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Factors that influence cooperation in networks for innovation and learning

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ABSTRACT

Innovation networks and learning networks share the same cooperative intention, but they too often fail as members of the network do not know which partnerships are valuable. If one plans to build a support service that provides insight into the value of future cooperation, one first needs to know what contributes to effective and efficient cooperation. In addition to carrying out a literature review, we invoked the eDelphi method to answer this question. eDelphi is a method to solicit knowledge from experts anonymously and without geographical constraints. Observations from two eDelphi rounds are reported in this article. The first round focused on factor generation and determined which factors influence cooperation networks; it was conducted with two groups of six representative experts. Experts list open communication, a positive attitude, trust, keeping appointments, and personality as influential factors for cooperation networks. A team of four moderators categorised the factors in a second round, resulting in four core clusters: personal characteristics, diversity, effective cooperation, and managerial aspects. Interestingly the experts failed to list some factors that are mentioned in the literature. This finding is discussed.

1. Introduction

In everyday life, we regularly face situations in which we have to work together with others. Even when we buy a product in a store, seller and buyer cooperate to the benefit of both. The seller earns money in order to make a living, and the buyer gets the product or service that she wants. When such cooperation involves more than two parties, a network-like structure of interacting actors emerges. Such networks are knows as *cooperation networks*.

Cooperation networks come in various kinds. Two kinds are relevant to our present purposes. The first are *innovation networks*. They fulfil a crucial role in the development of new and better products (innovation) and in sharing risks (Das & Teng, 1997). Ever more firms are now making their knowledge public in order to profit from the advancements others make with that knowledge, something called networked innovation or open innovation (Chesbrough, 2003). Indeed, several studies show that effective cooperation within a network can boost creativity and innovation (Burt, 2004; Cassiman & Veugelers, 2006; Kratzer & Lettl, 2008; Perry-Smith, 2006). Linking to new people beyond the firm or organisation gives access to new information, assets and knowledge. New insights can be brought back home to add new perspectives to current thoughts (Boland & Tenkasi, 1995).

Learning networks are the second kind of cooperation networks of interest to us. They are defined as 'non-organised groups of learners' (Berlanga et al., 2008) who all want to learn or acquire new skills by sharing and exchanging knowledge. Learning networks are made up of individuals or even organisations who try to learn (Simon, 1991). Sharing and exchanging knowledge are the cooperative actions that tie the participants together. Small, temporary groups of nodes (ad-hoc transient groups or communities) have been proposed to guide the interpersonal relationships that are formed within learning networks by promoting sociability, trust and a sense of belonging (Berlanga et al., 2008; Fetter, Berlanga, & Sloep, 2009).

In both kinds, as in all cooperation networks, successful cooperation depends on correctly deciding whom to cooperate with. A study among 40 managers found that one of the key determinants of effective relationships in terms of knowledge transfer and creation is correctly valuing others and their knowledge (Cross, Parker, Prusak, & Borgatti, 2001). Similarly, a study by Sie et al. (2013) found that peer value and characteristics are one of seven core factors that influence learning via networks. Selecting the right partnerships thus crucially affects future cooperation (Das & Teng, 1997). Finding the most valuable peers in the network, however, is not as simple as it may sound. As

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network size increases, so does the chance of experiencing information overload when searching (De Choudhury, Sundaram, John, & Seligmann, 2008). For example, in a social network of over 150 people it becomes almost prohibitively difficult to know who are valuable peers (Hill & Dunbar, 2002). This boundary to human rationality is imposed by inherently human, cognitive limitations (Gigerenzer & Selten, 2001; Selten, 1998; Simon, 1982).

These limitations may be overcome by employing a software service to carry out the calculations (e.g. Sie et al., 2014). Using software has a number of additional benefits. Precisely because it reveals who are valuable cooperation partners, it may give potential team members an incentive to work together. Providing team members with insight about each other may even foster reciprocal action. Furthermore, software increases the insight one has into one's network. Such insight has been found positively to correlate to power as perceived by others (Krackhardt, 1990).

A software service that helps overcome said human cognitive limitations obviously needs to exhibit the right kind of behaviour. At least two factors determine this. First, the software needs correctly to estimate the future value of cooperation. After all, the fruits of a decision to cooperate are reaped in the future only. Coalition theory helps to make such estimates. Generally speaking, coalitions are temporary alliances between distinct parties that cooperate. By cooperation, we mean that they share a common intention, based on individual goals (Sie, Bitter-Rijpkema, & Sloep, 2010). Organisational teams, in essence, are cooperative in behaviour. For example, they may share the common intention of inventing a new product. But they do not necessarily share the same goal of personal growth. Game theoretic solution concepts such as the Shapley value (Hart, 1987; Shapley, 1953) and the nucleolus (Kohlberg, 1971; Schmeidler, 1969) provide an *a priori* estimation of the value of future coalitions. Applying such calculations to teams or individuals that learn together, allows one to determine the value of their prospective cooperation, the coalition.

Second, to calculate what valuable coalitions are, the software service needs to know what factors determine effective cooperation and how they do so. The extensive literature on the topic reveals several such factors, such as social identity (Cheung & Lee, 2010; Keltner, Kleef, Chen, & Kraus, 2008), actor similarity (Ibarra, 1992; McPherson, Smith-Lovin, & Cook, 2001) and power (Burkhardt & Brass, 1990; Ibarra, 1993; Swan & Scarbrough, 2005). Not all of these may be practically relevant to cooperation networks for innovation and learning, though. Also, most of the theoretical knowledge predates the advent of online social networks. The extant literature therefore may report too many factors to include in said software tool or may lay the wrong emphases. Finally, some factors that the literature has uncovered may have little practical value, for example because their actual impact is negligible. Using the Delphi method (Linstone & Turoff, 1975) we questioned experts with practical experience with cooperation networks, hoping to uncover the main factors that are relevant to cooperation in networks.

The remainder of this paper is structured as follows. In Section 2, we lay out our research methodology, which includes a description of the specific variant of the Delphi method we used. Section 3 presents the results. It does so of each Delphi round separately as round 1 was conducted with two panels of experts, and round 2 was conducted with a team of moderators. Section 4 discusses results in Section 5 we draw conclusions from them.

2. Method

2.1. The eDelphi method

The Delphi method aims to solicit information and ideas from a panel of experts about a specific subject through a series of opinion expression. It is one of the most effective approaches for getting a consensual agreement among experts on particular issues (Davis & Alexander, 2009; Hasson, Keeney, & McKenna, 2000; Kennedy, 2004; Linstone & Turoff, 1975; McKenna, 1994). Because domain experts are likely to be well informed about the latest technologies and their adoption, the Delphi method is often used to identify trends (Davis & Alexander, 2009; Milkovich, Annoni, & Mahoney, 1972; O'Neill, Osborn, Hulme, Lorenzoni, & Watkinson, 2008; Rice, 2009).

The original Delphi method worked with a series of paper questionnaires sent out by regular mail; opinions mailed in were then fed back to participants in a follow-up questionnaire. In this way, agreement among participants could be reached. Today's technology (forums, chat, wikis) allows online discussion, which is not only much faster but also fosters more interaction. Therefore we developed the eDelphi method that uses a tailor-made, tested, online environment stocked with such online tools (Bitter-Rijpkema, Martens, & Jochems, 2002).

Our eDelphi comprised two rounds. In round 1 participants generated factors, in round 2 moderators clustered these factors. It took place on the Internet during a four-week period in April and May 2011. An introductory statement provided the participants with the main question *What factors influence cooperation networks?* and a description of its context in the form of a real life example. Next to the context description, we provided Twitter, Delicious and Google News feeds that contained the words 'cooperation' and 'network' (Figs. 1a and 1b) to provide a better understanding of the concepts cooperation and network. It also provided the necessary additional information to sufficiently create a context for the question at hand, without constraining the participants to think in a certain direction.

During the first round of four weeks experts could articulate factors via forum posts. Others could discuss these factors by leaving a reply on the individual page of a posted factor. The postings were quasi-anonymous only, still to allow the facilitator to prod participants who had become inactive. This factor generation round was about expressing opinions, taking perspectives and generating ideas. A wide range of perspectives is desirable. We therefore chose to recruit two kinds of experts: one that represented broad areas of expertise relevant to cooperation networks, a second one that represented a specific instance of cooperation networks, namely, learning networks. During this first round of generating factors, participants were also asked to indicate the importance of the factors collectively listed. Ratings on a scale of one to five could be assigned. We explicitly did not ask participants to rate each and every factor, as this would increase workload drastically. Ratings helped the facilitator to give feedback on the factors that were generated, thus to trigger new discussion and elicit new factors. They also helped the moderator team of round 2 correctly to summarise the Delphi session.

During the second round, that took one week, a team of moderators analysed the factors that had been generated. The development of a system model that simulates and recommends optimal future cooperation requires a set of core clusters, rather than a large set of factors that act as variables. It is commonly acknowledged that a system that uses more variables to represent reality is also more prone to errors. All factors were fed into the WebSort.net (http://websort.net) clustering environment. WebSort provides a variety of data aggregation (e.g. items vs. items, items vs. categories) and visualisation opportunities (e.g. tree structure, tables). Moderators could add factors to self-defined clusters with self-defined names. Purposely, we did not elect to use predefined cluster names, to prevent bias from the researchers. Subsequently, overlap between the clustering of the moderators was computed using agglomerative hierarchical cluster analysis. Fig. 2 summarises the workflow that was followed.

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