The Benefits of Trusted Bridging Chains for Open Innovation

BY

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ABSTRACT

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How organisations search for innovative ideas is central to open innovation (OI), but studies have shown that it is costly and ineffective for organisations to search too widely.

This study proposes and tests a novel approach for OI search processes. It will focus on indirect interpersonal relationships to the organisation: specifically, a bridging chain of referrals which generates innovative solutions via a sequence of agents (two or more people) based on trust.

Studies of innovation networks highlight the need to balance supporting relationships (which build mutual understanding) with bridging relationships (which enhance novelty). Trust and learning are integral to the former, while diversity (both knowledge-based and geographic) is central to the latter.

Most studies have examined OI in the context of one-to-many relationships with the focal organisation. Little, if any, attention has been given to OI processes which source deeper network horizons for innovative solutions. In extant theory the concept of “depth” refers mainly to organisations that draw intensively on existing external sources. Moreover, although some studies have shown that indirect relationships can generate new information, they suggest that this occurs more by chance than design.

By contrast, OI returns can be consciously derived from indirect interpersonal relationships to an organisation, facilitated by a bridging chain stretching across network horizons, by means of trust.

The study is based on a quasi-experiment in which members of a starter group were asked to solve a complex technical problem by tapping their social networks to source individuals who would – in turn – tap their own respective networks in search of a solution. Thus, a chain of individuals was assembled.

The study concludes that a chain of individuals facilitated by trust enables a deeper, rather than broader, search horizon for social capital returns. The study further demonstrates that competence-based trust, rather than benevolence-based trust, enables referrals, regardless of the quality of innovation solutions identified.

Finally, the study reveals a substitutive relationship between knowledge diversity and geographical distance. In fact, it suggests that too much diversity (in this case, knowledge diversity combined with geographical distance) leads to poor solutions.

Therefore, this study builds on existing analyses of OI and networks, by showing that depth of search, beyond a single horizon, can produce positive OI returns. It also reveals that the most effective vehicle in this regard is a bridging chain, powered by trust, and unburdened by a surfeit of diversity.

Key words: trusted bridging chains, social capital, indirect relationships, innovation, open innovation, indirect social capital, supporting features, bridging features, chains

DECLARATION

I, Margarethe Lombard, declare that this thesis, which I hereby submit for the degree of Doctor of Business Administration at the Gordon Institute of Business Science, University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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22 September 2016

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International input came from professionals and managers from many countries. Their involvement was made possible through the assistance of the International Association of Innovation Professionals (IAOIP) and the Southern African Institute of Mining and Metallurgy (SAIMM). I would like to acknowledge their generous participation. Furthermore, my warmest thanks go to those who participated in the research process itself.

I would also like to thank Vivienne and Fiona for their administrative skills. Their support was instrumental in providing me with the necessary tools to complete this journey.

Lastly, I would like to pay tribute to my family. To my children: thank you for tolerating many nights of take-outs. I will soon start cooking lavish meals again. To my husband: my apologies for incessantly asking your opinion on material that often made little sense. Thank you for making me laugh when I cried.

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LIST OF ACRONYMS

AUC	Area Under the Curve
CAT	Consensual Assessment Technique
CFA	Confirmatory Factor Analysis
CSDS	Creative Solution Diagnosis Scale
fsQCA	Fuzzy set Qualitative Comparative Analysis
IAOIP	International Association of Innovation Professionals
MSA	Measures of Sampling Adequacy
OI	Open Innovation
PI	Prime Implicant
R&D	Research and Development
ROC	Receiver Operating Characteristics
SAIMM	Southern African Institute of Mining and Metallurgy

CHAPTER 1: INTRODUCTION

This chapter describes the aim of the study: namely to argue the benefits of trusted bridging chains for Open Innovation (OI).

The background and context of the problem will be presented, as well as a summary of the extant theory that informed the study. The problem statement will then be defined, followed by a description of the significance of the study, highlighting how it will fill a gap in existing knowledge. The research design will be described, as well as the research question and hypotheses. The chapter concludes with a summary of the assumptions and limitations of the study.

1.1 Background

In today's tough economic environment, organisations are compelled to innovate, and to transform innovation processes, in order to stay ahead of the competition or to make inroads into new markets.

However, although incremental innovations are ubiquitous, innovation seems to be less than radical in nature (Leitner, Warnke & Rhomberg, 2016). Existing innovation strategies therefore require drastic transformation in order to remain key enablers of competitiveness.

Merely investing in internal research and development (R&D) functions, and/or resources for innovation purposes, may be insufficient.

Even though organisations have long exploited external knowledge for innovation purposes (Cohen & Levinthal, 1990), in recent decades they have begun to incorporate external technologies into their innovation processes through alliances and partnerships or in-licensing. Henry Chesbrough coined the term "open innovation" (OI) to describe this development (Chesbrough, 2003). Moreover, most OI/network literature follows an ego-network perspective which cannot sufficiently explain the individual search process for solutions or resources. Organisations forge relationships with innovators through alliances (Lambe & Spekman, 1997; Narula & Hagedoorn, 1999), joint ventures (Bingham

& Spradlin, 2011; Peck, 1986) or technology sourcing and acquisition (Arora, Fosfuri & Gambardella, 2001; Nicholls-Nixon & Woo, 2003; Veugelers, 1997). This process mostly involves one-to-one or one-to-many direct relationships with innovators or groups of people (Howe, 2008).

Most commonly, organisations have leveraged external networks for innovation performance. This is referred to as “network-centric innovation” (Nambisan & Sawhney, 2011). However, studies have shown that searching too widely for external innovations can be expensive and ineffective (Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Vanhaverbeke, Duysters & Beerkens, 2002) and can actually slow down the innovation process (Leitner et al., 2016).

This study explores a novel process of searching for innovative solutions based on depth rather than breadth. The study focuses on indirect interpersonal relationships, whereby organisations can search for innovative solutions through external bridging chains of referrals, driven by trust. Trust is seen as a supporting element of social capital, with diversity playing a bridging role. “Social capital” refers to the returns gained through social networks and interpersonal relationships (Burt, 1997; Coleman, 1988; Lin, 2001).

Existing studies suggest that a balance between supporting relationships and bridging relationships is integral to innovation. Trust is embedded within supporting relationships (Lee & Choi, 2003; Nooteboom, 2013; Phelps, 2010) which facilitate the learning that often takes place within communities (Gilsing, Nooteboom, Vanhaverbeke, Duysters & Van den Oord, 2008; Powell, Koput & Smith-Doerr, 1996; Sorenson & Audia, 2000). This may occur through better coordination and communication (Garton, Haythornthwaite & Wellman, 1997; Krackhardt, 1992; Laursen, Moreira & Markus, 2015; Reagans & Zukerman, 2001; Uzzi, 1996; Wellman & Wortley, 1990) or via social integration (Gnyawali & Srivastava, 2013; Laursen, Masciarelli & Prencipe, 2012).

Trust is therefore seen as an important element of innovation, although it should be balanced with access to diverse information.

Such access can be obtained through weak ties (Granovetter, 1973; 1983); across geographic distances (Beers & Zand, 2014; Capaldo & Petruzzelli, 2014;

Letaifa & Rabeau, 2013; Levin & Barnard, 2013; Todo, Matous & Inoue, 2015; Whittington, Owen-Smith & Powell, 2009) or via knowledge diversity (Baum, Calabrese & Silverman, 2000; Hargadon & Sutton, 1997; Phelps, 2010; Powell, Koput, Smith-Doerr & Owen-Smith 1999; Pullen, de Weerd-Nederhof, Groen & Fisscher, 2012; Reagans & McEvily, 2003; Rodan & Galunic, 2004; Vanhaverbeke & Cloodt, 2006; Westergren & Holmström, 2012).

However, this study will propose that innovative solutions can be sourced by dynamically searching trusted bridging chains that integrate the supporting (trust) and bridging (diversity) features of social capital for OI returns. A trusted bridging chain is therefore defined here as: *a chain of agents connected through trust relations and characterised by diversity*.

Although some studies have shown that indirect interpersonal relationships can generate new information, this is seen to occur more through chance than design (Ahuja, 2000; Almeida & Kogut, 1999; Burt, 1997; 2010; Jaffe, Trajtenberg & Henderson, 1993).

By contrast, OI returns can be intentionally derived via indirect interpersonal relationships to the organisation, by means of a trusted bridging chain that stretches across network horizons, driven by trust and infused with diversity.

1.2 Problem statement

Current studies indicate that searching too widely for innovative solutions is expensive and ineffective (Katila & Ahuja, 2002; Laursen & Salter, 2004, 2006; Leitner et al., 2016; Vanhaverbeke et al., 2002). Yet, in extant theory, “depth” implies searching only existing external sources extensively (Katila & Ahuja, 2002).

It would therefore be valuable to establish how OI processes might benefit from sourcing innovative solutions across network horizons.

Previous studies have examined the challenges of over-searching (Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Leitner et al., 2016; Vanhaverbeke et al., 2002) and the benefits of network-centric innovation (Nambisan & Sawhney, 2011), as well as spill-overs (Ahuja, 2000; Almeida & Kogut, 1999;

Belderbos & Carree, 2004; Burt, 2007; 2010; Jaffe et al., 1993; Owen-Smith & Powell, 2004).

Some studies have explored network ties that bridge organisational boundaries (Leenders & Dolfsma, 2016), while additional research has focused on the bridging and bonding aspects of social capital (Lin, 2005; Portes, 1998; Putnam, 2000). Yet, studies that bridge organisational boundaries are scarce (Leenders & Dolfsma, 2016).

This study refines ideas about network structure and diversity and how these could contribute to the success of OI. It shows that social capital is based on supporting elements (such as trust) as well as bridging elements (such as weak ties and structural holes) and that it can consequently be defined in terms of a combination of bridging and bonding.

There are also challenges in the conceptualisation of social capital (Patulny & Svendsen, 2007; Payne, Moore, Griffis & Autry, 2011) which the study attempts to clarify by refining the concepts of direct and indirect social capital.

Finally, there are methodological challenges for studies in collecting referral data (across fields) due to the limit to horizons of observability regarding indirect ties (Friedkin, 1982), which this study circumvented by means of the development and deployment of software that that drove the data collection process across chains of referrals. The study also has many other practical implications to leverage indirect social capital for innovation (and across other domains) and not merely by-chance.

To summarise: the research problem focuses on the benefits of searching more deeply for OI return, through trusted, external bridging chains which benefit the organisation, and exploring the extent to which such chains have a positive effect on OI.

1.3 Purpose of the study

Innovation is critical for organisational survival and long-term sustainability. Indeed, research has shown that the conscious search for OI solutions across organisational boundaries contributes to an organisation's innovation processes (Chesbrough, 2003; West & Bogers, 2014).

Yet, studies have also shown that searching too widely for new ideas can prove counter-productive (Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Vanhaverbeke et al., 2002) to the extent of impeding the innovation process itself (Leitner et al., 2016).

As mentioned earlier, little attention has been given to analysing the benefits of in-depth search that ventures beyond direct relationships, through indirect interpersonal relationships via a conscious chain.

Instead, studies of the benefits of indirect relationships upon organisational innovation have mostly focused on incidental benefits gained through spill-overs of knowledge (Ahuja, 2000; Almeida & Kogut, 1999; Belderbos & Carree, 2004; Burt, 2007; 2010; Jaffe et al., 1993; Owen-Smith & Powell, 2004).

By reframing the notion of "search" in terms of depth rather than breadth, it is hoped that this study will provide a foundation for future studies on the impact of trusted bridging chains upon OI: specifically, through focusing on the roles played by trust and diversity (whether knowledge-based or geographic).

1.4 Significance of the study

Innovation is critical for organisations today, not least because of the economic downturn. Indeed, we are seeing the phenomenon of "ubiquitous innovation" (Leitner et al., 2016).

Organisations have increasingly leveraged OI to support their innovation processes. In most cases OI is generated via one-to-many relationships with the focal organisation. This has often involved breadth of search, notwithstanding the detrimental effects. A related concern has been the slowing-down of innovation processes when too many parties have been included (Leitner et al., 2016).

As a report to the European Commission stated in 2007: "The regime of collective experimentation faces challenges because such embedded innovation is laborious, typically loosely-coordinated and slow; as it should be, because users and other stakeholders have their own contexts and logics to consider" (Nordmann, 2009, p. 302).

Studies on network ties that bridge organisational boundaries are scarce (Leenders & Dolfsma, 2016), hence the aim of this study: to identify novel, depth-based OI searching strategies, by means of a trusted bridging chain that dynamically spans indirect interpersonal relationships.

Given the challenges in conceptualising social capital (Patulny & Svendsen, 2007; Payne, Moore, Griffis & Autry, 2011), this study builds on existing theory to define and describe two levels of social capital: direct and indirect.

It is proposed that a distinction between direct and indirect social capital is useful. Current conceptualisations of social capital refer to all value that can be garnered through relationships, whether they are direct personal relationships or "contacts of contacts" (Burt, 1997; 2010; Granovetter, 1973). The evidence in this thesis suggests that a conceptual distinction between direct and indirect social capital can and should be made. Thus this study proposes that direct social capital, following Nahapiet and Ghoshal (1998) and Putnam (1995), be defined as: *the information or knowledge (new or improved resources), or else the preservation of unity and maintenance of current state, available to / for individuals or organisations through direct relationships*.

Indirect social capital, on the other hand, following Burt (1997; 2010), Granovetter (1973), Nahapiet and Ghoshal (1998) and Putnam (1995), will be defined as: *the information or knowledge (new or improved resources) available to individuals or organisations, through indirect social relationships by means of a trusted bridging chain or through by-chance indirect relationships*.

Apart from adding to the OI body of knowledge, this study also has practical relevance. Firstly, it is hoped that the research will assist organisations (and intermediaries) to leverage their existing external networks to form chains and solve innovation problems. The study therefore suggests a novel way for expanding the population of participants who contribute to the generation of OI solutions. Subsequently, this could lead to the development of systems and procedures which would enable the formation of referral chains in a quest to solve innovation problems. The methodological approach does not only apply in the field of innovation, but can be applied across fields.

Finally, the study also makes a methodological contribution: Software was developed that allowed for referrals and their real-time tracking, along with the simultaneous gathering of data which minimised data recall. In addition to this, the fsCQA analysis method used for this research, provided a configurational perspective, which is largely absent in OI research. Applying this analytical method in future OI research studies may create more insight around the complementarity and equifinality of OI processes.

1.5 Research design

A one-group, post-test, quasi-experimental design was used to conduct this study. It was necessary to design such an intervention because of the lack of any existing OI process that would enable searching through a chain of individuals not directly linked to the organisation.

Software had to be developed to facilitate the referral and solution submission processes. The research problem was sourced from a mining company, and the population from two associations: The International Association of Innovation Professionals (IAOIP), and the Southern African of Mining and Metallurgy (SAIMM).

A survey instrument of close-ended questions was posed during the referral process. The population for the study, an opted-in starter group of 121 individuals, was asked to solve a complex technical problem themselves, or tap into their social networks and source someone else who could do so. They, in turn, could tap into their own respective networks to seek a solution.

The unit of analysis was therefore the referral chain, which comprised two components: referrals and solutions. Seventy-five valid referrals stemmed from the starter population, which resulted in 60 referral chains. Six solutions were generated through chains, and three solutions were submitted by the starter population directly.

Individuals could search for innovative solutions in many different ways, along different search routes. For this reason, the fsQCA method was the most relevant and richest analytical method to use, in order to undercover the causal conditions in finding solutions (good and bad solutions). A quantitative method was added for regression analysis for finding solutions *per se* and not necessarily the quality of solutions. Apart from reliability analysis, logistic regressions were mainly used in the quantitative analysis. fsQCA is an analysis of set relations, whereby the effect of a combination of conditions on the outcome is more important than the evaluation of the effect of the independent variables on the dependent variable (quantitative analysis) alone.

1.6 Research questions and hypotheses

The over-arching research question probes the benefits of trusted bridging chains for open innovation:

Do trusted bridging chains have a positive effect on open innovation?

In order to answer the research question, the following research hypotheses were proposed:

- Hypothesis 1: Trust is positively correlated with the depth of search
- Hypothesis 2: Trust is positively associated with the quality of OI solutions
- Hypothesis 3: Diversity in knowledge bases is associated with the quality of OI solutions
- Hypothesis 4: Geographic diversity is associated with the quality of OI solutions
- Hypothesis 5: Depth of search is associated with the quality of OI solutions
- Hypothesis 6: Weak chains, more so than strong chains, are associated with the discovery of OI solutions, regardless of the quality of the solutions.

1.7 Assumptions and limitations

The study assumed that a referral would be an individual act and that one person would refer another individual, rather than an entity or organisation. Therefore, it assumed the use of interpersonal social network ties.

Considering that the referral chain went "forward" in terms of its assembly, questions were posed to the referring individual regarding their perception of the interpersonal relationship between themselves and the person referred.

The perception was not validated "backwards" to avoid complications over missing data. However, as studies have shown, trust is intrinsically reciprocal (Coleman, 1988; Ferrin, Bligh & Kohles, 2007; Putnam, 1995; 2000).

It was assumed that participants would have access to the internet and could communicate via email. For this reason, the platform was enabled through emails and hyperlinks via a website which facilitated the referral and solution submission process.

It was also assumed that anyone who referred another individual would have access to the latter's email address. However, this assumption may have negatively impacted the study. In fact, it is possible to connect with others solely through social media platforms, such as LinkedIn and Facebook, or a mobile phone, thereby circumventing email. Thus, if some participants were connected only through one of these other methods, this may have inhibited the referral process.

The software was coded so as to prevent anyone from referring an individual who had already been referred. It was assumed that this could cause cyclical chains. Yet, in hindsight, an individual may have been referred more than once by different participants.

At the onset of the study, the time-frame for solving an innovation problem was set at six weeks. Only later was this extended to just over two months. Most referral chains therefore comprised just two elements (i.e. only one referral), with a few extending to three.

The initial shorter time frame did not provide much opportunity after the first referral to refer a second or third individual. This inevitably affected the length of the chains and potentially the number of solutions found.

Finally, the lack of a true-experimental design may raise questions about validity. However, it should be noted that the context and nature of chains is grounded in complex “real life” situations which do not lend themselves to algorithm-based studies, even though these can be better controlled.

1.8 Organisation of the study

- **Chapter 2** sets out a detailed literature review and will provide evidence to show the benefits of trusted bridging chains in the search for OI solutions. The chapter describes the supporting and bridging features of social capital, and their impact on OI. Each argument culminates in a hypothesis.
- **Chapter 3** encompasses the research design and methodology. It describes the research paradigm, approach, methodological design, population, timing and unit of analysis. The research process is also included, followed by details regarding the instruments and data collection methods. The chapter ends by providing an overview of the analytical strategy, describing both fsQCA and the quantitative analysis.
- **Chapter 4** presents the results derived from the fsQCA as well as the quantitative analyses. The results are reviewed against the hypotheses.
- **Chapter 5** provides a brief overview of the study, including the problem statement and methods. It then presents a detailed discussion of the results, in relation to extant theory. The chapter is structured around the supporting and bridging features of social capital alongside each of the hypotheses.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

Organisations are continuously compelled to transform their innovation processes to counteract changing demand, economic downturn and severe competition.

Increasingly, they are looking outwards to do so: incorporating external technologies through alliances, partnerships and in-licensing – a paradigm known as “open innovation” (Chesbrough, 2003).

The quest for innovative ideas extends far and wide, but research has shown that searching too widely has a negative effect on innovation returns (Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Leitner et al., 2016; Vanhaverbeke et al., 2002).

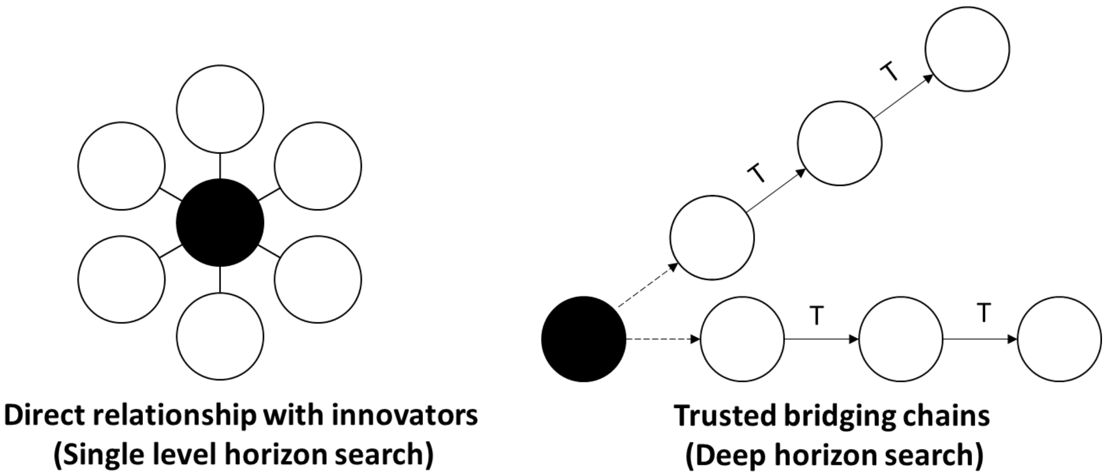
This study will reframe the notion of “searching”. It will show the effectiveness of depth as opposed to breadth of search, and will analyse the positive impact of building a chain – containing a sequence of agents (two or more) connected through trust relations – across deeper network horizons (see Figure 1).

For the purposes of this study, a trusted bridging chain is defined as*: a chain of agents, connected through trust relations characterised by diversity.*

By forming such a chain, an organisation can deliberately search for innovative solutions through indirect interpersonal relations (to the focal organisation), instead of passively waiting for indirect returns (Ahuja, 2000; Burt, 2007; 2010).

Figure 1 (below) shows the difference between the two approaches: single level horizon searching (based on one-to-many relationships) vs deep horizon searching (involving trusted bridging chains). It should be noted that most external OI relationships fall into the first category.

Figure 1: Single level horizon search vs. deep horizon search for OI



It has been shown that organisations may forge relationships directly with partners to source-in technology (Arora et al., 2001; Nicholls-Nixon & Woo, 2003; Veugelers, 1997); through alliances (Lambe & Spekman, 1997; Narula & Hagedoorn, 1999) or through R&D joint ventures (Peck, 1986). Some studies have also focused on the way in which organisations obtain information passively through indirect relationships (Ahuja, 2000; Burt, 2007; 2010).

In general, the following search strategies have been adopted in social network search: the screening search method (single level horizon search or eco-centric search), pyramiding (sequential) search (von Hippel, Franke & Prugl, 2009) and small world search (Milgram, 1967). Pyramiding is similar to the snowball sampling method (Goodman 1961; Welch 1975), whereby a starting population, with a high level of expertise, could be the starting point for the pyramiding search method, but unlike snowball sampling, the aim is to find people with better (or more of) a given attribute (Von Hippel, Thomke & Sonnak, 1999).

Little if any attention has been given to the search for innovative solutions specifically via a chain of interpersonal relationships across network horizon levels. By the same token, very few studies have focused on network ties that bridge organisational boundaries (Leenders & Dolfsma, 2016).

However, it is important to acknowledge research into the supporting features of social capital that have been shown to aid innovation performance. Such features include trust (Lee & Choi 2003; Nooteboom, 2013), learning, which often takes place in communities (Gilsing et al., 2008; Powell et al., 1996; Sorenson & Audia 2000), coordination and communication (Garton et al., 1997; Krackhardt, 1992; Laursen et al., 2015; Reagans & Zuckerman, 2001; Uzzi, 1996; Wellman & Wortley, 1990), as well as social integration (Laursen et al., 2012; Gnyawali & Srivastava, 2013).

Supporting relationships are generally seen to be reciprocal, with individuals supporting one another, learning from one another and sharing information and resources (Coleman, 1988; Levin & Cross, 2004; Lin, 2001; Putnam, 1995; 2000). In most cases it is posited that learning, coordination and communication would not be present in the absence of trust (Coleman, 1988; Putnam, 1995; 2000).

Furthermore, a cluster of concepts has been identified, relating to the bridging features of social capital. These concepts include diverse or new information obtained through weak ties (Granovetter, 1973; 1983); geographic distance (Beers & Zand, 2014; Capaldo & Petruzzelli, 2014; Letaifa & Rabeau, 2013; Levin & Barnard, 2013; Todo et al., 2015; Whittington et al., 2009); structural holes (Burt, 1982;1993; 2004) and knowledge diversity (Baum et al., 2000; Hargadon & Sutton, 1997; Powell et al., 1999; Pullen et al., 2012; Rodan & Galunic, 2004; Vanhaverbeke & Cloodt, 2006; Westergren & Holmström 2012).

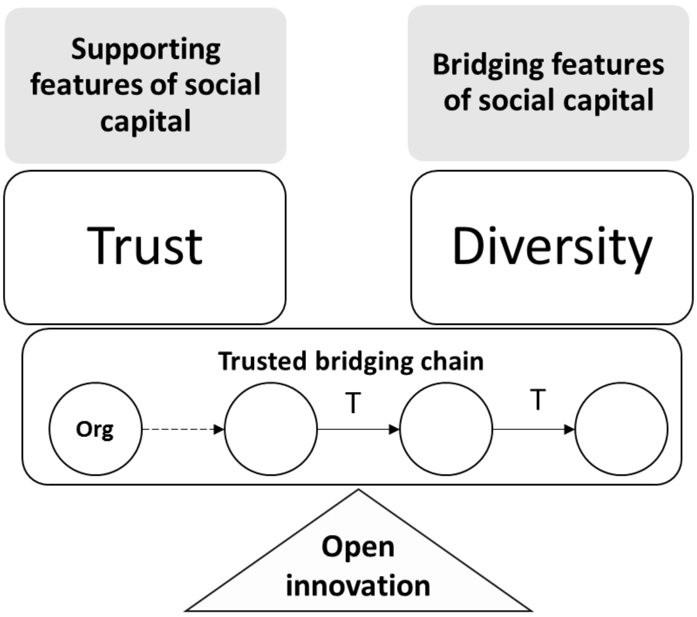
It has also been suggested that access to new information can be obtained through by-chance spill-overs of knowledge (Ahuja, 2000; Almeida & Kogut, 1999; Belderbos & Carree 2004; Burt, 2007; 2010; Jaffe et al., 1993; Owen-Smith & Powell, 2004).

Studies on innovation and networks have highlighted the importance of a balance of supporting relations (trust), and the bridging of relations (diversity) for returns, as depicted in Figure 2 (Burt, 2000; 2005; Fleming, Mingo & Chen, 2007; Gilsing et al., 2008; Rost, 2011; Savin & Egbetokun, 2016; Tiwana, 2008; Uzzi & Spiro, 2005; Watts, 1999; Watts & Strogatz, 1998).

Balance is important: it has been shown that a surfeit of supporting relations results in a closed network with limited novelty (Fleming et al., 2007; Uzzi & Spiro, 2005), while too much diversity can hamper mutual understanding (Nooteboom, 1992; 1999; Nooteboom, Van Haverbeke, Duysters, Gilsing & Van den Oord,

2007) and ultimately prove less effective and more expensive (Katila & Ahuja, 2004; Laursen & Salter, 2004; 2006; Vanhaverbeke et al., 2002).

Figure 2: A balanced approach of supporting and bridging features of social capital for OI returns achieved through a trusted bridging chain



This study proposes that a trusted bridging chain (as seen in Figures 1 and 2) which encompasses the supporting (trust) and bridging (diversity) features of social capital, can be the vehicle to unlock social capital for OI returns. By going deeper, and challenging the limitations of a single level horizon, such a chain can be leveraged to solve innovation problems for organisations, government departments and other entities, through harnessing the power of interpersonal relationships outside the boundary of the organisation.

Few if any studies have explored deep horizon search strategies for OI returns through indirect interpersonal relations to the organisation – a strategy which could offer an alternative to searching too broadly, and the challenges thereof (Katila & Ahuja, 2004; Laursen & Salter, 2004; 2006; Vanhaverbeke et al., 2002).

In most cases, chains have been studied retrospectively in job referral studies (Bian, 1997; Granovetter, 1973; Lin, 1999; 2005), and in small world studies (Newman, 2003; Uzzi & Spiro, 2005; Watts, 1999; Watts & Strogatz, 1998), with the latter mostly based on algorithmic problems rather than practical, “real world” challenges (Schnettler, 2009). Thus the small world phenomenon in principal suggests that we are all linked to one another by a short chain of acquaintances (Milgram, 1967).

The following sections of this literature review will focus on innovation and social capital, as well as the supporting and bridging features of social capital in relation to innovation networks. Finally, it will be argued that depth of search is the most effective strategy for building a trusted bridging chain.

2.2 Innovation

Without innovation no organisation can outsmart its competition or remain profitable. In today’s unpredictable economic climate, lack of innovation is tantamount to business suicide. Innovation is not merely an outcome, such as a new product, service or business model, but a process consisting of activities which produce, and capitalise on, the aforementioned outcomes.

Innovation might involve the reorganisation of a current production process; new functions or distribution arrangements which lead to increased efficiencies; and better support or lower costs (Kline & Rosenberg, 1986).

In 1947, Schumpeter first described innovation as “the doing of new things or the doing of things that are already being done in a new way” (Schumpeter, 1947, p. 151). Innovation, he suggested, was integral to the “creative response” of an economy or industry in reacting to changes in the environment in a different way, outside normal practices (Schumpeter, 1947, p. 150). Thus, it is neither ideas in themselves, nor scientific principles, that are key to economic practice: rather the application of ideas and “getting a new thing done” (Schumpeter, 1947, p. 153).

There is also a clear distinction to be made between an invention and an innovation. An invention is the detailed design of a new (and novel) product or process, while an innovation is the actual application of a novel product or process in practice (Slaughter, 1998).

Innovation has further been defined as “a sequence of activities involving the acquisition, transfer and utilization of information”, and “the initial market introduction of a new product or process whose design departs radically from past practice” (Abernathy & Clark, 1985, p. 3; p. 6).

Traditionally innovation occurred within the R&D, or strategy and marketing divisions of an organisation, and was thus considered a closed innovation process. By contrast, open innovation occurs when the innovation process is purposefully opened up to external ideas and knowledge.

2.2.1 Open Innovation

At least a decade before Chesbrough coined the term Open Innovation, scholars had highlighted the ability to exploit external resources as an important constituent of innovative performance (Cohen & Levinthal, 1990).

Then, Chesbrough (2003) explained that:

“Open Innovation means that valuable ideas can come from inside or outside the company and can go to market from inside or outside the company as well. This approach places external ideas and external paths to market on the same level of importance as that reserved for internal ideas and paths” (p. 43).

Chesbrough also pointed out that: “not all of the smart people work for us so we must find and tap into the knowledge and expertise of bright individuals outside our company”, adding that “we don’t have to originate the research in order to profit from it” (p. 38).

The definition of OI was later refined: “Open Innovation is the use of purposive inflows and out-flows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively” (Chesbrough, Vanhaverbeke & West, 2006, p. 1).

Subsequently, OI literature was divided into inbound and outbound pecuniary and non-pecuniary flows of knowledge (Dahlander & Gann, 2010). Thus, it was suggested that sourcing related to the non-pecuniary inbound flows of knowledge, ideas and information used to enhance the innovation capabilities of an organisation, whereas acquiring related to pecuniary inbound flows of expertise or technologies which are licensed-in, or acquired on the market, to enhance internal innovation capabilities.

This theoretical development led to a more nuanced definition of OI as: "a distributed innovation process based on purposively managed knowledge flows across organizational boundaries, using pecuniary and non-pecuniary mechanisms in line with the organization's business model" (Chesbrough, Vanhaverbeke & West, 2014, p. 17).

OI therefore encompasses two directions of knowledge flows: namely, outside-in (inbound) or inside-out (outbound). A third category was later identified as coupled open innovation, referring to combined knowledge in, and outflows between, actors (Chesbrough et al., 2014).

While it is clear that OI is not an entirely new concept, and that external knowledge has been incorporated into innovation processes for some time (Cohen & Levinthal, 1990), there is now greater acknowledgement of the contribution of purposive external resources.

Traditionally closed innovation processes relied most heavily on internal innovation resources (such as R&D, strategy or marketing departments) to produce innovations and would invest in their internal innovation capital – including human resources, laboratories and other innovation resources – in the production of innovations and associated returns. Such an approach requires internal control because organisations must generate their own ideas and then develop, build, market, distribute, service, finance, and support them on their own.

"This paradigm councils firms to be strongly self-reliant, because one cannot be sure of the quality, availability and capability of others' ideas" (Chesbrough, 2004, p. 23).

Closed innovation allowed organisations to control the complete innovation process: from inputs, through process to outputs, culminating in eventual returns. Thus, initial OI models followed an essentially controlled linear model: external source → focal organisation → commercialisation (West & Bogers, 2014).

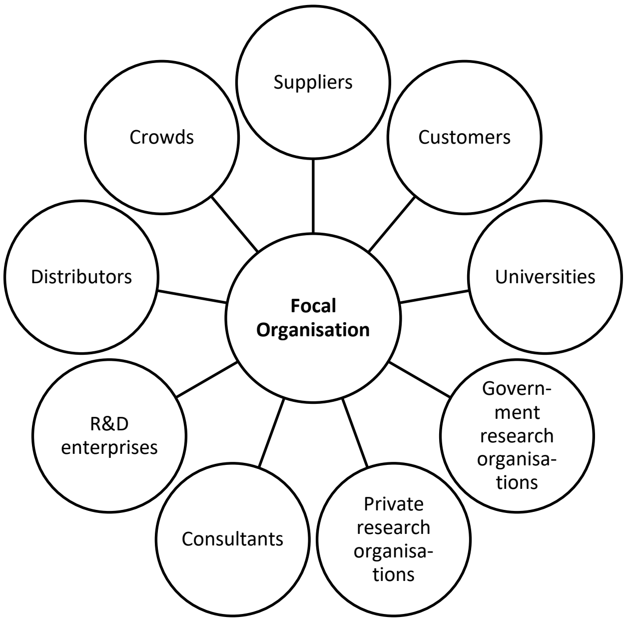
Recently however, more nuanced models for utilising external sources of innovation have been developed. These include interactive feedback loops, co-creation with external co-creators, and integration with innovation networks and communities (West & Bogers, 2014).

Over the last decade or so, organisations have started to practice a more open form of innovation by not merely relying on their internal innovation capital, but looking externally for innovations to solve problems or leverage opportunities. Organisations differ regarding the level of external R&D integration, which may include technology sourcing and acquisition (Arora, et al., 2001; Nicholls-Nixon & Woo, 2003; Veugelers, 1997; West & Bogers 2014); strategic alliances (Lambe & Spekman, 1997; Narula & Hagedoorn, 1999) with external suppliers; or collaborative R&D joint ventures (Peck, 1986).

The various channels through which organisations can practise OI include research organisations (e.g. universities) with direct contracts to the focal organisation; electronic requests for proposals raised by the focal organisation to solve problems (a tender process or innovation competitions); off-shoring; and crowdsourcing (Hagman & Sonde, 2011; Howe, 2008). The latter involves requesting ideas from large groups of people, generally in the form of an online competition that is broadcasted to relevant communities.

Other channels for OI include consulting with other organisations and entering into joint ventures (Bingham & Spradlin, 2011). The main external sources of knowledge are depicted in Figure 3, based on input from Gemunden, Ritter and Heydebreck (1996); Howe (2008); and Laursen and Salter (2006).

Figure 3: Main external sources of knowledge



So to date, OI has been operationalised mostly through direct inter-organisational links with innovators or by contracting an intermediary (such as NineSigma) to source innovators through its networks, which is almost always single horizon, at a direct level (see Figure 3).

The majority of mechanisms for OI include relatively formal arrangements through strategic alliances, joint ventures, license agreements or other types of agreements (Ye & Kankanhalli, 2013) between the focal organisation and the innovator. These are facilitated either directly by the focal organisation or through an intermediary organisation. However, there seems to be no OI strategy for seeking innovative solutions through a deeper horizon by means of a network chain of interpersonal relationships. In most instances, an organisation will build a network of innovators linked directly to the organisation, use an intermediary to find an innovator to solve a problem through the intermediary’s network, or broadcast the challenge directly to a group of people.

Considerable emphasis has been placed on external networks for innovation performance, referred to as “network-centric innovation” (Nambisan & Sawhney, 2011). Yet, although significant research has analysed the effect of inter-organisational networks on innovation, very little has focused on boundary spanning network ties (Leenders & Dolfsma, 2016), while even less has explored deep boundary spanning searching for innovative solutions through indirect interpersonal relationships.

Given the importance of network-centric innovation *per se*, the concept of social capital returns through networks has become increasingly relevant. Theories on social networks and social capital share key concepts: for example, the relational and structural qualities of networks, such as the strength of ties (Granovetter, 1973; 1983), and clusters (or groups) respectively (Coleman, 1998).

The focus of this study is on deep boundary spanning search through social network ties. It is therefore important to consider social capital at this point, as concepts of supporting and bridging relations are integrated across networked innovation and social capital bodies of knowledge.

Social capital

Essentially, social capital refers to the return/s that one (or many) can gain through social networks with innate structural and relational characteristics (Coleman, 1998; Lin, 2001). Thus, to enable innovation, it follows that social capital returns (or resources) would have to be novel and diverse.

However, the development of social capital theories has been hindered by manifold definitions with different and misaligned theoretical foundations and operationalisations (Payne et al., 2011). Considering the focus on resources (OI returns) derived through social networks, it is therefore appropriate to cite Nahapiet and Ghoshal’s definition of social capital as: “the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit” (1998, p. 243). Yet, the functional view of social capital is important, so it can also be identified “when and if it works” (Lin, 2001, p. 27).

Definitions of social capital vary, depending on whether there is a focus on the source, the substance, or the effects (Adler & Kwon, 2002). For this reason, conceptual clarity is lacking, and the causality and measurement of social capital are contested (Patulny & Svendsen, 2007). Moreover, social capital theory identifies bonding social capital and bridging social capital as separate categories (Lin, 2005; Portes, 1998; Putnam, 2000) but does not recognise the bonding or bridging features of social capital.

However, a trusted bridging chain can combine both the supporting and bridging features of social capital (as illustrated in Figure 2). OI returns can therefore be simultaneously derived from supporting (trust) and bridging (diversity) social capital.

2.2.1.1 Supporting features

It has been suggested that the components of “bonding social capital” (Putnam, 2000) should be grouped under “supporting features of social capital”, because of the density underpinning the concept of bonding, which creates ambiguities when the focus is on dyadic relations.

Historically, bonding social capital referred to closed, inward-looking networks (Putnam, 2000), making it more relevant to homogenous groups or clusters. There was evidence of a “structural tendency for strong ties to cluster in dense, island-like cliques and weak ties to scatter widely as non-redundant bridges that link cliques together” (Frenzen & Nakamoto,1993, p. 373). It was also found that strong ties could act as a substitute for the benefits derived from dense structures (Granovetter, 1973; Levin, Walter, Appleyard & Cross, 2015).

Cliques resemble the most inner layer of relations, which are characterised by intimate and confiding relationships between people who share sentiment and provide mutual support (Lin, 2005, p.12). Cliques also exhibit strong trust relations between individuals which facilitate coordination and cooperation (Putnam, 1995).

However, this study will suggest that the innate element of “bridging” within a chain contradicts the notion that a trusted bridging chain is a “clique”. Moreover, the social capital returns leveraged through cliques are motivated mainly by the desire to maintain status quo (or resources), rather than to seek the return of something new or improved (deliberate action). This is particularly due to the high rate of homophily between members of a clique (Lin, 2005; McPherson, Smith-Lovin & Cook, 2001; Putnam, 1995).

For example, if the house owners in a small neighbourhood take turns to patrol their boomed-off area to ensure communal safety and security, they can collectively gain from this action by enlisting the help of other house owners in their area. They all know one another, look out for one another's well-being in the community, and cooperate and coordinate actions that will help maintain the status quo of their safety, security and unity. However, if a homeowner wants to find a buyer for one of the houses in the community, the homeowner needs to reach out beyond the clique and leverage bridging features of social capital.

Such examples show how a chain differs from a clique, because the former is composed of trusted relationships between individuals in the chain, but bridges across deeper horizons to find innovative solutions to problems.

Features of bonding social capital include trust, obligations, expectations, reciprocity, norms and values (Coleman, 1988). At a dyadic level, the strength of ties can provide the same benefits as network closure and can therefore be a substitute for network closure, which stimulates sharing and cooperating behaviour (Coleman, 1988; Granovetter, 1985; Levin & Cross, 2004; Levin, et al., 2011; Levin et al., 2015).

It is therefore proposed that the notions of trust and strong ties be categorised as supporting features of social capital. In fact, trust facilitates obligations, expectations and reciprocity (Coleman, 1988) as well as learning (Nielsen & Nielsen, 2009). Moreover, some features of social organisation, such as trust, can have a positive effect on social capital returns, and consequently OI returns.

Putnam (1995, p. 66) referred to social capital as "features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit". Network features and resources (returns) are not equivalent, and network features are important antecedents of social capital (Lin, 2001). Therefore, supporting features (such as trust) can be necessary preconditions to achieve bridging (Levin & Cross, 2004; Levin et al., 2011; Levin et al., 2015).

Networked innovation studies have shown that many organisations innovate from within clusters, and that supporting relations provide the assistance for organisations to share, learn and innovate (Gilsing et al., 2008; Gnyawali & Srivastava, 2013; Krackhardt, 1992; Nielsen & Nielsen, 2009; Powell et al., 1996; Wellman & Wortley, 1990; Reagans & Zuckerman, 2001; Sorenson & Audia, 2000; Schilling & Phelps, 2007; Uzzi, Amaral & Reed-Tsochas, 2007; Whittington et al., 2009).

Most importantly, supporting features of social capital inhere trust, which underpins support for innovating organisations (Clegg, Unsworth, Epitropaki & Parker, 2002; Dakhli & Clercq, 2004; Landry, Amara & Lamari, 2002; Lee & Choi, 2003; Moran, 2005; Nooteboom, 2013; Powell et al., 1996; Tsai & Ghoshal, 1998). These trusted relationships can exist in groups, clusters or in the dyadic relationship between two entities (Granovetter, 1973), which may (or may not) form part of the same cluster or group. Context would determine whether to study the cluster or the dyadic tie (Marsden & Campbell, 2012), although supporting relations can represent both. In this study the context and nature of dyadic relations are important, considering that these types of relationships form a chain.

Trust

Trust is an important feature of social capital, facilitating cooperation, coordination and sharing of information (Coleman, 1988; Levin & Cross, 2004; Putnam, 1995; 2000). Trust can also enhance the utility of embedded resources (Lin, 2001). In fact, trust has been shown to have a more positive effect on knowledge transfer than emotional closeness and interaction frequency (Levin et al., 2011; Levin et al., 2015).

Innovation often requires the “willingness to take risks” (Johnson-George & Swap, 1982, p. 1306) and to share rich and sensitive information, which is founded on trust (Krackhardt & Hanson, 1993). Trust is defined as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis & Schoorman, 1995, p. 712).

According to the model developed by Mayer et al. (1995) the components of perceived trustworthiness are: ability (skills and competencies), benevolence (affect-based) and integrity. Similarly, McAllister (1995) showed that cognition-based trust (competence) and affect-based trust (benevolence) are two distinct, although related, dimensions.

To the extent that trust encourages voluntary and non-obligating exchanges between actors, it is a governance mechanism (Uzzi, 1996). Therefore, when working together towards a specific outcome (performance or innovation), there is an interdependence between people, because they depend on one another for information and cooperation (Nooteboom, 2013).

This kind of interdependence involves some risk, such as self-serving behaviours which may impede the sharing of information and cooperation.

There is a strong connection between trust and innovation. Trust is connected to uncertainty and in most respects, exploration for new ideas is underpinned by uncertainty, therefore trust is required to balance this uncertainty. Trust has also been shown to be the prerequisite for innovation network ties in project teams (Shazi, Gillespie & Steen, 2015).

Trust in general, as well as institutional trust, facilitates innovation (Dakhli & Clercq, 2004; Ellonen, Blomqvist & Puumalainen, 2008). Institutional trust occurs when individuals have trust in their institution or organisation – a situation which has a mediating effect on exchange, and protects individuals against any breach of trust (Dakhli & Clercq, 2004). Hence, when reaching across organisational boundaries to solve an innovation problem, institutional trust would not be a factor.

Thus, through referring a complex innovation problem to another person to solve, who may in turn refer another individual, a chain of rich information exchange – built on trust – is assembled (Inkpen & Tsang, 2005; Krackhardt & Hanson, 1993;

Levin & Cross, 2004; Levin et al., 2015; Nooteboom, 2013; Uzzi, 1996). The referrer depends on the person referred for information and cooperation (Nooteboom, 2013). They, in turn depend on the next person in the chain, and so on.

In addition to this, trust can be a causal proposition facilitating the use of embedded resources and thus a necessary precondition to achieve bridging (Levin et. al., 2011; Lin, 2001; Shazi et al., 2015). This reasoning suggests that a chain would be moved forward by trust, and the first hypothesis:

Hypothesis 1: Trust is positively correlated with the depth of search.

In many respects, the *value* of knowledge received during exchange, as well as innovation *per se*, is facilitated by trust (Clegg et al., 2002; Dakhli & Clercq, 2004; Inkpen & Tsang, 2005; Landry et al., 2002; Lee & Choi, 2003; Levin & Cross, 2004; Levin et al., 2014; Levin et al., 2015; Moran, 2005; Tsai & Ghoshal, 1998). Furthermore, learning often happens within the context of membership in communities (Powell et al.,1996) and is also facilitated by trust (Nielsen & Nielsen, 2009). New entrepreneurs arise more often from dense locations (incorporating supporting relationships) and survive better than others who do not, which suggests that they are in a position to learn and accumulate knowledge from supporting relations (Sorenson & Audia, 2000) and therefore innovate more effectively.

Relationships based on trust lead to better knowledge exchange (Inkpen & Tsang, 2005; Levin & Cross, 2004; Levin et al., 2015). As such, trustworthiness has been positively associated with resource exchange, which, in turn, positively affects innovation (Tsai & Ghoshal, 1998). Trust is also seen as important for the generation of new ideas and products (Clegg et al., 2002; Lee & Choi 2003); while trust and networks of learning are particularly important for innovation and sharing of resources (Clegg et al., 2002; Dakhli & Clercq, 2004; Landry et al., 2002; Lee & Choi, 2003; Moran, 2005; Powell et al.,1996; Tsai & Ghoshal, 1998). This leads to the hypothesis:

Hypothesis 2: Trust is positively associated with the quality of OI solutions

2.2.1.2 Bridging features

Bridging social capital suggests open networks and comprises people or entities linked across diverse social circles (Putnam, 2000).

In short, bridging features of social capital can be leveraged through relationships with others through weak or strong ties that bridge diverse information (Burt, 1993; 2004; 2005; Granovetter, 1973; Levin & Barnard, 2013; Levin & Cross, 2004), and also through brokerage that taps indirect relationships for returns (Bian, 1997; Granovetter, 1973; Lin, 1999; Lin, 2005), as covered in job referral studies.

Bridging features of social capital are needed to source something new or improved, although in most respects supporting features of social capital (such as trust) may be a requirement to bridge (Lin, 2001).

Weak ties can also provide access to diverse sources (Aldrich, Rosen & Woodward, 1987; Bloodgood, Sapienza and Carsrud, 1995; Hauser, Tappeiner & Walde, 2007) which are particularly important for innovation.

Bridging brings about diversity by means of weak ties (Granovetter, 1973; 1983; Hauser et al., 2007); geographic distances (Beers & Zand, 2014; Capaldo & Petruzzelli, 2014; Letaifa & Rabeau, 2013; Levin & Barnard, 2013; Todo et al., 2015; Whittington et al., 2009); and structural holes (Burt, 1982; 1992; 2004). Structural holes result from knowledge diversity through links to diverse relationships (Baum et al., 2000; Hargadon & Sutton, 1997; Hargadon, 2003; Powell et al., 1999; Pullen et al., 2012; Rodan & Galunic, 2004; Vanhaverbeke, et. al., 2006; Westergren & Holmström, 2012). Bridging can also occur through by-chance spill-overs of knowledge (Ahuja, 2000; Almeida & Kogut, 1999; Belderbos & Carree, 2004; Burt, 2007; 2010; Jaffe et al., 1993; Owen-Smith & Powell, 2004;).

Structural holes

A structural hole is a disconnect between individuals, companies or groups (Burt, 1993). It could provide an opportunity for diversity when an individual knows two different people who do not know one another. Burt's (1992) theory on structural holes is similar to Granovetter's (1973) theory on the strength of ties, in that both focus on how an individual is exposed to novel information.

According to Kilduff (2010) the difference between the theories is *inter alia,* that Burt's view is more strategic than Granovetter's, which emphasises by chance linkages to novel information and maintains that an individual (or organisation) may be a passive player but still gain information benefits.

However, control benefits require action in terms of the active distribution of information (Burt, 1993). Many organisations wishing to enhance diversity within their innovation process would specifically forge relationships with diverse (previously unconnected) organisations or individuals, instead of passively waiting for information. The focus is therefore on control benefits, or *tertius gaudens* - the third who benefits from the disconnection of two others (Simmel, 1950).

The pyramiding search method (von Hippel, Franke & Prugl, 2009) is an example of traversing structural holes in the search of experts (i.e. lead users), across domains. The pyramiding search process endeavours is to find people with better (or more of) a given attribute, at a higher level (Von Hippel, Thomke & Sonnak, 1999) also across domains (Poetz & Prügl, 2010). Furthermore, in pyramiding search, the search for each new member is very much reliant on the researcher's own motivation or that of the organisational team that manages the search process (Poetz & Prügl, 2010). For this reason, the pyramiding search method does not necessarily form a purposeful search chain, controlled by each referring individual.

The theoretical framework for the bridging of structural holes is covered by Burt in various publications (Burt, 1993; 1997; 2000; 2004; 2005). Burt further maintains that social capital can be gained through a person's relationships with "friends, colleagues, and more general contact through whom you receive opportunities to use for your financial and human capital" and that social capital is a function of "the brokerage opportunities in a network" (Burt, 1997, p. 340).

Therefore, innovation returns can be gained by dynamically searching through a chain of interpersonal relationships to solve an innovation problem. In this way it is possible to “traverse structural holes”. Individuals with greater access to structural holes have a higher chance of success in terms of sourcing potentially valuable ideas and opportunities (Burt, 2007). Such individuals are also more likely to know of someone else who may be able to solve an innovation problem. Thus, an individual may be a passive player, and yet still gain information benefits (Burt, 1993) although action is required to leverage these benefits.

In short, control benefits require action in terms of the active distribution of information (Burt, 1993). The dynamic search (action) required to solve an innovation problem, could trigger an individual to use their structural holes more actively, although the fact that they hear interesting new information may result from passively “listening” to information from within their network.

Therefore, in innovation network studies, structural holes represent access to diverse information from links to diverse types of innovation partners (Baum et al., 2000; Burt, 1982; Burt, 1993; Burt, 2004; Hargadon & Sutton, 1997; Powell et al., 1999; Pullen et al., 2012; Rodan & Galunic, 2004; Vanhaverbeke et al., 2006; Westergren & Holmström, 2012).

Knowledge diversity

Extant theory on innovation and networks has shown that forging relationships with diverse innovation alliance partners has a positive effect on innovation. Different associations can lead to creative ideas and innovation (Rodan & Galunic, 2004). Diverse portfolios of collaborations, which include non R&D relations, affect innovation performance positively (Baum et al., 2000; Powell et al., 1999). Thus, an OI strategy promoting knowledge exchange to multiple diverse sets of organisations, albeit within a regional cluster, would affect innovation positively (Simard & West, 2006).

Diverse partners are often able to contribute complementary resources and assets which are beneficial to an organisation’s innovative performance (Becker

& Dietz, 2004; Miotti & Sachwald, 2003; Pullen et al., 2012; Roper, Du & Lover, 2008; Vanhaverbeke, 2006).

Collaboration with different types of partners, inherent in the structure of an organisation's collaborative networks, has shown to breed novelty and innovation (Nieto & Santamaria, 2007). A larger variety of sources of information to develop and improve products has been shown to be particularly valuable to the innovation process (Amara & Landry, 2005), as long as it is accompanied by trust (Pullen et al, 2012; Vanhaverbeke et al., 2006; Westergren & Holmström, 2012).

Moreover, research shows that helping partners to interrelate and share information and knowledge between each other (technological interweavement) also affects innovation positively (Gemunden et al., 1996).

Technological interweavement covers the technology-orientated relationship of the organisation as a whole, including acquiring and cooperative development. This kind of collaboration is facilitated by trust and learning through the cumulative development of absorptive capacity over time. The concept of "absorptive capacity" was introduced by Cohen and Levinthal (1990) who argue that such capacity accumulates over time as it builds on prior knowledge. Thus, it is easier to learn and understand new technologies when there is a history of understanding of existing technologies in the same domain.

Yet, it is debatable whether long-term interweavement with the same partners could bring about novelty, as essentially the bridging aspect would gradually diminish (Levin et al., 2011). Indeed, studies have shown that frequent interaction may lead to knowledge saturation (McFadyen & Cannella, 2004): hence, dynamically searching among indirect interpersonal relationships to the organisation could access novelty from previously unknown resources.

The search for diverse partners can depend on an organisation's commitment to develop novel or incremental innovations, which is often driven by the organisation's environment or innovation context (Rowley, Behrens & Krackhardt, 2000).

The notion of exploration is frequently associated with searching for a number of diverse partners, whereas exploitation relates more to utilising current relationships to the fullest. Exploration and exploitation could also be separate innovation activities within a sequential process: for example, exploration followed by exploitation (Rothaermel & Deeds, 2004). Thus exploration alliances would lead to product development, while exploitation alliances would lead to products on the market (Rothaermel & Deeds, 2004). Over-exploration for novelty could however eventually result in decreasing innovation performance (Vanhaverbeke et al., 2002), as the concept of exploration (searching for diverse partners) is similar to search breadth, defined by Laursen and Salter (2006).

Search breadth equates to the number of an organisation's diverse partners. In effect, the openness of an organisation is believed to be related to the number of different external innovation network sources it has (Laursen & Salter, 2004; 2006). However, when organisations over-search it can have an adverse effect on innovation performance. The relationship between openness and innovation performance has therefore been shown to be curvilinear (Ahuja, 2000, Katila & Ahuja, 2002; Laursen & Salter, 2006; Vanhaverbeke et al., 2002).

It has been demonstrated that there is an optimum number of external sources (sources who are not known to one another and thus bring about diversity) in relation to innovation performance, beyond which performance decreases, as the relationship is a function of the context and benefits sought (Ahuja, 2000). Similarly, Laursen and Salter (2006) have shown that increasing the number of different innovation sources beyond a certain threshold also decreases innovation performance.

Considering the challenges of searching too widely for innovative solutions (Ahuja, 2000; Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Vanhaverbeke et al., 2002), this study will show the effectiveness of searching deeply across horizons, to solve innovation problems. In this context it is hypothesised that depth is driven by trust, and quality by trust and diversity. Knowledge differences are also inherent in industry differences, considering that each industry has its own distinct knowledge-base which forms the basis of inter-industry differences (Li & Vanhaverbeke, 2009). Large inter-industry differences (between the innovating organisation and a partner) can provide organisations with great novelty value (Li & Vanhaverbeke, 2009). For example, an organisation like IDEO can successfully innovate by forging relationships across diverse industries (Hargadon & Sutton, 1997).

Valuable breakthrough products often originate as a result of technology brokering, where ideas and concepts from one industry are applied in another unrelated industry (Hargadon, 2003). Therefore, considering that the potential differences in knowledge between individuals (or entities) would largely encapsulate industry differences as well, it is suggested that knowledge heterogeneity (measured by Rodan and Galunic, 2004) encapsulates industry differences as well. So when an individual refers another individual to solve a problem, then it would be relevant to review their dyadic knowledge diversity which encapsulates industry differences as well (Li & Vanhaverbeke, 2009; Rodan & Galunic, 2004).

Most studies on innovation and networks analyse the network around the ego (focal organisation) to determine diversity or measure technology distances between patent classes (Aharonson & Schilling, 2016; Ahuja, 2000; Ahuja & Katila, 2001; Laursen et al., 2015). Limited studies cover dyadic knowledge difference between only two entities and subsequent entities forming a chain.

Considering that a chain is formed by individual referrals, followed by further referrals and so on, it is suggested in this study that the knowledge heterogeneity of a tie should be measured by analysing the knowledge diversity between two agents (between the referrer and the referred individuals) in the chain.

The dyadic knowledge diversity of a tie is suggested to be a (probably linear) distance between the professional knowledge differences between agents which characterise a dyadic tie.

Since knowledge difference leads to innovation (Baum et al., 2000; Becker & Dietz, 2004; Hargadon, 2003; Miotti & Sachwald, 2003; Powell et al., 1999; Pullen et al., 2012; Rodan & Galunic, 2004; Roper et al., 2008; Vanhaverbeke, 2006), as do differences between patent classes which cover different knowledge bases (Aharonson & Schilling, 2016; Ahuja, 2000; Ahuja et al., 2001; Laursen et al., 2015), it can be hypothesised that dyadic knowledge diversity would affect the quality of innovation solutions located. This leads to the hypothesis:

Hypothesis 3: Diversity in knowledge bases is associated with the quality of OI solutions.

Geographic distance

Dense local clustering of alliance networks alongside relations across geographic distances (i.e. global reach) provides access to diverse information (Whittington et al., 2009). Many studies have indicated the importance of clusters as a supporting mechanism for learning and innovation, considering that they enable collaboration (Coleman, 1988). Yet, many clusters have failed to collaborate despite being geographically close.

For example, Letaifa and Rabeau (2013) studied one such ICT public-private innovation cluster. The study explored how geographic, institutional, cognitive and social proximities were interrelated. It was found that social interaction was the most important element for achieving collaboration. However, although social interaction facilitated communication, the transfer of knowledge and collaboration, the study revealed that too much close social interaction caused an overly closed-up community of people (Letaifa & Rabeau, 2013).

Hence, excessive proximity has a negative effect in that it may cause “lock-in” which inhibits the inflow of new information, although it facilitates learning (Boschma, 2005). In fact, greater geographic distance has been found to be an accelerator of entrepreneurship and innovation (Letaifa & Rabeau, 2013).

In effect, geographic proximity has little value unless there is access to unconstrained (by cognitive factors), open and diverse relationships (Crescenzi, Nathan & Rodríguez-Pose, 2016). It has also been shown that foreign partners are important conduits for new information, when access to local diversity is low (Beers & Zand, 2014). There is evidence that collaboration with geographically distant alliance partners can provide access to diverse resources (Capaldo & Petruzzelli, 2014). Even strong ties from abroad have presented useful information to the requester (Levin & Barnard, 2013) and relationships across distance have had a positive effect on innovation capabilities (Todo et al., 2015).

It is clear that distance matters, even though it complicates technological and scientific collaboration (Nooteboom, 1992; 1999; Nooteboom et al., 2007; Nooteboom, 2013). Organisations that are in better global positions can more easily reach across geographic boundaries to access novel information (Whittington et al., 2009). However, when an organisation lacks a global network position, then searching through individuals who may have such relationships could also facilitate the reaching across geographic boundaries for innovative solutions.

It is therefore suggested that the geographic distance of a tie is a probably linear distance between geographic locations of agents which characterises a dyadic tie. This leads to the hypothesis:

Hypothesis 4: Geographic diversity is associated with the quality of OI solutions.

2.2.1.3 Depth of search: Trusted bridging chains

A trusted bridging chain is defined in this study as a chain of agents, connected through trust relations characterised by diversity. Hence, a trusted bridging chain is balanced between trust and diversity.

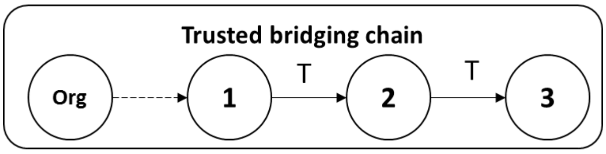
Previous research has indicated that a balance of supporting and bridging relations is optimum for innovation or performance (Burt, 2000; 2005; Fleming et al., 2007; Gilsing et al., 2008; Rost, 2011; Savin & Egbetokun, 2016; Tiwana, 2008; Uzzi & Spiro, 2005; Watts, 1999; Watts & Strogatz 1998).

Inventions by individuals who are not residing centrally in a dense network, but more on the periphery, though not so peripheral that other network members cannot be reached (i.e. in a bridging position) also have the highest impact on future technological knowledge (Gilsing et al., 2008). Considerable diversity has innovation potential but lacks integration, while too much integration leads to redundancy and minimal innovation potential (Tiwana, 2008).

Similarly, inventions by individuals that are embedded in dense networks, but not so dense that all exchanges are redundant, have the highest impact on future technological knowledge (Rost, 2011; Savin & Egbetokun, 2016). So, too much supporting and closed relationships inhibit access to diverse information (Fleming et al., 2007; Uzzi & Spiro, 2005) and too much diversity restrains mutual understanding (Nooteboom, 1992; 1999; 2013).

A trusted bridging chain could be the vehicle to unlock social capital for OI returns, represented by a balance of supporting (trust) and bridging (diversity) features of social capital (see Figure 4 below). So, trusted bridging chains can be beneficial for OI and bring about OI returns.

Figure 4: Trusted bridging chain



A chain of referrals (referred individuals) is formed through the act of brokerage which can be defined as “as a relation in which one actor mediates the flow of resources or information between two other actors who are not directly linked” (Fernandez & Gould, 1994, p. 1457). As illustrated in Figure 4, the ultimate recipient of the social capital return is the organisation and not the brokers (number 1, 2 and 3) *per se*.

This study therefore defines recursive brokerage as: The repeated act of brokerage in an instrumental search, where several actors (at least more than one) form a trusted bridging chain, whilst mediating the flow of interim resources or information (referrals) between themselves and the seeker to find an ultimate new or improved resource.

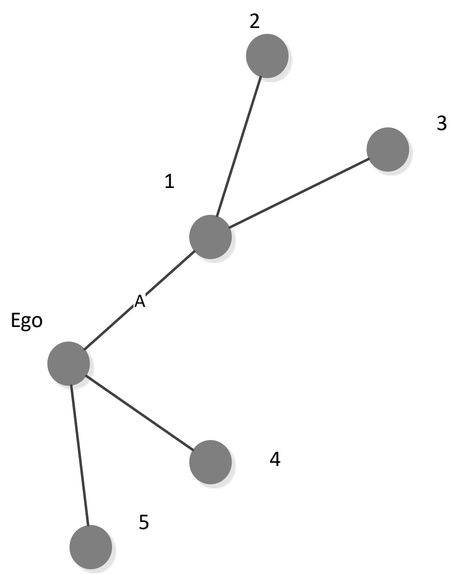
It will be argued that recursive brokerage is not the same as Burt’s (2007; 2010) notion of “secondhand brokerage”.

Secondhand brokerage

The concept of "secondhand brokerage" refers to the moving of information between agents who are connected to one another only indirectly (Burt, 2007: p. 121). Yet, there are no returns to being connected to a broker unless on is a broker oneself (Burt, 2007; 2010). This means, if individuals (see Figure 5) do not have their own structural holes from which to reap benefits (and broker information), they will not be able to reap benefits through another broker (See relationship A with number 1 in Figure 5 below).

In other words, if an individual does not socially integrate with many other diverse people (structural holes), then this individual will not gain the benefits of others' structural holes (access to diverse information).

Figure 5: Secondary hole example



Burt (2007) asserted that there is higher return from direct brokerage than secondhand brokerage if information is complex (such as a complex technical problem to be solved). Thus, secondhand brokerage would be an advantage when moving simpler information between groups, but solving a complex, technical problem between groups would specifically require direct brokerage.

Evidently, direct brokerage could take place recursively and form a chain as explained above. The advantages of secondhand brokerage (receiving new but not complex information) would be enabled through social integration, which often take places in clusters and groups (Gnyawali & Srivastava, 2013).

Organisations that operate with high levels of social interaction (supporting relations) are more likely to innovate products (Laursen et al., 2012). Therefore, people who socially integrate across supporting relations may learn about innovative ideas that have spilled-over (Gnyawali & Srivastava, 2013; Laursen et al., 2012): a notion similar to Burt's (1992) concept of secondhand brokerage. Thus, an individual may source an innovative idea through another individual, or hear about such an idea through their supporting relations during social integration, which may provide access to distant links that can bring about diverse information.

Therefore, secondhand brokerage can also be seen in terms of the benefits received as a result of spill-overs (involuntary leakage or voluntary transfers of knowledge) alongside partner relationships that affect innovation positively (Belderbos & Carree, 2004). Often, formal relationships between organisations allow for access to new knowledge through informal channel spillages (Owen-Smith & Powell, 2004). In addition to this, supporting relationships often invoke informal relationships which then become conduits for new and diverse knowledge (Jack, 2005).

Furthermore, similar to Burt's secondhand brokerage concept, studies have shown that indirect relationships to an organisation are also good for innovation because relationships can serve as a mechanism for knowledge spill-overs (Ahuja, 2000). Inter-organisational mobility of individuals (moving between organisations) also results in spill-overs, as ideas are transferred through labour markets (Almeida & Kogut, 1999).

However, other research has suggested that spill-overs tend to be geographically bounded within the region where the knowledge was created (Audretsch &

Feldman, 1996; Feldman, 1994; Jaffe et al., 1993). Hence, if new knowledge is generated in a different geographic location, it may not naturally spill across geographic boundaries, unless purposely searched for through relationships that reach across these boundaries. This will be a major focus of this study.

Spill-overs can also take place across different networks where members co-mingle when they reside on the overlap between networks, and thus belong to more than one network (Murray, 2002). Often pathways from dense clusters to diverse organisations can also bring about diversity (Fleming et al., 2007; Porter, Whittington & Powell, 2005; Uzzi & Spiro, 2005) which can happen as a result of overlapping networks.

Spill-overs therefore allow for diversity to enter the innovation process (Belderbos & Carree, 2004; Owen-Smith & Powell, 2004). Spill-overs imply that individuals from within groups and organisations are introduced to others beyond the normal bounds of the organisation, often through supporting relations (from within the group or collectively). These spill-overs bring about diversity which is positive for the innovation process (Jack, 2005). In practice, organisations do not formally leverage spillages for their OI processes; it happens by chance (Ahuja, 2000).

It is therefore important to describe and define a formal process for tapping these spillages (and searching deeper) by sourcing innovation solutions though indirect interpersonal relationships to the focal organisation. So far, this has not been explicitly covered in OI studies.

In today's world, spill-overs (and secondhand brokerage) happen all the time. Physically and electronically people know (or know about) more people than ever before, and as this knowledge proliferates, more people gain access to new ideas about innovation.

Job referral studies are yet another form of spillage that can be beneficial for individuals when finding a job, although the chain is not always purposely formed.

Job referral chains

Granovetter's 1973 work is iconic in network research, and it is telling that it explicitly deals with chains. His work has spurred a number of subsequent studies on job referral chains, but those studies have generally been conducted *post hoc*, by asking individuals how they found a job, or who helped them to find one. In most cases the chain was particularly short, demonstrating only one link between the ego and the employer – e.g. ego-contact-employer – Lin (1999) or at most involving one intermediary between the contact and the employer, e.g. ego-contact-intermediary-employer (Bian, 1997).

Granovetter's (1973) seminal paper on the strength of weak ties demonstrated how an individual could leverage weak ties to obtain the benefits of social capital, such as finding a job *post hoc*. The job seeker was asked who had helped them to find employment, and in the majority of cases jobs were found through weak ties (Granovetter, 1973). It can therefore be assumed that solutions to innovation problems may also be found through weak ties, although the quality of solutions may not be related to the strength of the tie, considering that both weak and strong ties generate useful information (Jack, Dodd & Anderson, 2004; Levin & Barnard, 2013; Levin & Cross, 2004; Lowik, Van Rossum, Kraaijenbrink & Groen, 2012; Tiwana, 2008).

Although studies by Bian (1997), Granovetter (1973) and Lin (1999) referred to "small world chains" (see below) they did not explicitly demonstrate deliberate search through a "small world" dynamic, but rather through incidental findings, similar to secondhand brokerage (Burt, 2007; 2010). Moreover, these studies did not highlight any strategy for a job search, and the motivation for the intermediaries supporting the process was not specifically tested. In fact, Granovetter (1973) stated that the process of finding jobs through intermediaries was closer to using formal intermediaries (e.g. agencies) than a process of hearing about jobs through short paths.

Furthermore, in Granovetter's study there was no clear explanation as to why these weak ties were enabled through the chain of ties in unlocking social capital, thus resulting in job referrals. Where the referral chain involved more than one person it was also not clear how adjacent linkages (especially trust) between dyads could have affected the motivation to provide referrals, and how the linkages (diversity of ties) could have affected the finding of a job. This is especially important when considering that trust can be a causal proposition enhancing the utility of embedded resources (Lin, 2001).

Granovetter made a theoretical assumption that the mobility of individuals (spill-overs) from one job to another, enabled bridging type ties between networks and that the “sense of community” could facilitate information exchange, which could implicitly refer to the notion of trust: “mobility sets up elaborate structures of bridging weak ties between the more coherent clusters that constitute operative networks in particular locations” (Granovetter 1973, p. 1373).

In Bian’s 1997 study, about 55% of randomly selected individuals found their jobs through direct ties which were mostly strong ties (supporting features of social capital). Furthermore, 45% of individuals found their jobs through an intermediary through whom they subsequently had a weak relationship with the ultimate helper, although they had a strong tie with the intermediary, who in turn had a strong tie with the ultimate helper. Once again, supporting features of social capital (strong ties) enabled the seeker to find a job.

Chains of ties, containing multiple nodes, are known to be useful in the search for information for instrumental purposes (Boissevain, 1974). For Bian (1997) and Lin (2005), chain strength is related to the strength of adjacent ties in the chain. Bian (1997) found some support for adjacent strong ties (strong chains) in the Chinese context, although job search chains are also particularly short, which Lin (2005) suggested was because it would become particularly difficult to maintain chains with extended length (number of referrals) if the adjacent tie strength was strong.

These job search studies were mostly word of mouth referrals which may have been consequential in the narrow network horizon. In Lin’s 2005 study, potential chains were reconstructed by interviewing all helpers, and the results were aligned: 52% reported a single node in the chain; 39% had two nodes in the chain; and 7% reported three nodes in the chain.

The same study found that there was a risk of knowledge and recall uncertainty beyond a certain distance. Over two thirds of egos looking for a job had a strong tie with the final contact in the chain, while over 90% of the seekers knew the last node well or very well (Lin, 2005). A separate study subsequently revealed a limit to horizons of observability regarding indirect ties (Friedkin, 1982).

Most of the job search studies examined the relationship between the individual job seeker and the employer (Granovetter, 1973; Lin; 2001). Brian (1997) and Lin (2005) also studied the strength of the chain, although from an adjacent tie perspective. Strong adjacent ties (strong chains) were important in finding a job (Bian, 1997; Lin, 2005). The notion of trust was not explicitly covered in job search studies, although strong ties and *Guanxi* (a Chinese-specific type of relationship based on reciprocity, which implies trust relations) were helpful to Chinese people in finding jobs (Bian, 1997).

None of these studies focused on what happens when an organisation (as distinct from an individual) uses individual social networks in search of information. However, it is likely that if an organisation is the seeker (see Figure 4) and purposively searches for an OI solution through a chain of referrals, there could be a combination of strong and weak ties in the chain.

Thus, this study suggests that the strength of a chain (“strength of chains”) is dependent upon the average of dyadic strength of ties between agents that make up a chain.

Job referral studies could embody yet another example of the benefits of obtaining social capital through spillages caused by social integration (supporting relations) and bridges (finding a job). Such studies are similar to those focusing on secondhand brokerage (Burt, 2007; 2010).

Hearing about a job does not involve sharing complex information, but rather chancing upon incidental information that has spilled into a person’s social network. Although breadth is important up to a point, for example knowing a number of people who do not know one another (Laursen & Salter, 2004; 2006), depth has been found to be just as important when a job can be sourced through indirect relations (Ahuja, 2000; Burt, 2007; 2010). It is further argued that depth can be deliberately enabled through a trusted bridging chain, as inferred by Bian (1997) and Lin (2005), albeit through strong ties which imply trust.

Small world chains

The term “small world” stems from the old saying which emerges from a serendipitous introduction or discussion, when people remark: “what a small world it is”, or: “everyone is just six handshakes away from everyone else in the world”.

On a more theoretical level, a targeted search (involving a seeker looking for a specific resource or provider) in a “small world” is also an example of a process “where an actor seeks a resource and uses a chain of intermediaries in a strategy to find a target that possesses the sought resource” (Schnettler, 2009, p. 168).

Research on small world studies has mostly focused on algorithmic “small world problems” and there is therefore a need to include other more naturally occurring social processes (Schnettler, 2009). Furthermore, apart from the work of Granovetter, Bian and Lin on job referral research, studies of directed search processes are rare: both in social sciences and small world studies. Most such studies have focused on a small world scenario *post hoc*: for example, when analysing the network around individuals in a creative industry (like the Broadway musicals study by Uzzi and Spiro, 2005) or as innovators (mostly by analysing patent citations).

The first reference to small world phenomena appeared in an unpublished manuscript by Pool and Kochen in 1958, which was finally published twenty years later in Social Networks (de Sola Pool & Kochen, 1979). Then, in 1967, Milgram published an article on the “small world problem” (Milgram, 1967).

Milgram offered two philosophical views. Firstly, he argued that any person in the world can be connected – in a relatively small number of steps – to any other person (even remotely) through intermediate acquaintances (Milgram, 1967). Secondly, he asserted that there are intermediate links between social groups that facilitate this process.

To prove this, he asked randomly selected individuals to send a package, through acquaintances, to a target person (which created a network chain). It was found that chains were completed only when (1) the potential sender was motivated to send the document closer to the target; (2) a sender had a strategy (like a search strategy) for moving the document closer to the target; (3) reasonably short paths were required to link to the target (Travers & Milgram,1969). Pyramiding search strategies are different from “small world” studies, as the search process is not controlled by the referrer in the chain, but rather by the motivations of the researcher or the focal organisation (Von Hippel, Franke & Prügl, 2009).

When social networks were seen to have a small world effect they were described as “small world networks” by Watts and Strogatz (1998). Such networks were found to have high clustering / density (e.g. clusters and groups) and short average paths (bridging structural holes) between agents (Watts, 1999, p. 12-13). This is similar to the supporting and bridging relations of innovation covered earlier. Newman defined the small world effect as: “the fact that most pairs of vertices in most networks seem to be connected by a short path through the network” (Newman, 2003, p. 181).

However, too much of a small world effect is not good for creativity (Uzzi & Spiro, 2005). The small world effect is calculated by the degree of clustering divided by the average path length between actors. If the clustering is too high, it would lead to separate, disconnected teams, and when the path length is too high it would take too many links to reach another actor. The more an organisation is embedded within a network of alliances of high density, alongside short average path lengths to diverse information (for example, through structural holes), indicating a small world effect, the higher the likelihood to access important knowledge for innovation purposes (Schilling & Phelps, 2007).

Therefore, a small world chain enabled through supporting features (trust) and bridging features (diversity) of social capital, should generate optimal social capital returns.

It was hypothesised that trust is associated with depth, hence the formation of a chain (see Hypothesis 1). Furthermore, job search studies and small world studies have shown that returns could be derived by means of network chains (Bian, 1997; Granovetter, 1973; Lin, 2005; Milgram, 1967). Other studies have shown that returns could also be derived from indirect relations (Ahuja, 2000; Burt, 2007; 2010). Better resources can be found by searching deeper (Von Hippel, Franke & Prügl, 2009) and can also be found across domains (Poetz & Prügl, 2010). It can therefore be argued that OI returns could be obtained through chains of indirect interpersonal relationships to the organisation, leading to the hypothesis:

Hypothesis 5: Depth of search is associated with the quality of OI solutions.

Strength of ties does not always suggest diversity, considering that both weak and strong ties bring about new information (Jack et al., 2004; Levin & Barnard, 2013; Levin & Cross, 2004; Lowik et al., 2012; Tiwana, 2008) and chains can bring about new jobs (Bian, 1997; Lin, 2005).

Still, the emergence and ubiquity of the web, as well as electronic and mobile communication have made it easier for people from different circles to be connected through weak ties. In fact, due to the lack of maintenance around such ties, many people could have a multitude (Friedkin, 1982; Granovetter, 1983).

Weak ties (when controlling for trust), have been shown to have a stronger effect on knowledge transfer than strong ties (Levin & Cross, 2004). Weak ties have also had a positive impact on innovation (Hauser et al., 2007). There is more of a probability that information will flow across weak ties when spanning across boundaries, by virtue of numbers (Friedkin, 1982). It is also easier to maintain weak ties than strong ties (Friedkin, 1982; Granovetter, 1983).

Online media, such as Facebook, have a large impact on the manner in which people maintain close and distant social relationships (Vitak, 2012; 2014). It is probable that innovative solutions can be found through chains of boundary spanning ties, although the quality of the solutions may not be related to the strength of these ties, but rather to diversity (geographic distance or knowledge diversity) as previously hypothesised. Following the insights of Levin and Cross (2004), it is proposed:

Hypothesis 6: Weak chains, more so than strong chains, are associated with the discovery of OI solutions, regardless of the quality of the solutions.

The next chapter discusses the research design.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

This chapter describes the research design, and the methodology used in addressing the research question and related objectives. It also sets out how data were acquired for the outcome (open innovation output), control and independent measures, as well as the methods used to prepare and analyse the data.

The over-arching research question probes the benefits of trusted bridging chains for open innovation:

Do trusted bridging chains have a positive effect on open innovation?

3.1 Research philosophy

The researcher has been in the field of OI for some time, albeit from a practical non-academic perspective. However, setting up and analysing OI processes in real life, is a critical and analytical process. OI outcomes are real and tangible, and independent from the company (or intermediary) that deploys the OI challenge to external innovators. Yet, one still deals with solution providers with their own perceptions and actions in relation to this process. Finding OI solutions can also have various causal condition, which are also aligned to human perception and action.

The researcher has a post positivism viewpoint, with a philosophical understanding that specific causes probably affect outcomes. This viewpoint is also aligned with the choice of using the fuzzy set qualitative comparative analysis methods, as a combination of conditions could affect outcomes in positive or negative ways.

The research therefore falls within the framework of critical realism. It recognises that individual-level variables are based on the perceptions and actions of individuals in relation to social phenomena at a particular point in time: namely when they refer other individuals to participate or submit solutions. The research approach is deductive, as hypotheses are construed from existing theory with subsequent empirical testing and fuzzy set qualitative comparative analysis to validate or reject these hypotheses.

3.2 Research design

3.2.1 Background

The study was embedded within an OI context, and was thus not possible to study in a laboratory setting. Moreover, the study required the discovery of unidentified innovators through indirect interpersonal relationships in the real world. These indirect relationships were not known at the onset of the study, but became known as a result of the treatment factor. For these reasons, a quasi-experimental study was required, where a specific treatment was applied to a group of individuals.

A **one-group post-test quasi-experimental design** was used to test the hypotheses and answer the research question: *Do trusted bridging chains have a positive effect on open innovation?* The intervention (to enable trusted bridging chains) was implemented and subsequently a post-test observation was made, as illustrated below (Campbell & Stanley, 2015).

Group A   X________________O

To facilitate the testing of the hypotheses, it was necessary to set up an intervention (field study) which enabled the formation of referral chains of individuals, with an aim of finding an innovative solution. There were no existing processes or platforms from which data could be extracted; neither could surveys be conducted, as individuals were unfamiliar with such OI processes. For this reason, software had to be developed where a referral chain could be electronically constructed (through a website) by means of referrals. Furthermore, functionality had to be developed so that innovators could submit innovative solutions.

It was necessary to source both a problem to be solved and a starting (seed) sample. A website was developed specifically to facilitate the referral and solution submission process. A database contained templates to set up starting and referral emails, and included: all survey questions triggered when one individual referred other; a facility to submit a solution; an overview of the research problem;

reporting facilities as well as contact details of the researcher. Statements about ethical clearance were embedded within the website and templates.

The research design was based on a survey integrated within the referral process: the referrer was required to answer various survey questions as he/she referred another person. Functionality also existed for an innovator to submit an innovative solution.

This necessitated a field study, because the hypotheses could not be tested in a laboratory setting; nor would it have been possible merely to run a survey without the intervention.

3.3 Research method

3.3.1 Approach

A combination of a quantitative approach, analysis of measurable data to uncover patterns by means of statistical methods; and fuzzy set Qualitative Comparative Analysis (fsQCA) was used to analyse the data. fsQCA is fundamentally an analysis of set relations – essentially a middle path between quantitative and qualitative analysis. The analytical strategy, described later in this chapter, outlines fsQCA in more detail.

3.3.2 Methodological Design

The study used a survey design based on close-ended questionnaires. The initial sample grew as individuals referred other individuals and so on recursively, so a questionnaire – used as a data collection procedure – was an economical way to collect the data with rapid turn-around for analysis.

3.3.3 Timing

Since evolution of time was not a factor, a synchronic approach was followed whereby relationships were evaluated at a specific point. However, it should be noted that the questionnaires were distributed during the referral stage (recursively) and not after the referral chains had formed, which meant that the questionnaire process occurred throughout the referral stage. This near-simultaneity of referring and data gathering safeguarded against memory bias.

3.3.4 Units of analysis

The unit of analysis signifies the “what” of the study: the object, process, entity, person, and so on (Babbie & Mouton, 2001). The unit of analysis for this study was the referral chain, which contained two components: referrals and solutions (where available). For example, when person A referred person B, and person B referred person C, there were two referrals that made up a referral chain. If person C submitted a solution, then the solution was a component of the referral chain, and so was the actual referral.

3.3.5 Population and Sample

Population

The population consisted of managers and specialists. Two associations, the International Association of Innovation Professionals (IAOIP), and the Southern African Institute of Mining and Metallurgy (SAIMM) participated in the research. An opt-in email was distributed to members and associates of both groups. The majority of the population consisted of managers and specialists across domains from the IAOIP. The email for the opt-in request contained a link to an opt-in website, where a person could choose to participate in the research. The email address, name and surname of the person were collected during the opt-in process.

Sample

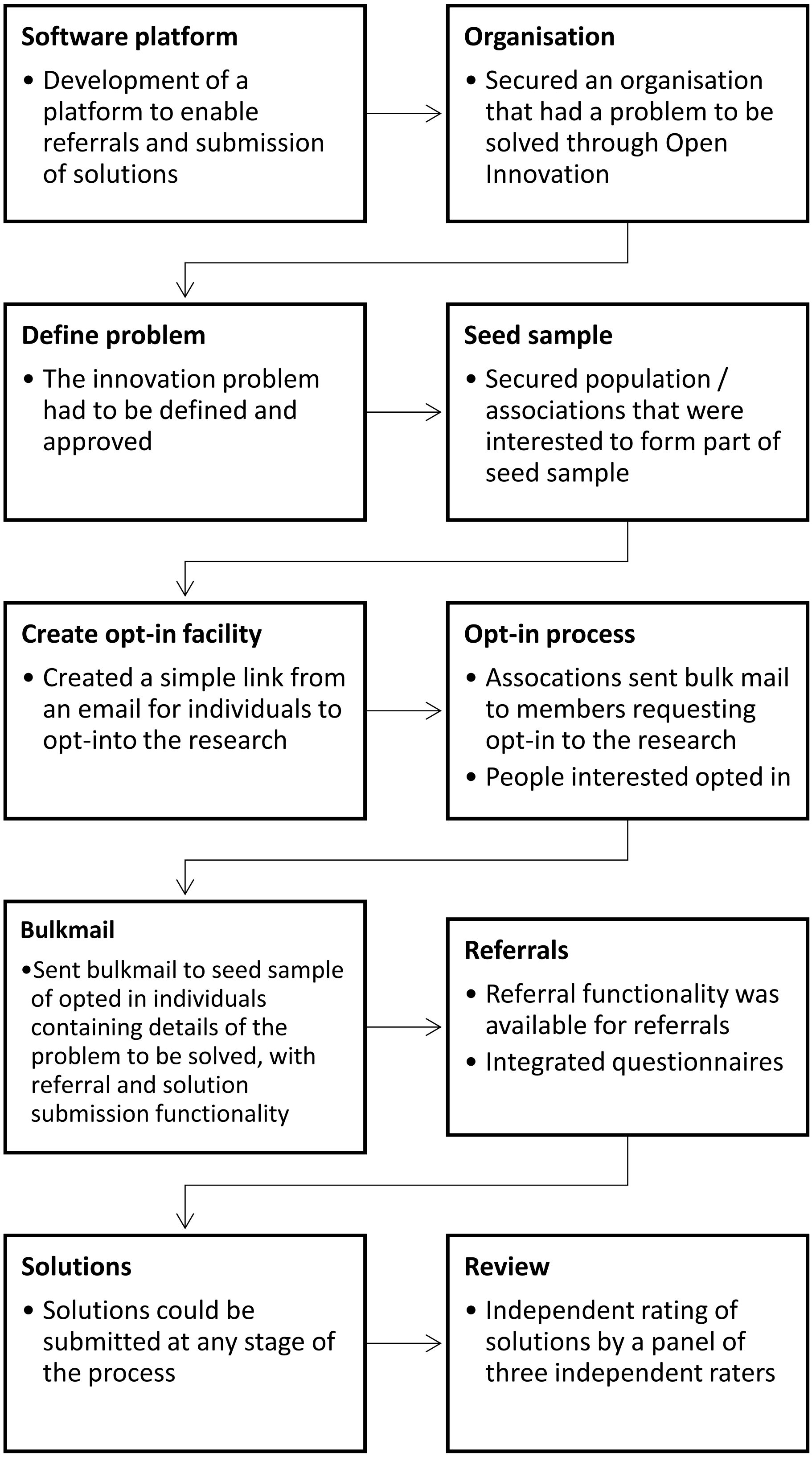
The opted-in individuals from the above population comprised the seed sample for the research. The problem to be solved was sent to this seed sample only.

Any subsequent referrals expanded the number of participants similar to snowball sampling. A total of 121 people opted in and thus comprised the seed sample.

3.3.6 Research process

The operational data gathering process is depicted in Figure 6 (below).

Figure 6: Operational research process



Problem

A problem to be solved had to be sourced from an organisation interested in the research. Details of the problem are tabled in Table 1 below.

Table 1: Problem to be solved

Title	**Identify methods to reduce copper cyanide build-up in process water circuits**
Introduction	A South African gold processing facility seeks to identify methods to reduce a copper cyanide build-up in the process water circuits which impacts negatively on operations.
Problem definition	A leading South African gold processing facility seeks to identify methods to reduce a copper cyanide build-up in the process water circuits, which currently impacts negatively on operations. A successful solution to the problem should: - Be implementable on a large scale - Not remove gold from solution - Use industrially available reagents - Not cause secondary problems - Be safely implementable and must not impact the environment negatively
Background	Intensive cyanidation of sulphide containing concentrates has resulted in more copper being put into the solution. The copper species are adsorbed into carbon in the adsorption circuit and concentrated into the eluate. These high levels of copper then negatively impact on the electrowinning of gold and cyanide consumption.

Software platform

A software platform was developed to facilitate the process (referrals and submission of solutions). It was necessary to facilitate the process by electronic means so as to formalise and make the data collection process simple and viable.

The software enabled functionality for referrals through emails. The problem to be solved was summarised in the email and elaborated on the website (see Table 1). A bulk mail was sent out to the seed sample. At the time of referral, the individuals were presented with the questionnaires, which facilitated the data collection process. Each referred individual could further refer someone else and the same process repeated itself via an email sent to the referred individual, with questions presented and so on.

The website had the functionality for an individual (the innovator) to submit an innovative solution. An individual could continue to refer, and also submit an innovation at the same time. The problem was “open” for just over two months to allow for the referral of individuals as well as the subsequent submission of solutions.

3.3.7 Instruments

Independent variables

As soon as a referral took place, a chain was started. Referral data were summarised into case data: the actual summarisation method is described in the next chapter. Reliability and factor analysis of the referral data then took place, and the referral data were used to create the referral chain data.

The most common instrumentation methods used in network studies are self-reports on the presence or absence of network ties. These are most often obtained from single-item questions (Borgatti & Cross, 2003; Ibarra, 1993; Levin et al., 2015; Marsden, 1990). However, where possible, more than one item was included in this study.

Trust

The notion of trust was an important predictor in the study and based on existing instruments (Levin & Cross, 2004, Levin et al., 2011; Mayer et al.,1995; McAllister, 1995).

Benevolence-based trust

Data were collected during the referral process and related to questions raised when referring another person. Likert-5 scales were used for all the benevolence-based trust questions as listed in Table 2 below.

Table 2: Benevolence-based questions

Questions	Scales
The person I am referring would always consider my best interest. I… (q1 in the survey)	5: strongly agree; 4: agree; 3: neither disagree or agree; 2: disagree; 1: strongly disagree
This person is very interested in my well-being. I… (q6 in the survey)	5: strongly agree; 4: somewhat agree; 3: neither disagree or agree; 2: somewhat disagree; 1: strongly disagree
If I need help, the person will do his / her best to help me. I… (q10 in the survey)	5: strongly agree; 4: somewhat agree; 3: neither disagree or agree; 2: somewhat disagree; 1: strongly disagree

Competence-based trust

Data were collected during the referral process and related to questions raised when referring another person Likert-5 scales were used for all the competence-based trust questions as listed in Table 3 below.

Table 3: Competence-based trust questions

Questions	Scales
This person is professional and dedicated. I… (q2 in the survey)	5: strongly agree; 4: agree; 3: neither disagree or agree; 2: disagree 1: strongly disagree
I see no reason to doubt the person's competence to solve the problem or refer someone else that can. I… (q9 in the survey)	5: strongly agree; 4: agree; 3: neither disagree or agree; 2: disagree; 1: strongly disagree

Questions	Scales
This person is a capable and proficient source of expertise and knowledge in his field. I... (q12 in the survey)	5: strongly agree; 4: agree; 3: neither disagree or agree; 2: disagree; 1: strongly disagree

Diversity

The dyadic diversity of a tie was defined as a linear combination of the distance between geographic (spatial) locations – i.e. geographic distance; and also professional knowledge differences between the agents which characterised the referral.

Two independent measures were used: geographic distance and knowledge diversity.

Geographic distance

The appraisal in the literature review showed that distance matters, and that organisations should reach wide and far to obtain diverse information. Previous studies measured distance in various ways, such as: ties from abroad (Levin & Barnard, 2013); geographic locations (Cummings, 2004); network positions (Powell et al., 1999); distance-weighted reach, calculated from existing data (Schilling & Phelps, 2007); and measured distance: for example, same floor, same building where a higher score represented a longer distance (Treviño, Webster & Stein, 2000), and similarly Finholt and Sproull (1990). In the two later studies measurement score was a useful basis for the measurement of dyadic geographic distance. Merely looking at ties from abroad would be too basic for analysis purposes, and regional codes would be difficult (considering that they had to be loaded across the world), while existing databases to measure weighted distances were not available.

The approach used in this study was to consider how geographic distance between the referrer and the referred individual could have an effect on OI solution ratings. A Likert-5 scale was used where the referrer rated the physical working distance between him/ her and the person they referred as depicted in Table 4 below.

Table 4: Geographic distance question

Questions	Scales
Rate the physical geographic working distance between you and this person", (q3 in the survey)	5: in another country; 4: in the same country; 3: in the same town / city / county; 2: in the same building; 1: in the same confined space, e.g. same office.

Knowledge diversity

Each industry has its own distinct knowledge-base which forms the basis of inter-industry differences (Li & Vanhaverbeke, 2009). Large inter-industry differences (between the innovating organisation and a partner) can provide organisations with great novelty value (Li & Vanhaverbeke, 2009). Rodan (2010) and Rodan and Galunic (2004, p. 548) measured knowledge heterogeneity, which was adapted for this study. Data were collected during the referral process and related to questions (Likert 4 and 5 scale) raised when referring another person as listed in Table 5.

Table 5: Knowledge diversity questions

Questions	Scales
How much knowledge would this person bring to your discussions, over and above what you already know? (q4 in the questionnaire)	4: a great deal; 3: some; 2: little; 1: very little
How similar is this person's knowledge to your knowledge? Choose 1 = "Very similar" if the knowledge of this person and yours is very similar, for example a football player and the football-team coach. (Here the two people should have a great deal of work-related knowledge in common.) Choose 5= "Very different" if the knowledge of the person you are referring and your knowledge is very different, for example an airline pilot and a computer scientist (q8 in the questionnaire)	5: very different; 4: somewhat different; 3: similar; 2: somewhat similar; 1: very similar

Strength of ties (closeness)

As mentioned in Chapter 2, Marsden and Campbell (1984) and Wellman and Wortley (1990) found that testing for closeness was a better indication of strength of ties than including the other measurements proposed by Granovetter (1973). In particular, frequency of contact (communication) was not shown to be a good indication of strength of ties (Jack et al., 2004; Wellman & Wortley, 1990). For this reason, strength of ties for closeness was kept separately from communication. Data were collected during the referral process and related to questions raised when referring another person. The questions for strength of ties (closeness) are listed in Table 6 and included Likert scale 4 and 5 scale questions.

Table 6: Strength of ties (closeness) questions

Questions	Scales
How close are you with this person? (q5 in the questionnaire)	4: very close friend; 3: friendly colleague; 2: distant colleague; 1: acquaintance
How close is your relationship with this person? Choose "especially close" if there is a close relationship between you and this person. Choose "very distant" if this person and you rarely work together or are total strangers as far as you know (q11 in the questionnaire)	5: very distant; 4: somewhat distant; 3: neither close or distant; 2: somewhat close; 1: especially close (scale was reversed prior to analysis)
How well do you know this person? (q13 in the questionnaire)	4: not at all well; 3: not very well; 2: somewhat well; 1: very well (scale was reversed prior to analysis)

Communication

Communication was used as a single, Likert 6 scale item question as depicted in Table 7.

Table 7: Communication question

Question	Scales
How often do you communicate with this person on average? (q7 in the questionnaire)	6: less often or never; 5: several times a year; 4: once a month; 3: several times a month; 2: several times a week; 1: daily (scale was reversed prior to analysis)

Branching and extensive branching

A categorical variable was set for branching: when a person referred more than one person in the referral process. A categorical variable was also set for extensive branching: when a person referred more than two people at the same time. The categorical variables were set after all the referral data had been collected.

Control data

Control data were collected during the referral process and related to questions raised about the person performing the referral.

- Gender – categorical variable (Brown & Konrad, 2001)
- Education (Brown & Konrad, 2001; Perry-Smith, 2006)
- Geographic location (free text)
- Industry description (free text)
- Employment status
- Reason for referring the person (free text)

Dependent variables

Solution flag

The dependent or outcome variables were: OI output (categorical variable) and OI solution rating (a score). OI output means that a solution was found, and not necessarily the rating for the solution. Hence, where there was a solution located within a chain, then the OI output was set to “1". The categorical variable was set after all the data had been collected. A referral that contained a solution had a solution flag of “1”; all other referrals were set to “0”.

Solution rating

There are numerous measures of creativity, which include the use of expert raters in the Consensual Assessment Technique (CAT) measurement tool (Amabile, 1996); scoring of solutions according to divergent-thinking based scores (Reiter-Palmon, Illies, Cross, Buboltz & Nimps, 2009); and the Creative Solution Diagnosis Scale (CSDS) (Cropley & Kaufman, 2012). As Cropley and Kaufman (2012) have noted, only a few tools assess the creativity of more technical or scientific products and many are domain specific.

The CSDS method is based on the consensual assessment of creativity, underpinned by a theoretical framework of functional creativity (Cropley & Cropley, 2005; Cropley & Kaufman, 2012). The tool allows for the evaluation by judges, who may not specifically be experts in their fields; secondly it is focused on functional creativity, which would be more relevant to this study. The method uses a 30-item scale that is based on the following criteria: relevance and effectiveness, novelty, elegance and genesis.

The solutions were scored independently by three individual raters from the organisation that presented the problem. The key stakeholder, who was head of metallurgy, appointed two other individuals whom he believed to be adequately knowledgeable to assist in the rating process. Hence three individuals scored the solutions independently.

All scales below were based on a Likert-5 scale as follows: 5: very much; 4: quite a lot, 3: somewhat, 2: slightly and 1: not at all. (Refer to Tables 8 - 11)

Table 8: Relevance & effectiveness questionnaire

RELEVANCE & EFFECTIVENESS	**ITEM**
Correctness	The solution accurately reflects conventional knowledge and/or techniques
Performance	The solution would do what it is supposed to do
Appropriateness	The solution fits within task constraints
Operability	The solution would be easy to use
Safety	The solution is safe to use
Durability	The solution is reasonably strong / durable

Table 9: Novelty questionnaire

RELEVANCE & EFFECTIVENESS	**ITEM**
Diagnosis	The solution draws attention to shortcomings in other existing solutions
Prescription	The solution shows how existing solutions could be improved
Prognosis	The solution helps the reviewer to anticipate likely effects of changes
Replication	The solution uses existing knowledge to generate novelty
Combination	The solution makes use of new mixture(s) of existing elements
Incrementation	The solution extends the known in an existing direction
Redirection	The solution shows how to extend the known in a new direction
Reconstruction	The solution shows that an approach previously abandoned is still useful
Reinitiation	The solution indicates a radically new approach
Redefinition	The solution helps the reviewer see new and different ways of using the solution
Generation	The solution offers a fundamentally new perspective on possible solutions

Table 10: Elegance questionnaire

ELEGANCE	ITEM
Recognition	The reviewer sees at once that the solution makes sense
Convincingness	The reviewer sees the solution as skilfully executed, well-finished
Pleasingness	The reviewer finds the solution neat, well done
Completeness	The solution is well worked out and rounded
Harmoniousness	The elements of the solution fit together in a consistent way
Sustainability	The solution is environmentally friendly

Table 11: Genesis questionnaire

GENESIS	ITEM
Transferability	The solution offers ideas for solving apparently unrelated problems
Germinality	The solution suggests new ways of looking at existing problems
Seminality	The solution draws attention to previously unnoticed problems
Vision	The solution suggests new norms for judging other solutions-existing or new
Pathfinding	The solution opens up a new conceptualization of the issues
Transferability	The solution offers ideas for solving apparently unrelated problems

3.3.8 Data

The data collected started off with the seed sample. The only data solicited from this sample was the name, surname and email address of the person who opted in to support the research. An optional field for contact details was available.

The seed sample was presented with an email briefly describing the research and the problem to be solved (see Table 12 below). Hyperlinks were available for "challenge to solved"; "Answer challenge"; "Forward challenge" and "Unsubscribe". When an individual clicked on "challenge to be solved", the details presented in Table 13 were displayed. The template referred to as part of the challenge (problem definition template) is available in Appendix 1. When an individual clicked on "Answer challenge", the challenge, as presented in Table 13, was displayed, as well as a facility to describe the solution briefly and upload a template (see Figure 7). Basic control data were collected during this process, as detailed earlier in this chapter.

When an individual clicked on “Forward challenge”, a window was presented to refer a second individual (with name, surname and email address) as well as the questionnaire data, covered in the instruments section (also see Table 14 for the header text and Figure 8). Refer to Appendix 2 for the detailed questionnaires.

The control questions were asked about the individual who was referring, and then the referral questionnaire was presented whereby the person referring described his/her relationship with the referred individual. The system had the functionality to refer more than one person, in which case the referral process was repeated. This was subsequently termed “branching”. Personal data were collected only once.

A referring individual also had access to an optional free text field in order to state why he/she was referring the next person. They were asked: “Why did you particularly choose this person to assist?” and were told “This is the only answer that this person will see and it is completely optional” (see bottom of Figure 8). The text captured by the referring person, appeared on the bulk mail of the referred person with the note: “The sender provided the following reason for sending this e-mail to you: [reason]”.

Table 12: Example of bulk mail sent at onset and as part of referral process

Hi [name] **Novel doctoral research on Open Innovation (OI)** You are largely bound to everyone on the planet by a trail of six people. The theory of six degrees of separation contends that, because we are all linked by chains of acquaintances, you are just six introductions away from any other person on the planet. It’s a small world indeed. To examine how this interconnectedness affects the outcomes of OI projects, Maggie Lombard, a doctoral student from South Africa, has decided to track referrals for an opt-in group interested in the research. If you are not part of the opt-in group, then you were referred by someone else who felt that you are particularly suited to solve the challenge or that you could refer someone else. The challenge to be solved is to identity methods to reduce copper cyanide build-up in process water circuits. You can choose to solve the problem yourself (Answer Challenge) or you can refer the challenge to someone who you believe (a) would be more suited to the nature of the

challenge or (b) may know someone else who can solve it or (c) is a well connected person; in this case, forward the challenge (Forward Challenge).

Please do not forward the email directly to another person via email, use the link provided to forward it or else the chain will be broken and the relationship data cannot be analyzed.

The challenge is open until the 4th of November 2015, but please start to trigger the small world as soon as you can.

To contribute to the research, you will be asked 6 general questions about yourself and 13 questions when you refer someone else. Remember that no one, apart from the researcher, will see these detailed answers. All results will be summarized for research purposes. You are not obligated at all to help the researcher; you can opt out at any stage.

Unsubscribe if you do not want to receive any more emails regarding this project.

Research by
Maggie Lombard
Doctoral candidate at the Gordon Institute of Business Science (GIBS)

Table 13: Challenge content when accessing challenge link

[problem definition and background]

Any approach will be considered.

The monetary value of a winning solution will be subject to negotiation.

Respond to the challenge by:

1. Completing the survey questions and a summary of your proposal
2. **Download** the document template available
3. Email the detailed solution to **maggie@polynate.co.za**

The closing date has been extended to the 4th of December 2015 to allow for referred individuals to respond.

Please note, that at this stage of the submission process, you should not include any other supporting documentation. If you feel further supporting documents will strengthen your proposal, please list these in the document template as an Annexures Section, with a short description of the content and purpose of each document. The review team will contact you if they feel this information is required during the first stage of the review process.

If you experience any problems during the submission process, please communicate this via email to maggie@polynate.co.za

***

You will be asked to complete a survey containing six general questions which will be used for research purposes. Your participation is voluntary and you can withdraw at any time without penalty. Of course, all survey data will be kept confidential. By completing the survey, you indicate that you voluntarily participate in this preparation of the research. By submitting a solution/response, you represent that the response does not contain any confidential information of any kind whatsoever. The researcher, Polynate and project partners will not be held liable for the loss of any intellectual property.

If it is not your name and details appearing on the challenge page, then it means that someone has sent the email to you manually. If you want to participate, please forward the email you have received to the researcher at maggie@polynate.co.za.

Figure 7: Solution submission window

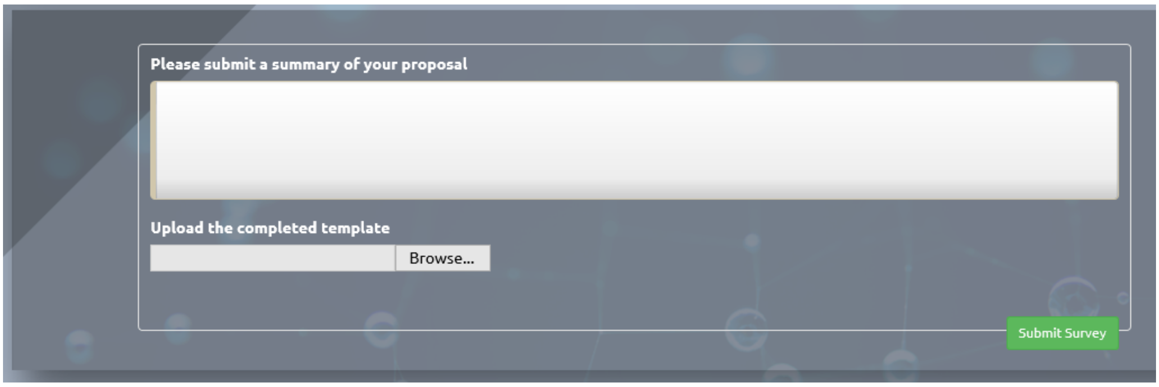
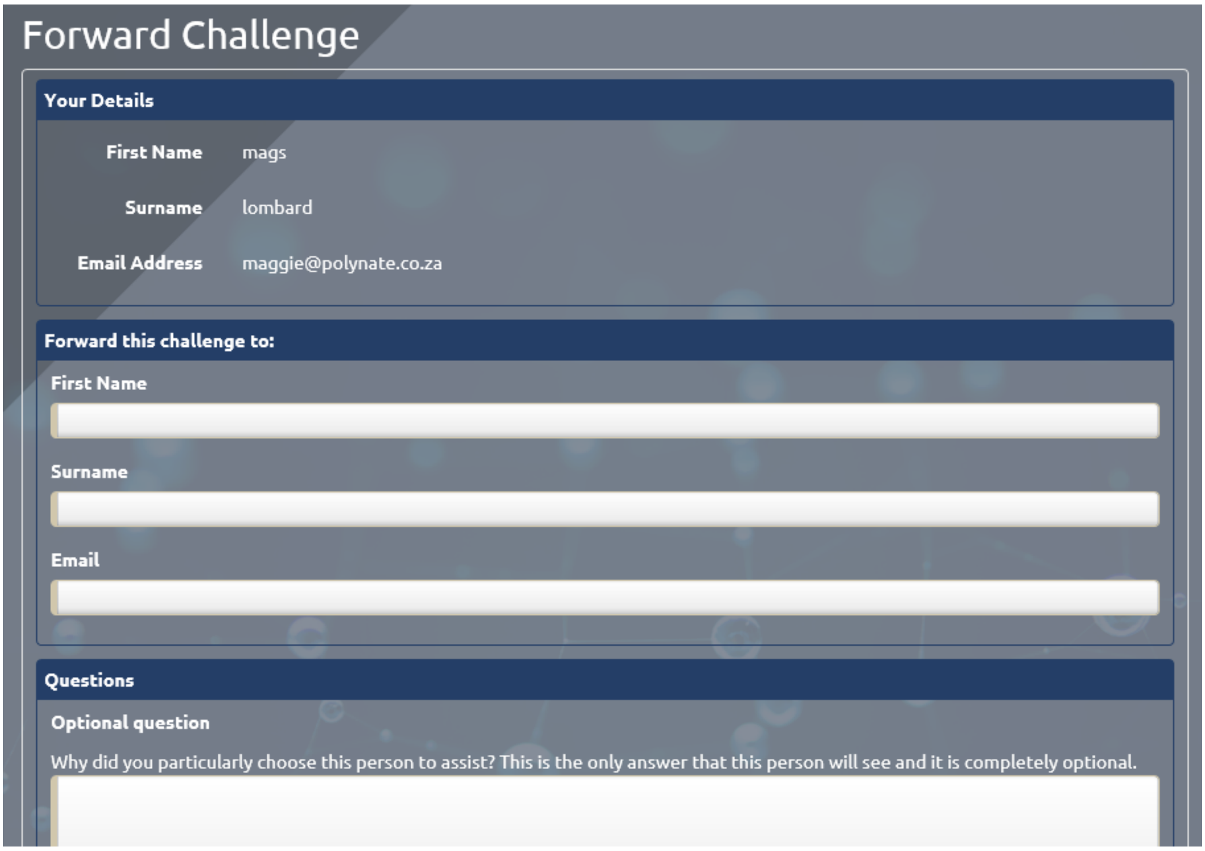


Table 14: Window heading body when a person chose to refer another person

I am doing research on the effect of indirect referrals on finding innovative solutions to problems. To that end, you are asked to either attempt to solve the problem or refer someone else who you think may solve the problem or who may know someone else who can solve the problem. You will be asked to complete 6 general survey questions (about yourself) and 13 other simple survey questions (about the referral) which will be used for research purposes. Your participation is voluntary and you can withdraw at any time without penalty. Of course, all survey data will be kept confidential. By referring a person and completing the survey, you indicate that you voluntary participate in this research. You can refer more than one person; after each submission, there is an opportunity to refer another person. No reimbursement is offered for referring a person.

If it is not your name and details appearing below then it means that someone has sent the email to you manually. If you want to participate, please forward the email you have received to the researcher at **maggie@polynate.co.za**.

Figure 8: Referral window



Referral and solution submission data

An individual had to answer all questions in the instrument to complete the referral process, and to ensure there was no missing data. Each referral was associated with a chain number, and a further data set was prepared where the referrals associated with a chain were averaged to form chain data per variable. This is described in more detail in the analysis chapter.

For the submission of a solution, uploading the template was optional. This was potentially a limitation of the data collection process, as some individuals submitting solutions described the solution in the summary field, which may have resulted in the collection of less solution information than would otherwise have been possible.

An individual was not able to refer a person who was already referred. This also proved to be a limitation, as it may have prevented the generation of interesting data when a person was referred more than once by different individuals. In limited cases the referrer seemed unsure of the email address of the referred person, and referred him/her twice. Duplicates were removed from the analysis.

Solution ratings

After all data were collected, the solutions were extracted and loaded as separate word documents, omitting any information of who had presented the solution to ensure anonymity. Nine packs were created, each containing the solution as well as a rating sheet.

The key stakeholder was briefed to request each rater to rate each solution independently and then scan and email the results to the researcher. Not having the rating sheet available electronically on the website resulted in some missing data, albeit a low percentage. In hindsight, this could have been prevented. Not all raters were metallurgists/experts in the field, but the CSDS rating scale allowed for inexperienced raters to also rate solutions. According to the key stakeholder they had enough technical knowledge to rate the solutions.

3.3.9 Analytical Strategy

The main techniques used to analyse the data included the following:

Quantitative analysis

Firstly, internal consistency and reliability of constructs were analysed by means of Cronbach's alpha to ascertain how closely items were related to the constructs.

Secondly, factor analysis, specifically confirmatory factor analysis (CFA), was administered to ensure these measures were consistent with the constructs. During this analysis, measures of sampling adequacy (MSA), communality and total variance were analysed.

In addition to this, interrater reliability was run by means of the interclass reliability analysis in SPSS, where (1) the rates by the panel of three raters were treated as items across all nine solutions and analysed for interclass reliability; and (2) where the transposed data, alongside the ratings per solution as cases, and the various questions were analysed for interclass reliability.

Finally, logistic regression was used as an analytical tool, on the basis that the dependent variable (solution flag) was categorical (solutions versus no solutions). Logistic regression was run to estimate the probability of finding OI solutions based on the available predictors. A linear regression could not be used to model the relationship between the quality of the solutions and explanatory variables, considering the low number of solutions (six). Accordingly, fuzzy set qualitative analysis (fsQCA) was used for this purpose.

Fuzzy set qualitative analysis (fsQCA)

fsQCA was employed to analyse the combination of conditions that were necessary and sufficient for the outcome (solution rating). Fuzzy sets make it possible to analyse fine gradations in the degree of membership to sets, or groups of things (Ragin, 2008). Unlike normal regression analysis, necessary and sufficient conditions are causally asymmetric. Therefore, the set of causal conditions necessary and sufficient for the outcome, might be very different for the absence of the causal condition (Fiss, 2011). The fsQCA analytical method provides a configurational perspective to the research, which is largely absent in OI research. Using this method allows for insight to more fine grained causal factors associated in OI processes. Furthermore, fsQCA was also used because of the small number of cases not requiring statistical power for analysis. It provided the configuration of causal conditions affecting solution ratings which would not have been possible with regression analysis.

Fuzzy set qualitative analysis

fsQCA is an analytical analysis method that uses set-theoretic instead of quantitative analysis correlational connections. It also uses calibration of variables instead of pure measurement scales. Conditions are calibrated to fuzzy scores, allowing for the interpretation of scores instead of merely relying of rigid measures, as is the case in quantitative analysis. All fuzzy sets must be calibrated using external standards and the practical knowledge of the researcher.

Furthermore, fsQCA describes the configuration of conditions that affect the outcome, instead of evaluating the effect of independent variables on the dependent variable, as is the case with quantitative analytical tools (Ragin, 2008).

This configuration of conditions can be seen as a "recipe" for the outcome. Therefore, in fsQCA – as compared to quantitative analytical analysis – the combined effects are more important than the independent effects, and there may be multiple paths (configurations) to the same outcome (equifinality).

These features distinguish fsQCA from traditional correlation analysis, together with the fact that fsQCA allows for combinations of causal measures, whereas traditional correlations find the independent and net effects of variables to be more important (Elliott, 2013).

Considering the low number of cases associated with solutions, it was necessary to address the many conditions of these cases and to analyse how the combination of these conditions could influence the outcome. fsQCA uses calibrated values to construct a "truth table" as an analytical tool to examine cases that share the same combination of causal conditions, in order to ascertain if they share the same outcome (Ragin, 2008).

An important aspect of fuzzy sets, as distinct from crisp (binary) sets, is that cases can fall in between: neither fully in nor outside the set. This makes it possible to evaluate greyer areas and to calibrate partial membership (Ragin, 2008).

This study uses the direct calibration method (Ragin, 2008): an appropriate way to transform interval scale variables into fuzzy-sets – although a review of the breakpoints will still determine whether a set is in or out, more in than out, or more out than in.

The direct method uses the estimates of the log odds of full membership in a set. The metric is not a probability, but rather the degree of membership (between 0 and 1) of a target set. Ragin (2008) advises that the calibration of the degree of membership of a set should be purposefully calibrated, and never calculated mechanically or automatically.

Fuzzy scores are not the same as ordinal scales, so the calibration should be based on the researcher's substantive, accumulated knowledge derived from studying specific cases (Ragin, 2008). It should also be externally determined and not inductively derived (purely based on calculations, such as averages).

The manner in which fsQCA was operationalised in this study is covered in detail in the next chapter.

fsQCA was run on software (fsQCA 2.5) downloaded from http://www.u.arizona.edu/~cragin/fsQCA/software.shtml . The fsQCA user guide by Ragin (2008) was used to operationalise the data using fsQCA alongside best practices as described by Schneider and Wagemann (2010; 2012).

3.3.10 Ethical considerations

Ethical principles were integrated into the developed software product. Firstly, the associations requested people to opt into the research. Participants had to access a specific link to do so. A bulk email (see Table 12), was sent to the opted-in sample. The following statements were included:

"Remember that no one, apart from the researcher, will see these detailed answers. All results will be summarized for research purposes. You are not obligated at all to help the researcher; you can opt out at any stage.

Unsubscribe if you do not want to receive any more emails regarding this project".

The unsubscribe link allowed the person to opt out immediately, and stored the email address in an opted-out database. The ethical statements were displayed again at the beginning of the referral process (Table 14) and prior to submitting a solution (see bottom of Table 13).

CHAPTER 4: RESULTS

The analytical strategy presented in the previous chapter was applied to the data in order to address the research question as to whether trusted bridging chains have a positive effect on open innovation. The results of the analysis are included in this chapter and aligned to the hypotheses. A descriptive analysis is presented at the onset, followed by a quantitative analysis. Subsequently, a fuzzy set qualitative comparative analysis (fsQCA) is presented culminating in a core and peripheral causal analysis.

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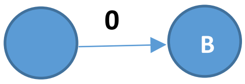
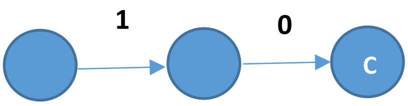
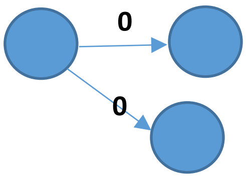
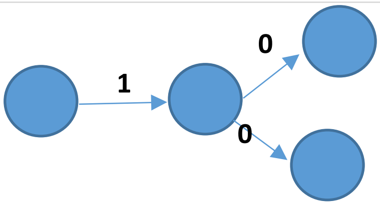
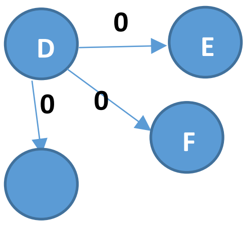
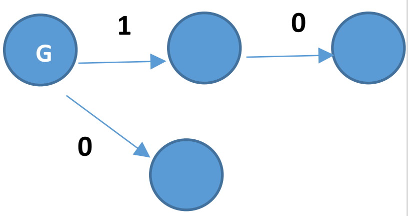
4.1 Descriptive analysis

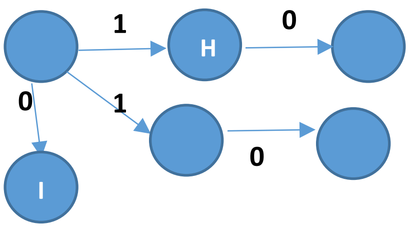
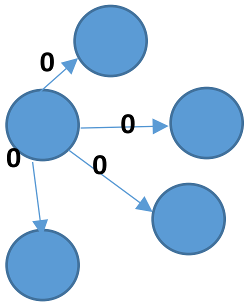
Table 15 (below) illustrates the different graph types that emerged from the intervention. A graph contains a number of referrals that form chain/s. More than one chain can be present in the same graph. The table also includes the number of chains per graph configuration and shows whether solutions emanated from the starter group (seed sample) or through a chain (through indirect relationships). All scores are listed on the far right. A score that contains the symbol "⊗" next to it, means that the solution was submitted by a starter, hence not by means of a chain and therefore not by anyone who has an indirect interpersonal relationship with the focal organisation.

A chain was formed when a starter referred another individual. Therefore, as a minimum it can comprise two entities: the starter and referred individual. If a starter (the person who opted in) submitted a solution, this was derived from a direct link to the focal organisation. If a person who was referred by the starter, or referred by another referred individual, submitted a solution, then the solution was derived though a chain of referrals: hence through indirect relationships to the focal organisation.

When a circle stands alone, it means that there was no referral chain assembled and that a solution was submitted by a starter. A "0" on the referral link means that the chain was not passed forward further, while a “1” means that the chain was progressed further, beyond an initial referral.

Table 15: Types of chains configurations

#	Graphic representation of chains obtained in responses*	Number of chains per graph	Scores for obtained solutions
1		0	A: 48%⊗
2		1	B: 60%
3		1	C: 94%
4		2	No solutions obtained
5		2	No solutions obtained
6		3	D: 78%⊗ E: 86% F: 82%
7		2	G: 49%⊗

#	Graphic representation of chains obtained in responses*	Number of chains per graph	Scores for obtained solutions
8		3	H: 59% I: 100%
9		4	No solutions

⊗These solutions were not submitted by indirect relations to the focal organisation but were solution submitted by the starter population

*1 refers to referrers, 0 to non-referrers

Type 1 graphs, Table 15, related to people who opted in but did not refer someone else, so theoretically there was no referral chain. There were 121 people who opted in, of whom 77 never referred anyone else, while 44 did start a referral process.

There were 77 referrals in total, emanating from the 44 starters. Two cases had to be filtered out due to invalid data, leaving 75 valid referrals. One of the opted-in individuals did not refer another person but submitted a solution which rated the lowest solution score (see A in Table 15) of 48%. Two other starters submitted solutions but subsequently still referred someone else.

Solutions A, D and G originated from the seed sample (starters), so these solutions did not come about through indirect relationships by means of a chain. Solutions B, C, E, F, H and I came about by means of indirect interpersonal relationships to the focal organisation, through a chain.

There was only one Type 2 graph and it resulted from the starter referring just one other individual. One solution was generated from this form of chain and scored 60%.

There were nine Type 3 graphs (containing one longer chain) where the starter referred an individual and this person referred another. One of these chains scored the second highest solution score: 94%.

All the other types occurred only once. Graph Type 4 was a branch, where the starter referred two people, but the process did not produce any solutions.

Graph Type 5 comprised an initial referral, followed by a branch referral (thus two chains) and did not result in any solutions.

Graph Type 6 was particularly interesting. An individual submitted a solution which scored 78%, then referred three other people, of whom two submitted solutions rated 86% and 82% respectively. Hence, the last two scores in this case were derived from chains.

Graph Type 7 reflects the case where the starter submitted a low-scoring solution of 49% and then instigated a branch referral (more than one referral and therefore two chains), through which one of the referrals passed the chain forward

Graph Type 8 was a three-way branch referral where two chains moved forward. Person H submitted a solution but also passed it forward again by referring someone else.

In total, there were three cases where a person submitted a solution, but also passed it forward (D, G and H). Two of these individuals received the lowest scoring solutions: G with 49%; H with 59%. This might imply that they did not have confidence in their own solutions, and therefore passed the problem forward.

Solutions submitted through starters (without involving a chain) were not analysed further, as these solutions did not come about through a referral. Moreover, there was no referral data associated with these solutions to enable further analysis.

In total, from the six solutions emanating from chains, and therefore indirect interpersonal relationships to the focal organisation, five solutions came from just one indirect link (one referral); and one solution from two referrals. One individual also passed the chain on after submitting a solution. However, it appeared that the solution scores from starters (no chains), scored on average much lower than solutions derived from chains.

In summary, and before any additional analysis has been conducted, it appears that:

- Chains produced more solutions (six as opposed to three), with a higher average score than solutions not derived through chains (starters).
- The highest scores came about through chains.
- Most solutions (in five out of six chains) resulted from just one referral.

4.2 Quantitative analysis

4.2.1 Reliability and factor analysis

Dependent variables

Solution rating

As discussed in the previous chapter, the CSDS instrument was used to score solutions independently by three raters.

Firstly, the consistency of scores from raters (inter-rater reliability) combined was computed where the rates were treated as items across all nine solutions, which indicated a Cronbach alpha of 83%. Secondly, the data were transposed to show the ratings per solution as cases and the items being the various questions of the CSDS instrument. There were limited missing values (4%) where averages were taken and one specific item had to be removed in totality. Across all items and cases, the reliability was 97.8%.

The reliability per construct was as follows: relevance and effectiveness (96%); novelty (93%); elegance (98%); and genesis (92%). This was reviewed and showed high reliability for all elements across cases. For the purposes of the study, the split of the constructs was not important. Hence, the average of all constructs per solution was utilised for further analysis.

Independent variables

Benevolence-based trust

The Cronbach alpha for the three items of benevolence-based trust rated 76%, which was acceptable. When performing dimension reduction, the Measure of Sampling Adequacy (MSA) for all items and the communality ratings were well above 50%. The total variance explained was 68%. The items were presented apart from one another in the questionnaire so as to decrease the likelihood of consistency motif and item priming effects (Podsakoff, MacKenzie, Lee & Podsakoff, 2003).

Competence-based trust

The Cronbach alpha for the three items of competence-based trust indicated that q2 (This person is professional and dedicated), had to be deleted as it caused the reliability score to be very low. Removing the item resulted in a Cronbach alpha of 69.4% which is just 0.6 below the acceptable limit. The word “dedicated” in this question might have caused internal inconsistency issues across items, particularly when a person did not know the referred person well enough to know if this person is dedicated. The other questions: q9 (I see no reason to doubt the person’s competence to solve the problem or refer someone else that can) and q12 (This person is a capable and proficient source of expertise and knowledge in his field) were less personal in nature.

When performing dimension reduction, the MSA was acceptable at 0.50. Communalities were also acceptable at 76.9% and the total variance explained was also 76.9%.

Considering that the coefficient was so close to an acceptable level, q9 and q12 (see above) were used as the items for the competence-based trust construct further in the analysis. As can be seen from the question numbers presented in the previous chapter, the items were presented apart from one another so as to decrease the likelihood of consistency motif and item priming effects (Podsakoff et al., 2003).

Knowledge diversity

Q4 (How much knowledge would this person bring to your discussions, over and above what you already know?) and q8 (How similar is this person's knowledge to your knowledge?) together showed unacceptable levels of reliability. Q8 was followed by a detailed skills-based example. Upon more detailed analysis, it was decided to use q8 as a single item scale (for knowledge diversity), considering the very detailed description provided in the instrument, and the focus on professional knowledge. Q4 was more general and could have been interpreted as general discussion points instead of more specifically professional domain knowledge differences.

Geographic distance

Geographic distance (q3: Rate the physical geographic working distance between you and this person) was analysed as a separate item.

Strength of ties (closeness)

The scales were reversed for q11 (How close is your relationship with this person?) and q13 (How well do you know this person?) to depict strong ties (closeness) on the higher side of the scale when an individual knew a person very well, or was a very close friend. Q5 (How close are you with this person?) was already in the correct state. When performing dimension reduction after the removal, the MSA for all items and the communality ratings were above 90%. The total variance explained was 86%.

Communication

Communication (q7: How often do you communicate with this person on average?) was analysed as a separate item, which was in line with extant theory (Jack et al, 2004; Wellman & Wortley, 1990). The scale was reversed prior to analysis to depict frequent communication on the higher end of the scale.

Branching

Branching took place when an individual referred more than one other person, as can be seen from graph types 4, 5, 6, 7, 8 and 9 (Table 15). Extensive branching was evident when an individual referred more than two people at the same time.

Branching and extensive branching flags were created on a referral level. When an individual referred more than one person, branching was set to “1”. When an individual referred more than two people, then extensive branching was set to “1”. If a chain resulted from branching, or extensive branching, the same two flags were set on a chain level.

4.2.2 Referral Chain Analysis

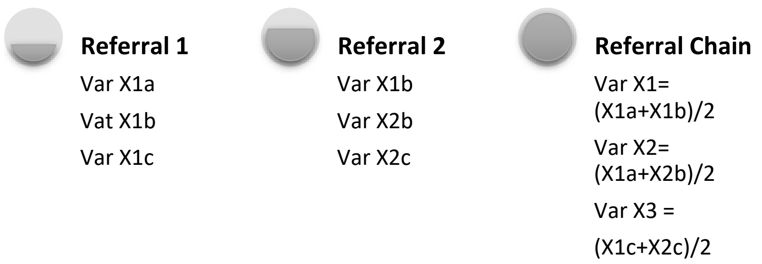
As described in the previous chapter, the core unit of analysis in this study was the referral chain, the components of which were referrals and solution ratings. For example, if person A referred person B, and person B referred person C who then submitted a solution, the referral data were available for the referral between A and B (case 1); and the referral between B and C (case 2) as two separate cases. Considering that C submitted a solution, the solution flag and rating were carried on case 2.

At the onset, the referral data were imported into SPSS as a case per individual referral, in order to perform statistical reliability tests and factor analysis. Thereafter all referral cases associated with chain numbers were exported to MS Excel where the referral data were summarised on a referral chain level (per chain number).

It should be noted that chain data were calculated up to the point that an OI solution was submitted. In one case (Chain 15), an individual submitted a solution, then passed the chain further forward. In this instance, the further referral did not contribute to the discovery of the solution and was therefore excluded from the chain calculations.

Each construct was averaged to provide a score per referral chain as illustrated in Figure 9 below. As depicted, variable X1a (strength of ties for the first referral for example) was added to variable X1b (strength of ties for the second referral) and then averaged on a referral chain basis. This therefore implies the strength of the chains. The maximum chain size contained two referrals as indicated in Figure 9 below, hence a total of three: person A – starter, person B – referred individual and person C who was referred by person B and then submitted a solution. The summarised chains were then imported into SPSS for further analysis.

Figure 9: Referral chain data



With reference to Table 15, in a simple case such as Types 2 and 3, there was only one chain per graph. Types 4 and 5 both contained two chains; Type 6 three chains, and so on as listed. As soon as a chain had more than one referral, averages were calculated as illustrated in Figure 9 above. Reliability and factor analyses were performed on the referral data prior to exporting for further chain summarisation and analysis. There were 75 valid referrals which resulted in 60 valid chains.

Gender, qualifications and job status data were not associated with a referral itself, and data were available about the referrer and not the referral. Also, considering that a chain could be made up of more than one referrer, gender, job status, etc. would be meaningless for the chain level analysis and were therefore excluded.

If a chain resulted in a solution, the solution flag was set to “1”, otherwise it was set to “0”. When a chain was formed by means of branching, where an individual referred more than one person, the branching flag was set to “1”.

When a chain was formed by means of extensive branching (more than two people referred at the same time), the extensive branching flag was also set to “1”.

The mean chain length was 2.28 and the median two. The minimum length of chains was two and maximum three. Furthermore, 71.7% of chains (43 chains) had a length of two and 28.4% of chains (17 chains) had a length of three.

4.2.3 Assumptions

The 75 referrals resulted in 60 chains, but only six chains resulted in OI solutions, which is a very low sample size. The dependent variable (solution flag) was binary and coded in respect of the designated outcome (chain with solution = “1”; and chain without solution = “0”).

The most common assumption in most statistical tests is that the data should have a normal distribution (Hair, Black, Babin & Anderson, 2010). For this reason, outliers were reviewed.

Outliers are observations which are distinctly different from other observations and typically depict a very high or low value on a variable or an inconsistent combination of variables (Hair et al., 2010). All variables were converted to standard values in order to detect such outliers, which usually have a greater or smaller than 2.5 standard score (for smaller sample sizes) (Hair et al., 2010).

When referral data cases were checked for outliers, two chains indicated standard scores well above the threshold and were removed, as no explanation could be inferred from the data.

Three chains had item scores above the threshold but, when analysing these on a case to case basis, there seemed to have been confusion regarding the order of the Likert scales which was corrected.

There were two further chains that had an item above the threshold. However, when considering the optional narrative of the rater's description of the referred person, it was clear that the rating contradicted the narrative. For example, in one case, a person received the lowest score on competence, but then described the person as a "competent engineer". It was evident that the referrer had chosen the incorrect side of the scale, which was corrected.

None of the outlier cases mentioned above had OI solutions associated with them, so they did not form part of the six solution cases which were further analysed using fsQCA.

The skewness of individual variables on a chain level was covered in Table 22 (further on). None of the individual independent variables exceeded the skewness threshold. Skewness refers to the balance of the distribution, as shifted to the left or the right (Hair et al., 2010). A positive skew indicates a distribution shifted to the left and a negative skew shows a distribution to the right (Hair et al., 2010).

A small sample size may severely affect the skewness of a distribution (Hair et al., 2010). Considering that the study only yielded 60 chain cases, which resulted in just six solutions, the sample size was limited, which may affect the estimation of the model.

A chosen statistical model should fit the condition (Siegel, 1957). In this case, the dependent variable was categorical and there were only six cases with a value of "1" for the solution flag (dependent variable). Hence a binary logistic model was selected for further analysis. In a binary logistic model, the initial assumption is that the independent variable is linearly related to the log odds of the response. Logistic regression models are therefore direct probability models (Harrell, 2015).

Although the assumption of normality held for the individual independent variables (skewness and kurtosis were within acceptable thresholds as per Table 22), the Shapiro-Wilk's W test was not significant as it reported a significance of less than 0.05. However logistical regression, using maximum likelihood estimation, is more robust in response to this violation to normality (Steenkamp & van Trijp,1991).

Harrell also stated that logistic regression models do not make distributional assumptions: "Since the distribution of a binary random variable Y is completely defined by the true probability that Y = 1 and since the model makes no assumption about the distribution of the predictors, the logistic model makes no distributional assumptions whatsoever" (Harrell, 2015, p. 221). Hence, logistic regression is not prohibited by strict assumptions and are robust when these assumptions are not met (Hair et al., 2010). In fact, the error term of the discrete variable would have a binomial instead of a normal distribution, which violates normality (Hair et al., 2010). Furthermore, heteroscedasticity could be evident as the variance of dichotomous variable is not constant.

It should also be noted that, although the starting sample may have been drawn from a normally distributed population, the chains were made up by referrals and consequent referrals, which were driven by individual referrals of individual people and not chosen from the original sample.

The model was also not overfilled and only meaningful independent variables were retained. Furthermore, it was assumed that the independent variables in the model were independent of one another and that multicollinearity did not exist between the independent variables.

It was important to assess the "goodness of fit" in terms of how well the model described the data and for this purpose the Hosmer and Lemeshow (2000) statistic was used.

Solution flag as dependent variable

Binary logistic regression

Firstly, all variables were added to the model but only strength of ties and extensive branching were significant. Subsequently the model was rerun only containing these two variables.

The overall model was significant: The Hosmer and Lemeshow test of the goodness of fit suggested the model was a very good fit to the data as p=0.675 (>0.05), at eight degrees of freedom (df) and at a Chi-square of 5.753. Specifically, to be a good fit, the p-value should be greater than the cut-off of 0.05 and closer to 1 (Hosmer & Lemeshow, 2000).

The Omnibus test was significant (0.006 sig.), at a Chi-square of 10.092 at two degrees of freedom (df). The initial likelihood ratio test was a -2 Log of 39.010 in Block 0 which improved to a -2 Log to 28.918 in Block 1, and which showed an improvement between the initial and final model. The Nagelkerke R square suggested that the model explained 32.4% of the variance in outcome. The Cox and Snell R square explained 15.5%. The classification model at the onset was 90% and the final model was 93.3% which was an overall improvement (see Table 18).

The variables in the equation are depicted in Table 16 and bootstrap for variables are listed in Table 17.

Table 16: Variables in the equation

		B	S.E	Wald	df	Sig.	Exp (B)
Step 1[a]	extensive branching	-1.783	.997	3.199	1	.074	.168
	Strength of ties	-1.056	.490	4.648	1	.031	.348
	Constant	2.101	1.547	1.846	1	.174	8.178

a. Variables entered on step 1: extensive branching, strength of ties

Table 17: Bootstrap for variables in the equation

		B	Bias	Std. Error	Sig. (2-tailed)
Step 1[a]	extensive branching	-1.783	-2.773[b]	14.659[b]	0.031[b]
	Strength of ties	-1.056	-1.009[b]	7.626[b]	0.001[b]
	Constant	2.101	2.243[b]	21.361[b]	0.029[b]

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

b. Based on 996 samples

Table 18: Classification table[a]

Observed	Predicted		
	Solution flag		Percentage correct
	0	1	
Step 1 solution flag 0	54	0	100.0
1	4	2	33.3
Overall percentage			93.3

a. The cut value is .500

Extensive branching (at a value of "1") in Table 16, was not significant at 0.074, although it affected the overall model. The model was also run with bootstrapping. When running the model with bootstrapping, extensive branching was significant (see Table 17) and the model results (covered at the onset), were the same.

The coefficient B, in Table 16, represented the relationship between the explanatory variable and the outcome variable and showed exactly how much the outcome (solution flag) variable could change after a one-unit change in the explanatory variable.

In this model, extensive branching (at a value of "1") showed a negative B coefficient which indicated that more extensive branching would make the outcome event (having solutions) less likely. The predicted odds [Exp (B)] were 0.168 which was less than 0, indicating the negative prediction. Therefore, the odds ratio of having a solution when extensively branching was 0.168. Hence the more people branched extensively (referring more than two people at the same time), the less chance there would be of a solution being presented. This finding was not specifically hypothesised.

Strength of ties was significant at 0.031 with a negative B coefficient of 1.056 and a Wald score of 4.648. The negative B coefficient indicated that the more strength of ties increases, the less likely it becomes to obtain solutions.

The correlation between strength of ties and extensive branching was 0.011 which indicated a lack of multicollinearity. Refer to Table 19.

Table 19: Correlation matrix strength of ties and extensive branching

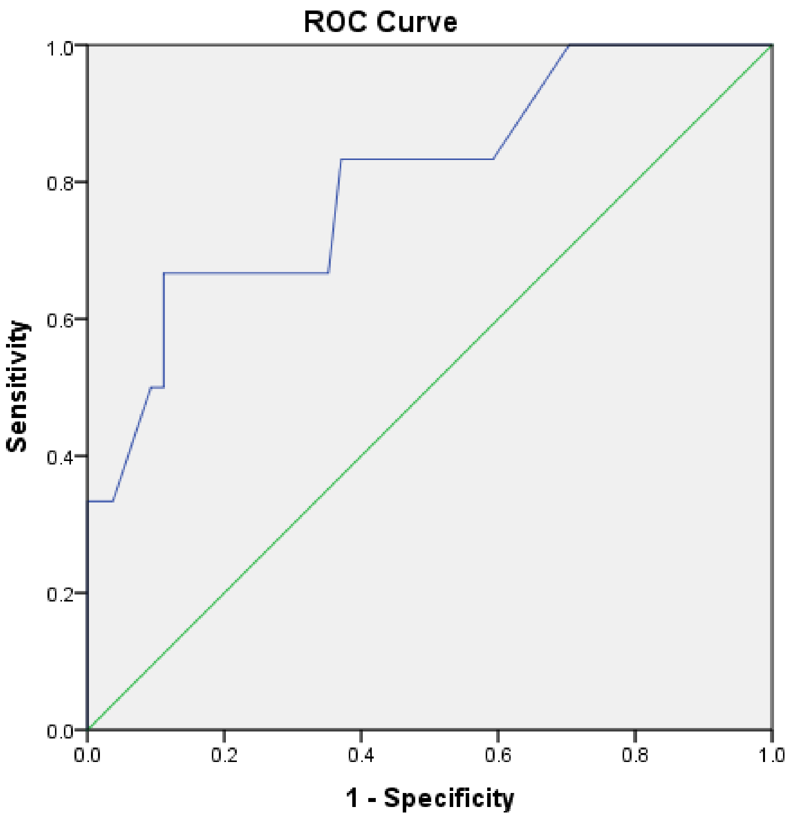
		Constant	**ext_branching**	**sot**
Step 1	Constant	1.000	-.292	-.905
	ext_branching (1)	-.292	1.000	0.11
	sot	-.905	0.011	1.000

Two cases were marked as misclassified cases, which did not warrant further analysis.

The predicted probability was saved for the logistic regression. Thereafter a Receiver Operating Characteristics (ROC) curve (see Figure 10) was run to plot the sensitivity or ability of the model to predict an event (solution vs no solution) correctly (Hanley & McNeil, 1982). The cut-off classification when the model was run was set at 0.5, which was the default cut-off value. The area under the curve (AUC), also called the index of accuracy (A), was significant (0.016 asymptotic sig.) at 0.802 (80.2%).

This indicates that a randomly selected case from the positive group has a test value larger than that of a randomly chosen case from the negative group 80.2% of the time.

Figure 10: ROC Curve based on predicted probability for solutions



Diagonal segments are produced by ties.

Thus, it was found that weak chains increase the probability of finding OI solutions, whereas extensive branching (broad search) decrease the probability of finding solutions.

There was enough evidence to support Hypothesis 6.

However, as mentioned earlier, weak chains by no means, affect the quality of solutions, considering that both good and bad solutions originated from such ties.

It was necessary to analyse the conditions under which people branched extensively, although this was not specifically hypothesised.

Extensive branching as dependent variable

A binary logistic regression model was run with the extensive branching flag as the dependent variable on the summarised chain data. The model was run to ascertain the determinants of extensive branching. Only benevolence-based trust was significant in the model (see Table 20).

The overall model was significant: The Hosmer and Lemeshow test of the goodness of fit suggested the model was a good fit to the data as p=0.824 (>0.05) (Hosmer & Lemeshow, 2000). The Omnibus test was significant (0.002 sig.) at a Chi-square of 9.251. The initial -2 Log was 69.59 in Block 0 and improved to – 2 Log 60.338 in Block 1. The Nagelkerke R square suggested that the model explained only 20.8% of the variance in outcome and Cox and Snell suggested an explanation of 14.3%.

The classification model at the onset was 73.3% and the final model was 76.7% which was an overall, albeit marginal, improvement (see Table 21).

The variables in the equation are depicted in Table 20.

Table 20: Variables in the equation

		B	S.E	Wald	df	Sig.	Exp (B)
Step 1[a]	Benevolence-based trust	-1.674	.620	7.277	1	.007	.188
	Constant	5.522	2.378	5.349	1	.021	250.012

b. Variable(s) entered on step 1: benevolence-based trust

Table 21: Classification table[a]

Observed	Predicted		
	Solution flag		Percentage correct
	0	1	
Step 1 solution flag 0	43	1	97.7
1	13	3	18.8
Overall percentage			76.7

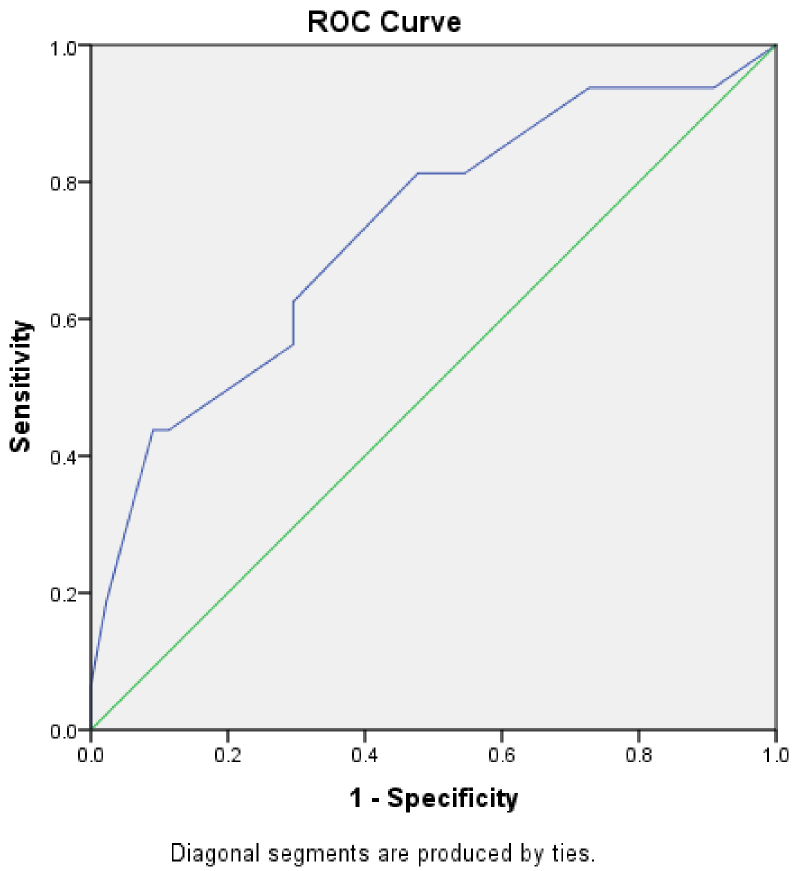
b. The cut value is .500

The coefficient B (see Table 20) represented the relationship between the explanatory variable and the outcome variable, and showed exactly how much the outcome (extensive branching) variable could change after a one-unit change in the explanatory variable (benevolence-based trust). In this model, benevolence-based trust showed a negative B coefficient which indicated that stronger benevolence-based trust would make the outcome event (of extensive branching) less likely. Hence, people would extensively branch (referring more than two people) if they thought that there was less of a chance that the referred people would help him/her (less benevolence-based trust).

There was only one misclassified case, which did not warrant further analysis.

The predicted probability was saved for the logistic regression and thereafter a ROC curve was run (see Figure 11) to plot the sensitivity or ability of the model to predict an event (extensive branching or not) correctly (Hanley & McNeil, 1982). The cut-off classification when the model was run was left at 0.5, which was the default.

Figure 11: ROC Curve based on predicted probability for extensive branching



The AUC was significant (0.007 asymptotic sig.) at 0.729 (73%). This indicates that a randomly selected case from the positive group had a test value larger than that of a randomly chosen case from the negative group 73% of the time.

Therefore, individuals may refer more than two others when they believe those individuals would be less likely to help them find a solution (low benevolence-based trust). In so doing, it seems that they are using “luck of the draw” logic.

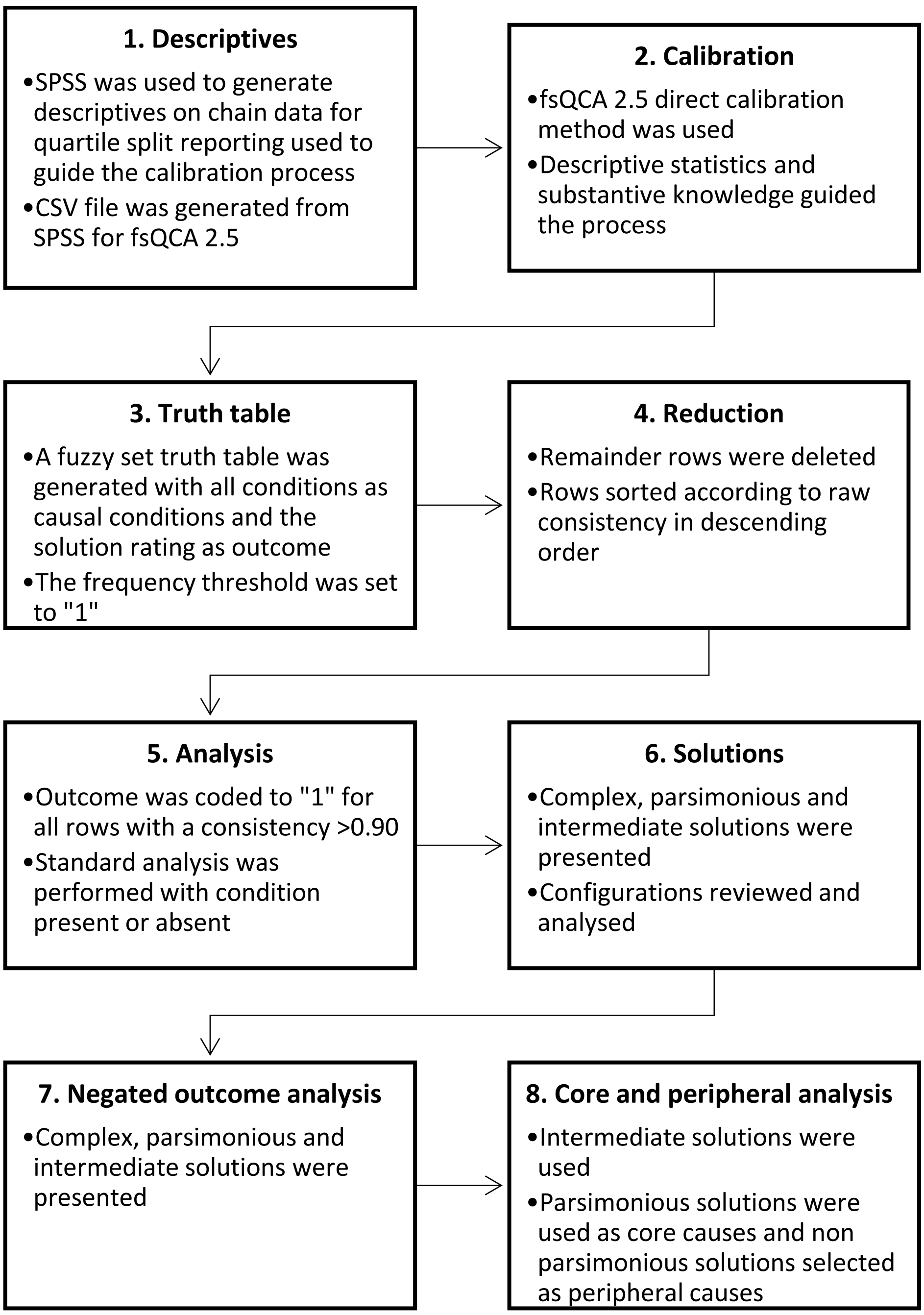
The quantitative analysis provides insights into when solutions are more likely to be obtained. To better understand the quality of solutions obtained, fuzzy set qualitative analysis is used. This is done in the next section.

4.3 Fuzzy set qualitative comparative analysis

4.3.1 Operationalisation

fsQCA was used as an analytical tool to analyse the configurations that affected the solution rating (quality of solutions). fsQCA was operationalised as illustrated in Figure 12 below.

Figure 12: Operationalisation of fsQCA



4.3.2 Descriptive statistics and file

The software used for the analysis was fsqca 2.5, downloaded from http://www.u.arizona.edu/~cragin/fsQCA/software.shtml.

The analysis was performed on a referral chain basis. The referral chain is covered in detail in the subsequent quantitative section of this analysis.

fsQCA was used to analyse solution associated data to ascertain what configurations presented a pathway for the outcome: in particular, good solutions. The descriptive statistics were extracted from SPSS which contained the full set of chain referral data, analysed in a later section of this chapter. This was necessary as only the six cases for solution data were analysed in fsQCA, although the descriptive statistics from the full set of chain data were used to guide the later calibration process.

Each of the scores was calibrated into fuzzy scores. The chain data were exported as a “comma separated” Excel file, and only cases with a solution rating greater than zero were kept for further analysis, as the aim was to ascertain the configurations of conditions with an impact on the solution score *per se*. The descriptive statistics for all chain data are presented in Table 22 and were used as input for the calibration process.

Table 22: Chain data descriptive statistics

Description		Knowledge diversity	Geographic distance	Communication	Benevolence-based trust	Competence-based trust	Strength of ties
N	Valid	60	60	60	60	60	60
	Missing	0	0	0	0	0	0
Mean		3.575	3.508	2.285	4.019	4.396	3.457
Median		3.750	3.500	2.292	4.000	4.500	3.533
Std. Deviation		1.196	1.006	1.089	0.594	0.541	0.894
Minimum		1.00	1.00	0.83	2.33	3.25	1.08
Maximum		5.00	5.00	5.00	5.00	5.00	5.00
Skewness		-0.314	-0.501	0.561	-0.240	-0.454	-0.872
Percentiles:							
	25	2.500	3.000	1.667	3.667	4.000	3.052
	50	3.750	3.500	2.292	4.000	4.500	3.533
	75	5.000	4.000	3.229	4.333	5.000	4.281

4.3.3 Calibration

Calibration should be based on external criteria and the substantive knowledge of the researcher (Ragin, 2008; Schneider & Wagemann, 2012). The direct method of calibration was used in this analysis.

This method uses three breakpoints: full membership, non-full membership and a crossover point (Ragin, 2008). The direct method uses a pre-set function in the fsQCA 2.5 software product by using the facility Variables -> Compute… choose/create the target variable, using function calibrate (X, n1, n2, n3), where X is the source variable, n1 is the anchor point for full membership, n2 is the crossover point and n3 is the anchor point for full non-membership).

The direct method uses the estimates of log of full membership in a set. The metric is not a probability, but rather a degree of membership (between 0 and 1) of a target set. The crossover point is the point of maximum ambiguity as to whether a case is part of, or not part of, a set. Ragin (2008) stated that a precise score of 0.5 should be avoided as the algorithm would ignore such a score. He suggested that 0.001 should be added to, or deducted from, all the scores once calibrated.

At the onset, frequency descriptive statistics were produced from the complete chain dataset (see Table 22). This input was then used to guide calibration for the subset of data, which included only the solution data (six cases) for further fsQCA analysis. Considering that the solutions from the seed sample were not obtained through referrals, no data were available for further analysis and only a descriptive analysis could be performed against the solutions.

Descriptive statistics for the six cases only would not have been meaningful for percentile split analysis, which was purely used as a guide in the calibration process. So the complete chain data set was useful for the percentile splitting of data into percentiles: 25th percentile (full non-membership), 50th percentile or mean as crossover points and 75th percentile (full membership).

Fiss, Cambre and Marx (2013) used these percentile values as guidelines for the breakpoints, similarly with the 50th percentile as the crossover point. Equally, Fiss (2011), used the 50th percentile and 75th percentiles as cut-off points for calibration of performance based on return on assets (ROA). Ford, Seers and Neumann (2013) used the 75th and 25th percentile for fully in, and fully out, cut-off points respectively, with the mean as the crossover point. The crossover point is the “point of maximum ambiguity (i.e., fuzziness) in the assessment whether a case is more in or out of a set (Ragin, 2008, p. 30).

In most cases external and substantive knowledge were used for the cross-over point and not merely the mean. The frequency data were used as a guide, then the cut-off points were examined against the Likert scales and modifications made, based on substantive and theoretic knowledge. Only then was the direct calibration performed and reviewed once again to ensure that it made theoretic sense. Each causal factor was individually calibrated, reviewed and recalibrated where necessary to ensure that it was aligned with external and substantive knowledge.

From the six chains containing solutions, two chains (Chains 15 and 53) had more than one referral within the chain. Although Chain 15 had two referrals, only the first referral resulted in the solution. The person who submitted the solution then passed the chain further on afterwards. The chain data up to the point of the submission was used for analysis purposes.

Outcome: solution scores

The solution scores are listed in Table 23. For the purposes of analysis, scores for solutions derived from chains were used in the analysis, as these solutions stemmed from indirect interpersonal relationships to the organisation. Solutions originating from the seed sample did not contain any referral data that could be used, so it was irrelevant to calibrate those scores as they would not fall within the analysis. The mean was 80 and the median 84. The mean was used as the cross-over point, considering the large gap between the score of 82 score and that of 60.

Consequently, the lowest two scores of 59 and 60 were calibrated to be more out than in, using a breakpoint of 61 and a crossover point of 80, which meant that 82 and 86 would also be more in than out.

The upper break-point was set at 93, which meant that the two top scores would be fully in. The calibration facility of fsQCA 2.5 was used to calibrate: *calibrate (sol_score, 93, 80, 61)* and thereafter 0.001 was added to the scores as was done for all other conditions. The results are listed in Table 23.

Table 23: Solution rating calibration

Solution no	Chain No	Solution rating	Fuzzy score
4	14	100	0.991
5	15	59	0.041
6	36	82	0.611
7	38	86	0.801
8	53	94	0.961
9	57	60	0.041

Condition: knowledge diversity

According to Table 22, the minimum score for knowledge diversity was 1, the maximum was 5, mean was 3.575 and median was 3.75. The upper and lower percentiles were 5 and 2.5 respectively.

The scores in the 75th percentile were coded as “fully in”, those in the 25th percentile were coded as “fully out”. A score of 4 was “Somewhat different” according to the scale.

Chain 53, which scored 3.5, was very close to the mean and was analysed in greater detail to ascertain if the case should be classified as more “in” or “out”. This chain was made up of two referrals. The first respondent stated that there were differences in the knowledge bases between themselves (the referrer) and the referred person. The second respondent chose a midpoint “3” on the referral scale. On average, this resulted in a 3.5 score. Q4 (How much knowledge would this person bring to your discussions, over and above what you already know?), another item for knowledge differences, was also reviewed to assist in the calibration process. This item was not used in the statistical analysis because of low internal consistency, but it was reviewed from a qualitative perspective to provide some further input.

For q4, the highest score was chosen by the referrer, demonstrating large differences in knowledge. It seemed that the score for this chain should be more in than out. Hence the decision to use the cross-over point of 3.5 instead of exactly the mean: a 0.08 difference.

Considering that a fuzzy score of 0.5 would be computationally disregarded in the fuzzy analysis, 0.001 was added to each score less than 1. As can be seen from Table 24, the metric scales for 4 and 5 were more in than out; and 3.5 more in than out. This was aligned to the intention of the instrument.

The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 24. The calibrate function in fsQCA was used as follows: *calibrate (know_div, 5, 3.5, 2.5)*.

Table 24: Knowledge diversity calibration

Chain no	Metric scale	Fuzzy score
14	2	0.011
15	5	0.951
36	2	0.011
38	4	0.731
53	3.5	0.501
57	5	0.951

Condition: geographic distance

According to Table 22, the minimum score for geographic distance was 1; the maximum 5; while median and mean were 3.5. In reference to the Likert-5 scale for geographic distance, metric score 3 was coded as a geographic distance which was still relatively close, i.e. same town/city/county, whereas 4 was when individuals were further apart but still in the same country. A score of 5 was the furthest geographic distance, in another country. Proximity to a score of 4 would signify more in than out, so using the median of 3.5 as the crossover point would be in line with the intention of the scale.

The percentiles were 3; 3.5; and 4 respectively for the 25th, 50th and 75th percentile. The scores in the 75th percentile were coded as "fully in"; those in the 25th percentile were coded as "fully out"; and the 50th percentile was used as the cross over point. A figure of 0.001 was added to all scores (less than 1) to ensure that all rates were included in the analysis.

The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 25. The calibrate function in fsQCA was used as follows: *calibrate (geo_dist, 4, 3.5, 3)*. As can be seen from Table 25, the metric scores of 3, which represented people in relatively close proximity, were calibrated as more out than in, and scores where people were further apart, namely 4 and 5 metric scales, were more in than out, with the metric scores of 5 being completely in.

Table 25: Geographic distance calibration

Chain no	Metric scale	Fuzzy score
14	4	0.951
15	5	1
36	3	0.051
38	3	0.051
53	3	0.051
57	5	1

Condition: communication

According to Table 22, the minimum score for communication was 0.83 (the original scale was a Likert-6 which was converted to a Likert-5 and reversed; hence the fraction of less than 1 in this case); the maximum was 5; with a median and mean of 2.29.

However, using the mean and median as crossover point of 2.29 was not possible as it was not in line with the interpretation of the scale. For example, a score of 2.5 (after conversion from Likert 6 from Likert 5) stated the communication level as “once a month”, which was more out than in, so it was important to translate this to the fuzzy score.

The percentiles were 1.67 and 3.23 respectively for the 25th and 75th percentiles. The scores in the 75th percentile were used for “fully in”; those in the 25th percentile were coded as “fully out”; and 2.5 was used as the crossover point, which was in line with the meaning of the scale. In this case, 0.001 was deducted from the score to ensure that a score of 2.5, calibrated to 0.5 would be more out than in.

The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 26. The calibrate function in fsQCA was used as follows: *calibrate (comm, 3.23, 2.5, 1.67)*.

Table 26: Communication calibration

Chain no	Metric scale	Fuzzy score
14	0.83	0
15	0.83	0
36	1.67	0.049
38	1.67	0.049
53	2.92	0.849
57	1.67	0.049

Condition: benevolence-based trust

According to Table 22, the minimum score for benevolence-based trust was 2.33; the maximum 5; while median was 4 and mean was close, at 4.02.

In line with the Likert-5 scale for benevolence-based trust, and taking as an example the statement: "If I need help, the person will do his/her best to help me", a rate of 4 was recorded for the response: "somewhat agree". The same result was produced for the statement: "The person is very interested in my well-being".

This rate of 4 represented fuzziness, which also resonated with the mean, so 4 as a crossover point was appropriate. The percentiles were 3.67; 4; and 4.33 respectively for the 25th, 50th and 75th percentile. The scores in the 75th percentile were coded as "fully in", those in the 25th percentile were coded as "fully out" and the 50th percentile was used as the cross over point, considering the closeness to the mean where most of the fuzziness occurred in terms of the actual Likert scale as well.

A figure of 0.001 was added to scores less than 1 to ensure that all rates were included in the analysis. The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 27. The calibrate function in fsQCA was used as follows: *calibrate (ben_trust, 4.33, 4, 3.67)*.

Table 27: Benevolence-based trust calibration

Chain no	Metric scale	Fuzzy score
14	3.67	0.051
15	3.67	0.051
36	3	0.001
38	3	0.001
53	4	0.501
57	4.33	0.951

Condition: competence-based trust

According to Table 22, the minimum score for competence-based trust was 3.25; the maximum was 5; median was 4.5; and mean was lower at 4.39. Considering that the mean was less than the median, the distribution was left skewed. This may be as a result of some individuals not referring others if they lacked trust in their competence. The Likert 5 scale question was: “I see no reason to doubt this person’s competence to solve the problem or refer someone else that can”, where a rate of 3 was “neither disagree or agree”, which represented fuzziness.

A score of 3.5 (which represented a rate of 4 for one item, and a score of 3 for the other) was considered more in than out. The figure of 3.5 was used as a crossover point to ensure that the calibration was aligned with the intention of the scale. A rate of 4 (“agree” on the scale) was more in than out, and the minimum score was more out than in. A figure of 0.001 was added when necessary to ensure no score was excluded from the analysis.

The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 28. The calibrate function in fsQCA was used as follows: *calibrate (comp_trust, 4, 3.5, 3.25)*.

All the fuzzy scores for competence-based trust indicated more in than out. This could be a result of the referral process, as individuals would not refer someone without believing that such a person could either solve the problem, or be able to refer someone else who could do so.

It was logical to include competence-based trust across all cases, although this did not assist with the lack of variance in terms of the quality of solutions.

Table 28: Competence-based trust calibration

Chain no	Metric scale	Fuzzy score
14	4	0.951
15	5	1
36	5	1
38	3.5	0.501
53	4.75	1
57	5	1

Condition: strength of ties

According to Table 22, the minimum score for strength of ties was 1.08; the maximum was 5; median was 3.53; and mean was similar, at 3.46. The percentiles were 3.05; 3.53; and 4.28 respectively for the 25th, 50th and 75th percentile. In reference to the Likert scales for strength of ties for q5 (How close are you with this person?), a “good friend” and a “very close friend” (scoring 4 and 5 respectively) were at the high end of the scale.

Similarly, for q11 (How close is your relationship with this person?), a relationship that was “especially close” (score 5), together with knowing the person “very well” (score 4 on the Likert 4 scale) for q13 (How well do you know this person?), was at the high end of the scale. Furthermore, “Somewhat close”: q11 (score 4 on Likert 5 scale) and “Somewhat well”: q13 (score 3 on Likert 4 scale) indicated a lesser degree of closeness.

The Likert 4 for q13 scale was converted to a Likert 5 scale prior to the analysis. The fuzziness around the score of 3.53 was appropriate, considering that both the mean and median had similar scores and there was no anomaly regarding the interpretation of the scales.

The scores in the 75th percentile were coded as “fully in”; those in the 25th percentile were coded as “fully out”; and the 50th percentile was used as the cross-over point. The calibration facility of fsQCA 2.5 was used to calibrate to metric scale to the fuzzy scores as indicated in Table 29. The calibrate function in fsQCA was used as follows: *calibrate (sot, 4.28, 3.53, 3.05)*.

As can be seen from Table 29 most of the metric scores, apart from chain 57, were more out than in, with Chain 57 more in than out (hence stronger). This also corroborated the quantitative binary logistic analysis which pointed out that weaker ties increased the probability of finding a solution *per se*, although not the quality of solutions, considering that most of the solutions resulted from weak ties.

Table 29: Strength of ties calibration

Chain no	Metric scale	Fuzzy score
14	1.08	0.001
15	1.08	0.001
36	3.25	0.151
38	2.92	0.021
53	3.08	0.061
57	3.58	0.551

4.3.4 Truth table

After the calibration process, a fuzzy set truth table was generated by selecting the calibrated fuzzy score (solution score) as the outcome, and all other fuzzy scores as causal conditions.

Fuzzy set analysis is underpinned by the truth table which consists of all possible combinations of causal sets per row (Elliott, 2013). Each row in the table represents causal conditions and the "number" gives an indication as to how many cases fall within the combination of these conditions. The number of rows (six in this study) equals 2^k where k is the number of causal conditions (Ragin, 2008).

The rows of the table list the various possible combinations of causal conditions. In this study, many of these rows were empty cases as there was no such combination of conditions The fuzzy sets construct a multidimensional vector space which has 2^k corners (Ragin, 2005). The input to the truth table is listed in Table 30, the fuzzy set frequency results in Table 31, and the truth table after reduction is listed in Table 32.

Table 30: Input to truth table

chain	fz_know (knowledge diversity)	fz_dist (geographic distance)	fz_comm (communication)	fz_ben (benevolence-based trust)	fz_comp (competence-based trust)	fz_sot (strength of ties)	fz_score (solution score)
14	0.011	0.951	0	0.051	0.951	0.001	0.991
15	0.951	1	0	0.051	1	0.001	0.041
36	0.011	0.051	0.049	0.001	1	0.151	0.611
38	0.731	0.051	0.049	0.001	0.501	0.021	0.801
53	0.501	0.051	0.849	0.501	1	0.061	0.961
57	0.951	1	0.049	0.951	1	0.551	0.041

Table 31: Fuzzy set frequency results

Condition	Membership set	Frequency	Percentage
fz_know (knowledge diversity)	0.011	2	33.3
	0.501	1	16.7
	0.731	1	16.7
	0.951	2	33.3
fz_dist (geographic distance)	0.051	3	50
	0.951	1	16.7
	1.0	2	33.3
fz_comm (communication)	0.0	2	33.3
	0.049	3	50.0
	0.849	1	16.7
fz_ben (benevolence-based trust)	0.001	2	33.3
	0.051	2	33.3
	0.501	1	16.7
	0.951	1	16.7
fz_comp (competence-based trust)	0.501	1	16.7
	0.951	1	16.7
	1.0	4	66.7
fz_sot (strength of ties)	0.001	2	33.3
	0.021	1	16.7
	0.061	1	16.7
	0.151	1	16.7
	0.551	1	16.7

Table 32: Truth table after reduction

fz_know (knowledge diversity)	fz_dist (geographic distance)	fz_comm (communication)	fz_ben (benevolence-based trust)	fz_comp (competence-based trust)	fz_sot (strength of ties)	number	fz_score (score)	raw consist.	PRI consist.	SYM consist
1	0	0	0	1	0	1	1	1	1	1
1	0	1	1	1	0	1	1	1	1	1
0	1	0	0	1	0	1	1	0.986667	0.983471	0.983471
0	0	0	0	1	0	1	0	0.819423	0.651026	1
1	1	0	0	1	0	1	0	0.183601	0.015054	0.015054
1	1	0	1	1	1	1	0	0.158416	0.022989	0.022989

The number field in the truth table (Table 32) shows the number of cases with a greater than 0.5 membership (frequency). The raw consistency is the degree to which membership is a consistent subset of the membership in the outcome. The outcome column (fz_score / score) was presented as a blank space at the onset. The frequency threshold selected was “1”, as the number of cases with solutions was so low. With fuzzy sets, unlike crisp sets, where membership can only be in or out, each of the cases can have varying degrees of membership in the different corners of the vector space (Ragin, 2005).

Chain 15 had the lowest raw consistency (59% solution score) of 0.158, followed by Chain 57 with the second lowest consistency (60% solution score) of 0.184 raw consistency.

4.3.5 Reduction

Remainder rows are rows in the truth table that do not meet the frequency threshold selected, which was set to “1” for this study. These rows were deleted from the truth table, in accordance with a recommendation made in the study by Ragin (2008). The other rows were then sorted in descending order according to the raw consistency score. Consistency assesses the degree to which cases share the same conditions for the outcome.

The outcome was then coded as “1” for all raw consistency scores >= .90.

The rest were coded as “0” (see fz_score /score in Table 32). There was a natural gap between 0.987 and the next row 0.819, notwithstanding the fact that 0.987 as a cut off was well above 0.90: a good consistency score threshold.

Schneider and Wagemann (2007) stated that consistency scores across rows of a truth table can demonstrate a gap between high and low values. This can often prove useful in terms of setting a threshold (Schneider & Wagemann.,2007). Rows that show a high consistency represent combinations that almost always lead to the outcome. Schneider and Wagemann (2007) argued that the threshold can vary depending on the number and knowledge of cases.

4.3.6 Analysis

When a standard analysis was performed, the prime implicator chart did not pop up for further selection. Prime implicants (PIs) are the product terms provided when using minimisation rules of the algorithm (Ragin, 2008; Elliott, 2013). The algorithm tries to minimise rows and therefore tries to combine rows that differ only on one cause, if the output values are the same. During the minimisation process, if the algorithm cannot fully reduce the truth table, the prime implicator chart will pop up when a user selects the PIs, based on theoretical and substantive knowledge. Therefore, if the chart does not pop up, it means that the algorithm was essentially able to minimise the truth table, without requiring further intervention.

Intermediate solutions were set to be present or absent, and no specific exclusions or inclusions were made. The prime implicates were then presented as a parsimonious and intermediate solution. The complex solution takes the rows coded against the outcome as it is, and applies Boolean simplification to combine the rows. Taking into account that there were not many causal conditions, the result was not overly complicated.

A complex solution makes no assumptions, and takes the rows related to the outcome as they are presented. The result also displayed the coverage associated with consistency.

Coverage indicates the degree to which the outcome is accounted for by the causal combinations presented. Coverage and consistency are distinct from one another and can sometimes conflict. For example, high consistency can result in low coverage, especially for more complex solutions (Ragin, 2008). If cases share several relevant causal conditions equally, they represent a sub-set of instances for the outcome. This combination of conditions can be seen as being "sufficient" for the outcome (Ragin, 2008).

The same applies to other sets of cases sharing conditions, which may also be sufficient for the outcome. Hence, there can be more than one causal path to the outcome. The frequency cut-off was 1, and the consistency cut-off was 0.987 in this study.

4.3.7 Solutions

Complex solution

Complex solutions work from the basis that all remainders are false. A complex solution does not use any assumptions to simplify the analysis. The complex solution in this research generated two paths of acceptable consistency towards good solution ratings (see Table 33). The solution consistency was high at 0.992, and the solution coverage (0.605) was good.

Table 33: Complex solution to good solutions

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_dist*fz_comp*~fz_know*~fz_comm*~fz_sot*~fz_ben [geographic distance] AND [competence-based trust] AND [limited knowledge diversity] AND [limited communication] AND [weak ties] AND [limited benevolence-based trust]	0.343587	0.307603	0.986667
2	fz_know*fz_comp*~fz_dist*~fz_comm*~fz_ben*~fz_sot [knowledge diversity] AND [competence-based trust] AND [limited geographic distance] AND [limited communication] AND [limited benevolence-based trust] AND [weak ties]	0.195589	0.130586	1.000000
3	fz_know*fz_comp*fz_comm*fz_ben*~fz_dist*~fz_sot [knowledge diversity] AND [competence-based trust] AND [communication] AND [benevolence-based trust] AND [limited geographic distance] AND [weak ties]	0.145966	0.101567	1.000000

Parsimonious solution

Parsimonious solutions take advantage of counter-factual analysis and engage with easy or difficult remainders in order to generate simpler solutions, and logical remainders automatically. In the study this solution generated two paths of acceptable consistency towards good ratings (see Table 34). The solution consistency was equally positive at 0.993, with a good coverage of 0.672 as well.

Table 34: Parsimonious solution

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_know*~fz_dist [knowledge diversity] AND [limited geographic distance]	0.363900	0.327916	1.000000
2	fz_dist*~fz_know [geographic distance] AND [limited knowledge diversity]	0.344167	0.308183	0.986689

Intermediate solution

An intermediate solution is in-between a complex and a parsimonious solution, and is a subset of both (Schneider & Wagemann, 2012). In this study, the intermediate solution generated three paths of acceptable consistency towards good solutions (see Table 35). The solution consistency was very high at 0.992 and the solution coverage was 0.605, which was adequate.

Table 35: Intermediate solution

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_dist* fz_comp*~fz_know*~fz_comm*~fz_sot* ~fz_ben [geographic distance] AND [competence-based trust] AND [limited knowledge diversity] AND [limited communication] AND [weak ties] AND [limited benevolence-based trust]	0.343587	0.307603	0.986667
2	fz_know*fz_comp*~fz_dist*~fz_comm*~fz_ben*~fz_sot [knowledge diversity] AND [competence-based trust] AND [limited geographic distance] AND [limited communication] AND [limited benevolence-based trust] AND [weak ties]	0.195589	0.130586	1.000000
3	fz_know*fz_comp*fz_comm*fz_ben*~fz_dist*~fz_sot [knowledge diversity] AND [competence-based trust] AND [communication] AND [benevolence-based trust] and [limited geographic distance] AND [weak ties]	0.145966	0.101567	1.000000

4.3.8 Good Solutions

This thesis focuses particularly on the intermediate solution, but with core and peripheral conditions, as covered in full after the presentation of the negated solution. The approach is based on the method of analysis set out by Fiss (2011) and described in more detail subsequently.

Three pathways generated good solutions, as demonstrated in Table 35. The first path had the highest raw coverage of 0.344 with 0.987 consistency. It is suggested that the combination of geographic distance and competence-based trust, as well as limited knowledge diversity, limited communication, limited benevolence-based trust and weak ties led to this result.

In Path 2, geographic distance was limited, whereas knowledge diversity was present (the inverse of these two determinants in Path 1), whilst all other determinants remained the same.

In Path 3, knowledge diversity was present, whilst geographic distance was absent and – contrary to Paths 1 and 2 – benevolence-based trust, alongside communication, was present in the configuration.

With reference to Table 34 (parsimonious solution), signifying core causal condition configurations for good solutions, geographic distance and knowledge diversity indicated a substitutive relationship across the two paths alongside a coverage of 0.67 and consistency of 0.993.

The pathways showed similar coverage. As such, when geographic distance was limited (Path 1) knowledge diversity was present; conversely, when knowledge diversity was limited, geographic distance was present.

In all cases competence-based trust and weak ties were evident. In most cases benevolence-based trust was limited, except when communication was present.

4.3.9 Negated outcome

As recommended by Schneider and Wagemann (2010) the outcome, and negation of outcome, should be analysed separately. Table 36 presents the truth table for the negated outcome (bad solutions).

Table 36: Negated outcome truth table

fz_know (knowledge diversity)	fz_dist (geographic distance)	fz_comm (communication)	fz_ben (benevolence-based trust)	fz_comp (competence-based trust)	fz_sot (strength of ties)	number	~fz_score (negated score	raw consist.	PRI consist.	SYM consist
1	1	0	0	1	0	1	1	0.987522	0.984946	0.984946
1	1	0	1	1	1	1	1	0.980198	0.977011	0.977011
0	0	0	0	1	0	1	0	0.482549	0	0
1	0	0	0	1	0	1	0	0.382789	0	0
0	1	0	0	1	0	1	0	0.206667	0.016529	0.016529
1	0	1	1	1	0	1	0	0.081511	0	0

The same conditions were loaded, with the difference that the negated solution score was selected. The frequency cut-off was “1” and the consistency cut-off selected was 0.980198, which was well above the lowest acceptable value. Between 0.98 and 0.48 there was also a large gap.

Complex solution

The complex solution generated two paths of acceptable consistency towards bad solution ratings (see Table 37). The solution consistency was high at 0.991 and the solution coverage was 0.630, which was quite good.

Table 37: Complex solution for negated outcome

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_know*fz_dist*fz_comp ~fz_comm*~fz_ben *~fz_sot [knowledge diversity] AND [geographic distance] AND [competence-based trust] AND [limited communication] AND [limited benevolence-based trust] AND [weak ties]	0.433829	0.397807	0.987522
2	fz_know*fz_dist* fz_comp*~fz_comm*fz_ben* fz_sot [knowledge diversity] AND [geographic distance] AND [competence-based trust] AND [limited communication] AND [benevolence-based trust] AND [strong ties]	0.232576	0.196554	0.980198

Parsimonious solution

The parsimonious solution generated one path of acceptable consistency towards bad solution ratings (see Table 38). The solution consistency was high at 0.993, and the solution coverage of 0.788 was very good.

Table 38: Parsimonious solution for negated outcome

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_know*fz_dist [knowledge diversity] AND [geographic distance]	0.787784	0.787784	0.993090

Intermediate solution

The intermediate solution generated two paths of acceptable consistency towards bad solution ratings (see Table 39). The solution consistency was high at 0.991, and the solution coverage of 0.630 was good.

Table 39: Intermediate solution for negated outcome

Path number	Paths	Raw coverage	Unique coverage	Consistency
1	fz_dist*fz_know*fz_comp*~fz_comm*~fz_ben*~fz_sot [geographic distance] AND [knowledge diversity] AND [competence-based trust] AND [limited communication] AND [limited benevolence-based trust] and [weak ties]	0.433829	0.397807	0.987522
2	fz_dist*fz_know*fz_comp*~fz_comm*fz_ben* fz_sot* [geographic distance] AND [knowledge diversity] AND [competence-based trust] AND [limited communication] AND [benevolence-based trust] AND [strong ties]	0.232576	0.196554	0.980198

4.3.10 Bad solutions

Table 39 illustrates two configuration paths for bad solutions. The first, at a raw consistency of 0.433 and a consistency of 0.988, shows that a combination of geographic distance, knowledge diversity, competence-based trust, limited communication, limited benevolence-based trust and weak ties results in bad solutions.

The second pathway shows a similar configuration for bad solutions, although with a lower raw coverage and consistency of 0.233 and 0.980 respectively. Similar to Path 1, geographic distance, knowledge diversity and competence-based trust were all high, and showed limited communication. Benevolence-based trust, associated with strong ties, also formed part of the configuration for bad solutions.

Essentially, when comparing good solutions to bad solutions in this study, it was found that the former never included knowledge diversity and geographic distance at the same time, whereas in bad solutions both were present.

Regarding the parsimonious solution for bad solutions, the combination of knowledge diversity and geographic distance had a coverage of 79% at a consistency of 99%.

Significantly, a review of the textual evidence of the related case (Chain 57) to Path 2 (Table 39), showed that the individual who submitted a bad solution worked in an unrelated field (knowledge diversity), was a good friend of the referrer (strong ties), and resided in a different country (geographic distance). Moreover, benevolence-based trust was strong.

It is indeed evident that a surfeit of simultaneous diversity (geographic distance and knowledge diversity) generates bad solutions. This will be discussed in detail in the next chapter.

4.3.11 Core and peripheral analysis

Fiss (2011) introduced the concept of core and peripheral conditions as dual concepts for the understanding of typologies. Coreness relates to elements which can be causally connected to specific outcomes. Coreness can also be defined as “those causal conditions for which the evidence indicates a strong causal relationship with the outcome of interest”, while peripheral elements are “those for which the evidence for a causal relationship with the outcome is weaker” (Fiss, 2011, p. 398).

As mentioned in the introduction to fsQCA, several pathways can cause an outcome, and these are therefore called equifinal configurations.

Within any configuration, there are different peripheral causes which may surround core causal conditions. Solutions, therefore, may be complex, parsimonious or intermediate. Core conditions are common to both parsimonious and intermediate solutions, while peripheral conditions are eliminated from the parsimonious solution and hence only exist in the intermediate solution (Fiss, 2011).

A solid black circle “●“ was used to show the necessary presence of a condition, and a circle that was crossed out “⊗“ was used to represent the necessarily absence of a condition, similar to the presentation used in Fiss (2011). Larger circles represented core causal conditions and smaller circles represented peripheral conditions.

An intermediate solution is a subset of the most parsimonious solution and a superset of the conservative solution (Schneider & Wagemann, 2012). This thesis presents the intermediate solutions, but with signalling core and peripheral conditions. When conditions appear in the parsimonious solution, these conditions are shown as core conditions. Conditions not appearing in the parsimonious solution are indicated as peripheral conditions.

Table 40 shows the configurations for good and bad solutions. The summary of findings at the end of the chapter, describes the table in more detail.

Table 40: Configurations for good and bad solutions

Configuration	Solutions				
	Outcome (good solutions)			Negated outcome (bad solutions)	
	1a	1b	1c	2a	2b
Diversity					
Geographic distance	●	⊗	⊗	●	●
Knowledge diversity	⊗	●	●	●	●
Trust					
Competence-based trust	●	●	●	●	●
Benevolence-based trust	⊗	⊗	●	⊗	●
Strength of ties	⊗	⊗	⊗	⊗	●
Communication	⊗	⊗	●	⊗	⊗
Consistency	0.987	1.000	1.000	0.988	0.980
Raw coverage	0.344	0.196	0.146	0.434	0.233
Unique coverage	0.308	0.131	0.102	0.398	0.197
Overall solution consistency	0.992			0.991	
Overall solution coverage	0.605			0.630	

4.3.12 Summary of findings

4.3.13 Supporting features

Trust

Competence-based trust was prominent across good and bad solutions. It is therefore probable that individuals generally refer others whom they regard as competent and professional, and not necessarily because they have a close emotional bond with these people (benevolence-based trust). In addition to this, the mean and median for competence-based trust was 4.39 and 4.5 respectively (refer to Table 22), which was very high.

Apart from solution 1c, which was the lowest coverage solution for good solutions, benevolence-based trust did not emerge as a core or peripheral determinant for good solutions. Solution 1c showed that frequent communication accompanied benevolence-based trust. The only bad solution relating to benevolence-based trust occurred when ties were strong. So it seemed that benevolence-based trust was part of configurations where communication was frequent, or ties were strong.

It was hypothesised (Hypothesis 1) that trust is positively correlated to the depth of search (forming a chain). Support was not obtained for trust as a whole (competence-based trust and benevolence-based trust at the same time), although competence-based trust featured strongly in referrals (forming chains), considering the high mean and median. Competence-based trust also featured in good and bad solutions, as well as weak and strong ties.

Hence, Hypothesis 1 was supported in part, seeing that it was not trust as whole but competence-based trust specifically that featured strongly.

Hypothesis 2 was also not supported, as trust was not positively associated with the quality of OI solutions, because competence-based trust featured in good and bad solutions, while limited benevolence-based trust featured for most of the good solutions, and was also evident in some bad solutions.

Communication, which was noted as a supporting feature of social capital, was evident only in one of the solution paths alongside benevolence-based trust.

4.3.14 Bridging features

Diversity

It was hypothesised that diversity in knowledge bases is associated with the quality of OI solutions (Hypothesis 3). Furthermore, it was also hypothesised that geographic distance is associated with the quality of OI solutions (Hypothesis 4). The first configuration path for good solutions (1a) indicated that geographic distance affected the quality of solutions which supported Hypothesis 4. This was also the configuration with the highest coverage.

Furthermore, the second and third configuration paths for good solutions (1b & 1c) indicated that knowledge diversity affected the quality of solutions. This provided support for Hypothesis 3. Not one of the solution paths for good solutions contained knowledge diversity and geographic distance simultaneously.

However, the negated outcome (bad solutions) indicated that if both geographic distance and knowledge diversity appeared in the same configuration path (2a and 2b) bad solutions resulted. Both Chains 15 and 57 (related to bad solutions) showed knowledge diversity and geographic distance at the same time.

Hence, when knowledge is different and people are further apart, there seem to be too many barriers, especially in terms of learning from others, to enable good quality solutions.

It is probable that a substitutive relationship exists between knowledge diversity and geographic distance. Having both geographic distance and knowledge diversity simultaneously are associated with bad solutions. It is therefore suggested that too much diversity (geographic distance and knowledge diversity at the same time) is bad for the quality of OI solutions.

Therefore, the pathways to good solutions, appear to illustrate a substitutive relationship between knowledge diversity and geographic distance, where a high level of geographic distance substituted for limited knowledge diversity for good solution ratings and *vice versa*.

The substitutive relationship of these two conditions means they can be seen in terms of core conditions (see parsimonious solution in Table 34).

Hence, in view of the high coverage of solution 1a, geographic distance was indicated to be a core determinant of good solutions, when the knowledge diversity was low and people were in similar knowledge domains.

For technical problems to be solved through chains (indirect interpersonal relationships to the focal organisation) it seemed that knowledge diversity created barriers and resulted in people referring others who were perhaps not technically competent to solve the problem, especially when proximity was not close. In contrast, when individuals had similar knowledge bases, geographic differences brought about the diversity needed to solve the problem.

Depth

Depth was achieved by the formation of chains, as illustrated in Table 15. It was hypothesised that depth was associated with the quality of OI solutions.

The descriptive results indicated that solutions derived directly from the starters (with no chain and thus no depth) scored lower on average than the solutions derived through chains (58% versus 80% respectively). It should however be noted that good and bad solutions were obtained through chains as well.

Therefore, Hypothesis 5 can only be supported in part. Depth alone was not the only important determinant of good solutions: diversity was also a factor, as long as there was no surfeit.

The quantitative analysis for finding solutions (not necessarily quality solutions) pointed out that such solutions were more likely to be found through weak rather than strong chains. It was suggested that the strength of a chain is dependent upon the average of dyadic strength of ties between agents that make up a chain.

Furthermore, the results also indicated that solutions are less likely if people branch extensively. This was not specifically hypothesised, although it was embedded within the research problem.

Finally, the fsQCA analysis indicated that weak chains brought about good and bad solutions. Thus the strength of a chain did not seem to affect the quality of solutions. Therefore, Hypothesis 6 was supported by the results.

When analysing why individuals branch extensively, the results indicated that they do so when they believe referrals would not necessarily be helpful (low benevolence-based trust).

Thus, it is probable that individuals refer others extensively in the hope of finding a “luck of the draw” solution to the problem. This was not specifically hypothesised.

CHAPTER 5: SUMMARY, DISCUSSION, CONCLUSION AND IMPLICATIONS

This final chapter begins with a brief overview of the study, including a statement of the problem and the research methods employed. The chapter focuses particularly on summarising and discussing the hypotheses as they relate to the main themes of this study: namely, the supporting and bridging features of social capital. The chapter culminates in a discussion about the pertinence of the results for OI practices and future research.

5.1 Summary of the Study Problem and Methodology

In today's demanding economic environment, organisations are compelled to innovate, and to transform innovation processes, in order to stay ahead of the competition or to make inroads into new markets.

However, although incremental innovations are ubiquitous, they seem to be less than radical in nature (Leitner et al., 2016). Existing innovation strategies therefore require drastic transformation in order to remain key enablers of competitiveness. Merely investing in internal research and development (R&D) functions, and/or resources for innovation purposes, may be insufficient.

Even though organisations have long exploited external knowledge for innovation purposes (Cohen & Levinthal, 1990), in recent decades they have begun to incorporate external technologies into their innovation processes through alliances and partnerships or in-licensing, a process termed "open innovation" (Chesbrough, 2003).

Most commonly, organisations have leveraged external networks for innovation performance. This is referred to as "network-centric innovation" (Nambisan & Sawhney, 2011). However, studies have shown that searching too widely for external innovations can be expensive and ineffective (Katila & Ahuja, 2002; Laursen & Salter, 2004; 2006; Vanhaverbeke et al., 2002) and can actually slow down the innovation process (Leitner et al., 2016).

The objective of this study was to explore a novel process of searching for innovative solutions based on depth rather than breadth. The study focused on indirect interpersonal relationships. It was hypothesised that OI returns could be intentionally derived via indirect interpersonal relationships to the organisation, by means of a trusted bridging chain that stretched across network horizons, driven by trust and infused with diversity. Organisations could search for innovative solutions through external bridging chains of referrals, driven by trust.

Trust was seen as a supporting element of social capital, with diversity playing a bridging role. “Social capital” referred to the returns gained through social networks and interpersonal relationships (Burt, 1997; Coleman, 1988; Lin, 2001).

The study was based on a quasi-experiment where members of a starter group of 121 individuals were requested to solve a complex technical problem by tapping their social networks, and identifying other individuals who would, in turn, tap their own respective networks in an attempt to solve the problem.

In the process, 60 valid chains of individuals were assembled from 75 referrals. Nine solutions were found, of which six were from chains and three from starters (not through indirect relationships). A combination of set fsQCA approach and quantitative analysis was used to analyse the data.

The roles played by trust (benevolence-based and competence-based), and diversity (knowledge diversity and geographic distance) were core to the study. Essentially, it was argued that both supporting (trust) and bridging (diversity) features of social capital were crucial for OI returns through indirect interpersonal relationships to the organisation.

The results indicated that chains of referrals, inhering trust and diversity, enabled the unlocking of social capital for OI returns. Although it was revealed that competence-based trust (supporting feature of social capital), particularly enabled the formation of chains that facilitated depth of search, it was found that trust did not contribute to the quality of solutions found.

Moreover, although weak ties proved to be instrumental in finding solutions, they did not determine the quality of these solutions. It is increasingly understood that weak ties are not necessarily an indicator of novelty (Levin & Barnard, 2013; Levin & Cross, 2004). Rather, the study revealed the importance of knowledge diversity and geographical distance as two sources of novelty. Moreover, it showed a substitutive relationship between knowledge diversity and geographical distance, suggesting that too much diversity led to bad solutions. This finding is also consistent with what has been previously found (e.g. Lahiri, 2010).

Searching broadly was not specifically hypothesised as being detrimental to OI returns. However, the results of the research indicated that when individuals referred others extensively there was less likelihood of finding solutions. Indeed, it emerged that extensive referrals occurred when the initial individual had minimal trust (low benevolence-based trust) in the efficacy of these referrals.

5.2 Discussion of results

5.2.1 Supporting features

Trust

Trust is an important feature of social capital, facilitating cooperation, coordination and the sharing of information (Coleman, 1988; Levin & Cross, 2004; Putnam, 1995; 2000). Trust can also be a causal proposition that enhances the utility of embedded resources (Lin, 2001). In fact, trust has been shown to have a more positive effect on knowledge transfer than emotional closeness and interaction frequency (Levin et al., 2011; Levin et al., 2015).

This study confirmed that a trusted bridging chain simultaneously contains supporting (trust) and bridging (diversity) features of social capital. The study also clarified extant theory in situations where bonding social capital (which involves strong ties) concomitantly leverages bridging social capital (when strong ties bridge).

The study further demonstrated that trust is one of the most important features of bonding social capital, as it facilitates obligations, expectations, reciprocity

(Coleman, 1988) and learning (Nielsen, 2009). Strong ties also play a strong role in this regard (Coleman, 1988; Granovetter, 1985; Levin & Cross, 2004; Levin et al., 2011; Levin et al., 2015).

In short, the interdependence required in innovation processes is facilitated by trust (Nooteboom, 2013), and most innovation activities are founded on trust, as they involve the sharing of sensitive information.

Trust, in particular competence-based trust, was shown in this study to facilitate the formation of referral chains, thus enabling an organisation to search through deeper horizons for innovative solutions (Hypothesis 1). Hence, competence-based trust was seen to be a supporting feature of a bridging chain in unlocking social capital for OI returns. Competence-based trust also seemed to be more conducive to depth of search than benevolence-based trust.

Studies on trust and networks of learning have indicated the importance of trust in knowledge-sharing and innovation (Clegg et al., 2002; Dakhli & Clercq, 2004; Ellonen et al., 2008; Landry et al., 2002; Lee & Choi, 2003; Moran, 2005; Powell et al., 1996; Tsai & Ghoshal, 1998). Forming a chain of referrals to solve an innovation problem is essentially creating a chain of knowledge exchanges. In this regard, rich knowledge exchange is strongly associated with trust (Inkpen & Tsang, 2005; Krackhardt & Hanson, 1993; Levin & Cross, 2004; Levin et al., 2011; Nooteboom, 2013; Uzzi, 1996).

In extant theory there is negligible reference to “indirect trust” in terms of social and innovation networks, although its role in computerised recommender systems has been acknowledged (Jamali & Ester, 2009; Walter, Battiston; Schweitzer, 2009). In the light of the findings of this thesis, indirect trust can be defined as: *the trust relations between agents not directly linked to the organisation but leveraged for organisational returns.*

Studies on trust and knowledge transfer have yielded mixed results. Some research has focused on competence-based trust (Chowdhury, 2005; Holste & Fields, 2010); other studies have focused on benevolence-based trust in terms of emotional bonding (Ko, 2010; Zhou, Siu & Wang, 2010).

This study highlighted the importance of analysing the effects of different types of trust, especially those which reach outside organisational boundaries. It therefore discounted institutional trust which is a key aspect of intra-organisational studies, as explored by Levin and Cross (2004) and Levin et al., (2011).

Based on the earlier work of Gillespie (2003), Alexopoulos and Buckley (2013) explored professional and personal trust as distinct constructs, associated with competence-based and benevolence-based trust respectively. It was also suggested that the distinction between professional and personal trust was more noticeable in the exchange of tacit knowledge (Golden & Raghuram, 2010): an insight relevant to this study which focuses on finding a solution to a highly technical problem.

In their review of trust measurement, McEvily and Tortoriello (2011), called for greater clarification of the different categories of trust, particularly in relation to other dependent factors and different contexts. Subsequently, Alexopoulos and Buckley (2013) demonstrated the moderating effect of tie longevity on professional and personal trust during knowledge exchange.

The sourcing of useful knowledge is connected to perceptions of professionalism and competence (Levin & Cross, 2004). Moreover, Chowdhury (2005) showed that competence-based trust is positively associated with complex knowledge sharing because it relates to ability, and is thus competence-based.

Benevolence-based trust

In this study, benevolence-based trust featured in only one configuration for good solutions, and another for bad solutions. In both cases the solution coverage was the lowest. By contrast, competence-based trust featured strongly across all cases. The statistical mean for benevolence-based trust across referrals was also lower than that of competence-based trust. So, benevolence-based trust was not seen to facilitate either the depth of search or the quality of OI solutions.

Benevolence-based trust featured in one of the configuration paths for good solutions, alongside frequent communication, linked to weak ties. This finding is consistent with research by Levin and Cross (2004) which showed evidence of benevolence-based trust in such ties.

Frequent communication has also been shown to promote benevolence-based trust (Abrams, Cross, Lesser & Levin, 2003), as well as closeness and frequency (Levin & Cross, 2004; Tsai & Ghoshal, 1998), although these factors are not exclusive (Levin et al., 2015).

However, Solution 2b (Table 40) in this study revealed the presence of benevolence-based trust alongside strong ties. This concurs with extant theory (Currall & Judge, 1995; Glaeser, Laibson, Scheinkman & Soutter, 2000; Levin, Cross & Abrams, 2002) and may well be a consequence of greater emotional bonds (Levin & Cross, 2004).

Thus, it can be said that strong personal trust is dependent upon strong inter-personal bonds, built through long-term relationships. It is also positively associated with the ability to source useful knowledge and safeguard personal vulnerabilities (Alexopoulos & Buckley*,* 2013).

The results of this study show that either frequent communication or strong ties could be indicators for benevolence-based trust. Equally, strength of ties has not always been related to frequency of communication (Jack et al., 2004; Marsden & Campbell,1984; Wellman & Wortley, 1990), as evidenced in Solution 2b.

This concurs with an insight by Burt, also cited by Levin et al. (2015, p.7): “Managers, like people in the general population, do not distinguish relations on a single dimension of strong versus weak. They distinguish on orthogonal dimensions of intimacy and activity” (Burt, 1997, p. 363).

Closeness (strength of ties) and frequency of communication are not only distinct but are shown in this study to operate independently (Marsden & Campbell, 1984).

Benevolence-based trust did not necessarily drive the depth of search, and neither did it affect the quality of solutions. Indeed, the formation of innovation ties was positively associated with trust in the other individual’s ability (competence-based trust), although this was moderated by benevolence-based trust in the Shazi et al. (2015) study.

In both the Levin and Cross (2004) and Shazi et al. (2015) studies, the individuals formed part of the same organisation which invariably inhered a radius of trust (Dakhli & Clercq, 2004; Ellonen et al., 2008; Fukuyama, 2001;). As mentioned earlier, institutional trust, associated with organisations, can have a mediating effect on exchange (Dakhli & Clercq, 2004; Ellonen et al., 2008).

This study shows that when interpersonal ties bridge across organisational boundaries, benevolence-based trust does not appear to be a significant factor, unless frequent communication or strong ties are present.

In their frequently cited study, Jarvenpaa, Knoll and Leidner (1998) reported that during the early stages of virtual team formation, benevolence-based trust was low and the ability and integrity of the trustee contributed more significantly to team trust. Although their research focused on team trust, it was also applicable to virtual teams: specifically, referring a weak tie to help solve a problem in the early stages of team formation.

Over an extended period, benevolence-based trust should increase, considering that building such trust requires information which takes time to gather (Mayer et al., 1995). In their study, Levin and Cross (2004) found that benevolence-based trust mediated the relationship between the sourcing of useful knowledge and weak ties, although the exchange was within an organisation which assumed a radius of trust or institutional trust (Dakhli & Clercq, 2004; Ellonen et al., 2008; Fukuyama, 2001).

Overall, when reaching outside the boundaries of an organisation, weak ties may not inhere high levels of benevolence-based trust. Accordingly, when ties are weak and there is no sphere of trust related to an organisation, benevolence-based trust may be lower than anticipated – especially when referring another individual to help solve a complex problem across organisational boundaries, unless they communicate frequently or have strong ties.

To summarise: benevolence-based trust is more likely when ties are strong (Currall & Judge, 1995; Glaeser et al., 2000); and when associated with relationships built over time (Alexopoulos & Buckley, 2013). Conversely, early stage relationships are not conducive to the building of such trust (Jarvenpaa et al., 1998).

This study found that benevolence-based trust was limited unless ties were strong, or where there was frequent communication. This is consistent with evidence of how trust functions when reaching outside organisational boundaries, in situations where institutional trust, or a radius of trust, is lacking (Dakhli & Clercq, 2004; Fukuyama, 2001). It can similarly be theorised that benevolence-based trust would not play much part in the formation of the referral chain when searching deeply across organisational boundaries and horizons, although competence-based trust would do so.

Competence-based trust

This study demonstrated that competence-based trust was a factor in the referral of organisational problems (recursively), through forming a chain, and through in-depth probing of indirect, interpersonal relationships.

According to Mayer et al. (1995), ability is a task-related skill which determines how an individual's competence is perceived by others. However, it can be risky to rely on an outside source for quality information or advice, and it demands confidence and positive expectations on the part of the instigator.

Unlike benevolence-based trust, competence-based trust develops relatively quickly, prior to the accumulation of meaningful information, as a result of social categorisation, reputation, institutional roles and structure (McKnight, Cummings & Chervany, 1998).

McAllister (1995) found that cognitive-based trust (competence-based trust) was a precursor to affect-based trust (benevolence-based trust). The Javenpaa et al. (1998) study further showed that during the early stages of virtual team formation benevolence-based trust was low, while trust associated with ability and integrity was much higher. In a later study, it was found that confidence in co-workers' task-related competence and skills was conducive to interpersonal knowledge sharing (Politis, 2003).

Trust, based on perceptions of professional competence, is a strong positive predictor of the gathering of useful knowledge (Levin & Cross, 2004). Similarly, cognition-based trust has been associated positively with complex knowledge sharing (Chowdhury, 2005). In fact, competence was shown to be critical when knowledge is highly tacit (Levin & Cross, 2004). Competence-based trust has been shown to mediate the gathering of useful knowledge from weak ties (Levin & Cross, 2004) and has been identified as a predictor for the formation of innovation ties (Shazi et al., 2015).

When referring another individual, a level of knowledge sharing also takes place, because a problem is shared with and explained to the referred person. Competence-based trust has been associated positively with complex knowledge sharing (Chowdhury, 2005; Levin & Cross, 2004).

Considering that OI reaches outside an organisation, most of the referrals would not be to a person from within the same organisation – a dynamic which limits the effects of institutional trust (Dakhli & Clercq, 2004; Ellonen et al., 2008). Moreover, competence-based trust can happen quickly: even prior to the accumulation of meaningful knowledge about the referred individual, and can be based on status or social categorisation (McKnight et al., 1998).

Therefore, when referring a person from outside an organisation to solve a complex problem, there is a stronger likelihood that competence-based trust will be present than benevolence-based trust. For this reason, it can be assumed that competence-based trust would be high in most referral cases. Indeed, this study did show a high level of competence-based trust, thereby partially supporting Hypothesis 1.

However, competence-based trust did not determine the quality of OI solutions as it formed part of the configuration of good and bad solutions, even though it did generate solutions *per se* and new information sharing. This finding did not support Hypothesis 2. Instead, some bridging element was also required.

Significantly, the element of communication was lacking in most respects across the solutions generated in this study. Considering that trust facilitates collaboration and communication (Reagans & Zuckerman, 2001), and is thus associated with supporting features of social capital, a discussion on communication now follows.

Communication

Apart from one case, frequent communication did not feature in most of the solutions (good or bad). Yet, extant theory shows that supporting relations aid coordination and communication (Reagans & Zuckerman, 2001), especially through facilitating the spread of ideas (Uzzi et al., 2007).

It has also been shown that frequency of communication and closeness are distinct concepts (Jack et al., 2004; Marsden & Campbell, 1984; Wellman & Wortley, 1990), while communication and collaboration have been identified as important for successful innovation (Ebadi & Utterback, 1984). However, a surfeit of communication can lead to knowledge saturation (McFadyen & Cannella, 2004).

Related studies have demonstrated that R&D has become more global (Gassmann, Enkel & Chesbrough, 2010) because it has become easier to communicate due to the decreased costs of communication. Thus, technology facilitates OI coordination, opening up opportunities across industries (Chesbrough & Appleyard, 2007; Gassman, 2006) and globally (Gassman et al., 2010).

New communication platforms have also enabled virtual R&D teams to communicate effectively (Boutellier, Gassmann, Macho & Roux, 1998).

Communication is often directed towards ideas rather than people (Awazu, Baloh, Desouza, Wecht, Kim & Jha, 2009); or towards project platforms rather than individual team members (Boutellier et al., 1998). In fact, OI contests are supported mostly through ICT platforms that provide support to many through broad, but not deep, communication (Boudreu & Lakhani, 2013; Boudreau, Lacetera & Lakhani, 2011; Jeppesen & Lakhani, 2010).

Social media platforms continuously facilitate the flow of communication and broadcasts, yet interpersonal, two-way communication might be limited, as the results of this study indicate. This suggests that people are currently exposed to extensive, indiscriminate communication which is not necessarily aimed at them specifically. Thus, interpersonal communication in support of OI seems to be increasingly redundant, although communication through social media platforms enables consumers to “listen” passively. This phenomenon is similar to Burt’s concept of secondhand brokerage (2007; 2010).

In order to leverage knowledge about innovation via these platforms, organisations must consciously search through deeper horizons (not merely directly), to empower themselves and refer others to solve problems. As Lin points out, social capital is: “resources embedded in a social structure that are accessed and/or mobilised in purposive action”, (2001, p. 29).

5.2.2 Bridging features

Diversity

The results of this research suggest that bridging features of social capital (diversity), positively affect the quality of innovative solutions. Both knowledge diversity (Hypothesis 3) and geographic distances (Hypothesis 4) had an impact on the quality of OI solutions found, which means that both these hypotheses were supported.

The effects of a combination (or not) of knowledge diversity and geographic distance were not specifically hypothesised. Yet in the results, geographic distance and knowledge diversity essentially indicated a substitutive relationship. When geographic distance and knowledge diversity were present at the same time, the configuration resulted in low quality OI solutions.

Knowledge diversity is important for innovation and is enabled through diverse relationships (Amara & Landry, 2005; Baum et al., 2000; Becker & Dietz, 2004; Miotti & Sachwald, 2003; Nieto & Santamaria, 2007; Powell et al., 1999; Pullen et al., 2012; Vanhaverbeke et al., 2006; Roper et al., 2008). Furthermore, different industries associated with diverse knowledge bases have had a positive influence on innovation (Hargadon & Sutton, 1997).

The differences in knowledge bases are derived from the cognitive distance between the resources held by organisations (Nooteboom et al., 2007). On a more interpersonal level, when people have different knowledge bases or technological focus (which includes industry differences), their cognitive distance would be larger (Nooteboom et al., 2007; Nooteboom, 2013). Therefore, if one person refers another person from a totally different knowledge domain, their cognitive distances would be large, which could impede mutual understanding (Cohen & Levinthal, 1990; Mowery, Oxley & Silverman, 1996; Nooteboom, 1992; Nooteboom, 1999; Nooteboom et al., 2007; Nooteboom, 2013).

Cognitive distance facilitates novelty, given the combination of complementary resources (Ahuja & Katila, 2004; Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001). However, a surfeit of cognitive distance results in too little absorptive capacity, which in turn negatively affects learning and innovation (Cohen & Levinthal,1990; Nooteboom et al., 2007; Tsai, 2001;).

When an organisation's business units are distributed globally, and where the organisation itself is technologically diverse (Lahiri, 2010), external technological knowledge would be involved in some aspect of the organisation's existing knowledge domains (Cohen & Levinthal, 1990). In general, cost constraints would inhibit an even spread of similar technologies across all business units, which would lead to considerable inter-business unit technological diversity (Lahiri, 2010). Thus, when knowledge was sourced from a specific location, it would be relevant to that location specifically.

Lahiri's (2010) research indicated that if an organisation increases its levels of technological diversity, the impact of geographic distribution becomes less positive. Therefore, when organisations are very technologically diverse, and have many widely distributed R&D activities, the quality of innovation is often adversely affected.

Nevertheless, when geographic distance is close, such as in membership of communities or clusters, learning is facilitated by these supporting relationships (Powell et al., 1996; Sorenson & Audia, 2000). Supporting relations enhance the build-up of absorptive capacity, which is often necessary to screen or interpret novel information (Gilsing et al., 2008).

For example, IDEO's buildings are all on the same street, within a few blocks of each other. This enables designers, focusing on different industries, to meet physically on a regular basis (Hargadon & Sutton, 1997). Moreover, the areas where design engineers work are open-plan offices which encourage formal and informal discussions between engineers working across different industries. During product development, they meet and brainstorm ideas (Hargadon & Sutton, 1997).

In relation to this study, it is clear that an individual must initially understand the problem to be solved in order to refer someone else, and should also have an understanding of that person's knowledge, so as to gauge their potential in terms of providing a solution (Cohen & Levinthal, 1990; Mowery et al., 1996; Nooteboom et al., 2007).

Too large a gap in knowledge diversity between the referrer and the referred individual could have a negative effect on the quality of the solution, as it would lead to cognitive distance between these individuals – unless, of course they are geographically close. The close working proximity at IDEO, and the open plan office design that facilitates discussions, compensates for cognitive distance (Hargadon & Sutton, 1997). Thus, it is evident that close physical proximity counteracts cognitive distance when innovating across knowledge bases.

Conversely, a surfeit of support, coupled with closed relationships inhibit access to diverse information (Crescenzi et al., 2016; Fleming et al., 2007; Letaifa & Rabeau, 2013; Uzzi & Spiro, 2005). Thus, too great geographic proximity could stifle diversity and innovation (Letaifa & Rabeau, 2013). Indeed, studies have shown that greater geographic distance, or global reach, actually facilitates access to new information (Beers & Zand, 2014; Capaldo & Petruzzelli, 2014; Levin & Barnard, 2013; Letaifa & Rabeau, 2013; Nooteboom, 2013; Todo et al., 2015; Whittington et al., 2009).

It is also evident that greater diversity increases innovation potential, but can inhibit mutual understanding (Nooteboom, 1992; 1999; Nooteboom et al., 2007; Nooteboom, 2013); while a surfeit of integration leads to redundancy and diminishes innovation potential (Burt, 2000; Letaifa & Rabeau, 2013; Schilling & Phelps, 2007; Tiwana, 2008; Uzzi & Spiro, 2005).

The relationship between these elements is therefore substitutive. When knowledge diversity is large, closer geographic proximity is crucial – as exemplified by the IDEO case study (Hargadon & Sutton, 1997). Equally, when knowledge diversity is limited, geographic distance can generate innovation (Beers & Zand, 2014; Letaifa & Rabeau, 2013). Thus, distance can be positive, even if it complicates technological collaboration (Nooteboom, 2013).

At the same time, cognitive proximity (limited knowledge diversity) across geographic distance can facilitate access to new information: specifically, information which has not been spilled across to the local cluster from outside, considering that spill-overs are geographically bounded (Audretsch & Feldman, 1996; Feldman, 1994; Jaffe et al.,1993).

Depth

It was hypothesised that depth of search can be associated with the quality of OI solutions (Hypothesis 5). However, depth of search *per se* (returns derived through indirect interpersonal relationships to the organisation), did not necessarily have a positive effect on the quality of OI solutions. Indeed, although best quality solutions were generated via a chain (representing depth), bad solutions were also found through the same dynamic. Hence, Hypothesis 5 was only supported in part.

To summarise: firstly, it was found that competence-based trust drove the depth of the chain (Hypothesis 1); secondly, that a substitutive relationship between geographic distance and knowledge diversity was responsible for the quality of solutions (Hypotheses 3 and 4 in part). Thus the element of trust coupled with diversity, constituted a “trusted bridging chain”.

“Trusted” here finds expression especially through competence-based trust; “diversity” supports the novelty provided by “bridging”; and a chain exemplifies the “depth” of search. The element of balance is crucial: diversity is positive, but not in surfeit; geographical distance is positive, but not when combined with knowledge diversity.

The descriptive results of this research indicate that the mean chain length was 2.28 across all chains, and 2.2 for completed chains. The maximum chain length was three. By contrast, Dodds, Muhamad and Watts (2003) found the average, over completed chains in a small world, was approximately four, but argued that the ideal chain length is more likely to be between five and seven, taking attrition into consideration. Their study had a 60,000 sample size, and the scope was 18 individuals across 13 countries: a context which would not be appropriate when solving a complex innovation problem.

Chain length does indeed depend on context, and it has been recognised that more research is needed about individuals’ knowledge of their networks, and how they use them for searching (Granovetter, 2005).

Although not specifically hypothesised, it was anticipated in this study that chain lengths would be longer, considering that there were no challenges with knowledge recall, as is the case in job referral studies (Friedkin, 1982). In such studies, chain length has generally been found to be short because of the limited horizons of observability about indirect ties.

This study, however, was enabled through a software system that drove the referral process. In hindsight, the time frame for the submission of solutions may have been problematic. The time frame was initially set to six weeks, which is generally the norm for OI challenges, but was later extended by a further six weeks. This may have been too short a time for the last individuals in the chain to refer others to solve the problem, especially during the initial six-week phase.

Weak chains

The statistical results in this study indicated that OI solutions (good and bad) were generated mostly through chains made up from weak ties: a finding which supports Hypothesis 6. The statistical model indicated that solutions were less likely to be found if the strength of ties across the chain increased (strong chains). Therefore, there was a higher probability of finding solutions through weak chains. However, weak chains were not responsible for the quality of OI solutions as they generated both good and bad solutions.

Extensive research has shown that resources and returns can be found through acquaintances or weak ties (Burt, 1997; Granovetter, 1973; 1983; Levin & Cross, 2004; Levin et al., 2011; Milgram, 1967); as well as through informal spillages (Almeida & Kogut, 1999); and in the overlap between networks (Fleming et al., 2007; Murray, 2002; Porter et al., 2005; Uzzi & Spiro, 2005).

In fact, it has been suggested that any resource in the world can be accessed via a minimum of just six intermediate acquaintances (Milgram, 1967). Diversity can also be catalysed through spill-overs alongside formal, informal, and indirect relations – all of which has a positive effect on innovation (Ahuja, 2000; Belderbos & Carree, 2004; Jack, 2005; Owen-Smith & Powell, 2004).

Thus, although chains constituted by weak ties were seen in this study to support the discovery of OI solutions, they did not have a significant effect on the quality of solutions – unlike the element of balanced diversity.

Breadth of search

The quantitative study indicated that when an individual refers others extensively, then there is less likelihood of sourcing OI solutions. This finding was not specifically hypothesised, although it resonates with the research problem and shows that searching too widely lowers innovation performance (Katila & Ahuja, 2002; Laursen et al., 2004; 2006; Vanhaverbeke et al., 2002).

It was also necessary to analyse the conditions under which individuals extensively branched (referred others). The statistical model indicated that they did so when benevolence-based trust was limited.

Therefore, it appears that an individual may refer others extensively if he or she lacks confidence in those individuals' ability to solve the problem (low benevolence-based trust). By casting the net widely, individuals may be hoping for "luck of the draw" solutions. This research therefore suggests that searching too widely whilst simultaneously probing deeply (through chains) could hamper the process of finding OI solutions.

Finally, this thesis proposes and describes a clear distinction between direct and indirect social capital.

5.2.3 Direct and Indirect social capital

Definitions of social capital vary, depending on whether there is a focus on the source, the substance, or the effects (Adler & Kwon, 2002). However, as noted previously, the concept of social capital is not well defined and lacks conceptual clarity (Patulny & Svendsen, 2007; Payne et al., 2011). The findings from this study provide an opportunity to make suggestions to refine the concept, especially regarding indirect relationships.

As set out in Chapter 2, earlier theories proposed separate categories for bonding social capital and bridging social capital (Lin, 2005; Portes, 1998; Putnam, 2000) but did not recognise the bonding or bridging features of social capital.

According to Coleman (1988) bonding social capital includes trust, obligations, expectations, reciprocity, norms and values. By the same token, trust facilitates collaboration, cooperation, sharing and learning.

This study has shown that a trusted bridging chain combines both the supporting and bridging features of social capital. OI returns can therefore be leveraged from the simultaneous occurrence of supporting (trust) and bridging (diversity) social capital.

It is important to frame this concept in terms of “supporting and bridging features” – particularly when considering Putnam’s reference to social capital as “features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit” (Putnam, 1995, p. 66).

Furthermore, Lin (2001) suggested that while network features and resources (the returns) are not equivalent, network features are important antecedents of social capital (Lin, 2001). Hence, supporting features (such as trust) can be seen as necessary preconditions to achieve bridging (Levin & Cross, 2004; Levin et al., 2011).

Extant theories concerning indirect social capital have focused mainly on by-chance access to resources through indirect ties (Ahuja, 2000; Burt, 2007, 2010; Lazega, Jourda & Mounier, 2013), which could positively affect performance. The connection between indirect social capital and indirect relationships is also highlighted in entrepreneurial studies (Salaff, Greve, Siu-Lun & Ping, 2003), international studies (Agndal, Chetty & Wilson, 2008; Kontinen & Ojala, 2011); and various papers on education. Most of these studies regard indirect social capital as a proxy for indirect relationships, resulting in returns through serendipitous (by-chance) indirect relationships and not through instrumental search.

Extant theory has identified two categories of social capital: direct and indirect. However, indirect social capital, as a concept, has not yet been clearly defined.

Direct social capital

Research has shown that organisations can gain innovation returns through direct relationships: for example, between an individual in R&D and an acquaintance (Levin & Cross, 2004). However, in such instances, supporting features of social capital (specifically trust) would be required in order to bridge (obtain new information) via direct social capital.

As previously described, social capital returns could also come about through maintaining the *status quo*: an example being the closed home owners’ community mentioned in Chapter 2, which relates to bonding social capital (Coleman, 1988; Lin, 2005; Putnam, 2000). In this instance, the return on social capital for home owners would be to maintain their current state of safety and security. It is suggested that these returns would be relevant to direct social capital, and it follows that the supporting features of social capital, particularly trust, facilitate returns on direct social capital (See Figure 13).

Thus this study proposes that direct social capital, following Nahapiet and Ghoshal (1998) and Putnam (1995), be defined as: *the information or knowledge (new or improved resources), or else the preservation of unity and maintenance of current state, available to / for individuals or organisations through direct relationships*.

Figure 13: Direct social capital

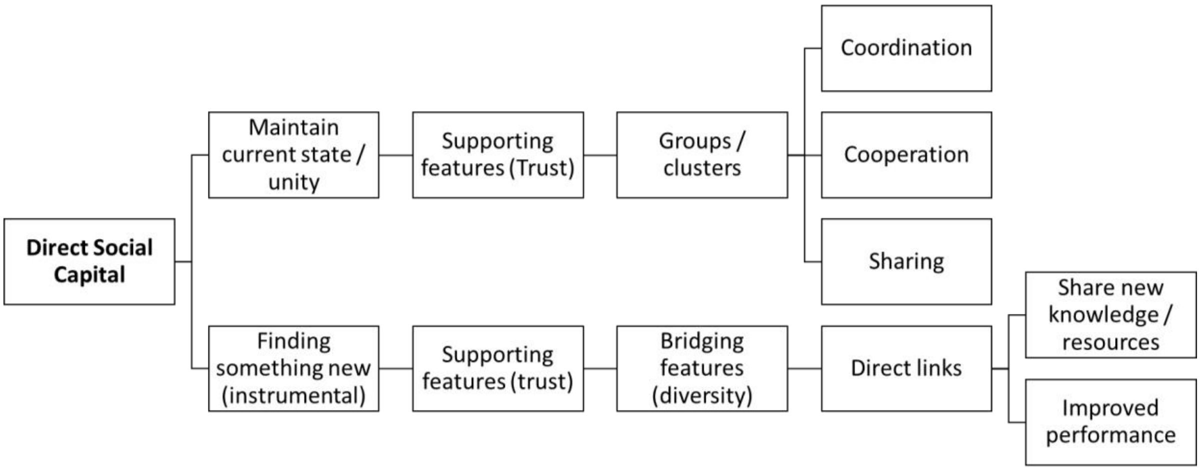


Figure 13 summarises the current state of knowledge about direct social capital. Social capital returns can essentially relate to the maintenance of the current state (as in the example of the homeowners), or to sourcing something new (knowledge or information through direct ties). In both cases trust is a feature of social capital, generating both types of returns from within groups (or clusters), or through bridging.

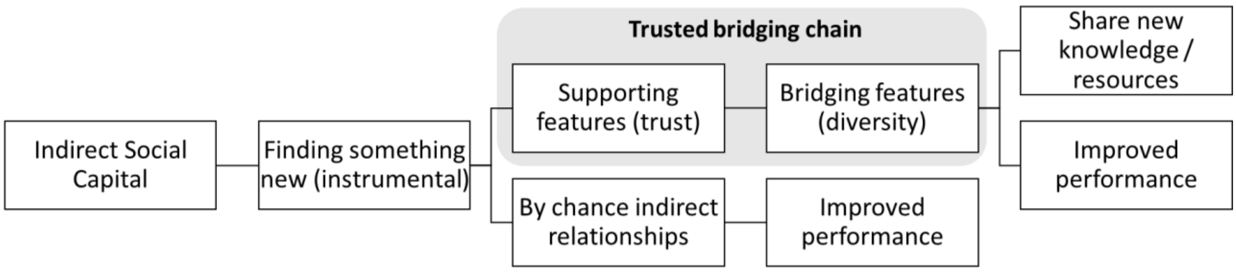
In maintaining the current state, the community (as an example) is able to maintain a sense of security and safety by means of coordination, cooperation and sharing. In the second example, direct links enable access to new information

/ knowledge, or improved performance, such as when a member of a community seeks a buyer for a property.

Indirect social capital

Indirect social capital is instrumental in sourcing something new or improved (including improved performance) through indirect interpersonal relationships, either purposively through a trusted bridging chain (see top section in Figure 14), or through by-chance indirect relationships, such as described in Burt's (2007, 2010) notion of secondhand brokerage (see bottom section in Figure 14).

Figure 14: Indirect social capital



Indirect social capital, following Burt (1997; 2010), Granovetter (1973), Nahapiet and Ghoshal (1998) and Putnam (1995), is proposed to be defined as: *the information or knowledge (new or improved resources) available to individuals or organisations, through indirect social relationships by means of a trusted bridging chain or through by-chance indirect relationships*.

The study further suggests that secondhand brokerage differs from recursive brokerage as it implies passively waiting for information (simple rather than complex) that is generated through the network. Conversely, recursive brokerage is purposively brokered information generated through a chain of referrals.

Hence, the returns derived from indirect social capital could either be purposively sought by means of a trusted bridging chain, or through by-chance indirect relationships.

5.3 Conclusion

OI studies have focused extensively on the role of search strategies in sourcing innovations and ideas. However, it has been demonstrated that searching too widely can be expensive, ineffective and debilitating. Research into networked innovation has shown that trust is embedded in the supporting features of social capital, while diversity is intrinsic to bridging features.

Trust is evidently essential for innovation; knowledge variety and geographic distance can generate diversity. Both are important ingredients in innovation processes.

This study envisaged that a trusted bridging chain, driven by trust and imbued with diversity, could reach across deeper horizons in search of innovative solutions, and offer an alternative to searching widely for innovative solutions. It was also proposed that a trusted bridging chain could be assembled via trusted interpersonal relationship referrals to unlock social capital.

Research results indicated that competence-based trust determined the depth of chains, although it did not affect the quality of solutions. However, benevolence-based trust was not significant in this regard.

The study noted the minimal role of frequent communication. Knowledge diversity and geographic distance both affected the quality of solutions, although not at the same time. In fact, bad solutions were indicative of knowledge diversity and geographic distance across the same chain. The results indicated that solutions were discovered through predominantly weak chains, although the strength of chains did not have an effect on the quality of solutions. It was also shown that greater numbers of referrals diminished the likelihood of finding solutions.

Finally, the research showed that trusted bridging chains did not specifically influence the quality of solutions, as chains constituting mainly of weak links generated good and bad solutions. However, trusted bridging chains proved to be a viable alternative to searching too widely, and therefore this study opens the door for further research on the benefits of trusted bridging chains for OI.

5.4 Implications for practice

Most OI network models search for innovative solutions through direct links with diverse partners (eco-network search), or through an intermediary with the same kind of direct links (one-to-many, as shown by Figure 3). To some extent, organisations leverage informal spillages through social integration, although not purposively.

There is evidence that searching too widely is detrimental for organisations. However, little attention has been given to boundary-spanning ties (Leenders & Dolfsma, 2015), and probably less to the leveraging of external interpersonal network ties for OI purposes.

Despite the low number (121) of starters in this study, 60 referral chains were generated, leading to six solutions from indirect organisational referrals. This contrasts to the typical results of similar OI challenges, where the number of starters is much higher, and the number of solutions still relatively low.

Searching through deeper horizons across social relations does not seem to be a current practise when seeking OI solutions. However, organisations could set up the necessary technology or systems to facilitate this through indirect interpersonal social relationships to the organisation.

The research proposes a practical new way of expanding the population of participants who contribute to the generation of OI solutions. Software was developed to track the referral process and collect data real-time, which minimised data recall. This methodological approach creates opportunities for practical application as well as research unrelated to OI. Hence, the developed process can also be used in practice across fields, such as for head hunting and marketing processes.

The research results in this study suggest that geographic distance, together with limited knowledge diversity, has an impact on the quality of solutions. Thus, organisations can tap networks from within the same industry (low cognitive distances) but request global reach (geographic distance) in search for innovative solutions through a chain of indirect social relations. This purposive request for distant referrals could allow organisations to tap into international spillages which would not otherwise reach them.

Alternatively, an organisation could use diverse local industry networks to launch the problem, then request local referrals. In such a case it might be important to define the problem in more industry agnostic terms.

The same practical implications apply to intermediaries. An intermediary (for example, NineSigma) could send a challenge to its current network of innovators, and then provide an electronic referral facility requesting existing network members to refer competent acquaintances from within the same industry to try solve the problem, and so on.

In order to follow such a referral chain to a potential OI solution, it would be necessary to drive and maintain the chain electronically. Furthermore, it would be more practical to extend the open time frame for individuals to refer others and submit OI solutions, considering that provision should be made for later referrals.

5.5 Implications for future research

The fsCQA analysis used for this research provided a configurational perspective which is largely absent in OI research. Applying this analytical method in future OI research studies may create more insight around the complementarity and equifinality of OI processes.

Furthermore, studies on ties that bridge organisational boundaries are scarce and therefore this study may become the basis for further network studies focusing on bridging organisational boundaries. In addition to this, the study refines many ideas about network structure and diversity and how these would contribute to the success of OI, which future studies could expand on.

Future studies could also focus on the analysis of chain patterns, with regards to diversity and trust across the chains (especially for longer chains), instead of using variable averages across the chain. As such, measurement of the type of networks that are bridged by different types of chains might highlight well-known combinations of the trust and diversity across these chains.

Future studies could investigate the implementation of incentives across successful chains, although this may result in extensive referrals, which was shown in this research to lessen the probability of finding innovative solutions. Nonetheless, such referrals can be deactivated electronically. Moreover, this study showed that competence-based trust drove chains forward, but this may not be the case when implementing incentive schemes.

Future research could also further investigate the role of trust when spanning boundaries, taking into account the fact that competence-based trust drove the referral process but benevolence-based trust was low, except when communication was frequent, or ties were strong.

In summary, this thesis makes contributions methodologically, theoretically and practically. Methodologically, it has developed software that allows not only for referrals and their real-time tracking, but also for the simultaneous gathering of data, minimising data recall which often plagues scholarship on networks.

Theoretically, this study demonstrates the benefits of the co-occurrence of bonding and bridging features of social capital, especially across organisational boundaries. Through the activation of trusted bridging chains, OI solutions are generated that rely on existing ties, yet generate novel knowledge. This study also demonstrates the usefulness of making a distinction between direct social capital and indirect social capital, where people consciously activate more distant connections.

In terms of practice, this study suggests a novel way for expanding the population of participants who contribute to the generation of OI solutions. Relying on the contacts of contacts, a firm can deepen its search, and with a smaller initial search horizon, arguably obtain at least the same quality solution, if not better.

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APPENDICES

APPENDIX 1: PROBLEM DEFINITION TEMPLATE

Figure 15: Problem definition template

Challenge response form for:

Identify methods to reduce copper cyanide build-up in process water circuits

Deadline: 4 December 2015
Contact: Maggie Lombard | Email: maggie@polynate.co.za

DISCLAIMER AND NON CONFIDENTIAL DISCLOSURE

By submitting a response, you represent that the response does not and will not be deemed to contain any confidential information of any kind whatsoever. Maggie Lombard, the researcher, Polynate (Pty) Ltd and its project partners will not be held liable for loss of any intellectual property. You also acknowledge that Maggie Lombard, Polynate (Pty) Ltd and its project partners reserve the sole and absolute right and discretion to act upon all, some, or none of the responses received for this Challenge.

Contact Name: [Name and surname of person posting the solution]

Organisation Name: [Company or entity name]

Organisation Type: [Small, medium or large-sized company, research institute, individual]

Email:

Telephone:

Primary Operating Address:

Web Address:

Title

[Write the title of your proposal]

Summary of Working Principle

[Provide a brief summary of the working principle of proposed technology including the proposed application thereof. The summary should be the same as used in the online template]

Detailed Description

[Provide a detailed description of your response to the Challenge including an explanation of the technical and commercial merits of your proposed solution].

A successful solution to the problem should:

- Be implemented on a large scale

- Not remove gold from the solution
- Use industrially available reagents
- Not cause secondary problems
- Be safely implemented and not impact the environment negatively

High Level Proof of Concept/ Pilot Project Plan

[Please indicate estimated high-level timelines and the corresponding deliverables for implementing the technology as a proof of concept or pilot]

Experience

[Include a brief overview of the entity / person's experience]

APPENDIX 2: QUESTIONNAIRES

Figure 16: Forward the challenge

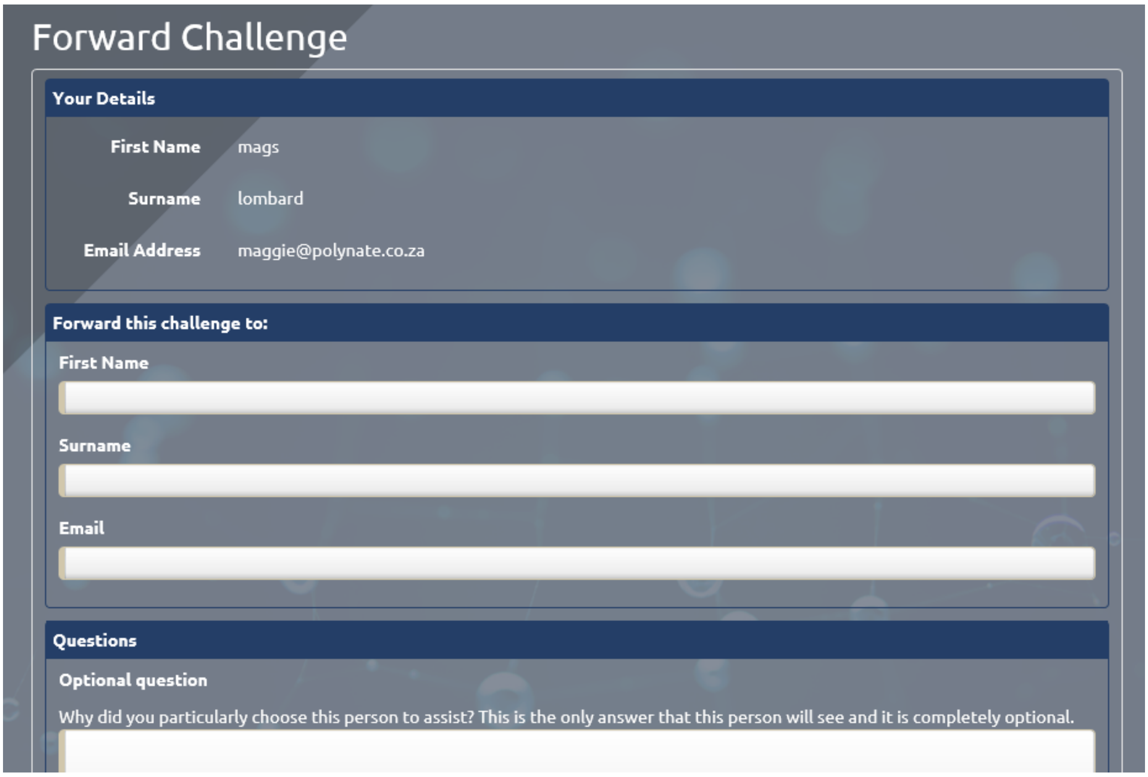
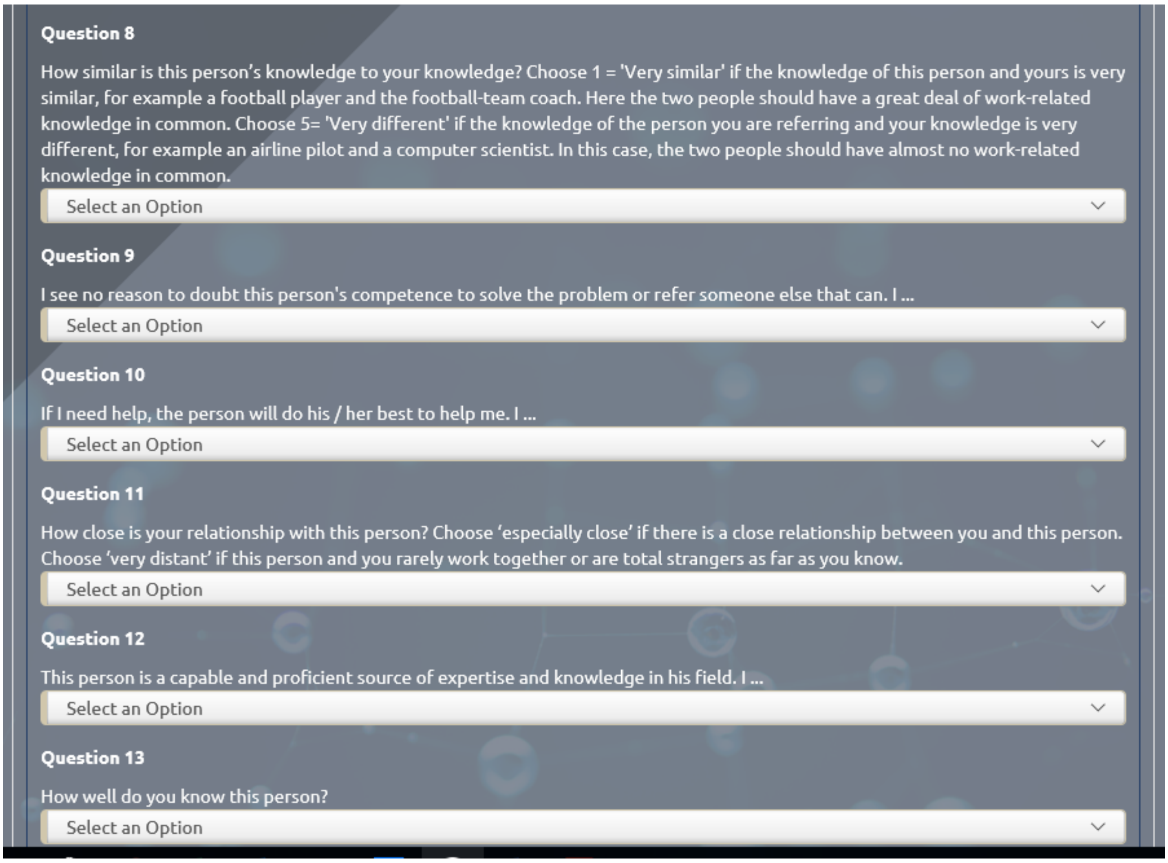


Figure 17: Forward questions q1 to q7

Figure 18: Forward questions q8 to q13



Question 8

How similar is this person's knowledge to your knowledge? Choose 1 = 'Very similar' if the knowledge of this person and yours is very similar, for example a football player and the football-team coach. Here the two people should have a great deal of work-related knowledge in common. Choose 5= 'Very different' if the knowledge of the person you are referring and your knowledge is very different, for example an airline pilot and a computer scientist. In this case, the two people should have almost no work-related knowledge in common.

Select an Option

Question 9

I see no reason to doubt this person's competence to solve the problem or refer someone else that can. I ...

Select an Option

Question 10

If I need help, the person will do his / her best to help me. I ...

Select an Option

Question 11

How close is your relationship with this person? Choose 'especially close' if there is a close relationship between you and this person. Choose 'very distant' if this person and you rarely work together or are total strangers as far as you know.

Select an Option

Question 12

This person is a capable and proficient source of expertise and knowledge in his field. I ...

Select an Option

Question 13

How well do you know this person?

Select an Option