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Social capital and knowledge sharing performance of learning networks

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ABSTRACT

The purpose of this study is to empirically investigate the relationship between the social capital accumulated among network members and the performance of learning networks in terms of their ability to enhance knowledge sharing among network members. A network level perspective guided the sampling strategy adopted for this survey involving 150 members of 16 European learning networks. Hierarchical multiple regression and structural equation modelling were employed to investigate the inter-relationships between dimensions of social capital and knowledge sharing in learning networks. The results reveal that social interaction and cognitive social capital are positively and significantly related to knowledge sharing in learning networks. Social interaction is also shown to play an important role in the development of shared vision and shared language (i.e. cognitive social capital) in learning networks. This paper sheds further light on the inter-relationships between different dimensions of social capital from a network (rather than firm) level perspective, and contributes to emerging theory on the antecedents to, and assessment of, performance in learning network entities.

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1. Introduction

According to the knowledge-based view of the firm, knowledge is considered the most important resource for the competitiveness of firms as its creation and application offers the firm new opportunities (Grant, 1996). Organizational learning contributes to an increase in the firm's "reservoirs" of knowledge and implies knowledge transfers among different levels of action within the firm but also often from entities outside the firm (Argote & Ingram, 2000; Huber, 1991).

Successful knowledge transfer within the firm is argued to be difficult (Argote & Ingram, 2000), but successfully sharing knowledge between organizations is seen as even more challenging due to a variety of factors (Easterby-Smith, Lyles, & Tsang, 2008). In inter-organizational collaborative processes, significant efforts must be deployed by organizations in screening and testing several sources (Lazzarotti & Manzini, 2009). In addition, formal and social coordination mechanisms must be adopted in order to deal with ownership of assets and differences in mentality between parties, and to reduce risks of opportunism and unintended knowledge leakages (Easterby-Smith et al., 2008).

In that context, new types of organization have emerged that aim to support such collaboration and knowledge sharing between organizations, which can encompass both innovation intermediaries (Howells, 2006) and brokers (Winch & Courtney, 2007). Of these, inter-organizational entities referred to in the literature as 'learning' (Bessant & Tsekouras, 2001; Sherer, 2003) or 'knowledge transfer' networks (Bond Iii, Houston, & Tang, 2008) are the focus of attention in this paper. These 'learning' or 'knowledge transfer' networks are established to act as a channel of knowledge distribution. Although learning networks have already been proven useful for facilitating knowledge transfer (e.g., Bond Iii et al., 2008), studies that investigate the factors that influence their outcomes and success are still scarce (Bessant, Alexander, Tsekouras, Rush, & Lamming, 2012). In particular, previous studies have predominantly focused on factors that influence participant level performance, which negates the importance of how collective entities perform (Kenis & Provan, 2009; Turrini, Cristofoli, Frosini, & Nasi, 2010). To address this gap, this study investigates the relationship between the social capital accumulated among network members and the performance of learning networks in terms of their ability to enhance knowledge sharing among network members. The choice to adopt a social capital perspective on the performance of learning networks was driven by the very

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essence of both networks and knowledge sharing processes. The core of both is about social relationships, and social capital represents the overarching concept that allows capturing the different properties of the social system of relationships (Inkpen & Tsang, 2005; Wei, Zheng, & Ehang, 2011). The study also constitutes a welcome contribution to social capital research as it explores the interrelations between different facets of social capital, an area that has been so far largely ignored by empirical studies (Lee, 2009).

In the next section, the authors provide a brief overview of the literature on knowledge sharing, social capital and learning networks. The relationships examined in the paper are then discussed and testable hypotheses are developed. The authors subsequently describe the study methodology and present the findings. In the final section, the authors discuss these findings, their implications and limitations, and provide future research directions.

2. Theoretical background

2.1. Knowledge sharing and social capital

Knowledge sharing refers to the process of exchanging knowledge between organizational actors (e.g., individuals, groups, or organizations) (Chow & Chan, 2008). It is closely related to knowledge transfer as knowledge sharing helps to gain experience from another actor (Argote & Ingram, 2000). Previous research has investigated a wide variety of antecedents of knowledge sharing. While a first stream of research has focused on organizational and knowledge characteristics as important antecedents of knowledge sharing, another stream of research has centered on the characteristics and dynamics of the inter-organizational context where knowledge sharing takes place (Easterby-Smith et al., 2008; Van Wijk, Jansen, & Lyles, 2008). Given that inter-organizational knowledge sharing is social in nature and involves the resources embedded in relationships, many scholars have investigated it through a social capital perspective (e.g., Chow & Chan, 2008; Wei et al., 2011).

As the concept of social capital has been utilized in a wide range of social, organization and management studies and at varying levels of analysis, it has been defined in various ways (Adler & Kwon, 2002). Still, most management scholars generally agree that social capital represents the resources an individual or social entity gain through its network of relationships (Payne, Moore, Griffis, & Autry, 2011). The central propositions of social capital theory are that networks of relationships are a valuable resource for the individual or social entity and that value lies both in the network ties and in the assets that can be mobilized through these ties (Nahapiet & Ghoshal, 1998).

Because social capital has been defined in different ways, it has also been conceptualized and operationalized differently by scholars (Payne et al., 2011). In this paper, similarly to other studies (e.g., Inkpen & Tsang, 2005; Martínez-Cañas, Sáez-Martínez & Ruiz-Palomino, 2012), the authors operationalize social capital following the framework of Nahapiet and Ghoshal (1998). Nahapiet and Ghoshal's (1998) framework groups the various facets of social capital into three dimensions: the structural dimension, the cognitive dimension and the relational dimension. The structural dimension refers to the configuration and pattern of connection between network actors. It has been analyzed from different perspectives (e.g., tie strength and centrality, network stability and size) (Zheng, 2010) but in this research, it focuses on social interaction between network actors who refer to the members of the formal networks in this study (Lee, 2009; Yli-Renko, Autio, & Sapienza, 2001). The cognitive dimension involves the resources providing shared meaning and understanding between network members. In their framework, Nahapiet and Ghoshal (1998) had originally related it to shared language and shared narratives, but other authors have later described it also through shared goals or vision, and shared culture (Inkpen & Tsang, 2005; Tsai & Ghoshal, 1998). In this study, the cognitive dimension entails shared language and shared vision. Finally, the relational dimension of social capital represents the kind of personal relationships people develops with each other through a history of interactions (Nahapiet & Ghoshal, 1998). Among the facets of this dimension, this study focuses on trust, one of the most researched and critical factor affecting knowledge sharing and transfer (Inkpen & Tsang, 2005; Lee, 2009). Because previous studies have suggested that the three dimensions of social capital and their different facets are interrelated (Bond Iii et al., 2008; Tsai & Ghoshal, 1998), the investigation of the links between them is essential for understanding their role as antecedents of knowledge sharing.

2.2. Learning networks

Learning networks are defined as '*networks formally set up for the primary purpose of increasing knowledge*' (Bessant & Tsekouras, 2001). They are characterized by boundaries defining participation and have a clear strategy and ground operations to support knowledge sharing and to generate valuable learning for their members (Bessant & Tsekouras, 2001). So defined, they encompass a variety of forms of organization such as formal business networks (e.g., Schoonjans, Van Cauwenberge, & Vander Bauwhede, 2013), professionals networks (e.g., Kimble, Grenier, & Goglio-Primard, 2010), and innovation networks where the collaborative aim is about developing e.g., new products or processes (e.g., Batterink, Wubben, Klerkx, & Omta, 2010).

Like strategic alliances, learning networks are in fact one form of structure that provides the necessary context for significant knowledge sharing to occur (Easterby-Smith et al., 2008). Yet, although learning networks have already proven valuable in terms of facilitating knowledge transfer among their members (e.g., Bond Iii et al., 2008) and supporting members' growth (e.g., Schoonjans et al., 2013), they are not always successful (e.g., Huggins, 2000). Existing evidence suggests there is a series of social and non-social factors that come into play in their success of failure. Some studies have highlighted for example the positive impact that spatial proximity, trust, good network management practices, and compatibility have on the success of collaborative activities (Bessant et al., 2012; Huggins, 2000). Nonetheless, there are still important gaps in the understanding of how learning networks operate in order to facilitate effective knowledge sharing (Bessant et al., 2012). This study contributes to addressing this gap by focusing on the role that social factors identified through the social capital literature play in the success of learning networks in terms of their ability to enhance knowledge sharing among network members.

3. Hypotheses and conceptual model

As exemplified by several reviews of the literature on social capital (Lee, 2009; Payne et al., 2011), the concept of social capital has been utilized at various levels of analysis. Similarly to other studies (e.g., Martínez-Cañas et al., 2012), this research focuses on the relationships among network members of the learning network as a source of social capital and operationalizes it as a three dimensional construct following Nahapiet and Ghoshal's (1998) framework. This study examines the relationship between network level outcomes (i.e., performance of the network in terms of its ability to enhance knowledge sharing among network members) and the accumulation of social capital at the relationship level. A cross-level model, which is characterized by the independent and dependent constructs being at different levels of analysis (Payne et al., 2011),

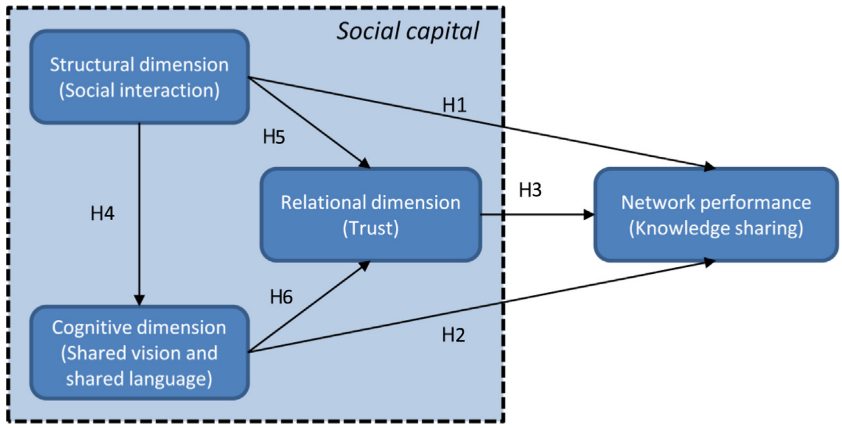

Fig. 1. Conceptual model and hypotheses.

is thus developed. In addition, the study also explores the links between the three dimensions of social capital (See Fig. 1).

3.1. Social capital and network performance

Social interaction (i.e., structural social capital) refers to the process of building and forming social ties, and thus, the propensity to make contacts (Lee, 2009). It is assumed that, as information and resources circulate through social ties, an actor may potentially gain access to the resources of others through social interaction (Tsai & Ghoshal, 1998). Social interaction has been shown to be positively related to knowledge acquisition (Yli-Renko et al., 2001) and resource exchange and combination (Tsai & Ghoshal, 1998). Thus, as social interactions enhance exchange of knowledge, it is likely that their development among network members enhance the ability of the learning network to operate as a platform for knowledge sharing. Thus, the following hypothesis is developed:

H1. The greater the social interaction between a network member and the other network members, the greater will be the performance of the network in terms of knowledge sharing.

In this study, the cognitive social capital refers to shared language and shared vision. Shared vision represents the degree to which network members share goals, concerns and perceptions (Levin, Whitener, & Cross, 2006). It has been suggested that individuals who share the same vision can better see the potential value of exchanging and combining their resources (Tsai & Ghoshal, 1998). It has been found to enhance the willingness of individuals to share knowledge in organizations (Chow & Chan, 2008). Conversely, several studies have postulated that a lack of shared vision and perspective between team members can lead to misunderstandings and conflicts that may bring an end to knowledge being shared between members (e.g., Du Chatenier, Verstegen, Biemans, Mulder, & Omta, 2009; Horwitz, 2005).

Shared language embodies the degree to which network members use the same language, i.e., the means by which people discuss and exchange information. It is thought to influence knowledge sharing positively by enhancing the ability of people to access each other's information (Nahapiet & Ghoshal, 1998). Edelman, Bresnen, Newell, Scarbrough, and Swan, (2004) emphasize that shared language help project members to communicate effectively and function as a cohesive group. Furthermore, Tagliaventi, Bertolotti, and Macrì, (2010) provide evidence for the existence of shared language within inter-organizational communities of practice that enables knowledge flows within these communities but also the 'unambiguous interpretation of what is flowing'.

In sum, as both shared vision and shared language can be viewed as mechanisms that enhance knowledge exchange, their presence among network members is most probably associated with a higher ability of the network to enhance knowledge sharing. Thus, the following hypothesis is developed:

H2. The more a network member shares cognition with the other network members, the greater will be the performance of the network in terms of knowledge sharing.

Following Pirson and Malhotra (2011), trust (i.e., relational social capital) is defined as 'the psychological willingness of a party to be vulnerable to the actions of another party (individual or organization) based on positive expectations regarding the other party's motivation and/or behavior'. It is claimed that trust plays a key role in the willingness of network actors to engage in knowledge sharing processes as it erases any confusion that such actors might have about whether or not other network actors are allies or will act opportunistically (Inkpen & Tsang, 2005). Trust has been found to increase the success of cooperative agreements (e.g., Mora-Valentin, Montoro-Sanchez, & Guerras-Martin, 2004) and opportunities for knowledge exchange (e.g., Kale, Singh, & Perlmutter, 2000; Mu, Peng, & Love, 2008). Thus, as the existence of trust facilitates knowledge exchanges, its existence between network members should be positively associated with a network that is better able to promote knowledge sharing amongst its members. Thus, the following hypothesis is developed:

H3. The more a network member trusts the other network members, the greater will be the performance of the network in terms of knowledge sharing.

3.2. Relationships between social capital dimensions

Several scholars have argued that social interaction (i.e., structural social capital) encourages the development of shared cognition. Nooteboom (2004) for example emphasizes that close interactions between individuals allow them to share experience and increase their overlap of range, domain and thoughts. Newell, Tansley, and Huangw, (2004) provide evidence that low interaction and collaboration undermine the nurturing of teamwork, feeling of solidarity and sense of shared purpose. Similarly, Mu et al. (2008) find that cooperation pushes firms to develop common objectives which help them to share common mental codes with the other firms involved. Thus, it is expected that social interactions will help a network member of a learning network to develop share cognition with the other members with whom he/she interacts. Thus, the following hypothesis is developed:

H4. The greater the social interaction between a network member and the other network members, the more he/she will share cognition with them.

Besides, social interaction has also been found to reinforce the relational social capital, and trust in particular (e.g., Tsai & Ghoshal, 1998). It is argued that frequent interactions and communication help organization's employees and alliance partners to access more information about others and assess their abilities, intentions and behaviours within the relationship thereby creating trust (Abrams, Cross, Lesser, & Levin, 2003; Gulati, 1995). This suggests that a network member will benefit from frequent social interactions with other members because they permit the development of trust. Thus, the following hypothesis is developed:

H5. The greater the social interaction between a network member and the other network members, the more he/she will trust them.

Finally, several empirical studies provide evidence that the cognitive social capital enhances the development of trust. It has been shown that shared values (Morgan & Hunt, 1994), shared vision (Tsai & Ghoshal, 1998) and shared language (Levin et al., 2006) predicts the development of trust between actors in relational exchanges and knowledge transfer contexts. In their qualitative study, Abrams et al. (2003) also emphasize that the establishment of shared vision and language is crucial for the development of interpersonal trust in knowledge-sharing contexts. As such, the cognitive social capital should promote the development of trust among network members in learning networks. Thus, the following hypothesis is developed:

H6. The more a network member shares cognition with the other network members, the more he/she will trust them.

4. Research methodology

4.1. Study sample and data collection

Formal networks and their respective members were identified for inclusion in this study through the use of non-probability sampling techniques, namely snowball and purposive sampling. Formal networks were identified through a combination of prior awareness on the part of consortium partners, recommendations by colleagues, and through interactions with network managers, policymakers and industry personnel. Thereafter, the formal networks had to meet the following four criteria to be eligible to participate in this study: (1) have a defined membership, (2) be at least three years old, (3) contain two or more food manufacturers and (4) have learning and/or innovation as core objectives of the network. Data were collected by means of two questionnaires. A questionnaire administered to the relevant network managers collected data on the structural, management and governance characteristics of each network. It was administered by each consortium partner in Belgium, Denmark, Hungary and Ireland by means of a telephone or a face-to-face interview, depending on country circumstances. The potential for interviewer bias was not considered an issue in this instance given the objective nature of the data collected from each network manager. In total data were collected from sixteen networks that agreed to participate in this study (see Table 1).

A second questionnaire was subsequently administered to the members of each network which gathered information on the perceived level of social capital prevailing in each network. The members of each network were also asked to evaluate the performance of their respective network with regard to the extent of knowledge sharing between network members. These measures of social capital and perceived knowledge sharing performance were inter-dispersed with other measures included in the questionnaire (but outside the scope of this paper) to minimize the effects of retrieval cues (Podsakoff, Mackenzie, Lee, & Podsakoff, 2003). The consortium partners translated the questionnaires into their national language and then administered each member questionnaire in their respective home countries between January and July 2013 using an online questionnaire format (Qualtrics, 2013). Network members received an invitation email, which included a link to the online questionnaire. Follow-up emails were sent in line with normative practices for online surveys (Andrews, Nonnecke, & Preece, 2003). One hundred and fifty five completed questionnaires were returned out of a population of 1324 members across the 16 formal networks. This yielded a response rate of 11.7%, which was in line with the expected range of response rates for an online survey of corresponding length and complexity (Vehovar & Manfreda, 2008). Listwise deletion of respondents with missing data reduced the number of valid responses to 150 for statistical analysis and hypotheses testing.

4.2. Measures

4.2.1. Dependent variable

4.2.1.1. Knowledge sharing performance. A perceptual measure of knowledge sharing performance was deemed appropriate given the absence of hard objective indicators in the literature for measuring network performance (Huggins, 2001). Respondents rated how well their network had performed with regard to the extent of knowledge sharing between network members on a 7-point scale ranging from 'extremely poor' to 'excellent'.

4.2.2. Independent variables

4.2.2.1. Structural social capital. An unweighted aggregate measure of frequency of interaction for innovation with different categories of organizations that constituted the membership of each network (SINTERACT) was constructed as a general proxy measure for social interaction. This measure provided an indication of the level of intra-networking activity engaged in by each member, and allowed for reasonable comparisons to be made across networks. Respondents rated how frequently they interacted for innovation with up to 12 categories of organizations, ranging from food producers and research institutes to industrial support service providers and stakeholder organizations, which constituted their respective network, on a 7-point scale ranging from 'never' to 'always' (adapted from Soo, Devinney, & Midgley, 2004).

4.2.2.2. Cognitive social capital. Two facets of the cognitive dimension of social capital were measured i.e., shared vision and shared language. For each facet, three items were generated, similar to those used in the study of Levin et al. (2006) (see Appendix A). These items were assessed on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

4.2.2.3. Relational social capital. Trust was measured with one item assessed on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) (see Appendix A).

4.2.3. Control variables

4.2.3.1. Coordination mechanisms. Formal coordination mechanisms such as third-party enforcements of agreements and integrative process of conflict management have been shown to influence learning (Dyer & Singh, 1998; Kale et al., 2000). As they may also potentially impact knowledge transfer performance, they were included as a control variable. Four nominally scaled variables collected through the network manager questionnaire were summed to create a new continuous variable (NUMCM), which denoted the number of coordination mechanisms adopted by each network.

Table 1
Profile of the networks.

Variable	Range	Overall
Number of networks surveyed	–	16
Average age of networks (yrs)	3–65	15.94
Average size of networks	8–310	81.25
Heterogeneity of network membership (expressed as the average number of organisational categories present in networks)	1–8	3.69
Average number of coordination mechanisms employed by networks	0–4	2.0
Country of survey administration		
% Networks based in Belgium	–	18.8%
% Networks based in Denmark	–	18.8%
% Networks based in Hungary	–	37.4%
% Networks based in Ireland	–	25.0%
Geographic scope of network membership		
% Regional networks	–	18.7%
% National networks	–	75.0%
% International networks	–	6.3%

4.2.3.2. Geographic scope of membership. The geographic scope of alliance partners has been found to impact alliance outcomes and performance (Parkhe, 1993). As such, the geographic scope of membership of learning networks may also influence their performance. They were thus included as a control variable. Two dummy variables denoted the geographic scope of network membership in terms of either national (NAT) or international (INT) membership. The regional scope of network membership represented the baseline variable.

4.2.3.3. Heterogeneity of network membership. As the heterogeneity of sectors in networks has been suggested to affect cooperation (Huggins, 2001), it was included as a control. Twelve continuous variables collected through the network manager questionnaire concerning the proportion of the membership constituted by the different categories of organizations within each network were recoded as binary variables. These binary measures were then summed to create a new continuous variable (NETDIV), which denoted the number of categories of organizations that constituted the membership of each network, and served as a proxy measure for heterogeneity of network membership.

4.2.3.4. Structural control variables. In addition, five structural control variables commonly utilised in industrial organisation research were included in the questionnaire. The categorical variable concerning the '*country*' in which the member survey was administrated was transformed into three dummy variables, which denoted the country of survey administration: Belgium (BEL), Denmark (DEN) and Hungary (HUN). Ireland was selected as the baseline variable. The continuous variables NETSIZE and NETAGE denoted the *size* and *age of each network*. The two remaining structural control variables SECTOR and NETMEM were specific to the respondent (rather than to the network). The categorical variable INDCLAS represented the industry classification most closely associated with each *respondent*. This variable was then transformed into three dummy variables that grouped respondents as either supply chain actors (SCA), personnel from university & public research institutes (UPI), or other (non-food) industries (NON). Food producers were selected as the baseline variable. Finally, the continuous variable NETMEM denoted the *length of each respondent's network membership*.

4.3. Statistical method

In order to test the proposed model and hypotheses, the analyses have been conducted in multiple stages. As the cognitive dimension of social capital was a latent construct, the first step consisted of testing whether it exhibited sufficient reliability and validity by estimating the measurement model (Anderson & Gerbing, 1988). In the second step, hierarchical linear modelling (HLM) was used to analyze the data and test the main hypotheses (H1)–(H3) and potential effects of the controls. In the third and final step, the links between the different social capital dimensions (H4)–(H6) were also investigated through structural equation modelling.

Table 2
Correlation matrix across independent variables.

Variable		1	2	3	4	5	6	7
1	NETDIV	1						
2	NAT	−.007	1					
3	INT	−.304**	−.520**	1				
4	NUMCM	−.177*	−.466**	.486**	1			
5	TRUST	.071	−.038	.018	.208*	1		
6	SINTERACT	−.020	−.018	−.016	.209*	.336**	1	
7	COGNIT	−.006	.081	−.095	.120	.651**	.431**	1

Notes: * Significant at the $p \leq 0.05$ level ** Significant at the $p \leq 0.01$ level.

5. Analysis and results

All statistical analyses were carried out using the PASW statistical computer package, Version 18 (Spss Inc., 2009) and AMOS 21.0 (Amos, 2012).

A preliminary hierarchical multiple regression analysis was first carried out to test the explanatory power of the structural control variables selected for this study. This preliminary analysis suggested that none of the five original structural control variables significantly explained variance in perceived knowledge sharing performance. However, two of these variables COUNTRY and NETSIZE were still retained to account for country and size effects so that interpretation of the findings remained valid across networks of different sizes, and across partner countries. Inter-correlations between the independent and remaining control variables were examined (see Table 2). Significant bivariate correlations were observed between the dummy variables (NAT and INT) that constituted the geographic scope of network membership, as well as the cognitive social capital (COGNIT) and trust. The regression models were then re-estimated, and diagnostic tests for normality, linearity, multicollinearity and homoscedasticity confirmed that regression assumptions were not violated (Hair, Black, Babin, & Anderson, 2010).

5.1. Measurement model

The measurement model comprising the three dimensions of social capital was analyzed using a confirmatory analysis (CFA) with the maximum-likelihood estimator. One of the three items used to measure shared vision was dropped because it exhibited low loading (see Appendix A). During estimation to one-item measures (i.e.,

Table 3
Hierarchical regression analysis for knowledge sharing performance (Models 1–3).

	Model 1				Model 2				Model 3			
	Unstandardised coefficients				Unstandardised coefficients				Unstandardised coefficients			
	β	Std. Error	t	Sig.	β	Std. Error	t	Sig.	β	Std. Error	t	Sig.
(Constant)	5.281	0.173	30.496	0.000	5.100	0.203	25.116	0.000	4.810	0.414	11.619	0.000
BEL	−0.060	0.244	−0.245	0.807	−0.178	0.252	−0.707	0.481	0.103	0.358	0.288	0.774
DEN	−0.044	0.316	−0.14	0.889	−0.196	0.327	−0.599	0.550	−0.178	0.331	−0.539	0.591
HUN	−0.511	0.210	−2.431	0.016	−0.565	0.211	−2.672	0.008	−0.507	0.217	−2.339	0.021
NETSIZE	−0.002	0.001	−1.121	0.264	−0.002	0.001	−1.673	0.097	−0.002	0.002	−1.449	0.15
NETDIV					0.087	0.052	1.681	0.095	0.077	0.069	1.113	0.268
NAT									0.312	0.320	0.973	0.332
INT									−0.166	0.606	−.273	0.785
R square	0.045				0.064				0.073			
R square change	0.045				0.018				0.01			
F	1.722				1.96				1.607			
N	150				150				150			

trust) and aggregated measures (i.e., social interaction), 0% error variance was introduced. As a result, one-item and aggregated measures used in the analyses were totally free of measurement error (Hair et al., 2010).

The following indicators were used to report the fit of CFA: the chi squared (χ^2) and its associated probability value (p), the adjusted chi-square (χ^2/df), the goodness of fit index (GFI), the comparative-fit-index (CFI), the standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA). Recommended norms for good fit are a small χ^2 with a high p value, $\chi^2/df < 3$, GFI and CFI > 90, SRMR < 0.05 for good fit, and RMSEA < 0.08 for reasonable fit (Hu & Bentler, 1999).

Cognitive social capital is conceptualized as a two dimensional construct that includes shared vision and shared language. This calls for a second-order, two-factor model where the two dimensions represent two, first-order factors, and the cognitive social capital represents the overarching, second-order factor. The fit indices for this model showed a good fit ($\chi^2 = 15.766$ with $p = 0.150$, $\chi^2/df = 1.433$, GFI = 0.972, CFI = 0.993, SRMR = 0.0239, RMSEA = 0.054). Besides, the standardized factor loadings (see Appendix A) were all highly significant ($p < 0.001$), with values well above the recommended minimum of 0.40 for the social science (Ford, Mccallum, & Tait, 1986). The composite reliabilities of all multi-item constructs were also greater than the recommended minimum value of 0.70 (Nunally, 1978 in Acur, Kandemir, De Weerd-Nederhof, & Song, 2010; Hair et al., 2010). In addition, the average variance extracted (AVE) were all above the threshold of 0.50 (Fornell & Larcker, 1981). It was thus concluded that the measures demonstrated adequate convergent validity and reliability.

5.2. Hierarchical multiple regression analysis

Tables 3 and 4 present the results for perceived knowledge sharing performance regressed on the structural control variables (Model 1), control variables related to the heterogeneity (Model 2) and geographic scope of the network membership (Model 3), the number of coordination mechanisms employed by each network (Model 4), and on the independent variables related to social capital (Model 5). Model 1, which comprised the structural control variables was not statistically significant ($F = 1.722$, $p = 0.148$). The addition of the continuous variable NETDIV, which conceptualized the heterogeneity of network membership, did not significantly improve the explanatory power of Model 2 also ($F = 1.960$, $p = 0.088$). While Model 3 suggested that internationalization of the network membership was expected to have a negative relationship with perceived knowledge sharing performance; the geographic scope of the network membership was neither signif-

Table 4
Hierarchical regression analysis for knowledge sharing performance (Models 4–5).

	Model 4				Model 5			
	Unstandardised coefficients				Unstandardised coefficients			
	β	Std. Error	t	Sig.	β	Std. Error	t	Sig.
(Constant)	4.186	0.404	10.35	0.000	1.638	0.526	3.116	0.002
BEL	−0.267	0.341	−0.784	0.434	−0.341	0.300	−1.138	0.257
DEN	−0.825	0.334	−2.471	0.015	−0.762	0.296	−2.577	0.011
HUN	−0.925	0.218	−4.235	0.000	−0.817	.195	−4.187	.000
NETSIZE	0.002	0.002	0.971	0.333	0.001	0.002	0.422	.674
NETDIV	0.017	0.065	0.257	0.797	0.056	0.059	0.95	.344
NAT	0.360	0.297	1.209	0.229	0.254	0.261	0.974	.332
INT	−1.559	0.630	−2.474	0.015	−0.801	0.569	−1.408	.161
NUMCM	0.504	0.103	4.908	0.000	0.331	0.095	3.500	.001
TRUST					0.013	0.082	0.159	.874
SINTERACT					0.118	0.060	1.954	.053
COGNIT					0.499	0.126	3.947	.000
R square	0.209				0.408			
R square change	0.135				0.199			
F	4.645				8.644			
N	150				150			

Table 5
Structural equation modeling results: proposed model.

		Standardized coefficient	Standard error	Critical ratio	Hypothesis supported
H1	Social interaction → knowledge sharing performance	0.179*	0.063	2.241	Yes
H2	Cognitive dimension → knowledge sharing performance	0.312**	0.134	2.865	Yes
H3	Trust → knowledge sharing performance	0.139	0.085	1.484	No
H4	Social interaction → cognitive dimension	0.400***	0.056	4.614	Yes
H5	Social interaction → trust	0.112	0.066	1.481	No
H6	Cognitive dimension → trust	0.56***	0.126	6.053	Yes
Control	NUMCM → knowledge sharing performance	0.07	0.063	0.979	No

Notes: * <0.05, ** $p < 0.01$, *** $p < 0.001$.

icant ($F = 1.607$, $p = 0.138$) nor explained the variance in perceived knowledge sharing performance (see Table 3).

Model 4 was found to be statistically significant ($F = 4.645$, $p \leq 0.000$) and the total number of coordination mechanisms adopted by a network ($\beta = 0.504$, $p \leq 0.000$) explained 13.5% of the variation in perceived knowledge sharing performance (see Table 4). The addition of three variables conceptualizing social capital in the final block of the hierarchical multiple regression was also statistically significant ($F = 8.644$, $p \leq 0.000$). Social capital was found to explain a further 19.9% of the variance in perceived knowledge sharing performance. More so, the results suggested that the cognitive dimension (COGNIT) alone – which was measured with the factor score in the regression analysis – accounted for the variance found in Model 5 ($\beta = 0.499$, $p \leq 0.000$), and was more important than either the trust or social interaction (SINTERACT) in explaining perceived knowledge sharing performance.

5.3. Structural model

The whole conceptual model was estimated by using structural equation modelling with the maximum-likelihood estimator. Similarly to estimation to trust and social interaction, the error variance was fixed at zero during estimation to knowledge sharing performance and relationship mechanisms. The fit indices indicated that the model represented the data well, with $\chi^2 = 32.653$ with $p = 0.050$, $\chi^2/df = 1.555$, GFI = 0.956, CFI = 0.984, SRMR = 0.0392, RMSEA = 0.061. Our analysis shows that both social interaction and the cognitive dimension of social capital are positively and significantly related to knowledge sharing performance, providing support for H1 and H2 respectively (see Table 5). No significant relationship between trust and knowledge sharing performance is found, thus H3 is not supported. Furthermore, the data show that social interaction positively affects the cognitive dimension, supporting H4. They do not show however a significant relationship between social interaction and trust, in disagreement of H5. As predicted in H6, the cognitive dimension positively affects trust. Finally, regarding the control variable i.e., coordination mechanisms, no significant influence is found on knowledge transfer performance.

In addition to the proposed conceptual model, the authors tested an alternative model where direct paths were added between the coordination mechanisms and each of the social capital dimensions (see Fig. 2). This alternative model was justified by the complementary nature of both formal and social coordination mechanisms that has been put forward in the alliance literature (Kale et al., 2000). The fit indices indicated that this model represents better the data than the proposed model (with $\chi^2 = 28.903$ with $p = 0.068$, $\chi^2/df = 1.521$, GFI = 0.960, CFI = 0.987, SRMR = 0.0331, RMSEA = 0.059). In the alternative model, no change appears in the significant effects identified in the first model. But significant relationships are found between the coordination mechanisms and both social interaction and trust (see Fig. 2).

6. Discussion, implications and limitations

In this study, the authors answer to the call for more research on the operationalization of learning networks as successful platforms for knowledge sharing (Bessant et al., 2012; Bessant & Tsekouras, 2001). Starting from the premise that the core of both networks and knowledge sharing concerns social relationships (Inkpen & Tsang, 2005; Wei et al., 2011), the authors use a social capital perspective in order to understand the internal factors driving knowledge sharing performance of learning networks. Their findings reveal that more than any structural characteristics of networks, social capital plays a key role in explaining knowledge sharing performance. This paper also constitutes a welcome contribution to

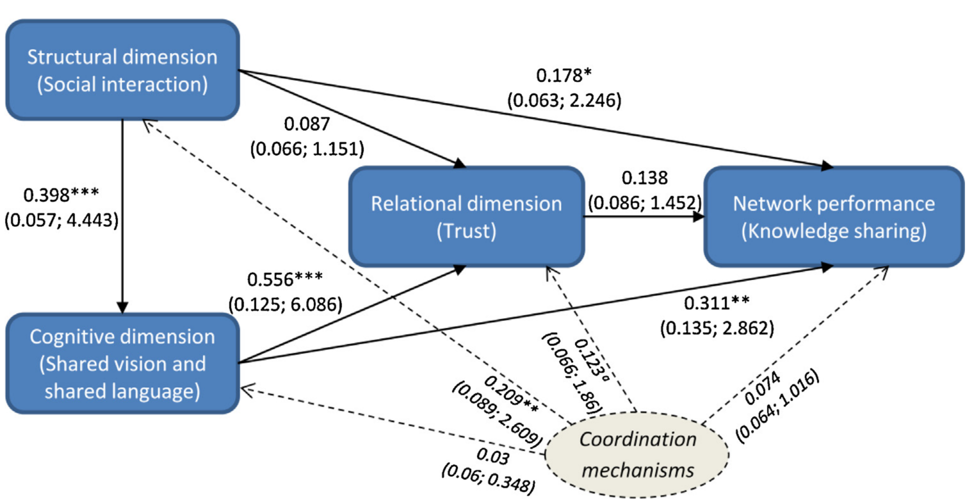

Fig. 2. Structural equation modeling results: alternative model.
Notes: Standardized solutions for hypothesized relationships ([a] $p < 0.1$, * <0.05, ** $p < 0.01$, *** $p < 0.001$); standard errors and critical ratios are in parentheses.

the social capital literature as it sheds further light on the inter-relationships between different dimensions of social capital; an important research area that has so far been neglected by empirical studies (Lee, 2009). The findings suggest that social interaction (i.e., structural social capital) has an important role to play in the development of shared vision and shared language (i.e., cognitive social capital). From a practical perspective, those responsible for setting up and managing these types of networks must ensure that social interactions are fostered and shared vision and shared language are established among network members. This implies that 'process' measures of social interaction and the dimensions of cognitive social capital should now form an integral part of the assessment criteria when evaluating the performance of learning network entities.

In addition, this study also contributes to the emerging literature on the antecedents of social capital (Mu et al., 2008; Zheng, 2010), by revealing the inter-relationships between social capital and the coordination mechanisms put in place in learning networks. This empirical research suggests that the presence of coordination mechanisms helps to develop both social interaction and trust. These positive associations are consistent with the assumption that in environments where risks of opportunism and appropriation concerns are high, firms view the actions of network partners with scepticism and hesitate to engage in cooperative behaviors (Dhanaraj & Parkhe, 2006). The presence of coordination mechanisms such as contracts, regulations and dispute resolution procedure probably help to reduce the risks and concerns that members may perceive within learning networks, and hence, increase their level of interaction and trustworthiness.

The authors acknowledge a number of limitations and/or delimitations of scope to this study. First, the authors only included certain facets of each social capital dimension in this study. However, the authors encourage future research to take a much broader perspective and to include more facets of social capital such as identity (Bond Iii et al., 2008).

Second, the use of cross-sectional data does not actually allow testing the direction of the proposed cause-effect relationships. The use of longitudinal data from a larger dataset in future research may aid in verifying the causal relationships described in this study.

This research also contributes to extending the body of knowledge concerning collective trust and its relationship with group performance. This study did not confirm a significant relationship between social interaction and trust. However, in line with the findings of previous studies, the results demonstrate that the cognitive social capital has a positive impact on trust (Levin et al., 2006; Tsai & Ghoshal, 1998). Quite unexpectedly however, the authors' prediction that the relational dimension of social capital, manifested as trust, would enhance significantly performance is not supported. A third limitation to this study could therefore relate to a deficiency in the measure of trust selected as a consequence of the authors' efforts to adapt an individual level construct to a group level of analysis. However, an equally valid explanation could represent a delimitation of this study, and relate to a paucity of understanding about the relationships between individual and collective trust, and the mechanisms by which they lead to improved performance at the network and/or firm level. Indeed, Zaheer, Mcevilly, and Perrone (1998) in their study on collective trust were hesitant to dismiss the existence of a mediated relationship between trust and performance where none was observed. Instead, they proposed, as do the authors of this paper, that further research should extend to investigating the mediating effects of other 'value-enhancing exchange processes' on the trust–performance relationship.

A further delimitation of scope of this study concerns the narrow scope of performance reported upon in this paper. Provan and Milward (2001) stress the importance of assessing the performance of networks at different levels of analysis (i.e., the environment, network, and participant levels) as it is only by minimally satisfying the needs and interests of stakeholders at these different levels that the network can be successful. Although this study constitutes a welcome contribution to the network performance literature by focusing on the under-researched network level performance (Turrini et al., 2010), the authors of this paper acknowledge that the measure of network performance adopted for this study does not address the impact of the network on it members or its external environment.

The findings presented in this paper have important policy implications in terms of how learning networks should be evaluated. To date, research on the performance of networks has mainly focused on firm performance and has often neglected the performance of the network entity itself (Turrini et al., 2010). This firm level perspective neither recognizes the various synergies that would be expected from increased coordination and integration at the network level nor acknowledges the importance of other key factors such as the legitimacy, maintenance and sustainability of the network entity (Turrini et al., 2010). On the other hand, the network level perspective does not necessarily translate into equivalent levels of member performance so a shift to include network level measures should not be at the expense of measures of member performance (Provan & Milward, 2001). Moreover, and as highlighted in this paper, the determinants of performance at network level can be different to those that determine performance from an individual member perspective. Although the geographic scope and heterogeneity of membership were not significant determinants of the knowledge sharing performance of networks, their relevance to firm performance should not be overlooked as a consequence of the network level perspective adopted for this paper. In fact, a greater diversity is likely to be beneficial from an individual member's perspective as they may have access to a greater range of knowledge.

The authors of this paper therefore argue that policy makers (and network managers) should adopt a broader framework when evaluating learning networks to address performance from a network as well as individual member perspective. Similarly, the authors of this paper encourage other researchers to address this equivalent research gap by investigating the extent of inter-relationships between the characteristics of networks, performance at the network (group) level, and impact on an organizational (individual/firm) level. Such research would provide for a more holistic understanding of those network-related characteristics that are most important for the proper functioning of networks, and those which are most important for realising improvements in performance at the firm level also.

Appendix A.

Table A.1

Table A.1
List of measures/items for social capital dimensions and results of confirmatory factor analysis.

Variable	Measurement items		Standardized loading	Z-statistic	CR	AVE
Cognitive social capital	Shared vision		0.886	8.266	0.94	0.88
	Shared language		0.897	a		
		We [the other members and I] share a common vision regarding the key success factors of the network	0.928	9.17	0.81	0.69
	Shared vision	I think that we [the other members and I] care about the same issues	0.717	a		
		I feel that we [the other members and I] have completely different goals towards the network[b]				
		It feels like we [the other members and I] can understand each other	0.926	16.995	0.94	0.84
	Shared language	It feels like we [the other members and I] use similar language	0.947	17.751		
		It feels like we [the other members and I] can communicate on the same 'wavelength'	0.876	a		
Relational capital (*manifested as trust*)	I trust the other members of the network		1	NA	1	1
Structural social capital (*manifested as social interaction*)	Unweighted aggregate measure of frequency of interaction for innovation with different categories of organisations that constituted the membership of each network		1	NA	1	1

Notes: CR = composite reliability; AVE = average variance extracted; a = parameter set to fix the scale; *NA* = not applicable
[b] This item was remove from the analysis because of low factor loading.

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