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Harnessing social interaction and intellectual capital in intergovernmental networks

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Abstract

Purpose – Intellectual capital creation (ICC) in networks has been considered as central to the processes for responding to wicked problems. However, our knowledge on the factors that explain ICC in networks is limited. We take a step towards filling this research gap by drawing on an extended view of social capital to identify specific network features that should explain ICC heterogeneity in engineered intergovernmental networks.

Design/methodology/approach – A sample of 655 local authorities participating in 8 networks was used to test the framework proposed. Data analysis followed a three-step approach. Firstly, confirmatory factor analysis was applied to assess the convergent and discriminant validity of the measures. Secondly, a non-parametric median test was conducted to determine whether the variables under study were statistically different for the eight networks. Lastly, the structural model underlying the conceptual framework was tested.

Findings – We found that the eight intergovernmental networks studied differed significantly in their levels of social interaction and ICC. At a structural level, three variables usually considered representative of social capital (social interaction, trust, and shared vision) and two supplementary variables (shared resources and shared decisions) were proven to have significant direct and/or indirect effects on ICC.

Originality/value – No previous cross-sectional research has studied the link between the creation of social capital and intellectual capital in engineered intergovernmental networks. As our research focuses on networks and climate change, it contributes to the fourth and fifth stages of intellectual capital research.

Keywords – Social capital, social interaction, intellectual capital creation, trust, intergovernmental networks.

Paper type – Research paper

1. Introduction

This research looks at the underexplored crossroads of intellectual capital (IC) and intergovernmental networking research streams.

On the one hand, IC researchers claim that IC studies should extend from organizations to networks, particularly those aimed at solving wicked problems that affect people's wellbeing (Guthrie and Dumay, 2019). Guthrie and Dumay (2019) use climate change (which is our research context) as an example. Climate change refers to long-term alteration of temperature and typical weather patterns that is affecting both particular locations and the planet as a whole, and is being largely influenced by human activity, particularly the burning of fossil fuels, like coal, oil, and natural gas (Adger *et al*., 2003). Harmful manifestations of climate change include warmer temperatures, extreme changes in weather, rising sea levels and drier soils, which are expected to negatively affect people's wellbeing. All societies need to learn how to mitigate climate change (i.e., tackling the causes) and adapt to it (i.e., minimizing the possible impacts) (Armitage *et al*., 2008). IC studies have mostly addressed climate change responses within the boundaries of companies. Guthrie and Dumay (2019) find this problematic as it may result in sustainability initiatives that provide benefits at an organizational level but have little or no impact on ecosystems.

IC researchers also claim that IC studies should extend from businesses to public organizations, which is consistent with the finding that the public sector is one of the least addressed areas of IC research (Guthrie *et al.*, 2012; Manes Rossi *et al.*, 2016). In their structured literature review on IC in the public sector, Dumay *et al*. (2015) found that only 3 out of 53 studies focused on local government (which is our specific research object). They highlighted that local governments have distinctive characteristics that may lead to different findings and could yield more accurate knowledge to properly guide public sector managers.

Meanwhile, intergovernmental networking researchers suggest that networks are an appropriate setting for tackling wicked problems. They view networks as key structures for fostering the intellectual capital creation (ICC) needed to tackle wicked problems, although usually using related terms, such as learning or improved knowledge (Alter and Hage, 1993; Keast *et al.*, 2004; Armitage *et al.*, 2008; Agranoff, 2012). A great deal of this literature focuses on climate change, as we do. Climate change is a "wicked problem": appropriate responses are far from clear and involve multiple parties, including governments, public agencies, firms, NGOs and individuals

(Ostrom, 2010). Although there is no consensus on how climate change could be better addressed, academics (e.g. Armitage et al., 2008; Bodin and Crona, 2009) and practitioners (e.g. recommendations from United Nations summits) have focused on promoting networks as a vehicle for co-creating new knowledge, bringing together complementary resources and coordinating efforts.

A core argument underlying the emphasis on networking is that networks are a suitable context for fostering social interaction and ICC (Galunic and Rodan, 1998; Armitage *et al*., 2008; Vătămănescu *et al*., 2016). However, in most studies, social interaction and ICC in networks are taken for granted instead of being measured and explained. The fact that social interaction is costly, energy- and time-consuming, involves opportunity costs, and is not necessarily productive in terms of ICC (e.g. members distrust each other) seems to have been neglected (Augier and Vendelø, 1999; Armitage et al., 2008). This leads to a paradox: while the idea of intergovernmental networks seems to be perceived as a mantra for solving the most important challenges facing governments and modern societies, our systematic knowledge of how intergovernmental networks work and achieve their learning goals is very limited (Armitage *et al*., 2008; Bessant and Tsekouras, 2001). Specifically, we do not have a systematic knowledge of how networks lead to social interaction and ICC (Bessant and Tsekouras, 2001). Many studies seem to assume that simply using the network label is enough to achieve ICC, instead of contributing evidence of ICC in networks, and systematically investigating the network features that explain ICC heterogeneity.

We have taken a step towards filling this research gap by trying to respond to three research questions (RQ) that are interrelated.

- RQ1. Are intergovernmental networks heterogeneous in terms of ICC?
- RQ2. Can an extended view of social capital theory explain ICC in intergovernmental networks?
- RQ3. What is the role and relative strength of the factors involved?

To identify the factors that should affect ICC heterogeneity in networks, we drew on an extended view of social capital theory that includes insights from collective intelligence systems and intergovernmental networks literature. Social capital theory led us to view networks as relationships and resources that facilitate exchanges and combinations of knowledge and, in turn, ICC, and to identify three dimensions of social capital (i.e. trust, social interaction and shared vision) (Nahapiet and Ghoshal, 1998; Adler & Kwon, 2002; Lin 2017). The collective intelligence framework supplemented social capital theory by focusing on the "why" and "how" of collaboration (Robert et al., 2008; Malone *et al*., 2010). Intergovernmental networking literature provided specific dimensions for the "why" (i.e. shared resources) and "how" (i.e. shared decisions) of collaboration in intergovernmental networks (Keast *et al*. 2004; Armitage *et al*. 2008; Agranoff, 2012).

Our conceptual approach is consistent with the research setting chosen. We focus on engineered networks (i.e. deliberately created) instead of organic networks (i.e. those that emerge in a natural, evolutionary manner) (Bessant and Tsekouras 2001), which has implications for the model proposed in this research (social interaction, in particular, has not been taken for granted but prompted by other social capital-related factors). Specifically, we studied eight Spanish municipal government networks, which were devised to foster sustainability, and that are sponsored by higher tiers of government (i.e. regional and/or provincial governments). The main reason for the growth of these networks is clear: most municipalities in Spain are small, with 84% having less than 5,000 inhabitants. Municipalities can hardly be expected to meet their sustainability-related goals in isolation because they lack the necessary resources, with IC being a crucial resource. Spanish networks are a suitable research setting. While the public value generated by the networks we studied is difficult to assess, there is enough anecdotal evidence to support the belief that collaboration has improved local authorities' skills, mind-sets and capacities, and has prompted the implementation of innovative solutions (e.g. bicycle-sharing, new forms of recycling, and green purchasing). However, networks seem to show different levels of social interaction and ICC, which we believe could be explained by our extended view of social capital theory. This research contributes to IC literature by adding evidence of the distinctive role of social interaction and ICC in intergovernmental engineered networks, and providing a deeper understanding on the complex link between both variables and their social capital-related predictors.

From a methodological perspective, we adopted a survey research approach. A sample of 655 local authorities participating in the 8 networks studied was used to test the framework proposed. While some conceptual developments and qualitative studies have highlighted factors that could promote knowledge co-creation in networks in a public sector context (Hartley and Benington, 2006), cross-sectional studies are needed to supplement the insights obtained from these research efforts (Dumay *et al*. 2015).

This kind of research may provide specific information on the relative strength of each of the factors involved.

The remainder of the paper is structured as follows. The next section goes deeper into the major concepts and frameworks that serve as a basis for this research and summarizes the findings from prior cross-sectional research. The third section develops the model and hypotheses that were tested. The fourth section examines methodological issues. The fifth section describes the results of the empirical test; and the final section present points for discussion, conceptual contributions, managerial implications, and avenues for further research.

2. Theoretical Background

This section aims to set out the conceptual and empirical bases of this research. It is organized into four subsections. Firstly, as the terms “ICC” and “network” may evoke different meanings, we specify our concepts of ICC and networks and explain how they differ from related concepts. Secondly, we provide an overview of previous public sector literature on IC. Thirdly, we justify the conceptual basis of our model in which ICC is explained by factors stemming from social capital theory and the collective intelligence approach. Finally, we test our framework by using cross-sectional research and, consequently, provide an overview of related cross-sectional studies. Table 1 summarizes the conceptual and empirical bases of this research.

(INSERT TABLE 1)

2.1. Definitions: Intellectual capital creation (ICC) and networks

This research is aimed at explaining how ICC may be harnessed within networks. Any conceptualization of IC is complex, as it may be addressed from ostensive and performative perspectives, and involves human, social/relational and organizational dimensions (Subramaniam and Youndt, 2005; Ramírez and Gordillo, 2014; Allameh, 2018; De Frutos-Belizón *et al.*, 2019). For simplicity, we adopted Nahapiet and Ghoshal’s approach (1998). Accordingly, in this study, ICC is understood as the acquired knowledge, skills, and capabilities that enable participants in networks to act in new ways that can create public value (Edvinsson and Sullivan 1996; Nahapiet and Ghoshal, 1998; Secundo *et al.*, 2016; Duff, 2018). This concept stems from the concept of human capital (Coleman, 1988) but recognizes that learning is a capability of a social collective (Malone *et al.*, 2010; Caputo *et al.*, 2016). Some complex codified knowledge, for instance, may only be accessed through organizational repositories, whereas some tacit knowledge may only be accessed through interactions involving several individuals (Nahapiet and Ghoshal, 1998; Haldin-Herrgard, 2000).

Broadly speaking, a network consists of a set of actors or nodes, along with a set of ties that link them (Borgatti and Halgin, 2011). A wide range of networks has been described and studied (e.g. Keast *et al.*, 2004; Armitage *et al.*, 2008), and it has been suggested that network management could be contingent on network type (Keast *et al.*, 2004). Therefore, it was important to narrow down which types of network to include in this study.

A concept that suited our research context was that of "knowledge networks." Warkentin *et al.* (2002, p. 149) defined knowledge networks as those that "facilitate improved communication of data, information, and knowledge, while improving coordination, decision making, and planning." Similarly, Bessant and Tsekouras (2001) referred to "learning networks," which they define as those networks specifically established to increase the knowledge base and skills of a group of members. These networks are characterized by being horizontal, meaning that participating organizations are on the same level. In the specific context of IC research, Vătămănescu *et al.* (2016, p. 601) developed the concept of "network-based IC," which "describes the configuration and process of value creation from the individual's micro-universe to the entire social system, by linking people, knowledge, information, expertise, competence and know-how within complex and dynamic social networks."

What all these concepts have in common is that they focus on networks whose direct purpose is to improve the knowledge of those taking part in them. While it is expected that knowledge enhancement leads to other benefits for participants, their organizations and social systems (indirect purpose), these benefits are defined at a very broad level (e.g. they contribute to competitiveness and sustainable development). As in the effectuation approach (Kerr and Coviello, 2019), the participants' only predictable goal is joint learning. They engage in iterative (dialogue) processes with other members of their network that enhance their IC (direct purpose), which could ultimately lead to the creation of an opportunity, in the form of discovering new means and goals (indirect purposes). This view contrasts with the more usual view of networks as mechanisms for solving particular, predefined, common problems, which involve specific stakeholders (e.g. various actors, such as governments, universities, citizens, businesses, farmers or associations, creating a network to reduce river pollution in a specific region). This latter view of networks underlies a great deal of networking literature (e.g. Keast *et al.*, 2004; Armitage *et al.*, 2008), but does not fit our research setting.

2.2. Intellectual capital (IC) and the public sector

The evidence shows that IC is under-researched in relation to the public sector (Dumay *et al.*, 2015). However, public organizations are subject to pressures to develop IC due to increasingly sophisticated citizens'/users' expectations, and greater demand for information, transparency and accountability about the use of public resources (Cohen and Vlismas, 2013; Serrano Cinca *et al.*, 2003). ICC has also been identified as central to the processes for improving public services (Farneti and Guthrie, 2008; Ramírez-Córcoles, 2010).

Furthermore, public organizations provide a distinctive context in which to study IC. Firstly, inputs and outputs in public organizations tend to be largely intangible, which confers particular salience to IC (Vătămănescu *et al.*, 2016). Secondly, the purpose, structure and key actors are different in the private and public sectors, which indicates that the nature of knowledge creation processes could differ as well (Guthrie and Dumay, 2015).

Moreover, IC content in the public and private sectors may differ, which implies that ICC processes may also differ. In particular, it has been suggested that the social-related knowledge embedded in public services may be singularly complex, as there is not a single clear customer as in the private sector, but multiple stakeholders with different views and interests (Osborne, 2018). The public sector is also facing wicked problems. In contrast, technology-related knowledge content could be more complex in many private-sector areas. Therefore, the over-reliance on the private sector as the principal source of theoretical development and empirical research is conceptually limiting when trying to understand IC (Dumay *et al.* 2015).

Studies at a local government level are particularly rare (Bronzetti and Sicoli, 2011; Cohen and Vlismas, 2013; Farneti and Guthrie, 2008; Manes Rossi *et al.*, 2016; Ramírez-Córcoles, 2010; Serrano Cinca *et al.*, 2003; Secundo *et al.*, 2016). It has been argued (Dumay, Guthrie and Rooney, 2018) that IC research covers five different stages, although not always sequentially:

1) raising awareness of the salience of measuring and reporting IC;
2) building theories and frameworks;
3) investigating IC in practice from a critical and performative perspective;

4) adopting an ecosystems approach; and

5) addressing the crucial wicked problems facing the world.

Most public sector research has focused on the development of IC measurement models, IC reporting, IC management and the impact of IC on organizations, which correspond to the first three stages of IC research. The conditions that foster ICC in public organizations under a networking perspective (i.e. the fourth stage) have been virtually ignored. Two exceptions in this regard are Secundo *et al.* (2016) and Vătămănescu *et al.* (2016), who studied universities, which is the context that has been most addressed in IC public sector research. Secundo *et al.* (2016) adopted the collective intelligence approach to conceptually explaining how IC may be created collectively through multiple stakeholder participation within a university network and beyond university boundaries (i.e. the fourth stage of IC research). As this research focuses on networks and climate change, it contributes to the fourth and fifth stages of IC research. We see our research as being close to that of Secundo *et al.* (2016). Although we draw on social capital theory rather than the collective intelligence approach, we see both frameworks as being closely related, and we used some insights from the latter to supplement the former when developing our conceptual framework. We have contributed to the research of Secundo *et al.* (2016) by proposing specific links between the concepts and variables considered and testing them empirically.

2.3. Drivers of intellectual capital creation (ICC) in networks

The overall idea that learning stems from social interaction, is facilitated (or constrained) by certain settings, and is embedded in those settings is viewed as critical in the most widely accepted conceptual learning frameworks (Nonaka and Takeuchi, 1995, Nahapiet and Ghoshal, 1998; Wenger, 1998). We have focused on one of these frameworks, which stems from social capital theory (Nahapiet and Ghoshal, 1998). While this framework has been broadly accepted and tested (e.g. Chiu *et al.*, 2006; Chang *et al.*, 2012; Fredette and Bradshaw, 2012; Zhang *et al.*, 2019), and provides a solid conceptual and empirical basis for this study, it is supplemented with insights from further social capital research (Adler & Kwon, 2002; Wasko and Faraj, 2005; Lin 2017) and other views that try to explain how knowledge is created collectively (Robert *et al.*, 2008; Malone *et al.*, 2010; Secundo *et al.*, 2016; Vătămănescu *et al.*, 2016).

Nahapiet and Ghoshal (1998) define social capital as the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit. Social capital thus comprises both the network of relationships and the resources that may be mobilized through that network. According to Nahapiet and Ghoshal (1998), social capital facilitates exchanges and combinations of knowledge that, in turn, lead to ICC. They argue that organizations are superior in creating social capital, which confers "organizational advantage" and provides a rationale for their existence beyond mere transaction costs. Nahapiet and Ghosal (1998) made an important contribution by conceptualizing social capital in three dimensions: structural, relational and cognitive. To sum up, the structural dimension involves the configuration of the network. This has usually been interpreted in terms of patterns of relationships between individuals (in an impersonal sense), involving traditional network analysis measurements, such as density, centrality, and hierarchy. The relational dimension involves the socio-emotional characteristics of relationships, in the form of trust, reciprocity, and identification. The cognitive dimension involves the degree of mental connectivity between participants in the form of shared vision, codes, and language.

While Nahapiet and Ghoshal (1998) developed their framework in the context of organizations, it has been extended to networks (Inkpen and Tsang, 2005; Wasko and Faraj, 2005; Chiu *et al.*, 2006; Lefebvre *et al.*, 2016; Zhang *et al.*, 2019). It could even be argued that networks are superior to organizations in terms of ICC creation because networks can provide access to less redundant and more dispersed pieces of information (Adler & Kwon 2002; Inkpen and Tsang, 2005; Hartley and Benington, 2006). Networks are also less pressurized by immediate results and more conducive to reflection and long-term thinking (Bottrup, 2005; Skyrme, 2007). While organizations tend to focus on single-loop learning (i.e. improvement by correcting errors from routines), networks are able to embrace both double-loop learning (i.e. re-examining values and policies) and triple-loop learning (i.e. redesigning forms of governance, for example, while looking at appropriate forms of citizen participation) (Bottrup, 2005; Armitage *et al.*, 2008).

Based on the analysis of large and disperse networks in which collaboration is voluntary and unpaid (e.g. Wikipedia), Malone *et al.* (2010) developed a collective intelligence approach in which intelligence (i.e. the ability to learn, understand, and adapt to an environment by using knowledge) is a property of groups, communities, or networks that emerges from collaboration and competition. This approach was used by Secundo *et al.* (2016) to develop an integrated IC framework for universities. An important contribution of the collective intelligence approach is the way in which it explains the underlying mechanisms of collaborative intelligence systems. The capacity of collaborative systems to create collective intelligence (i.e. their “genome”) is explained through the answer to four key questions (i.e. their “genes”): (1) What? (tasks); (2) Who? (participants); (3) Why? (motives for participation); and, (4) How? (how decisions are made and tasks are shared).

In our view, the collaborative intelligence framework supplements social capital theory by emphasizing aspects that are important for understanding participation in collaborative systems and are only implicit in Nahapiet and Ghoshal’s (1998) framework, particularly the “why” and “how” of collaboration.

Firstly, the collective intelligence approach explicitly incorporates the salience of a system’s resources as a motivation for assuming the costs of participating in social interactions (the “why”). Network resources are not alien to important pieces of social capital research (Adler & Kwon, 2002; Wasko and Faraj, 2005; Lin, 2017). Lin (2017) suggests that social capital is more than mere social relationships and networks; it evokes the resources that are embedded and accessed. He defines social capital as resources embedded in a social structure that are accessed and/or mobilized in purposive action. He further contends that investment in social capital is aimed at gaining access to embedded resources. However, resources are not explicit in Nahapiet and Ghoshal’s framework (1998), and most research efforts based on it.

Secondly, the way in which decisions are taken in the collective intelligence approach is incorporated as an explanation of the collective intelligence created within the system. This aspect of networking could be considered as having been included in the structural dimension of Nahapiet and Ghoshal’s framework (1998), but only implicitly. However, the way in which decisions are made in networks seems to be important when explaining participation (Keast *et al.*, 2004). To sum up, the traditional view of Nahapiet and Ghoshal’s framework (1998) is supplemented in this research with insights regarding the collective intelligence approach; the role of network resources and decision making are considered when explaining ICC.

2.4. Related cross-sectional research

We have not found any cross-sectional research that uses the social capital framework to explain ICC and related outcomes in an intergovernmental setting. In connection with our study, Lefebvre *et al.* (2016) studied a sample of 150 members of 16 European learning networks in the food sector. They argued that social interaction (the structural dimension), a composite measure of shared vision and shared language (the cognitive dimension), and trust (the relational dimension) contribute to knowledge sharing. They also proposed several links between these three social capital dimensions. While structural and cognitive dimensions affected knowledge sharing, trust did not contribute.

Other authors have studied virtual communities, which are also relevant to our context. Chiu *et al.* (2006) used a sample of 310 members of a professional virtual community in Taiwan, involved in sharing knowledge about programming databases and operating systems. The study looked at the drivers of the quantity and quality of knowledge sharing. The structural dimension (represented by social interaction), the relational dimension (represented by trust, reciprocity and identification), and the cognitive dimension (represented by shared language and shared vision) were expected to affect both the quantity and quality of knowledge sharing. While some hypotheses were confirmed, social interaction, reciprocity and identification did not contribute to knowledge quality, and trust and shared language did not contribute to the quantity of knowledge shared. Chang and Chuang (2011) tested a similar model by using 282 members of virtual communities. Most social capital variables affected the quantity and quality of knowledge shared. However, social interaction and trust did not contribute to the quantity of knowledge shared. Zhang *et al.* (2019) found that the three dimensions of social capital affected knowledge sharing effectiveness.

Research in public and non-profit settings is limited. Leana and Pil (2006) studied 88 urban public schools. They distinguished between internal social capital (relationships between teachers) and external social capital (relationships between principal and external stakeholders). Results indicated that both predicted student performance in mathematics and reading. Internal social capital was measured by creating an index that included shared vision, trust and information sharing (the latter was assimilated to social interaction). Chang *et al.* (2012) found that nurses' perception of trust and shared vision contributed to knowledge sharing, but that social interaction did not. Fredette and Bradshaw (2012) used data collected from a survey of 234 organizations operating in the Canadian non-profit sector, and tested the relationship between social capital and governance effectiveness. They found social capital contributed positively to the capacity to govern effectively. Social capital was measured as a second order construct that included information sharing, shared vision, and trust.

In short, while previous cross-sectional research tends to confirm the capacity of social capital theory to explain knowledge exchange, combination and ICC, the results are not conclusive with regard to the specific variables involved and their interrelationships. Nahapiet and Ghoshal (1998) did not propose any link between the three dimensions of social capital. As this has been modelled differently in the various research contributions, it may indicate that context matters (Leana and Pil, 2006). No cross-sectional studies have been conducted in an intergovernmental setting. Our study was undertaken to improve knowledge on the subject by focusing on this neglected context.

3. Model and hypotheses

The proposed model was designed to explain ICC in intergovernmental networks (see Figure 1).

(INSERT FIGURE 1)

We built on social capital theory and cross-sectional research based on social capital as the starting point for developing the proposed model. Social capital theory suggests that the structural, relational and cognitive dimensions of a network's social capital should affect the learning levels of its members. Most cross-sectional studies have represented the structural dimension by social interaction, the relational dimension by trust, and the cognitive dimension by shared vision (Tsai and Ghoshal, 1998; Yli-Renko *et al.*, 2001; Leana and Pil, 2006; Chen *et al.*, 2014; Allameh, 2018; Ganguly *et al.*, 2019), although more comprehensive models have also been proposed (e.g. Chiu *et al.*, 2006; Chang and Chuang, 2011; van Dijk *et al.*, 2016). As this is the first cross-sectional study conducted in the context of intergovernmental networks, we adopted this more prudent approach. As argued in the previous section, additional variables were also considered to incorporate insights from other social capital frameworks and the collective intelligence approach.

3.1. Tsai and Ghoshal's (1998) view of social capital theory

3.1.1. Structural dimension: social interaction

Many scholars claim that learning does not occur solely in the individual mind or in isolation from others. Instead, learning happens through the social interactions that bring us together with peers and other actors (e.g. Nonaka and Takeuchi, 1995; Wenger, 1998). Some examples of social interactions include working with others, debating different issues, making joint decisions, and talking and observing others while they are doing their work. Drawing on Tsai and Ghoshal (1998), social interaction is defined in this research as the effort made by a network member to interact with other members, in the form of frequency (i.e., periodicity), and intensity of relationships (i.e. close relationships, face-to-face meetings and long conversations).

In-depth case studies have found that networks provide many opportunities for social interaction that lead to learning. Thus, Balestrin *et al.* (2008) showed that learning in networks stems from various forms of formal and informal social interaction including meetings, visits to the offices of other network members, international trips to co-participate in events, social gatherings, courses, assemblies, and web meetings. Frequent and intense use of the different forms of social interaction is expected to yield diverse and complementary pieces of information/knowledge that can be combined to generate valuable learning (Hartley and Benington, 2006; Grant, 2016; Leal-Millán *et al.*, 2016).

Cross-sectional studies have mostly confirmed that social interaction contributes to knowledge sharing and/or knowledge creation (Tsai and Ghoshal, 1998; Yli-Renko *et al.*, 2001; Chua *et al.*, 2002; Lefebvre *et al.*, 2016; Antonacci et al., 2017; Zhang *et al.*, 2019). In the context of virtual communities, Chiu *et al.* (2006) found that social interaction contributed to the quality of knowledge sharing but not the quantity. By contrast, Chang and Chuan (2011) found a significant effect of social interaction on quantity but not quality. While the results were contradictory, both studies confirmed the effect of social interaction on some facets of ICC. Hence, we hypothesize:

Hypothesis 1 (H1). The extent of social interaction a municipality engages in with other municipalities will be positively associated with the municipality's level of ICC.

3.1.2. Relational dimension: trust

Tsai and Ghoshal (1998) use trust to represent the relational dimension. Building on Zaheer *et al.* (1998), we define trust as an actor's expectation that others can be relied on to fulfil promises, will behave in a consistent and predictable manner, and will act and negotiate fairly when the possibility for opportunism is present. Social interaction is facilitated in two ways when high levels of trust exist (Khvatova *et al.*, 2016). Firstly, trust reduces the cost, effort, and conflict elements of social interaction (Dyer and Singh, 1998; Yli-Renko *et al.*, 2001; Warkentin *et al.*, 2018). Secondly, trust increases the expectation of positive reciprocity (i.e. the belief that others will have a desire to provide information to the trustee) (Adler and Known, 2002; Ma *et al.*, 2014; Oparaocha, 2016). Hence, we expect that:

> *Hypothesis 2a (H2a). The level of a municipality's perceived trust is positively associated with the extent of social interaction the municipality engages in with other members in the network.*

Trust positively affects ICC in three ways: (1) greater levels of transfer of tacit/sticky knowledge, (2) higher quality of the knowledge transferred, and (3) more time available for learning processes. Thus, several studies have shown that trust facilitates the transfer of knowledge, particularly tacit/sticky knowledge (e.g. Ardichvili *et al.*, 2003; Balestrin *et al.*, 2008; Mu *et al.*, 2008; Allameh, 2018; Zhang *et al.*, 2019). Also, Chiu *et al.* (2006) and Chang and Chuang (2011) showed that trust positively affects the quality (helpfulness) of knowledge sharing in virtual communities. Lastly, trust reduces the need to formally monitor relationships, allowing municipalities to invest more effort into learning tasks (Yli-Renko *et al.*, 2001). Hence, we hypothesize:

> *Hypothesis 2b (H2b). The level of a municipality's perceived trust is positively associated with the extent of ICC the municipality achieves.*

3.1.3. Cognitive dimension: shared vision

Tsai and Ghoshal (1998), among others, use shared vision to represent the cognitive dimension. They argue that a shared vision embodies the collective goals and aspirations of the members of a social system. In line with this, we argue that the common goals or interests shared by the members of a network help them to see the potential value of social interaction. As a result, network members who share a vision will be more likely to devote money, time, and energy to social interaction.

Literature on public sector networks consistently indicates that government is unlikely to involve itself in networks that do not pursue goals that are compatible or congruous with its own goals (Wood and Gray, 1991; Krueathep *et al.*, 2008). Several studies have shown that a shared vision (or similar constructs, such as goal congruence or shared goals) may hold a loosely coupled system together and promote knowledge sharing (e.g. Chow and Chan, 2008; Chen *et al.*, 2014; Allameh, 2018). We can thus view a shared vision as a bonding mechanism that leads various members of a network to enter into social interactions. Hence, we expect that:

Hypothesis 3a (H3a). The extent to which a municipality shares a vision with other municipalities and with the network as a whole will be positively associated with the extent of social interaction the municipality engages in with other municipalities in the network.

Knowledge transfer is not an easy undertaking; in particular, tacit knowledge is hard to articulate and difficult to transfer, and it is not clear which pieces of the information/knowledge that one party possesses are valuable to other parties and the whole learning process (Kogut and Zander, 1996). When social interaction efforts are guided by a shared vision, it is likely that they are more clearly focused, which could lead to greater effectiveness in knowledge exchange, combination, and integration in the form of ICC (Augier and Vendelø, 1999; Allameh, 2018). As what is learned fits their goals, municipalities may perceive it as being valuable. This may lead to a higher chance of it being integrated into municipal practices, which may, in turn, be the starting point for a virtuous circle of continuous learning by doing and reflecting (Nonaka and Takeuchi, 1995; Wenger, 1998). Hence, we expect that:

Hypothesis 3b (H3b). The extent to which a municipality shares a vision with other municipalities and with the network as a whole will be positively associated with the extent of ICC the municipality achieves.

3.2. Extended view of social capital

We further introduced two variables that, in our view, are linked to the structural dimension of social capital, but are not usually considered in cross-sectional social capital research. These variables (specifically, shared resources and shared decisions) are not explicit in Nahapiet and Ghoshal's (1998) framework, but emerge consistently in related literature, including in other contributions on social capital (Adler and Known, 2002; Lin *et al.*, 2017), the collective intelligence approach (Malone et al, 2010; Secundo *et al.*, 2016) and public sector networks (Agranoff, 2012; Alter and Hage, 1993; Ansell and Gash, 2008).

3.2.1. Shared resources

When explaining the structural dimension of social capital, Nahapiet and Ghoshal (1998) refer not only to the relationships, but also to the resources that may be accessed through relationships and the social system as a whole. However, this idea is relatively implicit. As explained above, network resources are more explicit in other social capital frameworks and the collective intelligence approach. In the IC field, Edvinsson and Sullivan (1996) argue that structural resources (e.g. financial support, methodologies, codified best practices) should be important in explaining ICC. The variable "shared resources" were then input into our model to recognize: (1) that networks may differ in the resources accumulated throughout a relationship, and (2) that members devote their money, time and effort to participating in networks in which valuable resources are available.

We define shared resources as resources that are contributed, co-created (by building on different input resources and pieces of information/knowledge) and shared by all network members. Shared resources include physical, financial (e.g. financial aid to improve recycling systems) and human resources. These resources include experts/consultants and a shared intelligence system, made up of technical (e.g. methodologies) and information-related related resources that reside on a common website.

Edvinsson and Sullivan (1996) attach great importance to this type of structural capital in their model for managing new intellectual capital. They argue that human resources by themselves are of little value. People have limited money, knowledge, time, and energy, and need supporting resources. Similarly, in the tripartite classification of IC (human, structural and relational), structural capital refers to what remains without the employees, including databases, studies, processes, methods, research infrastructure, culture, etc. (Secundo *et al.*, 2016). This fits with our concept of shared resources.

The presence of shared resources makes social interaction between members more valuable by increasing the efficiency and effectiveness of social interaction efforts (Dyer and Singh, 1998). Network members may then feel that their social interaction efforts are worthwhile, which motivates them (i.e. the "why" dimension in Malone *et al.*, 2010, and Secundo *et al.*, 2016). The above arguments are consistent with those that appear in public sector network literature, which attaches great salience to network resources when explaining the participation of members in networks (Agranoff 2012; Alter and Hage, 1993). Hence, we expect that:

Hypothesis 4a (H4a). The extent to which a network's shared resources are valuable will be positively associated with the extent to which the municipality engages in social interaction with other municipalities in the network.

When knowledge sharing efforts are supported by the appropriate structural resources, learning tends to be more effective and is more likely to be implemented in municipal practices. This is the starting point for a virtuous circle of continuous learning by doing and reflecting (Kolb, 1984). Hence, we hypothesize:

Hypothesis 4b (H4b). The extent to which a network's shared resources are valuable will be positively associated with the extent to which the municipality achieves ICC.

3.2.2. Shared decisions

Similarly, the concept of "shared decisions," an unusual variable in previous cross-sectional research on social capital in private contexts, is introduced. This variable is important as some network orchestrators may have a more democratic mind-set than others. We define shared decisions as those that are reached through dialogue, which is used to achieve consensus and/or consent (Ansell and Gash, 2008; Armitage *et al.*, 2008). Shared decisions comprise one of the elements of an IC framework based on the collective intelligence approach (Secundo *et al.*, 2016).

When municipalities share decisions, they may promote their worldviews and aspirations and influence network-level goals, priorities, programs and activities (Ansell and Gash, 2008). Therefore, they influence knowledge sharing content, which leads to higher interaction efforts (Adger, 2003; Armitage *et al.*, 2008; Ansell and Gash, 2008). Hence, we expect that:

Hypothesis 5a (H5a). The extent to which a network's decisions are shared will be positively associated with the extent to which the municipality engages in social interaction with other municipalities in the network.

When social interaction efforts are oriented toward agreed goals, programs and activities, greater effectiveness is to be expected in knowledge exchange, combination and integration in the form of ICC. As what is learned fits their interests, municipalities may perceive it as being valuable, leading to a higher chance of it being integrated into municipal practices. Again, this may be the starting point for a virtuous circle of continuous learning by doing and reflecting (Kolb, 1984). Hence, we hypothesize:

Hypothesis 5b (H5b). The extent to which a network's decisions are shared will be positively associated with the extent to which the municipality achieves ICC.

3.3. Covariates

We controlled for municipality size, which may influence the availability of resources for participating in social interactions and transforming social interaction efforts into ICC (Krueathep *et al.*, 2008). It is not entirely clear how municipality size affects social interaction and ICC. Krueathep *et al.* (2008) suggested that large municipalities may be interested in joining social interactions due to having the organizational resources needed to manage them, whereas small municipalities may be interested due to their needs. Large municipalities may have a greater absorptive capacity, but may be less flexible when it comes to implementing what is learned by running the learning-by-doing cycle. We also control for the network of which the respondent is a member to capture possible characteristics of the network that are not explicit in our model.

4. Methods

4.1. Data collection

We studied eight Spanish municipal government networks that were devised to foster sustainability, and which were promoted by higher tiers of government (i.e. regional and/or provincial governments). Municipalities constitute the lowest level of government in Spain. The country (first tier) is divided into autonomous communities or regions (second tier), provinces (third tier) and municipalities (fourth tier). Spain is a relatively decentralized country, which means that resources and powers are distributed over the four tiers of government.

These particular networks were fostered in the early 2000s, with 17 networks being created. After identifying the networks, we invited their orchestrators to participate in the study and obtained positive responses from eight, meaning that we investigated eight municipal government networks. The orchestrators' participation was as follows: each of the municipalities had a municipal representative in the network and their orchestrators asked them to take part in the study. They encouraged the participation of municipal managers in different ways. While some networks used virtual channels (e.g. website, emails) to promote the study, while others also used face-to-face events. One sponsor asked us to present the research project at an event that brought together most of the network's participants. Facilitated by this support, the participation levels of municipal managers in the study were high, with an average of 71.66% for the 8 networks, ranging from 45.71% to 93.75%. In all, we obtained 655 valid responses.

Several procedures contributed to the validity and reliability of our data. Firstly, we interviewed professionals who had a good understanding of the content of the issues included in the questionnaire (five years' experience in the network, on average). Secondly, response levels were high. Thirdly, most interviews were conducted by phone, which helped us to control for the validity of our data (e.g. suitable respondent or time spent in answering questions). Fourthly, we guaranteed the confidentiality of the responses received.

4.2. Measurements

The measurements used also contributed to the reliability and validity of the study. The questionnaires used Likert-type scales with scores between 0 (completely disagree) and 10 (completely agree), which are usual in this cultural context. The measurements for the study constructs were in line with the concepts in the previous sections of this paper and were adapted from valid and reliable existing scales. A pre-test of the questionnaire was conducted using seven municipal managers. We asked for suggestions on the content and structure of the items in order to assess their ease of understanding, logical consistency, and contextual relevance (Hair *et al.*, 2010). The comments received from these experts led to several modifications in the wording and the elimination of some statements that informants considered confusing or redundant. Additionally, a pilot study was carried out involving another 20 municipal representatives.

Table 2 summarizes the measurements used for all of the study constructs.

(INSERT TABLE 2)

ICC was measured based on managers' perceptions. This approach has been successfully used in previous research (e.g. Yli-Renko *et al.*, 2001; Allameh, 2018). Glazer (1991) argued that the value of knowledge is not unique but is determined in context, which means that it largely depends on the subjectivity of the learner's perception. Cohen (1990) suggested that knowledge measurement cannot be absolutely objective**.** We used three perceptual items referring to the salience of belonging to the network for improving pro-sustainability skills and competencies.

Social interaction was adapted from Chiu *et al.* (2006), who studied virtual networks. We eliminated one item that made no sense in our context (i.e. I know some members in the virtual community on a personal level) and added an alternative one to capture the particular characteristics of our setting (i.e. we have face-to-face meetings with other network members to discuss sustainability issues). Trust was measured by adapting three items from Chiu *et al.* (2006), assessing the extent to which people in the network keep their promises, behave consistently and are trustworthy. Shared vision was adapted from Tsai and Ghoshal (1998), who used a two-item measurement aimed at assessing whether the focal actor (i.e. the municipality) shared the same ambitions as other participants (i.e. sustainability) and was enthusiastic about these collective goals.

Shared resources were measured by adapting three items from Frels *et al.* (2003), which were used to assess quantity, quality and accessibility (sample item: network resources are of a high quality). Shared decisions were assessed by using three items adapted from Carson *et al.* (2007) (sample item: decisions are made in assemblies in which consensus is sought).

4.3. Common method bias

We used the survey questionnaire as a method for collecting data. Our questionnaire provided the information used to measure both the independent and dependent variables. Therefore, a potential concern of this research is common method bias (CMB); i.e. the systematic variance shared among the variables, which is attributable to the measurement method rather than the theoretical constructs the measures are assumed to represent (Podsakoff *et al*. 2003; Richardson, Simmering, and Sturman 2009; MacKenzie, and Podsakoff 2012). CMB implies that the estimated effect of one variable on another is at risk of being biased.

To minimize CMB, we adopted some of the procedural precautions recommended by Podsakoff *et al*. (2003). Our respondents were highly knowledgeable of the networks as they represented their municipalities in these intergovernmental structures. We mostly used previously tested items to avoid item ambiguity, conducted a pre-test of the questionnaire and counterbalanced item order. We also protected anonymity.

As only using a data source has been identified as one of the main causes of the CMB (Podsakoff *et al*. 2003; MacKenzie, and Podsakoff 2012) we tried to obtain a second informant where possible. Finally, we obtained responses from two local representatives in 236 municipalities. The second informant was only questioned about the outcome variables. The complete model was tested for both samples and the results proved to be similar. While it is not possible to ensure that there is no CMB in our data, the above procedural precautions minimized its potential effect (Podsakoff *et al*. 2003; Richardson, Simmering, and Sturman 2009).

4.4. Data analysis

Covariance-based structural equation modeling (CB-SEM) was used for data analysis. CB-SEM is a statistical approach that allows the simultaneous estimation of a series of structural equations. The advantages of CB-SEM over other statistical techniques (such as multiple regression and path analysis) have been widely documented (Fornell and Larcker, 1981; Gerbing and Anderson, 1998; MacKenzie, 2001; Hair *et al.*, 2010). Among the advantages are that CB-SEM makes it possible to control for measurement error, enhances the ability to test complex theoretical structures, allows more powerful, simultaneous tests of measurement reliability, validity, and structural relations, and provides measures of fit to assess an entire model (MacKenzie, 2001; Hair *et al.*, 2010).

CB-SEM is the method most used to test complete theories and concepts due to its ability to evaluate the measurement of latent variables, while also testing relationships between them (Hair *et al.*, 2010). In our specific area of research (i.e. social capital and knowledge sharing/creation), most cross-sectional studies have used CB-SEM (e.g. Tsai and Ghoshal, 1998; Yli-Renko *et al.*, 2001; Chiu *et al.* 2006; Lefebvre *et al.*, 2016; Bhatti *et al.*, 2020). Another form of SEM (i.e. PLS-SEM) is being increasingly accepted and applied, particularly when the research is aimed at developing theory, and some features are present in the data (e.g. low sample size or formative measures) (Hair *et al.* 2014). Accordingly, some recent studies in our field have applied PLS-SEM (Fredette and Bradshaw, 2012; Ganguly *et al.*, 2019; Zhang *et al.*, 2019). However, as our paper is mainly aimed at confirming theory, and we have a large sample and use reflective measures, we preferred to estimate our model following the most traditional approach (i.e., CB-SEM), which provides broadly accepted measures of overall model fit. A limitation of using CB-SEM in social sciences is the frequent lack of multivariate normality of data, which can lead to underestimated standard errors and inflated model fit measures (Lei and Lomax, 2005). Several alternative estimation procedures have been developed to respond to this problem (Hair *et al.* 2014). We used an Mplus option for maximum likelihood estimation with robust standard errors (i.e., MLR).

Data analysis used a three-step approach. The first step involved analyzing the measurement model to test the convergent and discriminant validity of the measurements. After proving the fit of the measurements, a preliminary analysis of the eight networks was conducted (step 2). Lastly, the structural relationships between latent variables were estimated (step 3). Steps 1 and 3 are usual in SEM research (Gerbing and Anderson, 1998). Step 2 was added in this research to enrich the analysis with the potentially different behavior of the eight networks studied, in terms of the involved variables. The results are presented in the next section.

5. Findings

5.1. Measurement model

Confirmatory factor analysis (CFA) was applied to assess the convergent and discriminant validity of the measures with MPlus. Each item was modeled as a reflective indicator of its latent variable, and all variables were allowed to co-vary in the CFA model. For a measurement model to have enough goodness of fit, the comparative fit index (CFI), and Tucker-Lewis index (TLI) should exceed .9. Also, the root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR) should not exceed .07 (Hair *et al.*, 2010). The convergent validity of the scales is usually verified by using three criteria suggested by Fornell and Larcker (1981): (1) all indicator loadings should exceed .7; (2) variable reliabilities should exceed .8; and (3) the average variance extracted (AVE) of each variable should exceed the variance due to measurement error for that variable (i.e. AVE should exceed .50).

As shown in table 2, the measurement model comfortably meets the above criteria, with chi-square = 227.55 (d.f. = 120), CFI = .985, TLI = .981, RMSEA = .037, and SRMR = .031. Table 2 also presents the results of the analyses of reliability and convergent validity for the model. Scale wordings, composite reliability, and average variance extracted (AVE) are shown. All items significantly load on their respective dimensions, ranging from .718 to .985. All variables show good internal consistency, with construct reliabilities ranging from .817 to .972. The AVE values obtained are between .598 and .919 (all above .50). Hence, all the three conditions for reliability and convergent validity were met.

Discriminant validity was tested using the most demanding form of verification, which requires the correlation between two factors to be lower than the square root of the AVE for each variable (Hair *et al.*, 2010). Table 3 shows the correlation matrix and the results for the assessment of discriminant validity. All comparisons between construct pairs meet the requirements of the criteria. The correlations between the variables are below the .65 threshold, indicating that our results are probably not biased by multicollinearity (Tabachnick and Fidell, 1996).

(INSERT TABLE 3)

5.2. Preliminary analysis of the eight networks

The means of variables under study for the eight networks are presented in Table 4. A simple overview of the data shows that the networks seem to behave differently. For instance, social interaction ranged from 3.0 to 8.6 and ICC from 3.2 to 8.2.

(INSERT TABLE 4)

We used the non-parametric median test to determine whether the variables under study were statistically different for the eight networks. This test was chosen as the variance of our variables was heterogeneous in the eight networks, which violates ANOVA assumptions. The non-parametric Kruskal-Wallis H test was also discarded as it requires the distribution of the variables to have a similar shape for the eight networks, which is not true in our data.

The median tests showed that there was a statistically significant difference in social interaction ($\chi2= 99.97$, $p = 0.000$), ICC ($\chi2= 58.76$, $p = 0.000$), shared resources ($\chi2= 23.07$, $p = 0.002$), trust ($\chi2 = 35.79$, $p = 0.000$), and shared decisions ($\chi2 = 35.83$, $p = 0.000$) between the eight groups. However, there was no statistically significant difference in shared vision ($\chi2= 8.09$, $p = 0.324$). Chi-squared data indicate that the most important differences between networks refer to social interaction and ICC, which could be interpreted to mean that social interaction and ICC are the most distinctive characteristics of our engineered networks.

5.3. Structural model

The structural model incorporating the assumed linear relationships between the variables was tested with the data calculated from the validated measures. Table 5 shows the results of the structural model, together with the fit indices.

(INSERT TABLE 5)

Most hypotheses were confirmed. The linear effect of social interaction on ICC was proven to be positive ($\beta = .181$; $p = .000$), corroborating H1. Trust had a positive effect on ICC ($\beta = .368$; $p = .000$), which confirms H2b. The linear effect of shared vision on social interaction was proven to be positive ($\beta = .220$; $p = .000$), corroborating H3a. Shared vision also contributed positively to ICC ($\beta = .235$; $p = .000$), which confirms H3b. Shared resources had a positive effect on social interaction ($\beta = .282$; $p = .000$), which confirms H4a. The expected positive effect of shared decisions on social interaction was also confirmed (β = .275; p = .001), which corroborates H5a. Shared decisions positively contributed to ICC (β = .199; p = .019), which confirms H5b.

Two hypotheses were rejected. The expected direct positive effect of shared resources on ICC (H4b) was not confirmed (β = .084; p = .197), although an indirect significant effect existed (mediated by social interaction). Trust did not contribute to social interaction (β = .002; p = .982), which rejects H2a. As shown above, the contribution of trust to ICC was direct.

Covariates were proven to have different effects on social interaction and ICC. Although municipality size did not affect interaction levels, when the remaining variables were considered, it contributed to ICC. This result could be interpreted to mean that small municipalities are less able to take advantage of their social interaction efforts due to their lower absorptive capacity and resources availability.

Social interaction is affected by other characteristics of the network that were not specifically included in the model. This result could indicate that social interaction is also explained by historical and cultural reasons, which may be insufficiently captured in the social capital variables we considered. Other characteristics of the network, however, seem to have very little influence on ICC as significant effects were only found in two networks.

As Table 5 shows, the estimated model appears to satisfactorily explain the data variance. A substantial proportion of variance in social interaction and ICC was explained (46.0% and 56.6%, respectively). The fit indices fell within the recommended limits (CFI = .977, TLI = .969, RMSEA = .038; see Table 5) (Hair *et al.*, 2010).

5.4. Post hoc analyses

To further explore the links between the model constructs, we examined all of the possible quadratic and interaction effects of our independent variables. To estimate these effects, we used latent moderated structural equations (Klein and Moosbrugger, 2000). We did not find any quadratic or interaction effects that significantly improved model fit.

6. Discussion and implications

We used a sample of 655 municipalities in eight intergovernmental networks to test the effect of an extended view of social capital on ICC. Three variables usually considered representative of social capital (social interaction, trust, and shared vision) and two supplementary variables (shared resources and shared decisions) were proven to have significant direct and/or indirect effects on ICC. This finding corroborates and extends previous studies in other contexts at organizational (e.g. Tsai and Ghoshal, 1998) and network levels (e.g. Chiu *et al.*, 2006).

We examined engineered networks in which sponsors try to foster social interaction that did not already exist or occurred at low levels only. Our specific context matters, as some previous research has focused on networks that could have a more organic nature, and/or involve fewer interaction costs, leading to more spontaneous social interaction. For instance, Tsai and Ghoshal (1998) studied an inter-firm network in which units were motivated to interact due to this being a requisite of belonging to the same organization. Chiu *et al.* (2006) studied a virtual community of professionals in which spontaneous interactions were likely. This was because professionals could see that participation would be low cost (i.e. virtual interaction), and require low levels of commitment (i.e. free riding is easier when behind a computer) to improve their personal skills and competencies. In our case, however, before the networks were engineered, municipalities only interacted occasionally with neighboring peers to address particular issues. Consequently, higher tiers of government tried to foster greater levels of social interaction, which were expected to enhance sustainability-related ICC. This led us to see social interaction as a dependent variable that mediates the link between the variables representing the other social capital dimensions and ICC. This means that context matters when representing social capital, establishing the link between the different social capital dimensions and explaining social capital outcomes (in our case, ICC).

In their seminal proposal, Nahapiet and Ghoshal (1998) did not establish specific links between the three social capital dimensions. While they recognized that those links should exist, they found them too complex to be addressed in their first approach to the subject. Consequently, further cross-sectional works adopted different approaches that (consciously or not) could be affected by the specific setting studied. Our contribution to social capital literature emphasizes the specific nature of social interaction in engineered, intergovernmental networks. There are plenty of case studies in the public sector and environmental literature in which learning is a normative goal and the major challenge is to get people to interact (e.g. Armitage *et al.*, 2008). For instance, addressing the contamination of a river requires the interaction of all of the stakeholders involved, and it does not always arise spontaneously (due to free-riding behaviors or for historical reasons). Interaction then needs to be orchestrated to avoid the worst possible scenarios. Our engineered, intergovernmental setting led us to include shared resources and shared decisions to supplement the structural part of social capital. These variables are implicit in the conceptualization of the structural dimension of Nahapiet and Ghoshal (1998), but have not been explicitly considered in previous cross-sectional research grounded in social capital theory. Drawing on Secundo *et al.* (2016), other social capital frameworks, and literature on public sector networks we considered that the structural dimension of our networks could not be properly captured without including these variables, and our data confirmed that these variables matter when explaining ICC. We viewed shared decisions as a variable that could be important in our setting but not in other settings (e.g. in the context of research contributions by Tsai and Ghoshal (1998) and Chiu *et al.* (2006)). In addition, shared resources (accumulated by the network and its members through a history of social interactions), although usually neglected, are shown to be crucial when explaining interaction in our context.

Another relevant finding of our research refers to the role of trust. Although there is wide consensus that trust matters, the results of previous social capital research in relation to the specific role of trust are not conclusive. For instance, Yli-Renko *et al.* (2001) found that relationship quality (similar to trust) is negatively related to knowledge acquisition, which is counterintuitive and seems to contradict the results of other studies that find a positive relationship between trust and the quality of knowledge shared (e.g. Chiu *et al.*, 2006). We expected that trust would affect both social interaction and ICC. However, although the effect of trust on ICC is strong, it does not affect social interaction. One explanation could be that high levels of trust may make interactions less necessary (e.g. a formal, nervy, cost-intensive meeting between two managers who do not know each other could be replaced by a quick, direct, telephone call between two managers who have become friends). Similarly, where trust reaches a high level, members expect information to be accessed when needed, so that the incentive to take part in all interaction opportunities that arise is reduced. Another possible explanation is that trust is not crucial to explaining social interaction in less risky relationships (Chiu *et al.*, 2006). Coleman (1988) argued that trust is only needed in risky situations.

Trust, however, seems to act as a mechanism that makes social interaction efforts more effective. Members of a network may embrace social interactions with other members when they share a vision, participate in decision making and expect to find valuable resources in the network. In that particular case, trust acts as leverage on the effects of social interaction in terms of ICC. This result is consistent with other studies that find that trust does not affect the quantity of knowledge shared (e.g. Chiu *et al.*, 2006).

These findings have important implications for research and practice, and provide avenues for further research.

6.1. Implications for research

This research responds to recent claims suggesting that research efforts on ICC should extend from organizations to networks/ecosystems, particularly those designed to solve crucial societal challenges that affect people's wellbeing (Dumay, Guthrie and Rooney, 2018; Guthrie and Dumay, 2019), and from measuring IC to explaining ICC (Dumay, Guthrie and Rooney, 2018). In particular, the link between social capital and ICC in intergovernmental sustainability-led networks has been virtually unexplored, and we see this research as a first attempt towards covering this gap.

While Nahapiet and Ghoshal's (1998) approach to social capital is considered to be a starting point (which leads us to consider social interaction, trust, and shared vision as antecedents of ICC), the particular mediating role that our model attaches to social interaction, and the addition of two supplementary explanatory variables (shared resources and shared decisions) are novel. Our research could induce further empirical works in the area of ICC in public sector-driven networks, which consider, for instance, different explanatory variables and links between them, and/or different conceptual lens.

6.2. Implications for practice

We studied eight engineered networks and found high heterogeneity in their levels of social interaction and ICC, with some networks showing very low levels of both variables. It was evident that using the fashionable "network" label is not enough to achieve sufficient levels of social interaction and ICC. An appropriate management approach is therefore necessary. Consequently, we provide orchestrators with some management direction by proving the salience of shared vision, trust, shared decisions and shared resources, and estimating their specific effects on both social interaction and ICC.

While social interaction leads to ICC, orchestrators should not take it for granted (as it involves costs), but stimulating it. To do this, orchestrators should encourage a shared vision and shared decisions, and develop a platform of shared resources. More specifically, our findings suggest that network orchestrators cannot predefine a closed network vision. On the contrary, they should facilitate the co-development of a shared vision through in-depth multi-participant dialogue. At most, orchestrators could provide a starting point for developing a shared vision. For instance, one of our orchestrators did so by emphasizing climate change threats and the need to undertake collaborative work as the most appropriate way to tackle this challenge. This starting point should be debated, enriched and reformulated until an agreed network vision is achieved that integrates the diverse views of network participants. Similarly, all network strategies and actions should be co-decided, meaning that orchestrators should provide consensus-oriented forums in which all participants have a voice and influence. Lastly, promoters should contribute resources (e.g. money, consultants) and promote the co-development of shared resources (e.g. strategic plans, methodologies, websites) through the creation of work groups that could create new knowledge in common interest areas (e.g. green procuring, public participation, gender considerations) and share it via meetings, reports and virtual platforms.

Our findings are also insightful for municipalities, as they show that participating in appropriately managed networks is a suitable avenue to ICC. Municipalities should consider this way of enhancing their IC, when evaluating all possible strategic options of assigning resources to learn how to respond to climate change and other wicked problems that affect people's wellbeing.

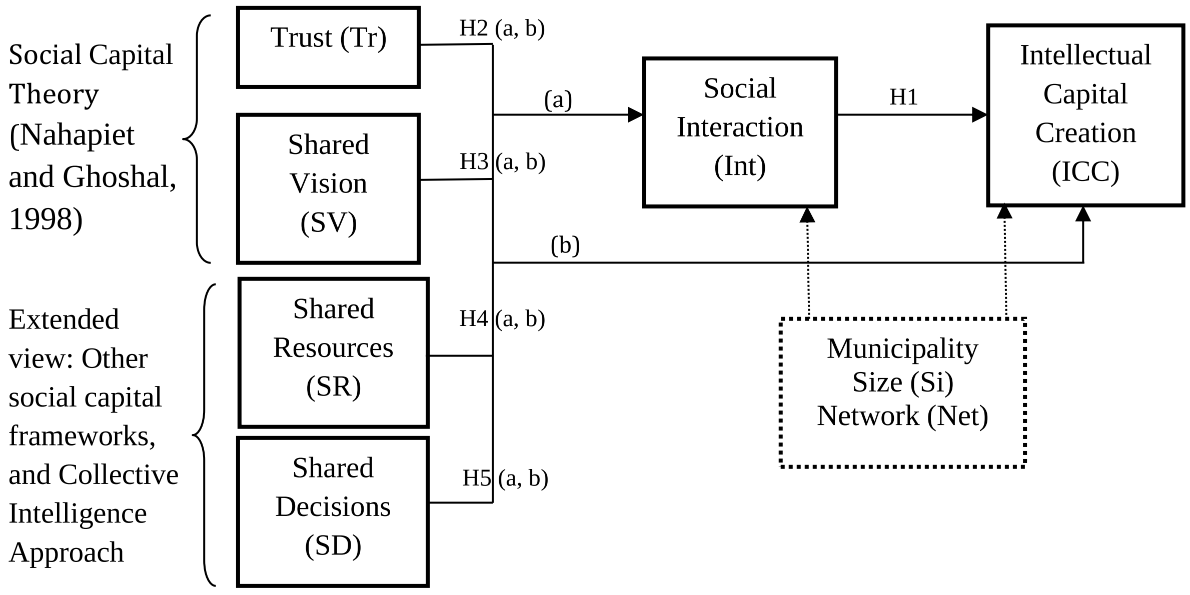
6.3. Limitations and further research

This study shares the usual limitations of cross-sectional studies conducted in a specific context. Although causal relationships have been proposed in this study, the cross-sectional nature of our design makes it impossible to test the direction of relationships. While we have rooted our arguments in an in-depth knowledge of our context, existing theory and past findings, we are aware that our proposals are open to debate. Although our data are static, the development of social capital leading to ICC is an ongoing phenomenon. Further research could include a longitudinal assessment of the different variables involved. Lastly, factors unique to our context may limit the applicability of the results to other settings. Further studies conducted in other settings may shed light on the generalizability of our results.

Table 1. Theoretical background and its implications for this research

Concept / Topic	Description	References	Implications for this research
Intellectual capital creation (ICC)	The acquired knowledge, skills, and capabilities that enable participants in networks to act in new ways that can create public value	Edvinsson and Sullivan (1996); Nahapiet and Ghoshal (1998); Duff (2018).	This research focuses on how networks of local governments can create intellectual capital to respond to a wicked probem (i.e. climate change). ICC is therefore the outcome variable in this research.
Knowledge / learning, engineered networks	Deliberately created networks whose direct purpose is to improve the knowledge of those taking part in them.	Bessant and Tsekouras (2001); Warkentin *et al*. (2002); Vătămănescu *et al*. (2016).	This research focuses on knowledge/learning networks, in which the participants' direct purpose is ICC. ICC could ultimately lead to discovering new means and goals (indirect purposes).
Intellectual capital (IC) and the public sector	The conditions that foster ICC in public organizations under a networking perspective have been virtually ignored.	Dumay *et al*. (2015); Guthrie and Dumay (2019).	This research identifies several factors that foster ICC in networked local governments and test their effects empirically.
Social capital theory	Social capital facilitates ICC by affecting the conditions necessary for knowledge exchange and combination to occur. Social capital is conceptualized in three dimensions: structural, relational and cognitive.	Nahapiet and Ghoshal (1998).	ICC is explained in this research by the three dimensions of social capital: structural, relational and cognitive.
Social capital-related, cross-fuctional research	Most cross-sectional studies have represented the structural dimension by social interaction, the relational dimension by trust, and the cognitive dimension by shared vision.	Tsai and Ghoshal (1998); Yli-Renko *et al*. (2001); Allameh, (2018); Ganguly *et al*. (2019).	Social interaction, trust and shared vision are explanatory variables of ICC in our model. We argue that in engineered networks social interaction needs to be orchestrated; social interaction is then explained in this reseach by trust and shared vision.
Collective intelligence systems	The capacity of collaborative systems to create collective intelligence depends on the "why" (motives) and "how" (how decisions are made) of collaboration.	Malone *et al*. (2010); Secundo *et al*. (2016).	Social capital theory is supplemented in this research with the collective intelligence framework by considering the "why" and "how" of collaboration.
Literature on public sector networks	Provides specific dimensions for the "why" (i.e. shared resources) and "how" (i.e. shared decisions) of collaboration in intergovernmental networks	Keast *et al*. (2004); Agranoff (2012).	Shared resources (representing the "why") and shared decisions (representing the "how") are explanatory variables of social interaction and ICC.

Figure 1. Model



Note: The model specification is as follows: *(1)* $\boldsymbol{ICC_i} = \alpha_1 + \beta_{11} (Int_i) + \beta_{12} (Tr_i) + \beta_{13} (SV_i) + \beta_{14} (SR_i) + \beta_{15} (SD_i) + \beta_{16} (Si_i) + + \beta_{17} (Net_i) + \varepsilon_{1i}$; *(2)* $\boldsymbol{Int_i} = \alpha_2 + \beta_{21} (Tr_i) + \beta_{22} (SV_i) + \beta_{23} (SR_i) + \beta_{24} (SD_i) + \beta_{25} (Si_i) + \beta_{26} (Net_i) + \varepsilon_{2i}$

Table 2. Convergent Validity and Reliability Assessment

Construct and item	Stand. Loading	CR	AVE
Indicate your degree of agreement regarding how well these statements describe (network name or municipality name) during the last three years.			
SOCIAL INTERACTION (Chiu *et al.*, 2006)		.917	.734
We frequently contact other network members to discuss sustainability issues.	.867***		
We have face-to-face meetings with other network members to discuss sustainability issues.	.916***		
We usually hold long conversations with other network members to discuss sustainability issues	.965***		
We have close relationships with other network members	.929***		
INTELLECTUAL CAPITAL CREATION (Yli-Renko *et al.*, 2001)		.972	.919
The information we get in this network improves our skills and competencies in response to sustainability challenges	.953***		
Because we belong to this network we have learned how to tackle sustainability challenges	.985***		
This network helps us to respond to sustainability-related issues	.938***		
SHARED RESOURCES (Frels *et al.*, 2003)		.926	.807
Many resources are accessible within this network	.859***		
Network resources are easily accessible	.930***		
Network resources are of high quality	.906***		
TRUST (Chiu *et al.*, 2006)		.940	.839
Network members keep their promises	.923***		
Network members behave consistently	.960***		
Network members are trustworthy	.863***		
SHARED DECISIONS (Carson *et al.*, 2007)		.817	.598
Decisions are made in assemblies in which consensus is sought	.718***		
Participation in decision-making is encouraged	.876***		
Those who participate in decision-making are supported	.773***		
SHARED VISION (Tsai and Ghoshal, 1998)		.916	.845
Influential people in this municipality are enthusiastic about pursuing the collective goals and missions of the network	.881***		
The relevant people in this municipality are great supporters of sustainability	.956***		
Model fit indexes (Robust): χ^2= 227.55; d.f.= 120; CFI = .985; TLI = .981; RMSEA = .037; SRMR = .031			

Notes: *** p < .01, ** p < .05, * p < .10; CR, composite reliability; AVE, average variance extracted. HTG, Higher Tiers of Government (e.g. Regional Government). N = 655.

Table 3. Correlation Matrix for Discriminant Validity Assessment

Dimensions	1	2	3	4	5	6
1. Social Interaction	*.856*					
2. Intellectual Capital Creation	.491*	*.958*				
3. Shared Resources	.373*	.278*	*.898*			
4. Trust	.323*	.436*	.392*	*.915*		
5. Shared Decisions	.403*	.416*	.561*	.535*	*.773*	
6. Shared Vision	.315*	.378*	.321*	.372*	.426*	*.919*

Notes: Correlations between construct pairs are shown below the diagonal. Square root of the Average Variance Extracted for each construct is shown on the diagonal. * Significant at a 1% level. N = 655

Table 4. Response rates and variable means by network

Network	# munic. (sample)	# munic. (network)	Response rate	Social Interaction	ICC	Shared Resources	Shared Vision	Trust	Shared Decisions
1	51	55	92.73%	8.6	8.2	6.2	6.2	7.7	5.8
2	161	183	87.98%	3.8	6.1	4.9	5.8	5.7	4.9
3	58	69	84.06%	4.4	6.3	5.3	6.7	6.3	5.4
4	30	32	93.75%	4.7	6.9	5.0	6.2	6.4	5.6
5	156	231	67.53%	4.8	7.1	5.6	6.6	5.7	6.0
6	120	202	59.41%	3.0	3.2	6.1	6.1	6.6	5.4
7	47	72	65.28%	3.5	4.9	5.5	6.8	6.5	6.5
8	32	70	45.71%	5.9	7.0	5.1	6.7	7.3	6.6
Total	655	914	71.66%	4.4	6.1	5.5	6.3	6.5	5.6

Note: ICC = Intellectual Capital Creation

Table 5. Structural Model Estimation

Hypotheses and other effects		**MODEL**		
Hypotheses (H) and covariates (C)		Estimate	Est. / S.E.	p-value
H1	Social Interaction → ICC	.181***	3.655	.000
H2a	Trust → Social Interaction	.002	.022	.982
H2b	Trust → ICC	.368***	5.225	.000
H3a	Shared Vision → Social Interaction	.220***	3.772	.000
H3b	Shared Vision → ICC	.235***	4.309	.000
H4a	Shared Resources → Social Interaction	.282***	4.263	.000
H4b	Shared Resources → ICC	.084	1.290	.197
H5a	Shared Decisions → Social Interaction	.275***	3.338	.001
H5b	Shared Decisions → ICC	.199**	2.347	.019
C	Municipality Size → ICC	.095***	3.436	.001
C	Network 1 → ICC	.323	1.241	.214
C	Network 2 → ICC	.490*	1.821	.069
C	Network 3 → ICC	.128	.455	.649
C	Network 4 → ICC	.566**	2.057	.040
C	Network 5 → ICC	.283	1.084	.278
C	Network 6 → ICC	-1.244***	-3.573	.000
C	Network 7 → ICC	-.660*	-1.806	.071
C	Network 8 → ICC	N.A.	N.A.	N.A.
C	Municipality Size → Social Interaction	-.048**	-1.588	.112
C	Network 1 → Social Interaction	1.359***	6.530	.000
C	Network 2 → Social Interaction	.-.733***	-3.597	.000
C	Network 3 → Social Interaction	-.625***	-2.677	.007
C	Network 4 → Social Interaction	-.414	-1.582	.114
C	Network 5 → Social Interaction	-.524**	-2.591	.010
C	Network 6 → Social Interaction	-1.508***	-6.802	.000
C	Network 7 → Social Interaction	-1.204***	-4.908	.000
C	Network 8 → Social Interaction	N.A.	N.A.	N.A.
R-square				
	Social Interaction		.460	
	ICC		.566	
Fit Indexes			χ^2= 424.69 ; d.f.= 216 CFI = .977; TLI = .969 RMSEA = .038; SRMR = .026	

Notes: *** p < .01, ** p < .05, * p < .10. N = 655. N.A. = Not Applicable (Network is a dichotomous variable and needs a reference category). ICC = Intellectual Capital Creation.

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