Business process improvement and the knowledge flows that cross a private online social network: An insurance supply chain case

Abstract: This paper analyses how the knowledge shared between employees and suppliers within a private enterprise social network affects process improvement. Data was collected from internal documents, and the internal and external enterprise social networks used by an international insurance company; the average cycle time for handling 8494 claims and 3240 messages posted on the internal and external social networks was analysed. Social network analysis techniques were combined with principal component analysis and structural equation modelling, and the results demonstrate that the knowledge shared within the internal and external social network can explain 35.10% of process improvement variability, while the knowledge shared within the internal social network explains 89.90% of external social network variability. The analysis also demonstrates that: (i) the knowledge shared among employees positively affects process improvement; (ii) the knowledge shared among suppliers negatively affects process improvement; and (iii) the knowledge shared among employees positively affects the knowledge shared among supply chain members. These findings have theoretical and practical implications. They extend the literature in the knowledge management and information management field by offering empirical evidence of how the knowledge shared through an enterprise social network affects business process improvement, using the objective data provided by Yammer. They also provide a strategic tool for managers that will allow them to better understand how they can use the enterprise social network for business processes improvement.

Keywords: social network analysis; knowledge; process improvement; principal component analysis; structural equation modelling; insurance supply chain.

Introduction

Communication theorists first acknowledged the role of ICT in knowledge sharing. Based on structuration theory, Yates et al. (1999) demonstrated that the patterns of adopting and using a new electronic medium in a company are reinforced and changed through the knowledge that is shared within the groups. O'Mahoney and Barley (1999) noted that digital communication buffers and links individuals, encourages them to share their opinions, and diminishes social cues. Alavi and Leidner (2001) suggest that ICT provides an effective and efficient means of knowledge acquisition, sharing and use. Hung et al. (2014) argue that, within ICT solutions, social networks are the most proficient knowledge sharing tools, since they are "web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system" (Boyd & Ellison, 2008, p.211).

Most studies that analyse knowledge sharing and its connection with social networks (Fang et al., 2015; Li et al., 2012; Massa, 2017; Xue et al., 2011) adopt a subjective perspective; data involving knowledge flows is collected through a survey based on a questionnaire which only reflects recent events, and is the subject of cognitive biases (such as the anchoring effect, current moment bias, heuristic affect or omission bias) and circumstances. Although these approaches are in line with traditional knowledge management theories, which assume that knowledge sharing appears as the result of a rational decision, cognitive psychologists (Galinsky et al., 2002; Weingart et al., 1993) offer empirical evidence about the irrationality of human behaviour in the context of knowledge sharing. Using online social networks as a framework and social media analysis as a research method can make this connection. Social media analysis is seen as opposite to the traditional use of questionnaires

(Holsapple et al., 2018), and involves the use of at least one of the following methods: (i) sentiment analysis; (ii) social network analysis; (iii) statistical analysis; (iv) image and video analysis (Lee, 2018). A researcher's choice depends on the type of data available and what they want to analyse. The current article thus combines social network analysis and statistical analysis because: (i) the aim is to quantitatively link knowledge sharing within a private social network with enterprise process improvement; (ii) online social networks provide real data (Leon et al., 2017); (iii) social network analysis understands individuals within their social context, acknowledging the influence of relationships with other people on an individual's behaviour (Kolleck, 2013, p.25); and (iv) it also has the capacity to predict how knowledge flows within virtual teams (Behrend & Erwee, 2009).

The specialised literature focuses either on analysing the knowledge shared through social media (Fronzetti Colladon & Vagaggini, 2017; Di Virgilio, 2017; El Ouirdi et al., 2015; Lee et al., 2018; Nisar et al., 2019; Oostervink et al., 2016) or on emphasising the effect of knowledge sharing on process improvement (Bakotic & Krnic, 2017; Rafiqueet et al., 2018; Von Krogh et al., 2018). To the best of our knowledge, none of the previously developed studies addresses the link between the knowledge shared within a private online social network and process improvement. This issue is even more important since social media and the application of other emerging technologies, such as artificial intelligence or augmented reality, have a powerful impact on how knowledge management and organisational development are applied (Kane, 2017).

Furthermore, a special attention is given to the insurance sector which reunites various types of players operating in different spaces and it experiences significant transformations of the business models (Deloitte, 2019). The insurance supply chain is formed by many actors, the focal company and its main service providers in this case study. Such a heterogeneity, together with the high IT capabilities and skills that the employees of these organisations posses, makes this sector adequate for implementing an online social network (both internal and external) to share knowledge (Grant & Preston, 2019). Besides, it is relatively easy to identify the main business processes whose improvement would have a direct impact on performance (Kaffash et al., 2019; Eling & Jia, 2019). In this sense, there is a clear relationship between the improvement of areas such as claims management, total assets or risk management and the sectorial competitive position of the insurance firm (Nourani et al., 2017). In order to measure the business process improvement, it is possible to define associate key performance indicators (KPI) to check whether the business process under study has improved its value or not. These KPI should be representative of the business process, realistic and measurable (Rodriguez-Rodriguez et al., 2009). In this case study, the KPI (chosen by the insurer) was the average cycle time of handling claims, as improvement of such a KPI would lead to business process improvement and, extensively, to business performance improvement.

The current research aims to fill the aforementioned gaps by analysing how a firm's process improvement can be affected by the knowledge shared by employees and suppliers within an inter-organisational online social network. It combines social network analysis with statistical techniques such as principal component analysis (PCA) and partial least squares structural equation modelling (PLS-SEM) and reports the results of a case study in an international insurance supply chain.

The remainder of the paper is structured as follows. Section 2 provides the theoretical foundation of the researched phenomenon while the third section reviews the relevant scientific literature regarding social networks and knowledge sharing, and emphasises the potential relationships among social networks, knowledge sharing, and process improvement. In line with the theoretical model, Section 4 brings forward the fact that the research aims to analyse how process improvement is influenced by the knowledge shared by employees and suppliers within an inter-organizational online social network. Thus, a case study methodology is employed and one of the most important British insurance companies is selected in order: (i) to analyse the knowledge flows that cross an internal and a suppliers' enterprise social network; (ii) to determine the influence that the knowledge shared among employees has on process improvement; (iii) to determine the influence that the knowledge shared among suppliers has on process improvement; and (iv) to analyse the relationship between the knowledge flows that cross the internal social network and those that cross suppliers social network. The results generated through the use of an integrative approach are highlighted in Section 5 and discussed in Section 6. The theoretical and practical implications of the main findings are highlighted in Section 7 while Section 8 closes the article by drawing conclusions and suggesting further research directions.

Theoretical foundation

Due to the complexity of the researched phenomenon, complementary and comprehensive theories were laid at the foundation of this investigation, Thus, business process improvement theory, social capital theory, and knowledge-based view were used in order to better understand the relationship between business process improvement and online knowledge sharing by employees and suppliers**.**

Business process improvement theory

Business Process Management comprises both Business Process Improvement (Harrington, 1991) and Business Process Reengineering (Hammer, 1990). The latter focuses on introducing substantial changes in processes even building new ones, whereas the former introduces medium-impact changes in existing processes. Then, business process improvement focuses on incrementally improving an existing process in order to make it not only more efficient but also more flexible. It pursues to identify critical processes whose improvement will lead to achieve better business performance.

Social capital theory

The social capital theory sheds light on the importance of the relationships established among individuals or social units and the resources embedded within them. On a general level, these are labelled as "social capital"; according to Bourdieu and Wacquant (1992, p.119), social capital is "the sum of the actual or virtual resources that an individual or group accrues by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" while Putnam (1995, p.67) defines it as "features of social organization such as networks, norms, and social trust that facilitate coordination and collaboration for mutual benefit". On a specific level, three components of the social capital can be distinguished, namely: structural capital, relational capital, and cognitive capital. The former brings forward the social navigation mechanism used to find relevant members and content (Parise, 2009) which is represented in the current study by the enterprise social network which connects employees and suppliers. The second one concentrates on "who knows who" (Fulk & Yuan, 2013) while the latter fosters the development of the social cognitive theory and reflects the values, attitudes, interests, and emotions that keep members together, and motivate them to contribute to knowledge creation and sharing (Jones et al., 1997).

Since the social capital theory is frequently used to explain how knowledge sharing occurs in online and offline environments (Berraies, 2019; Heimbach et al., 2015; Leon et al., 2017) and it is based on the idea that social structures facilitate action (Coleman, 1988), it provides the proper theoretical background for analysing the influence of the knowledge shared among employees and suppliers on business process improvement.

Knowledge-based view

The knowledge-based view functions as a complement that supports the social capital theory in explaining the relationship between knowledge sharing and business process improvement. Thus, it considers knowledge as the most strategically resource (Kogut & Zander, 1992) and it focuses on the competitive capabilities derived from it (Nonaka & Konno, 1998). It extends the resource-based view (Barney, 1996) by shifting the approach from tangible resources to intangible ones (tacit, socially constructed), and presenting the firm as "a social community specialized in speed and efficiency in the creation and transfer of knowledge" (Kogut & Zander, 1996, p.503). Due to the fact that knowledge is continuously shared and modified by the employees and suppliers who use an enterprise social network and then it is used for improving the business process and gaining competitive advantage, the knowledge-based view provides the theoretical foundation of the current research.

Hypothesis development

Krumeich et al. (2014) and Al-Thuhli et al. (2017) suggest that, in the current economic environment, it is necessary to monitor and optimise business processes for market demands, and Zellner (2012) notes the improvement of business processes (which ranges from marginal continuous improvements to re-engineering) as an organisational priority. Since these are seen as "a set of logically interlinked activities directed to filling gaps between functional areas and adding value by means of procedure" (Silva Melo et al., 2010, p.207), two lines of research can be identified in the business process management area: one that follows a technical approach and one that adopts a social perspective. The former involves the fact that business process management depends significantly on information technology (Bassano et al., 2018; Mueller & Daeschle, 2018; Uskarci & Demirors, 2017; Yousfi et al., 2019) and the latter emphasises the link between knowledge management and business process improvement (Choo et al., 2007; Hu et al., 2019; Khanbabaei et al., 2019; Linderman et al., 2010; White et al., 2019). Only a few researchers situate themselves at the nexus between the two approaches (Al-Thuhli et al., 2017; Brajer-Marczak, 2016; Massingham & Al Holaibi, 2017), and claim that information technologies can serve as a means for increasing the effectiveness of knowledge sharing and improving business processes. Al-Thuhli et al. (2017) focus on enterprise social networks and suggest that these convert classical business processes into more dynamic social business processes, as they enable employees to share experiences, thoughts, ideas, and any topics that can enhance their organisation's business processes.

The attention of both practitioners and academics has recently been caught by the use of enterprise social networks, which strengthen links between organisational members (Riemer et al., 2015), serve as knowledge repositories (Oostervink et al., 2016), and deliver analytics that add value to knowledge structure and business performance (Aboelmaged, 2018). According to UMass Dartmouth (2018), almost 98% of Fortune 500 companies use online social networks for communicating with their stakeholders, and 85% of them use Yammer for professional purposes (Cetto et al., 2018; Leroy et al., 2013). Despite this, little is known about the use of professional social networks and their impact on business process improvement (Aboelmaged, 2018; Al-Thuhli et al., 2017; Berraies, 2019; Cetto et al., 2018; Mäntymäkia & Riemerb, 2016). To the best of our knowledge, none of the studies developed so far uses conversations from an enterprise social network to provide empirical evidence about how the knowledge shared on a web-based platform affects the improvement of business processes.

Business process improvement and the knowledge shared among employees in an enterprise social network

As mentioned above, despite the increased importance of enterprise social networks, only a few studies (Aboelmaged, 2018; Balbi et al., 2018; Charoensukmongkol, 2014; Kaplan & Haenlein, 2010; Mäntymäkia & Riemerb, 2016; Turban et al., 2011) analyse the effects of their use in organisations and the results are contradictory. Kaplan and Haenlein (2010) suggest that their use increases work burdens and is a waste of time, whereas Turban et al. (2011) emphasised that Wells Fargo registered significant productivity improvements after its employees started to use a social networking platform. In line with this, Mäntymäkia and Riemerb (2016) suggested that enterprise social network platforms can improve employee productivity by 20 to 25%. Charoensukmongkol (2014) suggests that the use of enterprise social networks interrupts work, and Aboelmaged (2018), Kuegler et al. (2015), and Qi and Chau (2018) argue that the knowledge shared by employees through enterprise social networks improves work and task performance. Last but not least, Patroni et al. (2016) conducted a study in the retail industry, and argue that the ideas and best practices shared by employees through an enterprise social network may improve operational procedures.

Taking these findings into account, and the fact that knowledge sharing fosters process improvement (Bakotic & Krnic, 2017; Rafiqueet et al., 2018; Von Krogh et al., 2018), it can be suggested that:

Hypothesis 1: *Knowledge shared among employees, through an enterprise online social network, positively affects process improvement*.

Business process improvement and the knowledge shared among suppliers in an enterprise social network

Various theoretical frameworks, such as the resource-based view of the firm, social network theory, and evolutionary theory, support the necessity of developing inter-firm relationships for facilitating knowledge sharing, efficiently managing resource dependence, and adapting to the evolutionary process (Burt, 2000; Lin et al., 2007). The use of online social networks should therefore also be analysed from an inter-organisational perspective. Except for a few studies (Capo-Vicedo et al., 2011; Carter et al., 2007; Pathak et al., 2014), there is a paucity of social network analysis application in supply management theory. Since it is in an embryonic stage of development, most researchers focus on describing the dyadic and triadic relationships among suppliers, however, attempts (Roberts & Sterling, 2012; Tsai et al., 2011) have been made to consider the causality relationship between a supplier's network and a firm's performance. These make it clear that the links established among the members facilitate a firm's access to various resources.

This pitfall can be overcome if an online social network is considered, which can yield information about the behaviour adopted by each person and each company, and accentuates both cooperative and competitive behaviours. This is covered by various social network indicators; the actors who register a high level of centrality (degree, closeness, betweenness) are those who focus on cooperation, and are interested in both acquiring and sharing knowledge (Roelens et al., 2016), while those with a low level of centrality mainly concentrate on competition, and are interested in acquiring knowledge. Due to the "co-opetition" established among the supply chain members, it is expected that business processes will be influenced by the knowledge shared among the suppliers. Nevertheless, previous studies show that the intensity and direction of this influence depends on supplier interest, the existing stage of their supply chain management reform (Nakano & Oji, 2017), environmental uncertainties and supply chain flexibility (Topal & Sahin, 2018). Therefore, it can be assumed that:

Hypothesis 2: The knowledge shared among the supply chain members in a private online social network affects process improvement.

The relationship between the knowledge shared among employees and the one shared among suppliers in an enterprise social network

When the relationship between social networks and knowledge sharing has been analysed, the focus is either on internal (Berraies, 2019; Cetto et al., 2018; Fronzetti Colladon & Vagaggini, 2017; Olfat et al., 2019) or external stakeholders (Heimbach et al., 2015; Liu & Jansen, 2017; Liu et al., 2019; Neshati et al., 2017). Accordingly, individual behaviour is prompted by the relative outcomes that the individual aims to obtain, and may be classified into three categories: cooperative, individualistic, and competitive. From an organisational perspective, if employees think in "win-win" terms and hope that the parts involved are going to obtain benefits then they cooperate; the social network has a high density and several centres of power are identified. Collinson and Wilson (2006) demonstrated that the strong ties established among the members of Nippon Steel Corporation and Toyota facilitated knowledge sharing across organisational boundaries. If employees focus on maximising their gains without taking into account others' interests then their behaviour is individualistic, the network's density is low and most members focus on knowledge acquisition. As Vissa and Chacar (2009) demonstrate, in company acquisitions and mergers, the buying firm takes advantage of the knowledge shared among partners in order to improve the decision making processes and to shorten the product development cycle. Last but not least, if the employees aim to improve their position so that they can gain advantage and be respected by others, then they are competitive.

An organisation is an open system which cannot be isolated from the external environment or from the direct and indirect relationships in which it is embedded with other entities (Granovetter, 1985; Huybrechts & Haugh, 2018). Fluxes of knowledge thus flow from the internal to the external environment, and in reverse; knowledge of external events (the changes that occur in customer preferences and competitor actions) is processed inside the organisation and the firm's strategic decisions depend on both internal capabilities and its capacity to align its policy to supplier strategies. An integrative approach is needed in order to fill this gap; this should provide a better understanding of how the internal and external knowledge flows affect process improvement. Formally:

Hypothesis 3: In a private online social network, the knowledge shared among employees positively affects that shared among the supply chain members.

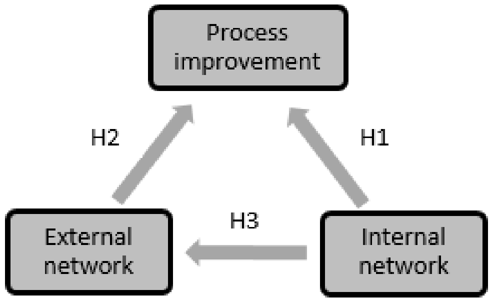

Figure 1. Theoretical model

The aforementioned hypotheses are synthesized in Figure 1 which presents the theoretical model and the causal relationships established among business process improvement and the knowledge shared among employees and suppliers in an enterprise social network.

Methodology

Research goal and strategy

This paper analyses how process improvement is affected by the knowledge shared by employees and suppliers within an inter-organisational online social network.

The main research objectives are: (i) to analyse the knowledge flows that cross an internal and a supplier's enterprise social network; (ii) to determine the effect that the knowledge shared among employees has on process improvement; (iii) to determine the effect that the knowledge shared among suppliers has on process improvement; and (iv) to analyse the relationship between the knowledge flows that cross the internal social network and those that cross the supplier's social network.

A case study strategy was developed to achieve the research objectives; this is the most appropriate method in terms of offering a suitable answer to the "how" and "why" questions (Yin, 2014). The research complies with the quantitative assumptions emphasised by Creswell (1994); so: (i) the reality is objective and singular (ontological assumption); (ii) the researcher is independent from that being researched (epistemological assumption); (iii) the research is value-free and unbiased (axiological assumption); (iv) the language is formal and impersonal (rhetorical assumption), and (v) the research process is deductive, has a static design, and its accuracy is ensured through validity and reliability (methodological assumption). A quantitative approach is adopted because: (i) the research seeks to confirm a hypothesis about phenomena; (ii) the analytical objectives focus on quantifying variation and predicting causal relationships; (iii) the study design is stable from beginning to end, and is subject to statistical assumptions and conditions; and (iv) the research concentrates on answering the "how" of a given situation (Amaratunga et al., 2002; Lancaster, 2005).

Description of the case study unit

The analysis was developed in one of the most important British insurance companies which uses Yammer® Enterprise Social Network for both internal and external purposes.

The size of the company (it has more than 10,000 workers worldwide) and manager commitments to implementing Yammer fostered not only many and meaningful information exchange flows but also knowledge flows, within and beyond the company through the supplier social network. All the workers at the insurance company in the UK use Yammer, but the current research focuses only on those who have direct contact with the suppliers included in the study and with the core process of claim management. The company's suppliers use Yammer in their daily activity for internal communication and interaction.

In 2013, the company started to use Yammer® as an internal communication platform and, at the beginning of 2014 it created a supplier social network, using the same platform. In March 2015, the network had 146 members from the multilevel supply chain. An insurance multilevel supply chain includes actors from the claim management area (suppliers level), technical expertise (contractors level), and repair and recovery providers (operational level). Each firm has at least one employee on Yammer®.

Research sample and design

A sample of 52 persons from 15 organisations was extracted from the research population, 27 of whom were members of the internal social network and 25 of whom belonged to the external social network. The selection criterion depended on a user's active presence on Yammer®; a user was considered to be "actively present" if they had participated in at least one conversation in the last 16 months. In other conditions, other values can be fixed depending on the corresponding context. Last but not least, the sample is statistically representative by structure; it includes members from suppliers (35.71%), contractors (21.43%), and at operational (28.57%) and partner level (14.29%).

A four-step methodology was followed (Figure 2); each step includes a set of distinct activities and the output of one step serves as input for the next one. Thus, data are collected from internal documents, internal and external social network platforms, and once their reliability and validity is proven, they become subject to social network analysis (SNA) and principal component analysis (PCA). The results obtained prove whether or not business process improvement and the knowledge flows that cross the internal and external social network can be grouped in the same component. If so, partial least square – structural equation modelling (PLS-SEM) is applied in order to determine how business process improvement is influenced by the knowledge shared by the employees and suppliers within an inter-organisational online social network.

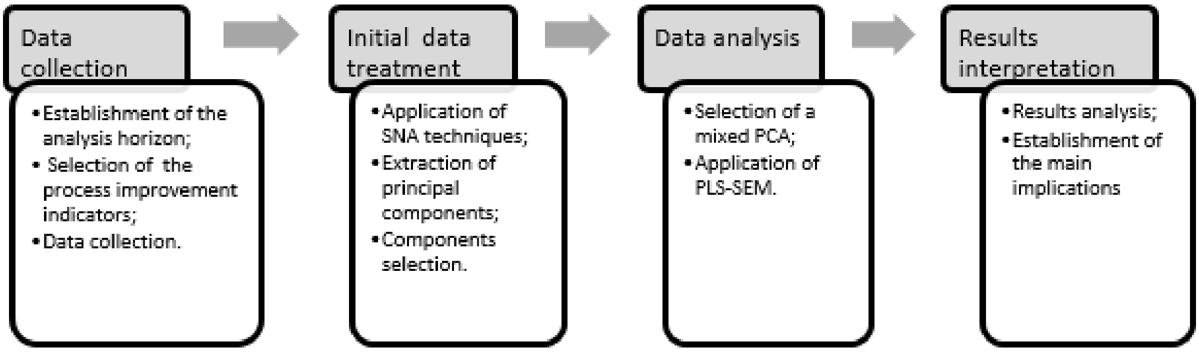

Figure 2. Research methodology

Data collection

Data was collected from internal documents, and internal and external social network platforms for the period May – December 2014.

The average cycle time for handling claims was used as a process improvement measurement (Mahlow & Wagner, 2016; Sarkar et al., 2013). Data was thus collected from the internal documents regarding the claims closed by the company during the established time period. The data included a list with 8494 claims. Each claim consists of metadata such as: claim ID, policy type, open date, incident type, validated supplier, instruction type, route to market, and closing date. The average cycle time for handling a claim was determined as the difference between the date on which the claim was closed and the date on which the notification was made by the client.

Data was collected from the internal and external social networks regarding the conversations established between employees and suppliers. Once data is provided by the system's administrators, data reliability and validity are considered. After the system administrator confirms that data was neither modified nor lost during the analysed time framework, and a lack of unreasonable truncation, steps, and phase changes is noted, the data was codified. The data contained 2632 messages posted on the internal social network and 608 messages posted on the external social network during the established timeframe. Each message consisted of metadata such as message ID, participant ID, thread ID, participant name, timestamp, content of the message, and attachments.

A content analysis was developed with the help of NVivo 10 software, which has been successfully used in other studies (Al Saifi et al., 2016; Aslam et al., 2018); the unit of analysis is represented by individual posts and only the manifest content (which incorporates the text-based data) is taken into consideration. The results show that the process of knowledge sharing among the company and its suppliers focuses on three topics: (i) news, innovation and progress; (ii) claims - experiences and customer satisfaction; and (iii) official and unofficial communication. The first category includes discussions which concentrate on the latest news from the insurance environment, technological progress, innovations and IT security; 25% of the suppliers support these knowledge flows. The second category reunites the knowledge flows that focus on best practices, and stakeholder reports and satisfaction; 91.66% of the suppliers participated in this type of knowledge sharing. The third category captured the attention of 75% of the suppliers and involved topics such as business events, workshops, personal experiences and small talk. Within this framework, the identified knowledge flows (Figure 2) were codified using a binary code where "1" represented the presence and "0" the absence of knowledge flows between users. Following the approach of Leon et al. (2017), a knowledge flow is assumed to be present when at least two individuals share what they know, think, believe or feel with one another, within the enterprise social network. The steps described by Cetto et al. (2018) were followed for the codifying process;

two researchers manually coded 5% of the messages, and after coding 100 messages, the Krippendorff alpha coefficient was estimated in order to determine inter-rater reliability (Hayes & Krippendorff, 2007). Given that $\alpha = 0.9473$, the inter-rater reliability was high and only a few mismatches were consolidated. The researchers coded the remaining messages by themselves, using 80% of the labelled data to train a classifier and apply the classifier to the entire dataset. At this stage, it is used the supervised learning machine algorithm based on existing human coding, embedded in NVivo software.

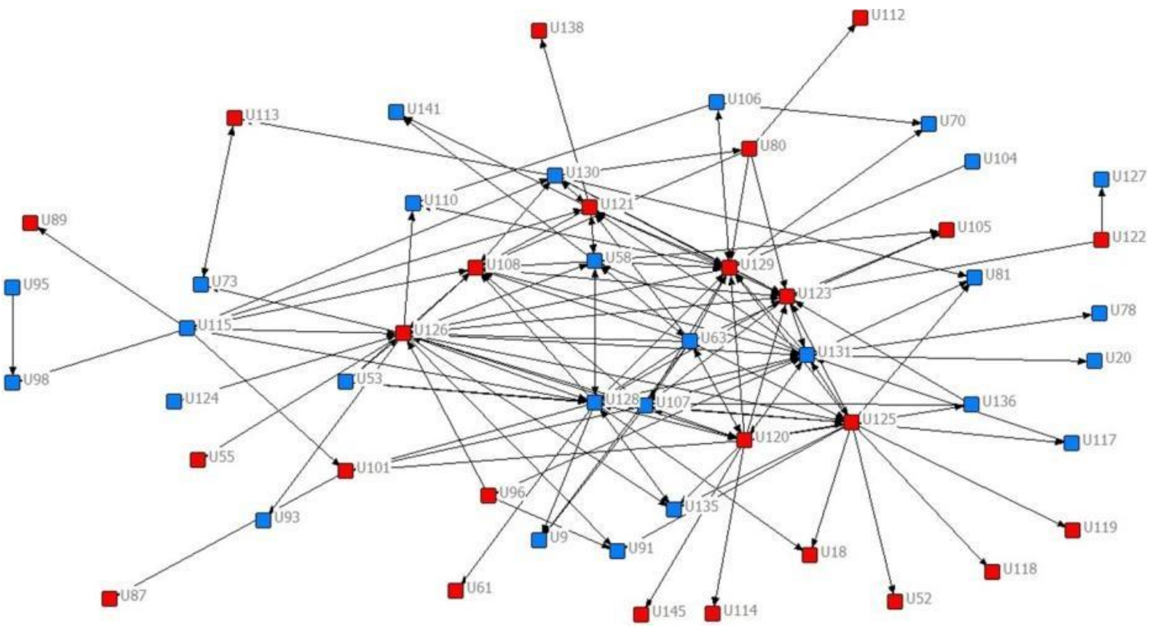

Figure 2. The knowledge flows established between the company (blue square) and its suppliers (red square)

Note: The relationships established among members are emphasized by arrows and lines; the former are used for highlighting the direction of the knowledge flows when a uni-directional relationship is established between members while the latter is used for mutual knowledge sharing (bi-directional knowledge flows)

Initial data treatment

Three social network analysis (SNA) techniques are applied, namely: cohesion, centrality and equivalence analyses. The first two shed light on the relationships structure and the embeddedness of each member while the latter brings forward the sub-structures of the network by taking into account the patterns of relationships established among members. As a consequence, the indicators that defined network dimension, cohesion, centrality and power, subgroups, roles and positions were extracted.

Network dimension reflects both the quantity and quality of the knowledge flows that cross the internal and external social networks, and emphasises potential knowledge flows (Chandra et al., 2015; Fronzetti Colladon & Vagaggini, 2017; Panahi et al., 2016). Quantity is reflected by the number of persons who become members of the networks and quality resides in their diversity; if more departments and suppliers are represented within the networks, then access to various types of knowledge increases.

Network cohesion and power reflect the actual knowledge flows that cross an internal and external social network (Reagans et al., 2015). Once its level increases it may be assumed that a company's employees and suppliers tend to obtain knowledge from various sources, trust each other, and share their experiences, values and beliefs with one another.

Network subgroups, roles and positions involve how the network is organised and how control is exercised (Cetto et al., 2018; Chandra et al., 2015; Idrees et al., 2018; Valverde-Rebaza et al., 2018). This indicates how knowledge flows from one group to another, and how long it takes for knowledge to get from the owner to all the other members. If the number of groups increases, the network is decentralised, knowledge travels faster from one group to another and the sources of diversity are more varied.

In order to determine how a network's characteristics are related and how they affect business process improvement, PCA is applied to all the collected indicators; in other words, the indicators describing process improvement, internal and supplier social networks become the subject of PCA. The oblique rotation is selected because the analysed variables are assumed to be correlated (Gorsuch, 1983; Tabachnick & Fiddell, 2007). The number of principal components is then decided, based on the Kaiser criterion (Field, 2005). The content of each principal component is established.

Last but not least, the principal component that includes the variables describing process improvement, and internal and supplier social networks is selected. Since the focus is on analysing the relationships established among them, the sample size is small, secondary data are analysed, and these are non-normally distributed, the use of PLS-SEM is recommended. According to Sarstedt and Mooi (2019), this is more robust and has greater statistical power than CB-SEM. Furthermore, it is the preferred model when using formative measures due to the fact that the multiple indicators and multiple causes models of CB-SEM impose several constrains that contradict the theoretical assumptions (Hair et al., 2019; Sarsredt et al. 2016). So, a PLS-SEM analysis is performed, using SmartPLS 3.2.9 software, and the cause-effect relationships developed between process improvement, internal social network and external social network are emphasised.

Results

SNA techniques were applied in order to measure the network's dimension, cohesion, centrality and power, roles and position; and the analysis was developed at both the internal and supplier social network level. Once the cohesion, centrality, and equivalence analyses were performed, 28 indicators (Ind) were extracted for each network (internal and supplier social network) as presented in Table 1. Fifty six indicators were collected. Together with the average cycle time, these constitute the subject of PCA; and 59 variables were considered, of which 28 describe the internal network, 28 describe supplier social networks, and one measured process improvement.

Table 1. Variables describing the internal and external network

Dimension	Variables	Code
Network dimension	No. of members	Ind.1
Network cohesion	Network density	Ind.2
	No. of ties	Ind.3
	Average degree	Ind.4
	Indeg H-index	Ind.5
	Component ratio	Ind.6
	Average distance	Ind.7
	Average clustering coefficient	Ind.8
	Weighted clustering coefficient	Ind.9
	Krackhardt connectedness	Ind.10
	Krackhardt hierarchy	Ind.11
	Krackhardt efficiency	Ind.12
	Arc reciprocity	Ind.13
	Dyad reciprocity	Ind.14
	Hybrid reciprocity	Ind.15
	Breadth	Ind.16
	Compactness	Ind.17
	Triplet transitivity	Ind.18
Network centrality and power	Degree centralisation	Ind.19
	Out-degree centralisation	Ind.20
	In-degree centralisation	Ind.21
	Network power	Ind.22
	Flow betweenness	Ind.23
	Nflow betweenness	Ind.24
Network subgroups, roles and position	No. of automorphisms	Ind.25
	No. of cliques	Ind.26
	No. of N-cliques	Ind.27
	K-plex	Ind.28

It can be seen from the results generated by the PCA technique that only the first six components have an Eigenvalue higher than 1.00, and together explain over 98.571% of the total variability in data (Table 2). According to the Kaiser criterion, a six factor solution is adequate, however, this criterion is accurate when there are less than 30 variables, and communalities after extraction are greater than 0.7, or when the sample exceeds 250 and the average communality is greater than 0.6. Since the communality average equals 0.985, the Kaiser rule is accurate on both grounds.

Table 2. Total variance explained

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulate %**	**Total**	**% of Variance**	**Cumulate %**	**Total**	**% of Variance**	**Cumulate %**
1	24.648	43.243	43.243	24.648	43.243	43.243	17.604	30.884	30.884
2	17.032	29.881	73.124	17.032	29.881	73.124	15.023	26.356	57.240
3	7.071	12.404	85.528	7.071	12.404	85.528	8.570	15.035	72.275
4	3.641	6.388	91.916	3.641	6.388	91.916	8.389	14.718	86.994
5	1.934	3.392	95.309	1.934	3.392	95.309	3.973	6.970	93.964
6	1.860	3.263	98.571	1.860	3.263	98.571	2.626	4.607	98.571
7	.814	1.429	100.00						

Extraction Method: Principal Component Analysis.

If the scree plot is taken into account (Figure 3) then a five-factor solution seems more appropriate. The slope of the curve levels out after five factors, rather than six.

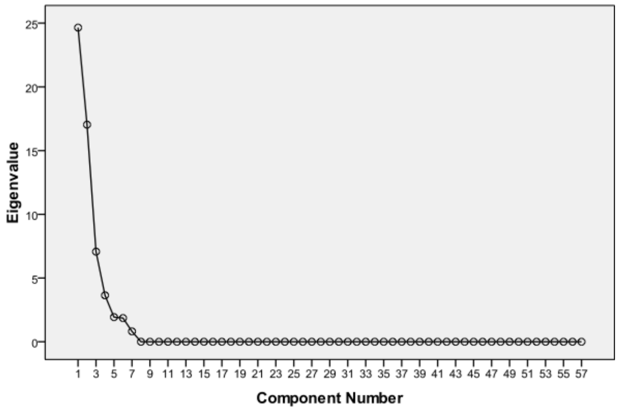

Figure 3. Scree plot generated by the PCA technique

Table 3. The factor loading matrix

Network	Variable	Code	Component				
			1	**2**	**3**	**4**	**5**
	Average cycle time	Ind.29			-.541	**-.843**	-.688
Internal	No. of members	Ind.1a				**.843**	.527
	Network density	Ind.2a	**.982**	.546			
	No. of ties	Ind.3a	**.992**	.553			
	Average degree	Ind.4a	**.992**	.545			
	Indeg H-index	Ind.5a	**.914**			-.523	
	Component ratio	Ind.6a	**-.988**	-.554			
	Average distance	Ind.7a			.473	.416	**.897**
	Breadth	Ind.16a	**-.968**	-.605			
	Compactness	Ind.17a	**.968**	.605			
	Degree centralisation	Ind.19a	.636		**.725**		
	Out-degree centralisation	Ind.20a	.635		**.725**		
	In-degree centralisation	Ind.21a	**.949**	.511			

	Average clustering coefficient	Ind.8a	.228	-.138	-.040	-.129	.216
	Weighted clustering coefficient	Ind.9a	**.842**			-.604	
	Arc reciprocity	Ind.13a	**.944**	.473			
	Dyad reciprocity	Ind.14a	**.939**	.525			
	Hybrid reciprocity	Ind.15a	**.950**	.524			
	Krackhardt connectedness	Ind.10a	**.769**	.667		.417	
	Krackhardt hierarchy	Ind.11a	**-.976**	-.445			
	Krackhardt efficiency	Ind.12a			.617	**.940**	.534
	Network power	Ind.22a	**-.907**			.478	
	Flow betweenness	Ind.23a	**.774**	.401			.499
	Nflow betweenness	Ind.24a	**.834**	.441			.422
	Triplet transitivity	Ind.18a	.517		-.572	**-.878**	
	No. of automorphisms	Ind.25a	-.520				.533
	No. of cliques	Ind.26a					**.914**
	No. of N-cliques	Ind.27a		.627		**.800**	
	K-plex	Ind.28a	.450	.435	.689	.530	**.701**
External	No. of members	Ind.1b	-.476		.435	**.940**	
	Network density	Ind.2b	.627	**.947**			
	No. of ties	Ind.3b		**.846**		.775	
	Average degree	Ind.4b	.457	**.987**		.464	
	Indeg H-index	Ind.5b		.720	.493	**.829**	.575
	Component ratio	Ind.6b	-.532	**-.969**			

	Average distance	Ind.7b		.529		**.944**	
	Breadth	Ind.16b	-.598	**-.975**			
	Compactness	Ind.17b	.598	**.975**			
	Degree centralisation	Ind.19b	.651	**.960**			
	Out-degree centralisation	Ind.20b	.646	**.963**			
	In-degree centralisation	Ind.21b	.661	**.958**			
	Average clustering coefficient	Ind.8b	.506		**-.699**		
	Weighted clustering coefficient	Ind.9b			**-.939**	-.562	
	Arc reciprocity	Ind.13b			**-.852**	-.755	
	Dyad reciprocity	Ind.14b			**-.874**	-.755	
	Hybrid reciprocity	Ind.15b	.411	.451	**-.774**		
	Krackhardt connectedness	Ind.10b	.570	**.966**			
	Krackhardt hierarchy	Ind.11b			**.986**		
	Krackhards efficiency	Ind.12b			**.958**	.580	.444
	Network power	Ind.22b		**-.699**			-.549
	Flow betweenness	Ind.23b	.479	**.987**		.437	
	Nflow betweenness	Ind.24b	.605	**.966**			
	Triplet transitivity	Ind.18b	**-.625**			.478	
	No. of automorphism	Ind.25b		-.514	-.729	**-.747**	-.483
	No. of cliques	Ind.26b		**.781**		.762	
	No. of N-cliques	Ind.27b		.553	.610	**.796**	.739
	K-plex	Ind.28b		**.953**		.575	

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalisation

Given the fact that the oblique rotation is used, two matrices are obtained, namely: the factor loading matrix and the pattern matrix; the former emphasizes the correlations or covariances between components and factors while the latter is the matrix of regression weights by which factors predict components (Tabachnick & Fidell, 2007). Thus, the factor loading matrix (Table 3) was analysed in order to determine the factors that load on each component. Although Tabachnick and Fidell (2007) argue that loadings higher than 0.4 are acceptable, most of the recent studies that use varimax and promax rotation (Xue et al., 2018; Yuen & Thai, 2017) adopt a more stringent approach and apply a 0.6 threshold. Since factors' loadings range from 0.040 to 0.992 and most of them are above 0.4, it can be considered realistic to apply a cut-off of 0.6. Thus, after applying this threshold, two indicators from the internal network are eliminated because their loadings are less than 0.6 on each component: the average clustering coefficient (Ind.8a) and the number of automorphisms of the internal network (Ind.25a).

Fifty-six indicators are retained and they are distributed among five principal components; the last one, PC5, is exclusively describing the internal social network and the second, PC2, is exclusively related to the supplier social network; the first (PC1), third (PC3), and fourth (PC4) components are mixed, including aspects related to both internal and external social networks. The variable measuring process improvement (Ind.29) is loaded negatively on the fourth principal component.

Table 4. Component correlation matrix

	PC1	**PC2**	**PC3**	**PC4**	**PC5**
PC1	1	0.495	-0.006	-0.159	0.038
PC2	0.495	1	0.079	0.359	0.142
PC3	-0.006	0.079	1	0.442	0.404
PC4	-0.159	0.359	0.442	1	0.384
PC5	0.038	0.142	0.404	0.384	1

Further, the patter matrix is obtained by multiplying the factor loadings matrix with the inverse of the component correlation matrix (Table 4). Based on the pattern matrix which presents “the regression coefficients of the variable on each of the factors” (Rietveld & Van Hout, 1983, p.281), the following relationships were identified:

$$PC1 = 0.900 * Ind.2a + 0.973 * Ind.3a + 0.940 * Ind.4a + 0.764 * Ind.5a - 0.957 * Ind.6a + 0.708 * Ind.9a + 0.775 * Ind.10a - 1.029 * Ind.11a + 0.900 * Ind.13a + 0.854 * Ind.14a + 0.871 * Ind.15a - 0.882 * Ind.16a + 0.882 * Ind.17a - 0.740 * Ind.18b + 0.893 * Ind.21a - 0.877 * Ind.22a + 0.884 * Ind.23a + 0.892 * Ind.24a$$

$$PC2 = 1.029 * Ind.2b + 0.779 * Ind.3b + 0.963 * Ind.4b - 0.872 * Ind.6b + 0.998 * Ind.10b - 1.017 * Ind.16b + 1.017 * Ind.17b + 0.739 * Ind.19b + 0.736 * Ind.20b + 0.764 * Ind.21b - 0.699 * Ind.22b + 0.945 * Ind.23b + 1.005 * Ind.24b + 0.602 * Ind.26b + 0.870 * Ind.28b$$

$$PC3 = -0.710 * Ind.8b - 0.914 * Ind.9b + 1.065 * Ind.11b + 0.9 * Ind.12b - 0.659 * Ind.13b - 0.684 * Ind.14b - 0.914 * Ind.15b + 0.769 * Ind.19a + 0.767 * Ind.20a$$

$$PC4 = 0.881 * Ind.1a + 0.881 * Ind.1b + 0.412 * Ind.5b + 0.951 * Ind.7b + 0.706 * Ind.12a - 0.672 * Ind.18a - 0.529 * Ind.25b + 0.762 * Ind.27a + 0.443 * Ind.27b - 0.820 * Ind.29$$

$$PC5 = 0.785 * Ind.7a + 0.912 * Ind.26a + 0.420 * Ind.28a$$

The elements included in PC4 were selected in order to analyse the cause-effect relationship among process improvement, internal social network and supplier social network. They become the subject of PLS-SEM analysis because this is capable of incorporating multiple dependent constructs, and dealing with both formative and reflective constructs

(Zhang, 2009).

According to the data presented in Table 5, the measurement model is adequate at the level of convergent validity; factor loadings and composite reliability overcome the level of 0.7, and the average variance extracted (AVE) is higher than 0.5. As a consequence, all items meet the acceptable limits as suggested by Hair et al. (2014).

Table 5. Convergent Validity Analysis

Construct	**Variable**	**Factor loadings**	**Composite reliability**	**AVE**
Process improvement	Ind.29	1.000	1.000	1.000
Internal network	Ind.1a	0.841	0.754	0.779
	Ind.12a	0.967		
	Ind.18a	-0.936		
	Ind.27a	0.774		
External network	Ind.1b	0.855	0.855	0.768
	Ind.5b	0.952		
	Ind.7b	0.756		
	Ind.25b	-0.873		
	Ind.27b	0.931		

If the discriminant validity is taken into account (Table 6), the model is shown to be adequate: the values of the diagonal elements are higher than the other values in their respective rows and columns.

Last but not least, the goodness of fit of the model reaches 0.710, which is high according to Wetzels et al. (2009); they argue that a value of 0.1 is a small fit, a value of 0.25 is a medium fit and a value higher than 0.36 demonstrates a large fit. The developed model is therefore valid.

Table 6. Discriminant Validity

	External network	**Internal network**	**Process improvement**
External network	0.976		
Internal network	0.948	0.883	
Process improvement	-0.443	-0.295	1.000

If the path coefficients are taken into consideration, the following statements can be made: (i) if the internal social network increases by one standard deviation from its mean, process improvement would be expected to increase by 1.239 its own standard deviation from its own mean while all the other constructs remain constant; (ii) if the internal social network increases by one standard deviation from its mean, the external social network would be expected to increase by 0.948 its own standard deviation from its own mean while all the other constructs remain constant; and (iii) if the external social network increases by one standard deviation from its mean, process improvement would be expected to decrease by 1.618 its own standard deviation from its own mean while all the other constructs remain constant. The internal and external social networks can explain 35.1% of process improvement variability while the internal social network explains 89.9% of external social network variability (Figure 5).

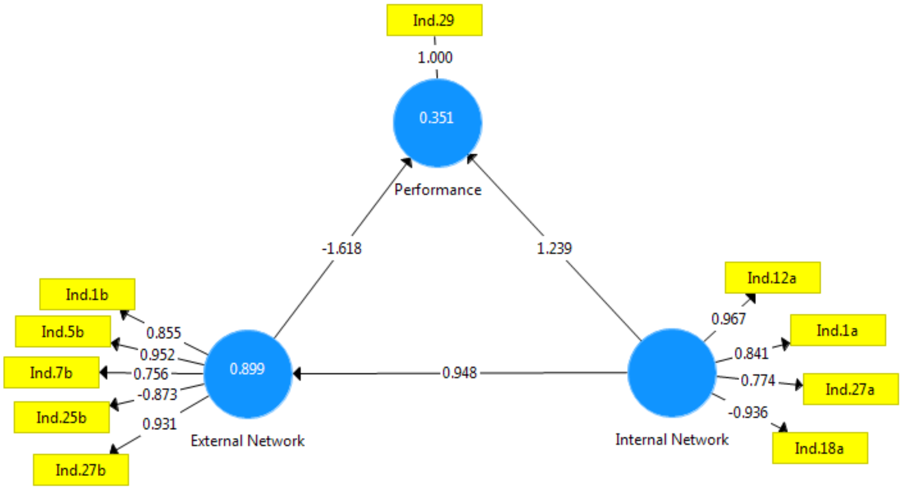

Figure 5. Relationship among process improvement, internal and external social network. PLS-SEM results

In summary, the three research hypotheses are validated since: (i) the knowledge shared among employees, in a private online social network, positively affects process improvement (β = 1.239; *t* = 6.15; $p<0.01$); (ii) the knowledge shared among supply chain members in a private online social network negatively affects process improvement (β = -1.618; *t* = 5.04; $p<0.01$); and (iii) the knowledge shared among employees positively affects the knowledge shared among the supply chain members (β = 0.948; *t* = 2.93; $p<0.05$).

Discussion

In the insurance services sector, process improvement is defined in terms of time spent handling claims, and therefore, managers aim to facilitate knowledge sharing inside and outside a firm's boundaries in order to support identification of the best practices and to diminish the average cycle time. Although both internal and external knowledge flows affect the average cycle time, several issues have to be considered.

1. The internal and external social networks have a different and powerful impact on process improvement. As previously demonstrated, Hypotheses 1 and 2 are supported; the internal social network is directly correlated with process improvement (the standardised partial regression coefficient equals 1.239) and the external social network is negatively correlated with process improvement (the standardised partial regression coefficient equals -1.618). At first glance, in order to diminish the average cycle time of handling claims, managers should focus on: (i) reducing the variability of the internal social network, and (ii) increasing the variability of the external social network. However, things are not as simple as they seem because knowledge sharing occurs on both internal and external grounds and the external social network acts as an intermediate variable between both the internal social network and process improvement; it represents an effect of the first and a cause of the second. In other words, the internal social network is positively correlated with both external social network (since Hypothesis 3 is supported) and process improvement. Simple logical reasoning therefore suggests that its development generates an increase in both external social network and average cycle time. When the partial regression coefficients are taken into consideration, however, the perspective changes; initially, it appears that an increase by 1 unit in the variability of the internal social network will increase the average cycle time by 1.239 units, and the variability of the external social network by 0.948 units. But, this increase by 0.948 units of the external social network will generate a decrease in the average cycle time by 1.533 units. As a consequence, on a general scale, the average cycle time of handling claims will decrease by 0.585 units. On the other hand, if the initial proposal is applied and the variability of the internal social network decreases by 1 unit, the average cycle time of handling claims increases by 0.585 units. Starting from here, it can be assumed that in order to reduce the time in which claims are solved, managers should focus on increasing the quality and quantity of the knowledge flows that cross the internal and external social networks.

2. *Not all the characteristics of the social network have an impact on process improvement*. Based on the results of the PCA, the fifty-six indicators describing the

enterprise social network and business process improvement were distributed among five principal components. The variable measuring process improvement was loaded on the fourth principal component together with several indicators related to network's dimension (number of members), cohesion (indeg H-index, average distance, Krackhardt efficiency, triplet transitivity), subgroups, roles and position (number of automorphism, number of N-cliques). None of the variables measuring network's centrality and power were loaded on the fourth principal component; in fact, they loaded on the first, second and third principal components together with the indicators measuring network's cohesion. These results complement the findings of Roelens et al. (2016) and Al-Thuhli et al. (2017). The former states that network's centrality and power reflect the level of "co-opetition"; a high level of centrality highlights the existence of a collaborative supply chain while a low level of centrality emphasizes a competitive supply chain. Al-Thuhli et al. (2017) go further and claim that collaborative networks may facilitate business process improvement. However, in light of the social capital theory, the intensity of "co-opetition" is influenced by supplier's interest of obtaining a mutual benefit. In other words, in the current study, it may be that the relationship between network centrality and power and the average cycle time of handling claims could not be proved due to the fact that the latter was not perceived as a benefit by all the suppliers involved in the process.

On the other hand, these results are in line with Modrik (2013) and Garcia-Hernandez (2014) who argue that network centrality and power provide valuable information regarding actors' behaviour but these are debatable when the analysis is made on network's level. Thus, network centralization is an excellent predictor for firm performance and process improvement in stable, structured and simple environments while network's decentralization provides better results in unstable, unstructured and complex circumstances. Furthermore, the study developed by Grant and Preston (2019) indicates that power plays a key role not only in supporting but also in sharing knowledge within a supply chain insurance sector. This indicates that the same variable, power in this case, may adopt different roles and achieve different degrees of importance within the supply chain online social network of the insurance sector depending on what is sought to achieve.

3. *The internal and external social networks affect the average cycle time of handling claims through different components*. On a general level, the time in which a claim is solved is related to the network's dimension, cohesion, subgroups, roles and positions but, on a more specific level, each network has its own levers. The external social network defines its cohesion through the in-degree h-index and the average distance and the internal social network focuses on Krackhardt efficiency and triplet transitivity. On the other hand, at the external level, a network's groups, roles and positions are evaluated through the number of automorphisms and the number of N-cliques, and at the internal level, only the last is taken into account.

Table 7. The components of the internal and external social networks that could reduce the average cycle time

Type of social network	**Component**	**Managerial action**	**Intermediate effect**
External	Number of members	Increase	The variability of the external network increases
	Average distance	Increase	
	Number of automorphisms	Decrease	
	Number of N-cliques	Increase	
Internal	Number of members	Increase	The variability of the internal network increases The variability of the external network increases
	Krackhardt efficiency	Increase	
	Triplet transitivity	Decrease	
	Number of N-cliques	Increase	

In summary, in order to reduce the average cycle time of handling claims, managers should focus on various issues (Table 7). An increase is recommended in: (i) the number of members from both external and internal social networks; (ii) the average distance of the external social network; (iii) the number of N-cliques of both external and internal social networks; and (iv) the Krackhardt efficiency of the internal social network. A decrease could be useful in: (i) the number of automorphisms in the external social network; and (ii) the triplet transitivity of the internal social network.

Theoretical and practical implications

This paper has both theoretical and practical implications. At the theoretical level it complements studies from knowledge management (Aboelmaged, 2018; Berraies, 2019; Kuegler et al., 2015; Patroni et al., 2016) and information management (Al-Thuhli et al., 2017; Fronzetti Colladon & Vagaggini, 2017; Liu & Jansen, 2017; Liu et al., 2019; Neshati et al., 2017). It is the first study situated at the nexus between the two aforementioned areas that analyses the actual knowledge flows that cross an enterprise social network and the topics that are approached. Previous studies from the knowledge management area (Aboelmaged, 2018; Berraies, 2019; Kuegler et al., 2015; Patroni et al., 2016) used questionnaires to identify how knowledge flows from one member to another, although 98% of Fortune 500 companies use at least one enterprise social network platform (UMass Dartmouth, 2018). Despite the fact that surveys based on questionnaires are valuable research tools, they “appeal to the short-memory of respondents and do not reflect the real knowledge flows” (Leon et al., 2017, p.103). This gap is filled by the current research, which analysed 3240 messages posted by employees and suppliers on an enterprise social network, and showed that the main topics of interest were: (i) news, innovation, and progress; (ii) claims – experiences and customer satisfaction; and (iii) official and unofficial communication.

This study also complements the findings of Patroni et al. (2016) by demonstrating that it is not only the knowledge shared among employees may improve operational procedure, but also that shared among suppliers. According to the results of the current research, business process improvement is affected by both the knowledge shared through the internal social network and the knowledge flows that cross the external social network.

Thirdly, although Kuegler et al. (2015) confirm that the intra- and inter-organisational use of enterprise social network platforms significantly affects task performance, and Aboelmaged (2018) demonstrates that employee productivity is strongly affected by both internal and external knowledge sharing through enterprise social network, neither analyses the relationship between the internal and external knowledge flows. The current research fills this gap by demonstrating that, within the enterprise social network, the knowledge shared among employees positively affects the knowledge shared among supply chain members.

The current research extends the information management literature by complementing the findings of Al-Thuhli et al. (2017), Liu and Jansen (2017), Liu et al. (2019), and Neshati et al. (2017). Although their analyses are based on real data provided by social networks, they focus on customers and not on suppliers. In fact, none of the studies developed so far take into consideration the knowledge flows that may cross a supplier's online social network. This research fills this gap by analysing the knowledge shared among suppliers through an enterprise social network, and emphasising its effect on business process improvement in the focal firm.

The current research has various practical implications, since it emphasises what managers should do in order to improve the organisational processes. On the one hand, they should increase: (i) the number of members from both external and internal social networks; (ii) the average distance of the external social network; (iii) the number of N-cliques of both external and internal social networks; and (iv) the Krackhardt efficiency of the internal social network. On the other hand, they should decrease: (i) the number of automorphisms of the external social network; and (ii) the triplet transitivity of the internal social network.

Last but not least, this study facilitates managerial understanding of how knowledge flows inside and outside a company's boundaries. As previously demonstrated, the knowledge that flows among employees positively affects the knowledge flows that cross the external network, and also the organisational process improvement. This is because an enterprise social network tends to serve as a means of sharing news from the business field, best practices, stakeholder information, and various opportunities for individual and organisational development.

Conclusions and further research directions

By collecting and analysing data from an inter-organisational private online social network, this paper has quantified how and to what extent the knowledge sharing process affects the supply chain's process improvement. The main results of applying the presented methodology to an international insurance supply chain has pointed out that: (i) the internal and external social networks have a different and powerful impact on process improvement; (ii) not all the characteristics of the social network have an impact on process improvement; (iii) the internal and external social networks affect the average cycle time of handling claims through different components, which have been identified in order to either increase (number of members, average distance, Krackhardt efficiency and number of N-cliques) or decrease (number of automorphisms and triplet transitivity) their values with the aim of reducing the average cycle time.

The research was limited by the size of the research unit and the characteristics of the analysis unit. These can be viewed as a limitation impeding generalizability although Chreim et al. (2007, p.1535) state that "naturalistic case studies should be judged not on the basis of generalizability, but on the basis of transferability and comparability". However, when it comes to generalisation, the distinction must be made between the analytical (theoretical) generalization and the statistical (empirical) generalization. The former is achieved due to the fact that the developed single case study fosters theory building; its theoretical implications were emphasized in the previous section. Nevertheless, the statistical (empirical) generalization of the current results are debatable. On the one hand, they are statistically representative for the British insurance supply chain given the fact that the composition of the analysed sample reflects the structure of the classical insurance supply chain. On the other hand, although the case unit was strategically selected (one of the most important British insurance companies was selected due to the fact that whenever its actions are successfully, their competitors imitate them), different results could be obtained in small and medium companies where the supply chains are shorter and face-to-face communication is preferred instead of enterprise social networks or in highly bureaucratic insurance companies. The research also concentrated only on the knowledge flows that crossed the internal and external social networks and neglected the knowledge shared through face-to-face communication.

Further research lines could be oriented: (i) to extend the analysis to similar sectors, such as: financial services, banking and risk-retention groups, in order to compare the results; (ii) to extend the analysis to other sectors with which the insurance industry comes in touch, such as hospitality, jewellery and high-tech, in order to generalise the model; (iii) to increase the diversity of the external network by taking into account the knowledge flows that a company receives from various categories of stakeholders, such as: customers, investors, non-governmental organizations, and members of the community.

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