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Collective Learning in Collaborative Networks: Understanding Actors' Perceptions

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Abstract

Collaborative networks which involve diverse public and private actors holding different views and interests are more and more common for coping with environmental problems. Collective learning, characterized by the development of shared understandings and by the alignment of actors' perspectives and goals, is crucial to achieve durable policy solutions and achieve cross-scale integration. Although recent theoretical developments suggest that collective learning in collaborative networks happens when communication is facilitated through social relations and structural characteristics of the network, more research is needed to specify factors of collective learning. In particular, little is known about what shapes individual's perception of collective learning, when collaborative success also depends on individuals' positive perception of its outcomes. Based on autocorrelation analyses of eight Belgian collaborative structures involved in environmental policy-making, this communication assesses the role of social relations, uses of one's idea, and procedural fairness for collective learning, defined as the extent to which individuals perceive that actors' objectives have aligned over time. Eights collaborative networks are composed of 10 to 20 individuals who were both surveyed and interviewed about their participation. It appears that an actor local transitivity and a positive perception about the uses of its ideas positively influence her perception of collective learning. Procedural fairness is not significant. In sum, this communication on individual perception of collective learning highlights the importance of tie strength and the balance between individual and collective objectives for collaborative networks success.

[Work in Progress – Please do not quote]

Introduction

Coping with complex social challenges that cannot be solved by one single actor or organization requires collaboration among a diverse set of actors (Ansell & Gash, 2008; Emerson et al., 2012). The call for collaborative mode of governance gave rise to collaborative networks in which various actors extensively interact within a relatively institutionalized environment in order to develop or implement public policies or services (Ansell & Gash, 2008; Sorensen & Torfing, 2014). Yet, the success of those collaborative networks—that is, their capacity to generate enhanced policy outcomes—does not emerge *per se*. One critical element in this context is the development of collective learning, characterized by shared understanding and a sense of common purpose and objectives (Ansell & Gash, 2008; Emerson & Nabatchi, 2015). Collective learning support fair and durable solution as well as joint action, which makes it an important indicator of the collaborative performance (Emerson & Nabatchi, 2015; Klijn & Koppenjean, 2016). Hence, understanding the drivers of collective learning and the formation of shared understanding is essential for evaluating collaborative network success.

The literature pinpoint to various drivers of collective learning—understood here as the emergence of shared understanding. Several works emphasize the role of social dynamics (Ansell & Gash, 2008; Heikkila & Gerlak, 2013; Emerson & Nabatchi, 2015; Klijn & Koppenjean, 2016). The main assumption is that the relations existing within the collaborative network shape collective leaning, as it is through relations that actors get to learn each other goals and align their objectives. The structure of the network, i.e. in terms of diversity of participants as well as the perception of the collaborative process—is the process considered as of good quality—are also considered as though as important drivers of collective learning—and more generally, collaborative success (Heikkila & Gerlak, 2013: Innes & Booher, 1999; Leach et al., 2014).

Yet, empirical research on the drivers of collective learning remains limited. Existing empirical studies explore collective action (Bodin et al., 2017; Sandstrom & Carlsson, 2008) or individual learning (Leach et al., 2014; Resh et al., 2014) while works evaluating collective learning (i.e. Gerlak & Heikkila, 2011), if they give valuable insights, are insufficient to disentangle causal mechanisms. This paper aim is to contribute to the collective learning literature by exploring the conditions under which collective learning occurs. Based on regression analysis of eight Belgian collaborative networks, this paper adopts an individual approach and look at the individual perception of collective learning—that is the degree of shared understanding perceived by a specific actor, with a focus on shared goals. In other words, it address the following question:

What explains that some actors perceive a higher degree of collective learning, defined as shared objectives?

The aim of this article is not to connect learning processes and products (i.e. Heikkila & Gerlak, 2013). Rather, it explores what shapes the individual perception of a specific collective learning product—in this case, shared understanding over goals. Exploring collective learning from the perspective of individual actors contribute to our understanding of the role of individuals in collaborative processes and the dynamics that contribute to a positive evaluation of collective learning (Emerson & Nabatchi, 2015). Moreover, by measuring collective learning among multiple individuals, the study will be able to show factors that influence the degree of shared understanding (Heikkila & Gerlak, 2013).

The paper is structured as following. First, it presents the theory of collective learning and the idea of shared understanding. Second, it develops three hypotheses with regard to collective learning emergence: Third, it presents the cases and the operationalization of the variables. It ends with the presentation of the analysis and a discussion of the result.

1. Theory: Collective Learning

Broadly defined, collective learning refers to a process through which actors engaged in a collective decision-making system develop common views and actions. Following Heikkila and Gerlak (2013) conceptual framework, collective learning refers to the process of information acquisition and knowledge diffusion among actors and the collective outputs arising from the process. Those products can be either cognitive, in the sense of shared ideas, beliefs, values or behavioural, i.e. a new policy programme. For Ansell and Gash (2008), collective learning is linked to shared understanding, which encompasses various ideas including common goals, shared values or shared vision of the problem. In Emerson et al. (2015) framework of collaborative governance regimes, the idea of collective learning relates to the "principled engagement process" (Emerson & Nabatchi, 2015:58), an interactive process through which actors discover each other perspective and explore multiple point of view in order to identify common interest, creates a common understanding of the problem and finally develop joint action. This paper adopts a cognitive perspective of collective learning and consider the emergence of shared understanding—it does not look at behavioural products, i.e. policy programme.

Collective learning is important for collaborative network success as it is through this process that actors with different views, goals and perspective achieve mutual goals and win-win solution (Ansell & Gash, 2008; Klijn & Koppenjan, 2016). Shared understanding should increase the quality of the collaborative decision, as it should reflect a diverse base of knowledge (Emerson & Nabatchi, 2015). Moreover, collective learning is what ensures a sense of common ownership which supports the durability of the decision. In the absence of collective learning and shared understanding, actors may block the implementation of any decision (Innes & Booher, 1999). This is particularly true for shared understanding over objectives: the alignment of actors goals increase their commitment and ensure actors provide sufficient support for the implementation of collaborative outcomes (Bryson et al., 2006; Vangen & Huxham, 2005; Thomson & Perry, 2006). When goals are sufficiently connected and that actors understand and respect each other position, it also generates a sense of internal legitimacy (Emerson & Nabatchi, 2015).

Two perspectives can be used to approach collective learning—or any other dimension of collaboration (Emerson & Nabatchi, 2015). First, researchers can use the group, i.e. the collaborative network, as the unit of analysis. With this perspective, one can explore the features of collaborative networks that drives the development of a specific type of collective learning and compare different collaborative networks (Gerlak & Heikkila, 2011). The second—and less explored—path to the study of collective learning is to take the participant in the collaborative network as the unit of analysis and explore the factors that shape individual perceptions of collective learning. This is also particularly interesting as, the way individual perceive collaborative outcomes have an important effect on the decision acceptance, and hence the durability and the implementation of the collaborative output (Newig et al., 2018). This paper adopts the second perspective and explores the factors influencing collective learning perception.

1.1. Determinants of collective learning perception

This section build upon insight of collective learning studies as well as the broader collaborative governance literature to uncover several factors that shape individual perception of collective learning.

Dense social relations and transitivity

Recently, scholars emphasize the role of social relations for collective learning (Ansell & Gash, 2008; Heikkila & Gerlak, 2013; Emerson & Nabatchi, 2015; Klijn & Koppenjean, 2016). The main assumption is that the relations existing within the collaborative network shape collective leaning, as it is through relations that actors share information with each other, learn about each other interests and views and build a common understanding (Crona & Bodin, 2006; Heikkila & Gerlak, 2013). Social relations also reduce uncertainty about other actors behaviour and increase trust, which in turn facilitates the alignment of actors interest (Berardo & Lubell, 2016; Berardo et al., 2010). Consequently, the structure of the network—that is the overall number and the distribution of relations—influence collective learning. One important characteristic in this regards is the density of relation, or total share of relations within a collaborative network (Newig et al., 2010). Dense interaction promote the creation of trust, common norms and shard understanding (Coleman, 1990; Emerson & Nabatchi, 2015; Newig et al., 2010). Dense and tight relations facilitate the solving of complex and conflictual issues by supporting the emergence of common goals that goes beyond individual objectives (Berardo et al., 2010 ; Bodin et al., 2017). Hence, collective learning is supposed to be driven by dense structure of relation.

This paper captures density at the individual level, which corresponds to the interconnectedness of an actor's neighbourhood—or the local transitivity, the fact that two actors linked to any other one are also linked together—for example, the friend of my friend is also my friend (Bodin et al, 2017). The hypothesis is therefore:

- H1: Actors having a higher local transitivity perceive a higher degree of shared understanding.

Personal Contribution

In collaborative networks, there is an intrinsic tension between individual actor's objectives and collective goals (Thomson & Perry, 2006). Actors engage in collaborative processes with specific individual goals that complicate the development shared understanding. Yet, the distinction between individual and collective aims is often blurred, and each actor has a different perspective of their own and others' objectives (Vangen & Huxham, 2005). At the same time, the commitment to the collaborative process is closely related to the fact that actors' perspectives and objectives are taken into account (Ansell & Gash, 2008). Actors engage in collaborative processes if they feel the collaborative network has effectively considered their perspectives and interests. By extension, the individual perception of collective learning may be driven by the perception that one's ideas have been taken into account and used.

H2: Actors perceiving their contributions have been taken into account perceive a higher degree of shared understanding.

Procedural Fairness

Procedural fairness refers to the perception that, during the collaborative process, all actors are treated consistently and with mutual respect (Leach & Sabatier, 2005). In collaborative networks, actors are particularly sensitive to issues related to power, equity and fear manipulation (Ansell & Gash, 2008). In this context, procedural fairness support actor commitment (Ansell & Gash, 2008) acceptance of collaborative outcomes—an actor will be more likely to accept the decision if he deems the collaborative process impartial (Newig et al., 2018). As Innes & Booher (1999) states, "No matter how good an agreement is by some standards, if it was reached by a process that was not regarded as fair, open, inclusive, accountable, or otherwise legitimate, it is unlikely to receive support" (Innes & Booher, 1999:415). For Emerson & Nabatchi (2015), fairness is a key dimension of principle engagement and the development of shared understanding. At the same time, researchers consistently pinpoint to the positive effect of perceived procedural fairness on individual learning (Leach et al., 2014; Reach et al., 2014; Siddiki et al., 2017). Following this, this article hypothesis that:

- H3: Actors perceiving the process as fair perceive a higher degree of shared understanding.

Control variables: network inclusivity and initial difference of actors' point of view

The composition of a collaborative network has an important influence on collaborative outcomes (Fischer & Leifeld, 2015). This paper control for network inclusivity, defined as the extent to which all the necessary actors took part in the collaborative network activities. Inclusive network ensure the legitimacy of the decisions and contribute to the quality of the decisions. With regards to collective learning, diversity can have a negative effect as it is more complicated to reach a common understanding with actors having a diversity of views (Newig et al., 2010).

This paper also control for the initial difference of points of view between actors involved in the collaborative network. Little difference at the beginning of the process can ease the identification of shared interest (Vangen & Huxham, 2005).

2. Eight cross-sector collaborative networks

This study takes place within the Belgian inter-university project "Public Sector Innovation through Collaboration" and explores collective leaning in eight Belgian cross-sector collaborative networks engaged in collaborative innovation processes in the public sector. Collaborative innovation is the process through which actors collaboratively generate, adopt and spread new ideas with the aim of innovating (Sorensen & Torfing, 2012). Those processes involve multiple public organizations across jurisdictional or sectoral levels, as well as in some cases private actors and citizens. Collective learning is particularly important in those processes as they require the creation of new and shared norms and ideas (Bekkers et al., 2013), as well as the establishment of common objectives (Gieske et al., 2016).

Innovation can be of several types. Bekkers et al. (2011) distinguish between (1) the creation of new policies or product, (2) the creation or uses of new technologies, (3) the improvement of administrative processes, (4) the creation of new organization or management techniques and (5), the introduction of new frames of reference and (6), the creation of new governance modes. Those types are not mutually exclusive and are driven by similar dynamics. Moreover, the innovative character of an outcome is dependent upon the context in which the outcome is developed. For instance, the implementation specific policy can be considered as innovation in one country but not in another one (Sorensen & Torfing, 2012).

This paper seeks to explain the perception of collective leaning among actors involved in collaborative networks dealing with collaborative innovation process in Belgium. To be included in our study, collaborative networks had to involve about 10 up to two dozen individuals, meet formally and regularly within a working group and be active between 2014 and 2016. Whether collaborative network activities were still undergoing or completed at the time of data collection was not a criterion.

With the advice of a practitioner committee involving civil servants from various Belgian public organizations, eight collaborative networks covering four policy sectors—social, environmental, health and crisis management—and different types of innovation have been selected. Three collaborative networks were active in the social policy field. The first aimed at the simplification of rules and bureaucracy to help parents with disability children in their day-to-day life, existing procedures being rather complex and demanding. It includes for instance the creation of a "single contact point", where parents could find all information about existing caring structure, activities and application form. The second collaborative network studied dealt with the development and the implementation of a policy aiming at empowering single mothers in poverty. The general goal was to reduce single women isolation through individual help and group sessions in which each woman could share their experience and receive advice on how to educate their children, find a job, etc. The third collaborative network active in the social policy field aimed at the implementation of a renewed version of the "expert-by experience" programme, in which citizen with a background in poverty are hired in public administration to formulate recommendations to improve access to public services of people in poverty and social exclusion. The next two collaborative networks studied were active in health policies. The first is a technological innovation which concerns the development of an IT tool that ensures healthcare actors have access to their patient's social rights. The aim is to improve access to information of health practitioners and reduce administrative burden. The second is the elaboration of an awareness-raising campaign to improve the uses of the medication scheme and avoid the misuse of medicine, which carries risk for health. Two collaborative networks were involved in environmental policy. A first was dedicated to the development of a Federal Plan for Sustainable Development 2015–2020, which include a set of actions—for instance the creation of new governing bodies or the elaboration of a new tool to help industry take into account biodiversity in their strategic decision—that should conduct to sustainable development in Belgium by 2050. The second collaborative network dealt with the elaboration of a co-operation agreement related to the prevention and management of invasive alien species and the creation of a new co-operation structure across Belgian federated entities. Finally, the last collaborative network included in this study deal with crisis management issue and concerns the elaboration of a formalized information exchange process in order to detect possible signs of radicalization within the group of asylum seekers or refugees. This collaborative network create a new formal system of information sharing between organizations that usually do not work together.

3. Methods

The following section describes the operationalization the dependent variables— collective learning—, the independent variable trusted exchange of information, the control variables—network composition, diversity of points of view at the beginning of the process, as well as the method used for the analysis. Data collection took part between May 2017 and January 2018 within a broader inter-university project on Public Sector Innovation through Collaboration in Belgium, using interviews, general surveys and social network surveys, in French and Dutch. With regards to interview, out of the 120 participants to whom a solicitation was sent, 78 complete the interview, or a 65% overall response rate. Response rates across collaborative networks range from 50% to 90%. The response rate for the survey is 78%, ranging across collaborative networks from 64% to 90%. For social networks survey, Response rates across collaborative networks range from 50% to 90%.

3.1. The dependent variable: perception of collective learning

In this study, individual perception of collective learning refers to the perception of the extent to which the objectives of the actors involved in each collaborative network have connected during the collaborative process. This was measured with the following item in the survey: "On a scale from 0 to 10, please indicate your position between the two statements: The different objectives of the participants have not been connected / The different objectives of the participants have strongly been connected"

3.2. The independent variables

Local transitivity—or individual social density is measured with social network analysis, using data on information exchange collected in each collaborative network. The information exchange network for each of the eight cases was constructed using data on the information reception and the information sending networks, collected by asking participants (1) to whom they have sent information and (2) from whom they have received information outside the formal meetings. This last specification ensures sufficient variation between individuals as it is likely that within meetings, everyone sends and receives information with everyone else. Data of both question information were combined in a single network matrix E by multiplying the value of the sender matrix S with the value of the receiver matrix R and symmetrizing the resulting network following the strong rules. As a result, information exchange exists between two participants if both have send and receive information from each other. Based on the reciprocate information tie, a clustering coefficient—that represents how densely the neighbourhood of an actor is connected—was then calculated for each actor. The index range from 0 to 1. A score close to 1 indicate a densely connected neighbourhood.

Procedural fairness is measured as the mean of the following two items in the survey (Cronbach's alpha of 0.8): "On a scale from 0 to 10, please indicate your position between the two statements:

- (1) In the collaborative network, none of the participant have been treated fairly / In the collaborative network, all participants have been treated fairly
- (2)The meetings of the collaborative network were not marked by mutual respect /The meetings of the collaborative network were strongly marked by mutual respect".

Personal contribution is measured with the following item in the survey: "On a scale from 0 to 10, please indicate your position between the two statements: My inputs were not at all used in the collaborative output / My input were very much used in the collaborative output"

3.3. Control variables

The composition of each collaborative network is measured by the extent to which actors perceive all needed actors were included, using the following survey item: "On a scale from 0 to 10, please indicate your position between the two statements: The actors needed to solve the problem were not included/ All actors needed to solve the problem were included".

The initial difference of points of view is measured with the following survey item: "On a scale from 0 to 10, please indicate your position between the two statements: At the beginning of the collaborative process, there was no difference between participants' points of view/ At the beginning of the process, there were a lot of differences between participants' point of view".

4. **Data Analysis and result**[1]

Figure 1 display the mean of our main dependent variable, that is perceived collective learning, by case. The mean range from 6.5 in case 1 to a little less than 9.5 for case 5, with most of the case scoring between 8 and 8.5. Yet, one-way Anova reveals that those differences are not significant between cases (p = .2)

The summary statistics displayed in Table 1 shows that across the case, the mean of perceived collective learning is 8.3 with a stand deviation of 2, which suggest substantial variation across individuals. The mean of transitivity index (0.428) coupled with the high standard deviation (0.381) suggests that actors neighbourhood is either densely connected or rather unconnected. There is a relatively high variation across individuals for personal contribution (mean = 8.5; sd=1.61). The mean of procedural fairness is higher (9.36), with a relatively small standard deviation (1.2), which indicates that most of the respondent across cases consider the collaborative process as fair.

Figure 1: Mean of collective learning perception by case

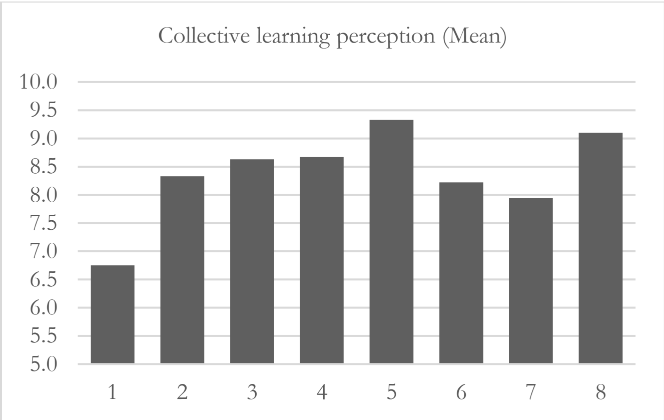

Table 1: Table 1: Summary statistics

Descriptive statistics

Variables	N	Mean	St. Dev.	Min	Max
Dependent variable					
Perception of Collective learning*	73	8.370	1.439	5	11
Independent variables					
Transitivity	73	0.428	0.381	0	1
Personnal contribution*	73	8.548	1.616	5	11
Procedural fairness*	73	9.363	1.205	6	11
Control variables					
Network composition*	73	8.932	2.091	2	11
Initial difference of opinion*	73	7.630	1.752	3	11

*** Note: The scale range from 1 to 11**

[1] NA were excluded of the analysis

To assess the factors that influence individual perception of collective learning, this paper uses ordinary least squares regression that correct for (1) the autocorrelation effect, that is the observation interdependencies of observation inherent with social network data (Doreian, 1989) and (2) heteroscedasticity, or the possibility that residuals are correlated for respondent part of the same collaborative network (Colin & Miller, 2015). Autocorrelation is estimated using the Temporal Network Autocorrelation Model function (TNAM, version 1.6.2), developed by Leifeld and Cranmer (2016) and heteroscedasticity with cluster-robust standard errors. Controlling for cluster effect rather than using a multi-level model is preferable as there are only eight level-2 units (Maas & Hox, 2004). Models were run in the statistical computing environment R (version 3.1.0, R Development Core Team 2014).

Two regressions were computed (table 2). The first only include the control variable network inclusivity and the initial opinion difference. The second model adds the main effect transitivity, personal contribution and procedural fairness, and lead to a significant improvement of the model fit, with an adjusted R^2 of 0.356 (0.185 for the control model). The Variance Inflation Factors (VIF) did not detect multicollinearity: score across variables range from 1.02 to 1.45. As expected, transitivity is statistically significant (β=.697, p<0.1) and positively related to perception of collective learning. In other words, actors embedded within a dense neighbourhood tend to perceive a higher degree of collective learning. Perception of personal contribution is also positively linked to the perception of collective learning (β= .311, p<0.05). This shows that an actor's perception of collective learning depends upon the feeling that her or his ideas have been taken into account. Procedural fairness is not statistically significant (p>0.1), contrary to the control variable inclusivity, positively related to collective learning perception. When the necessary actors are included, actors are more likely to perceive a higher degree of collective learning.

Table 2: Regression Models

Model of Collective learning

	Dependent variable: Collective Learning	
	(1)	(2)
Inclusivity	0.316***	0.148**
	(0.064)	(0.073)
Initial difference of opinion	-0.046	-0.136
	(0.088)	(0.085)
Transitivity		0.697*
		(0.383)
Personal contribution		0.311**
		(0.121)
Procedural fairness		0.252
		(0.173)
Constant	5.896***	2.773**
	(0.816)	(1.290)
Observations	73	73
R^2	0.207	0.401
Adjusted R^2	0.185	0.356
Residual Std. Error	1.299 (df = 70)	1.154 (df = 67)
Wald Statistic	12.324***(df =2;70)	12.182*** (df=5;65)

Note: $^{*}p<0.1^{**}p<0.05^{***}p<0.01$

1 Wald statistics is used instead of F* because of the uses of clustered standard errors.

Conclusion

The aim of this paper is to contribute to the theory of collective learning by looking at the factors that shape individual perception of collective learning. Looking at collaborative networks dealing with collaborative innovation processes, this paper shows that local transitivity is an important influencing factor of perceived collective learning. Actors embedded in clustered environment perceive actors objectives have connected to a greater extent. This confirms the idea that strong ties are needed for shared understanding to occur. Indeed, transitivity is a function of tie strength (Granovetter, 1973). Actors sharing strong relations with other are more likely to be embedded in transitive structure. Transitivity also indicates that actor nested within small clusters are more likely to develop a common worldview. The question that remains is whether those actors consider every actor objective in their evaluation of collective learning, or if they base their judgement on the objectives of their neighbourhood: actors may perceive higher collective learning because they only know about their neighbourhood objectives.

At the same time, personal contribution—that is the perception of an actor that his contribution was effectively used—do also correlate with a higher degree of collective learning. The perception of achievement regarding individual interest, i.e. My ideas were taken into account is hence closely related to the perception of common goal achievement. In other words, actors tend to judge collective benefit with the lenses of their individual benefits.

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