ecosystem. An understanding of the complex system-level factors influencing innovation development is essential for carrying out high impact regional development programs. Values and relationships that constrain and enable change are very real forces, yet often difficult to articulate, and pose huge challenges for measuring change. The successful use of data-driven network visualizations in this pilot study provides evidence that access to insights from an organization's knowledge assets can be facilitated with data-driven network visualizations.

In this regional context, network visualizations made the relationships—conduits of information, talent and resources—visually explicit in novel ways. Network visualizations, especially when interactive and used as shared objects, can empower and support the strategic and service decisions of program managers, policy analysts, business

executives and entrepreneurs, all who need to understand the complexities of the current situation so that they can orchestrate future opportunities. Additionally, multiple perspectives can be invited and exchanged in the process of developing and orchestrating transformation programs. With subsequent automated updating of data and tracking analyses, the assumptions and contingencies underlying decisions can be monitored for changes that would impact policy and program directions (Huhtamäki et al. 2015).

Familiarity with the metrics used to analyse data and with formats for reading those results are critical for utilizing data-driven visualizations for decision making. Among decision makers who participated in this study, prior use of interactive data visualization tools influenced the perceived utility of the interactive networked views. Those with prior experience rated them higher.

For the critical task of developing a shared vision as context in which decisions can be made, we propose that a shared visual object based on knowledge assets of the organization has high value. Cultural influences can be identified and explored as background or foreground of the visualization. A shared visual object can provide a foundation for exploring the alignment of decision makers' mind sets regarding value creation and risk taking. Goals for change and alternative pathways to accomplish those goals can be articulated, making evaluation of outcomes more transparent and objective. Importantly, an iterative process of exploration and decision making can be established to create a cycle of improved decision making.

## 5   Summary

At the core of this study was exploring the value and user experiences of visualizations of knowledge assets of relationships in the context of ecosystems and innovation. Based on the cognitive fit theory, we suggest that the fit between the task (innovation development) and the format of the data (interactive network visualizations) improves the dynamic and productive use of knowledge assets.

The interactive network visualization process Called 'Ostinato process model' was seen as the operational context, hence as a means of getting toward cognitive fit, which provided the theoretical context: it has several feedback loops that refine the cognitive fit. Also, the taxonomy of interactive visualizations supported using network visualizations toward sense making. The implementation of the experiment in Paris provided explicit real-world evidence on the use of network visualizations for knowledge asset understanding and subsequent innovation ecosystem development. Although the number of participants was small (10 board members), observations and feedback provide directional findings that support refinements of the method for larger-scale implementation.

Our results illustrate the importance of continual involvement and interaction between data analysts and decision makers; they highlight the importance of considering knowledge assets as value drivers that can support decision making regarding knowledge-based innovation. At the same time, it emphasizes the need to involve real users into the exploration process.

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