A Bayesian Belief Network Computational Model of Social Capital in Virtual Communities

A Thesis Submitted to

The College of Graduate Studies and Research

In Partial Fulfillment of the Requirements

For an Interdisciplinary Degree of Doctor of Philosophy

In

Computer Science and Educational & Communications Technology

University of Saskatchewan

Saskatoon, Saskatchewan

Canada

By

Ben Kei Daniel Motidyang

Permission to Use

In presenting this thesis in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis in any manner, in whole or in part, for scholarly purposes may be granted by the professors who supervised my thesis work or, in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to the University of Saskatchewan in any scholarly use which may be made of any material in my thesis.

Requests for permission to copy or to make other use of material in this thesis in whole or part should be addressed to:

Graduate Studies and Research

University of Saskatchewan
Saskatoon, Saskatchewan S7N 5A9

Abstract

The notion of social capital (SC) is increasingly used as a framework for describing social issues in terrestrial communities. For more than a decade, researchers use the term to mean the set of trust, institutions, social norms, social networks, and organizations that shape the interactions of actors within a society and that are considered to be useful and assets for communities to prosper both economically and socially. Despite growing popularity of social capital especially, among researchers in the social sciences and the humanities, the concept remains ill-defined and its operation and benefits limited to terrestrial communities. In addition, proponents of social capital often use different approaches to analyze it and each approach has its own limitations.

This thesis examines social capital within the context of technology-mediated communities (also known as virtual communities). It presents a computational model of social capital, which serves as a first step in the direction of understanding, formalizing, computing and discussing social capital. The thesis employs an eclectic set of approaches and procedures to explore, analyze, understand and model social capital in two types of virtual communities: virtual learning communities (VLCs) and distributed communities of practice (DCoP).

There is an intentional flow to the analysis and the combination of methods described in the thesis. The analysis includes understanding what constitutes social capital in the literature, identifying and isolating variables that are relevant to the context of virtual

communities, conducting a series of empirical studies to further examine various components of social capital and building a computational model.

A sensitivity analysis aimed at examining the statistical variability of the individual variables in the model and their effects on the overall level of social capital are conducted, and a series of evidence-based scenarios are developed to test and update the model. The result of the model predictions are then used as input to construct a final empirical study aimed at verifying the model.

Key findings from the various studies in the thesis indicated that SC is a multi-layered, multivariate, multidimensional, imprecise and ill-defined construct that has emerged from a rather murky swamp of terminology but it is still useful for exploring and understanding social networking issues that can possibly influence our understanding of collaboration and learning in virtual communities. Further, the model predictions and sensitivity analysis suggest variables such as trust, different forms of awareness, social protocols and the type of the virtual community are all important in discussion of SC in virtual communities but each variable has different level of sensitivity to social capital.

The major contributions of the thesis are the detailed exploration of social capital in virtual communities and the use of an integrated set of approaches in studying and modelling it. Further, the Bayesian Belief Network approach applied in the thesis can be extended to model similar complex online social systems.

Acknowledgements

"Think in terms of a community, but value and acknowledge individual contributions!"

[Uncle Ben, 2007].

Learning and writing is either a social or lonely process, or both. But behind every successful thesis and research, there is always a distributed community of people. Individuals in such a community are normally interested in one or more aspects of the thesis or the individual writing the thesis or sometimes both, whether before the process, during the process, or at the end of it.

A typical distributed community of thesis include the thesis supervisors, the thesis committee members, external examiner, faculty members, support staff, friends, colleagues, family and others, and of course, the individual doing the thesis. Within such a community, individuals contribute variously and in different ways.

Over the past years here at the University of Saskatchewan, I have had the privilege to work closely with two of the most extraordinary and outstanding people I know. First and foremost, I would like to express my sincere heartfelt gratitude to my supervisors; Dr. Gordon McCalla and Dr. Richard Schwier for their extraordinary guidance, support, patience and attentiveness throughout my program of studies. Thanks Gord and Rick for the support, motivation, inspiration, teaching and constantly offering me with the opportunities to travel, explore, learn and grow academically.

Second, I wish to thank my thesis committee members; Dr. James Greer, Dr. Leonard Proctor and Dr. Michael Mehta for their constructive feedback, encouragement and willingness to support my research. My external examiner, Dr. William J. Egnatoff who provided me with constructive and useful feedback, helped sharpened the focus of my final thesis. Thanks also go to Dr. Eric Neufeld, Dr. Ralph Deters, Dr. Robert Hudson, Dr. Mark Keil, Dr. Carl Gutwin, and Dr. M. McGregor for chairing committee meetings of my thesis over the years.

Third, during the course of my studies, there were various organizations which provided me with funding and work opportunities. In particular, I am grateful to the Natural Sciences and Engineering Research Council of Canada (NSERC), the Social Sciences and Humanities Research Council of Canada (SSHRC), the department of Computer Science Graduate Fellowship Program, Saskatchewan Technology Enhanced Learning (TEL), International Centre for Governance and Development (ICGD), Former University of Saskatchewan International, and Lorax Software Corporation.

Fourth, I wish to thank the faculty and colleagues at the Department of Computer Science and Educational Communication and Technology for their help and friendship during my student life at the University of Saskatchewan. I also extend thanks to the department of Computer Science support staff; Ms. Jan Thompson, Ms. Maureen Desjardins, Ms. Linda Gesy, Ms. Heather Webb, Ms. Lori Kettel, Mr. Guus van de Velde, Mr. Cary Bernath and Mr. Shane Doucette. Also special thanks go to Ms. Lenna Balon at the Department of Curriculum for providing me with all the necessary support I needed. Further thanks go to the staff of the College of Graduate Studies and Research, for providing me with the necessary support to complete my studies. There are other important individuals on this campus, who help international students like me settle and feel at home, special thanks to Mr. Kurt Tischler at the University of Saskatchewan International Students Office.

Fifth, in some cases, growing up academically and professionally involves standing on the shoulders of giants around you. During my graduate studies at the University of Saskatchewan, I was very fortunate to be able to work, network and collaborate with a number of very kind and interesting people. Among others, I would like to acknowledge mentorship and support received from Dr. Asit Sarkar, Dr**.** David O'Brien, Dr. Juan-Diego Zapata-Rivera, Dr. Permanand Mohan and Dr. Kathleen Matheos. My work with Asit and David on the Governance Knowledge Network (GKN) Project contributed immensely to the ideas presented in this thesis. Thank you very much Asit and David for all the support and mentorship. In addition, interaction with my colleague and friend, Diego led into some of the main ideas presented in the thesis. Thanks a lot for educating me Diego! Thank you Permanand for helping me extend my ideas to international audience. Kathleen thanks for collaborating on the TEL project and sharing your rich and interesting insights on technology enhanced learning.

Further, I would like to thank all the people I have closely worked with globally in higher institutions of learning and especially, those whose insights and talents have immensely contributed to my research and academic career. Just to let you know this is perhaps my last official PhD but I can not promise. I give thanks to: Mr. Robin Sawyer, Ms. Igbal

Osman, Dr. Leju Logor, Dr. Wani Sule, Dr. Martin Mulder (My academic Godfather), Dr. Bob Witziers (Bob, you were a good friend and a teacher, you will always be remembered), Dr. Saskia Tjepkema, Dr. Arild Tjeldvoll, Dr. Birgit Brock-Utne, Mr. Øyvind Nystøl, Dr. Peter Pitiya, Dr. Gordon McCalla, Dr. Richard Schwier, Dr. James Greer, Dr. Juan-Diego Zapata-Rivera, Dr. Asit Sarkar, Dr. David O'Brien, Ms. Lisa Sielski, Dr. Permanand Mohan, Dr. Veronika Makarova, Mr. Honggang Wu, Dr. John Cooke, Ms. Nancy Poon (PhD Candidate), Ms. Heather Ross, Mr. Frank Bulk, Mr. Randy Skurdal, Ms. Golha Sharifi, Dr. Pinata Winoto, Ms Tiffany Tang (PhD. Candidate), Ms. Xiaolin Niu, Honorable Mr. Rob Norris (MLA Candidate), and Mr. Graham Walker.

I am also grateful to all my former and current ARIES Lab and VLC research colleagues, who have provided me with the professional and social environment to freely interact and explore my ideas. Very special thanks go to my other close friends and family: Mr. Kamal el-Bashir, Mr. Brent Robertson, Ms. Kimberley Robertson, Dr. Kalid Atel Mannan, Mr. Teddy Bandima, Ms. Mary Dykes, Dr. Gale Parchoma, Ms. Debi Naigle, Ms. Yamini Upadrashta, Ms. Lucia Zapata-Rivera, Mr. Christian Zapata-Rivera, Dr. Stanley Mogga, Ms. Roda Kade Daniel, Ms. Cecilia Muja Daniel, Mr. John Mori Daniel, Mr. Cornelius Soma Daniel (brother, I will always remember you), Mr. Alakai Joseph, Mr. Emanuel Tunda Tundulous, Mr. Emmanuel Ayume Benjamin Lo'boka-kebir, Mr. Joseph Lo'Boka-Satani (Guru-Lotorr, Kimang!), Mr. Julius Lo'bworongtingtong and all my other friends and colleagues from Al-Farouk "Pass Away Centre" thanks for friendship and teaching me patience and determination.

There are a lot of people who open-heartedly welcomed me to their homes and families here in Saskatoon. In particular, I would like to extend my sincere thanks to the family of Dr. James Greer (Jim and Marianne thanks for letting me stay in your home and helping me settled in when I first came to Canada!), Dr. Gordon McCalla (Gord and Peta thanks for all the amazing treats, especially the X-Mas, boxing days holidays, the guitar summit was special and a living memory), Dr. Richard Schwier (Rick and Karin thanks for the friendships, the X-mas gifts and other regular goodies), the family of Ms. Nancy Poon (Nancy and Blaine thanks for the good company), Ms. Lisa Shiffman and Mr. Harold Shiffmen (Lisa, thanks for being such a good friend and supportive person). Further, thanks go to the family of Mr. Richard Ewen and Ms. Linda Ewen; the family of the president of the University of Saskatchewan; Mr. Peter MacKinnon and Dr. Janice MacKinnon and the family of Dr. Terry Wotherspoon and Ms. Barb Wotherspoon, all for welcoming me to spend X-Mas with them during my studies.

I am also honoured to be welcomed to Mr and Ms. Lavergne's family. Thanks to Mr. Louis Lavergne, Ms. Claudette Lavergne; Ms. Michelle Lavergne, Ms. Anne Lavergne, Mr. Denis Lavergne, Mr. Thomas Lavergne and not forgetting the other interesting family members: silent old Emma, crazy Marlo (Marlo you might have been a kuku in your first life), and reluctant Penguin (Penguin you need to live up man!), you are all a very good family.

Let me take this opportunity, once again to thank my parents; Motidyang, Ropi, and Kiden. You know what it meant to bring me up among all others, but you also know I was not all that bad—right? Thanks for all your patience and love! Father was a “tough gong!” A man who valued the importance of education, a man with principles, brilliant, highly organised, neat, hardworking, caring, great teacher and well disciplined. Father had always treated people and especially, his children equally, individually and with respect. Father was a man who believed in the principle that “education begins at home”. Violate this principle in his words; “you will be submerged”. Father, you will always be remembered! And further, special thanks go to all my sisters, brothers, cousins, nephews, nieces, relatives and friends around the world.

Behind every successful man, there is a special woman! Special heartfelt thanks go to my close relative and sweetheart Michelle Lavergne. Thanks for being patient and ultimately providing the “I-man” with the motivation, respect and love to complete this thesis.

Finally, thanks to those whose names have not appeared here, you know, you have contributed in one way or another to my success and I will always be thankful to you. Let me also take this last opportunity to thank those who are always negative, cynics and hardliners, you have helped making me a strong hardworking man, and above all, a veteran! Thank you! Thank you ALL!

Ben Kei Daniel Motidyang

Dedication

This work is dedicated to the memory of my loving father ("Tough Gong!"); Daniel Motidyang Lokuri Soma and brother Cornelius Soma Daniel Motidyang.

TABLE OF CONTENTS

List of Figures

List of Tables

Chapter 1

1.0 Setting the Research Scene

1.1 Overview

Chapter 1 introduces the research area, the problem statement, and justification for doing the research. The chapter also outlines the thesis research goals and associated questions. Methods employed in addressing each research question are also presented in this chapter. In addition, the scope of the thesis, contributions, its organization as well as an exposition of presentation style is all described in this chapter.

1.2 Introduction

The term social capital (SC) has increasingly become a concept with promise for addressing numerous social issues in communities. The basic tenet of SC rests fundamentally on the assumption that social relations are important sources of resources and support for individuals and groups. Though the notion of SC dates back to 1916 [Hannifin, 1916], its popularity only began in the late 90s as a basic policy proxy for examining civic engagement [Putnam, 1993].

Subsequently, the years that followed witnessed an increasing interest by public policy researchers, especially at the World Bank, who have been keenly interested in the idea of SC because of its promise to provide better ways to identify and understand how community resources or groups can be invested on to enhance development and to provide ways to benefit all people in communities in the underdeveloped and developing world.

The popularity of social capital in the fields of computer science and educational technology in particular can be linked to two recent developments: (a) the emergence of new socially oriented computing approaches aimed at better understanding the social dimension of users/learners in order to effectively build technologies that can promote collaboration, knowledge sharing and learning; and (b) increasing interest in the notion of online communities as hubs for knowledge sharing and learning. With increasing discourse about SC within these new disciplines, traditional definitions of the term have become less useful to new and emerging contexts and so alternative definitions need to be developed.

1.3 Problem background

Despite progress in research into SC in all the fields where it has been traditionally applied, little has been done to extend this understanding to technology-mediated learning communities (virtual learning communities (VLCs) and distributed communities of practice (DCoP)). In addition, there is a lack of concrete metrics for measuring SC within emergent technology-mediated contexts and as well in other contexts. Fukuyama [1999] for instance, earlier noted that a fundamental problem of social capital is the absence of consensus on how to measure it. Current research on SC in virtual learning communities suggests there are various reasons why a standard yardstick for measuring social capital has not been developed [Daniel, McCalla &, Schwier 2002; Daniel, 2003; Daniel, Schwier & McCalla, 2003]:

- SC is a multivariate and multidimensional construct and not a single entity with single measurement parameters.
- Different types of SC are useful for different purposes and a single measurement for one will not necessarily cover others.
- There are limited numbers of empirical studies that attempt to measure social capital in virtual communities.
- SC can be treated as both an output of one system and an input of another system, making the concept difficult to understand and use theoretically.
- SC is not necessarily associated with positive outcomes since it can be used to prevent others from entering into certain communities making it a liability to a holistic system.
- Theoretical approaches for measuring social capital in virtual communities are not comprehensive and still underdeveloped.

Table 1-1. The main thesis research questions and methods

Research Goals	**Main Research Questions**	**Methods**
[1] Explore what constitutes social capital	— What is the concept of social capital? — What are the fundamental variables of social capital? — Which characteristics of social capital are relevant to virtual communities?	— Literature review — Content analysis of online interactions — Social network analysis — Content analysis of online interactions
[2] Build a computational model of social capital in virtual communities	— How to build a model of social capital? — How can the model be updated and verified?	— Bayesian Belief networks — Sensitivity analysis — Survey

Table 1-1 overviews the main thesis goals and research methodologies. The thesis research began by addressing the first goal in Table 1-1, which is exploring what constitutes social capital through analysis of various definitions of social capital as they appear in current research. Common variables mentioned in various definitions of the term in the literature have been identified and new variables relevant to the context of virtual communities have been proposed.

In order to attain the first goal, methods employed in the analysis include literature review, content analysis and social network analysis. The outcomes of the analysis are identification of the fundamental variables constituting social capital and various ways in which social capital can be defined and analyzed. Further, three fundamental studies have been conducted to further explore the fundamental variables of social capital in three different environments: a virtual learning community, an informal virtual community and a distributed community of practice. Building on the first goal, the second goal of the thesis was to build a computational model of social capital, which has involved reducing the variables identified in the literature to those that are considered relevant to the context of virtual communities.

1.4 Why build a computational model of social capital?

Computational models are important components of scientific theories. Modelling is a procedure for knowledge representation and for understanding complex problems in many domains. Modelling involves a systematic and logical representation of a theoretical construct, with a set of variables and a set of logical and quantitative relationships between them.

The main purpose of computational modelling is to facilitate reasoning about certain properties and processes of an object or a phenomenon within an idealized confined logical framework. Model construction is often based upon explicit assumptions that may be justified. In many of the computational sciences, conceptual and theoretical modelling constructs are common and the constructs are often expressed as sets of algorithms and implemented as software packages.

Computational models are also built to simulate a set of processes observed in a natural or a social environment in order to gain deeper understanding of social or natural phenomenon. For example, changes in consumers' patterns can be modelled as seen in the domain of economics or the dynamics of atmospheric conditions e.g. weather predictions as used by meteorologists. Computational models are popular in economics and meteorology domains because of their ability to make consistent and accurate predictions of natural or social behavior of a system, given a specific set of input parameters.

A computational model of social capital provides researchers with a set of powerful tools and processes for handling imprecise and noisy data. More specifically, a model of social capital will allow a group of stakeholders (instructional designers, systems analysts and developers, instructors, and decision-makers) to understand the dynamics of social issues in virtual communities. In addition, researchers interested in studying virtual communities can use the model's predictions to help them build hypotheses about social phenomena in virtual communities and use alternative methods to further examine them.

Further, a model of social capital will have both theoretical and practical appeal to our understanding social issues that can affect learning and knowledge sharing in virtual communities. From a theoretical point of view, the model provides a detailed modelling process in which researchers can use to examine similar complex constructs in a systematic and consistent manner. Since there was no work done on social capital in virtual communities prior to this research, this research makes a strong theoretical contribution to the field. From a practical point of view, the model provides insights for instructional designers to enable them design learning environments that enable learners to build a strong sense of community and belonging.

1.5 Methods employed

A variety of methods were employed to analyze social capital. The integrated nature of these methods offers the following benefits:

- A multidisciplinary integrated methodology measured SC using several approaches other than narrowly addressing SC with only one method.
- The integrated methodology clearly identifies variables constituting social capital and isolating the most relevant ones in the context of virtual communities.
- The Bayesian Belief Network (BBN) modelling approach uses both qualitative and quantitative techniques for analysis and understanding of SC.
- Overall, the Bayesian Belief Network approach can also be extended to model similar complex issues in the social sciences and humanities.

1.6 Thesis scope and contribution

This research extends the notion of social capital to virtual communities using computational approaches. The thesis does not measure the effectiveness of social capital in these communities, but rather it examines the fundamental variables that can be used by others to measure the growth of social capital in these communities. The approach taken in the thesis, which starts with identification, analysis, modeling and predictions, can help domain experts make sense of complex data sets using the Bayesian techniques as interactive simulation tools. The thesis is also a starting point for formal discourse on social capital in virtual communities and ways of studying it.

1.7 Organization of the thesis

This thesis is divided into seven chapters. Chapter 2 presents a review of the literature and motivates the study of social capital in virtual communities. Chapter 3 presents three empirical studies exploring social capital in virtual learning communities, informal virtual communities and distributed communities of practice. Chapter 4 presents a Bayesian Belief Network model of social capital in virtual communities. The process involved in building and updating the model is provided in Chapter 5. Scenarios used to validate the model and the results of the model predictions and they are used to construct a further study to verify the model is described in Chapter 6. Chapter 7 concludes the thesis, outlining its major contributions and limitations as well as future research issues.

1.8 Exposition

There are many places in the thesis where the methods used and the model presented can possibly raise further questions. This is the strength of the thesis since this thesis marks the beginning of formally studying the notion of social capital in virtual communities. The methods and model presented in the thesis can raise questions that set us to think about alternatives. This will hopefully opens up important debates which can lead to the development of even more solid methods and procedures for extensively studying social capital in virtual communities.

There are sections where references are made to virtual communities implying both virtual learning communities and distributed communities of practice. The distinction between the two is discussed in detail in Chapter 2. In addition, the term “virtual communities” also implies online communities. In several places in the thesis, norms are referred to as “social protocols” and mutual understanding as “shared understanding”. And in places when references are made to the term “awareness”, this means all types of awareness unless, of course, references are made to a particular type, such as “competence awareness” or “demographic awareness”. The notion of awareness is proposed in the thesis as an important variable of social capital in virtual communities.

Chapter 2

2.0 Literature Review

2.1 Overview

The goal of this chapter is to present a review of current research on social capital (SC). This review motivates the study of social capital in virtual communities. In this review, various definitions of social capital are examined and key variables associated with social capital are identified. In addition, the chapter presents various dimensions and types of social capital. Benefits and shortcomings of SC, including measurement issues surrounding the concept are described here.

2.2 Research on social capital

Social capital has been used extensively to address social problems in terrestrial communities. For example, social capital has been used as a framework to address problems of lack of civic engagement [Putnam, 1993], the role of social capital and civic virtue [Putnam, 2000; Sirianni & Friedland, 1995], and as a gateway to economic gains [Sobel, 2002]. Social capital has also provided a theoretical framework for studying community development [Gittell & Vidal, 1998], organizational development [Cohen & Prusak, 2001), grief intervention [Preece, 2002], the economic performance of firms (Baker, 1990), the creation of intellectual capital [Nahapiet & Ghoshal, 1998], learning in response to change and sustainability in communities [Falk & Harrison, 2000], community and school achievement [World Bank, 1999], community development issues [Gittell & Vidal, 1998], and patterns of social disparity created by lack of technological skills in society and the benefits to those who possess such skills [Resnick, 2002].

2.3 Defining social capital

As suggested in earlier research, SC is an imprecise construct that has emerged from a rather murky swamp of terminology, but it is still useful for exploring culture, society and social networks [Daniel, Schwier & McCalla, 2003]. Although the notion of SC originated from studies of conventional or temporal communities, from an historical perspective, SC is often used to describe federated but interrelated research interests in the social sciences and the humanities.

Irrespective of disciplinary focus, building a consistent theory of social capital continues to be obstructed by the existence of at least two different, yet equally useful conceptual approaches. The first approach tends to define social capital primarily as an attribute of an individual i.e., a person's potential to activate and effectively mobilize a network of social connections based on mutual recognition of proximity (in a social space) and maintained by symbolic and material exchanges [Bourdieu, 1996]. In this context, social capital has the properties of private good, which individuals accumulate and use to achieve their own goals and personal advancement.

The second approach treats social capital as an attribute of a community, as a quality of networks and relationships enabling individuals to cooperate and act collectively

[Fukuyama, 1999; Putnam, 2000]. Within this approach, social capital is based on the degree of interpersonal trust, as well as on the trustworthiness of public and political institutions that establish and uphold the rule of law, making exchanges transparent and safe. For these reasons, social capital has the properties of the public good facilitating achievement of higher levels of efficiency and productivity; hence this form of social capital is often associated with economic growth. Table 2-1 presents a summary of different definitions used in the study of SC by contemporary authors.

Table 2-1. Common definitions of social capital and key variables

Researcher (s)	Definition	Key variables
Hannifin [1916]	Tangible substances [that] count for most in the daily lives of people - namely good will, fellowship, sympathy and social intercourse among the individuals and families who make up a social unit.	resources, good will, fellowship, sympathy, social interactions
Putnam [2000]	The connections among individuals – social networks and the norms of reciprocity and trustworthiness that arise from them.	connections, networks, norms/social protocols, reciprocity, trust
Coleman [1988]	Supportive relationships among adults and children that promote the sharing of norms and values.	relationships, norms, shared values
World Bank [1999]	The institutions, relationships, and norms that shape the quality and quantity of a society's social interactions.	relationships, norms/social protocols, social interactions
Cohen and Prusak [2001]	The stock of active connections among people: the trust, mutual understanding, and shared values and behaviors that bind the members of human networks and communities and make cooperative action possible.	connections, trust, mutual understanding/shared understanding, shared value/goals, networks
Bourdieu [1996]	The aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition.	relationships, resources, networks
Fukuyama [1999]	The existence of a certain set of informal values or norms shared among members of a group that permits cooperation among them.	informal values, norms/social protocols, cooperation
OECD [2001]	The network, together with shared norms, values and understandings that facilitates cooperation within and among groups.	network, norms, shared understanding, cooperation
Loury [1977]	Natural occurring social relationships among persons which promote or assist the acquisition of skills and traits valued in the market place.	social relationships, skills, traits
Woolcock [1998]	Information, trust and norms of reciprocity inhering in one's social networks.	information, trust, norms/social protocols, social networks
Resnick [2004]	Productive resources that inhere in social relations	resources, social relationships
Rafaeli, Ravid and Soroka [2004]	A collection of features of the social network created as a result of virtual community activities that lead to development of common social norms and rules that assist cooperation for mutual benefit.	social network, norms/social protocols, co-operation, mutual benefit

2.4 Dimensions of social capital

Clearly there is no single definition of SC, but existing definitions do share key variables that can be categorized as either content or structural in nature. In order to investigate the complex concept of social capital more thoroughly, it is possible to consider structural and content dimensions as broad approaches in which social capital is being explored in the literature. Figure 2-1 shows examples of different dimensions of social capital and individual variables associated with each dimension.

2.4.1 Structural dimensions of social capital

The structural dimension is found in the work of numerous researchers [e.g., Bourdieu, 1983; Coleman, 1988; Nahapiet & Ghoshal, 1998; Woolcock, 1998; World Bank, 1999]. The structural dimension of social capital refers to the fundamental elements of the social network of a group or community such as types of ties and connections and the social organization of the community. The structural dimension of social capital is not concerned with understanding social capital at an isolated individual level nor at the group level (community), but it is interested in the relationships between individuals and groups [Phillipson et al., 2004]. Analysis of structural dimensions requires understanding the social network configuration of the community by using social network analysis.

A social network analysis approach to the study of social capital covers common indicators used to provide an idea of the quantity and quality of social capital based on identifying structural elements of social networks [Nahapiet & Ghoshal, 1998]. Social networks can be differentiated on the basis of their size, density, and the extent to which they are open and closed.

Franke [2005] has pointed out that employing social network analysis to examine social capital suggests that at the level of the individual, we can explore interpersonal relationships, that is, ties between individuals, or social participation, and the ties between individuals and groups or organizations. The structural dimension of social capital in this sense can be regarded as an individual's ability to make weak and strong ties to others within a community.

The value of weak and strong ties is explored by Granovetter [1973]. At the level of collective social capital, we can explore the associative dynamic by focusing on the intra-organizational ties as well as ties that exist among groups and organizations, within a community and beyond a community. The potential of social network analysis as a measure of the structural dimension of social capital relates to its ability to investigate both the presence and the functioning of social capital.

2.4.2 Content dimensions of social capital

The content dimension of SC includes the types of norms, trust, shared understanding and social protocols that regulate community members' behaviours [Cohen & Prusak, 2001; Fukuyama, 1999; Hanifan, 1916; 1920; Putnam, 2000]. Trust is one of the most frequently cited elements of the content dimension of social capital [e.g. Putnam, 2000; Fukuyama, 1999; Grootaert and Bastelaer, 2002]. Trust, in relation to the content dimension of SC, regards SC as a measure of the ability of people to work together for common purposes in groups and organizations [Widén-Wulff & Ginman, 2004]. Trust is considered to be pivotal for developing relationships that lead to social capital [Lewicki et al., 1998; Cowles, 1997]. In current research, two types of trust are particularly important to social capital: benevolence-based trust and cognitive-based trust [Chua, 2002; Levin et al., 2002]. A summary of the structural and content dimensions of SC and their associated variables is presented in Figure 2-1.

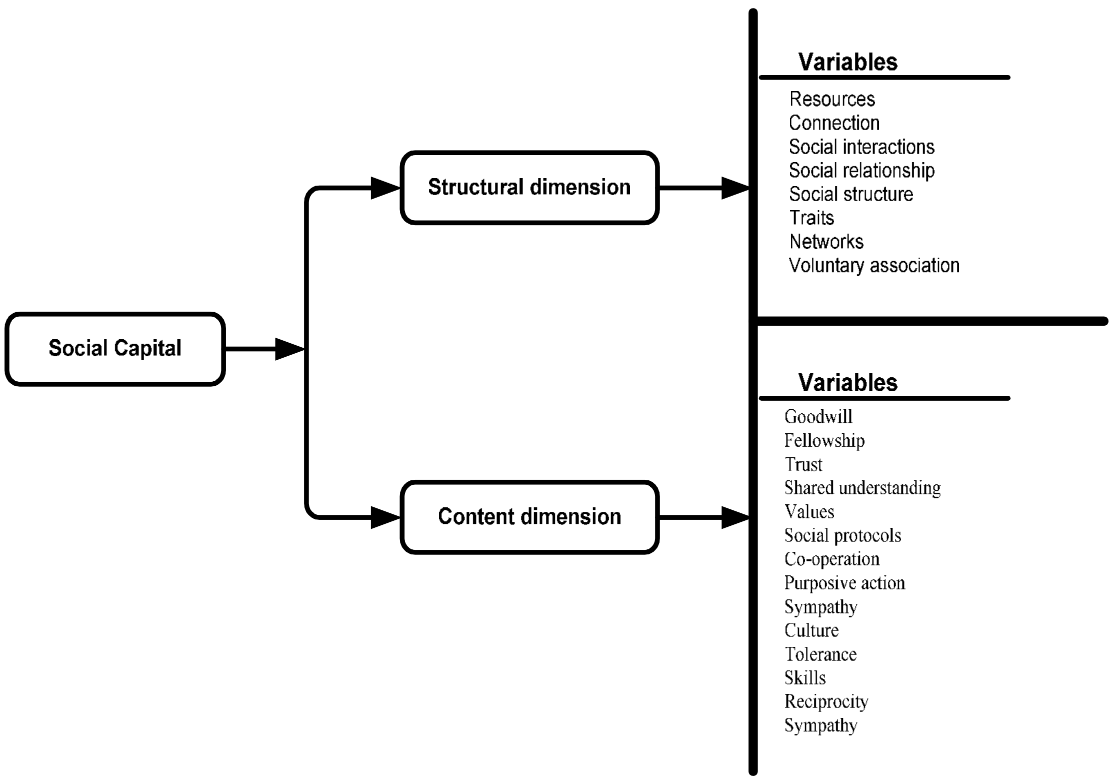


Figure 2- 1. Dimensions of social capital and its individual variables

2.5 Types of social capital

There are different types of SC identified in the literature. These can be broadly classified as bonding, bridging and linking. Bonding social capital refers to horizontal, tightly-knit ties between individuals or groups with similar demographic characteristics. Putnam [2000] refers to bonding SC as “social glue” that is found in homogenous groups such as close friends, family, ethnic, and religious groups. Bonding SC may be exclusionary and may not act to produce society wide benefits. Further, bonding SC is closely associated with both structural and content aspects of social capital.

Bridging SC on the other hand refers to relationships with distant friends, associates, and colleagues. Bridging SC is characterized by weaker, less dense but more cross-cutting ties, and it can be found in business associations, knowledge networks, acquaintances, friends from other religious or professional groups etc. These ties tend to be weaker and more diverse but are very important to "getting ahead" in groups, according to Putnam [2000].

Bridging SC is also similar to Granovetter’s [1973] notion of the strength of weak ties, suggesting that weak ties are an important resource in making possible mobility of resources, persons, tools, and ideas, and can facilitate incoming information from outside sources and provide economic opportunities such as acquiring jobs or marketing products to a larger market sector. Bridging social capital can be regarded as an example of a structural dimension of social capital.

Linking social capital is a third type of social capital [Woolcock, 2001]. This kind of SC refers to the relationships between individuals and groups across different social strata of a hierarchy where power, social status and wealth are accessed [Cote & Healy, 2001; Woolcock, 2001]. Examples of linking SC include for example social relationships manifested between students and professors. Linking SC can also refer to the capacity to leverage resources, ideas and information from formal institutions beyond the community [Woolcock, 2001].

Despite, the conceptual utility of these distinctions, types and dimensions of SC, it can be debated whether these distinctions hold empirically for all kinds of communities [Szreter, 2002]. The position taken in this thesis is that social capital is relative to the context in which it is investigated. Further, the influence of variables differs according to the kind of community under investigation, although it is possible to provide a general framework of social capital with common variables that apply to all kinds of communities, whether terrestrial or virtual.

2.6 Benefits of social capital

Researchers and writers in the social sciences and humanities have consistently pointed out the value of the notion of SC in terrestrial communities. Putnam [2000] has suggested that SC allows people to resolve problems more easily, especially when they collaborate and work together on common problems. Mechanisms such as social sanctions are used for coping with breaches in social protocols (e.g., individuals shirk their responsibilities, hoping others will do their work for them). He has also observed that when people are trusting and trustworthy, and maintain continuous interaction, everyday business becomes easier and more enjoyable.

Putnam [2000] has added that networks also serve as a conduit for the dissemination of helpful information that contributes to the achievement of personal and community goals. For example, people who are well connected usually receive valuable news first. Further, people who are well connected in a community and have active trusting connections with others are likely to behave in the accepted social manner of that community [World Bank, 1999].

The community benefits of SC appear to extend to formal educational institutions. The World Bank [1999] has found that schools were more effective when parents and local communities were actively involved in community and school programs. Teachers were more committed and students had higher tests scores. Coleman [1988] also suggests that the mentoring, networking and mutual support associated with high levels of SC contributes to success in education. Fukuyama [1999] further observed that firms benefit from SC because it facilitates cooperation and coordination, which minimizes transaction costs, such as negotiation and enforcement, imperfect information and layers of unnecessary bureaucracy.

SC can also bridge cultural differences by building a common identity and shared understanding [Daniel, Schwier & McCalla, 2003]. Furthermore, from the perspective of organizational management, Prusak and Cohen [2001] note that SC can promote better knowledge sharing due to established trust relationships, common frames of reference and shared goals.

Social capital generates different benefits in different communities. For instance Woolcock [2001] note that closed communities allow generalized reciprocity and trust can emerge within the dense networks of members characterized by frequent, multiple interaction and structural closure. In addition, Narayan and Pritchett [1997] have suggested that communities with high SC have frequent interaction among their members, which in turn cultivates norms of reciprocity through which members become more willing to help one another, and which improves coordination and dissemination of information and knowledge sharing.

2.7 Shortcomings of social capital

Despite benefits of SC in communities, including outcomes that lead to a better quality of health, education, cooperation, collaboration and trust, there are also a number of potential drawbacks. One important disagreement in both the theoretical and empirical literatures on social capital relates to the differences between those who view social capital as an individual attribute versus those who view it as a property of collectives (for example, communities or entire societies) [Ichiro, Kim, Coutts & Subramanian, 2004].

Other drawbacks challenge suggestions that SC is universally a societal benefit. Halpern [2001] has pointed out that organised crime or gangs involve a social network, whose members share norms, but they do not constitute a societal good. Portes [1998] lists the downside of SC as the exclusion of outsiders, restriction on individual freedom and a downward leveling of social protocols and collective norms. This refers to situations in which group solidarity is cemented by a common experience of adversity and opposition to mainstream society, for instance, in racial or religious hate groups. The resulting downward leveling of norms operates to keep members of a downtrodden group in place.

Highly cohesive communities that exhibit bonding forms of SC are not necessarily beneficial to a society and may engender internal trust among their members while spreading hate and terror to the larger society (examples include various kinds of terrorist gangs, racial hate groups and criminal organizations). Therefore, bonding forms of SC manifested in cohesive communities are therefore not necessarily beneficial to overall society.

In some circumstances, SC can also function as “a double-edged sword” as such close-knit communities become more and more isolated from their larger environments, and the benefits that its members derive from the network may begin to fall behind the costs. For example, exchange can go smoothly but there is insufficient diversity; knowledge is shared, but ideas begin to sound the same. In other words, a strongly bounded community if not linked to others might not access new ideas, innovation and the like. Groups with strong ties, clear boundaries and high levels of trust and generalized reciprocity can be said to rate high on exclusive, "bonding" SC. This type of inclusive "bridging" SC emerges in an exclusive type of network structure [Woolcock, 2001].

Further, most research on SC does not acknowledge the multivariate nature of SC [Daniel, Schwier & McCalla, 2003]. For instance, Putnam [2000] suggests that a decline in associational life leads directly to a lack of civic engagement. He also treats a decrease in trusting behavior in a community as direct evidence of a decrease in SC. While these relationships may exist, the underlying relationships between these variables and how they are correlated are probably much more complex than mere cause and effect.

2.8 Measurement issues

There is no widely held agreement on how to measure social capital, which is one of its weaknesses. It is possible to intuitively discern the level/amount of social capital in a group (any kind of relationship in a group regardless of type or scale used), but measuring it quantitatively has proven somewhat complicated. This has resulted in the development of different metrics for different functions of SC. Fukuyama [1999] points out that one of the greatest weaknesses of the notion of social capital is the absence of consensus on how to measure it.

Exacerbating the failure to reach consensus on a standard definition and measurement metrics for SC, almost everyone who writes about it appears compelled to provide a fresh definition rather than adopt an existing definition (see Table 2-1). Previous studies have shown that the measurement of SC is considerably complicated by the fact that most of the metrics in the literature have relied upon measures of outcomes and the benefits of SC in general rather than direct indicators of SC [Daniel, Schwier & McCalla, 2003; Daniel, McCalla & Schwier, 2005].

Compared to other forms of capital (financial or human), SC is difficult to measure SC because it is less tangible. In addition, since SC can assume a variety of forms (e.g., levels of trust, social protocols, shared understanding, density of civic associations), the measurement of this construct calls for the use of a variety of indicators.

Further, the validity of current SC measurements is often questionable, since much of the research is based on secondary data, drawn from statistical records that might not be accurate [e.g. Putnam, 1999]. In addition, SC is generally understood to be the property of the group rather than the property of the individual, yet studies that employ survey data often aim to discern individuals' social relationships to the group. Putnam [2000] for example has employed survey methods aimed at examining participation in groups (e.g., membership in voluntary organizations, churches or political parties) [Schuller, 2001]. Cote and Healy [2001] have suggested that measures of SC should be as comprehensive as possible in their coverage of key dimensions (networks, values, norms) and should be balanced between attitudinal/subjective data and behavioural data. Others argue that measures of SC should be culturally contextualized [Robinson, 1997].

Some studies have focused on measuring only one or few of the characteristics of SC, such as trust, rather than all of its components [*cf*. Fukuyama, 1999; Putnam, 2000]. The use of trust as a proxy for measuring SC is not appropriate in certain communities since trust is a nebulous concept in itself and it subsumes many variables [Daniel, Schwier & McCalla, 2005].

2.9 Studying social capital in virtual communities

The rapid growth of social software which increasingly supports the formation of virtual communities and an accompanying surge of interest among researchers in many disciplines raises many interesting questions. These questions include how to study social relationships that can lead to productive knowledge generation and sharing. These research questions suggest a need for the development of a comprehensive conceptual and theoretical framework for addressing social issues critical to collaborative learning and knowledge sharing.

The concept of social capital covers most of the social issues critical to design, development and sustainability of virtual communities, but since social capital is ill-defined and limited to terrestrial communities, this thesis explores the fundamental components of social capital and how it can be modelled. The thesis also opens up discourse on the construct of SC within virtual communities.

2.9.1 Virtual learning communities

Virtual learning communities are learning communities and they are one context for studying social capital in this research. Kowch and Schwier [1997] have described learning communities as collections of individuals who are bound together by social will and a set of shared ideas and ideals. Learning communities are also considered to be cohesive communities embodying a culture of learning, in which all members are involved in a collective effort of understanding [Bielaczyc & Collins, 1999]. Virtual learning communities describe a group of people using technology who gather to study some areas of interest, and who learn from each other throughout the process. Schwier [2007] has proposed a model of VLCs; describing thirteen fundamental elements of virtual learning communities (see Figure 2-2). The model is grounded on research and practice into virtual learning communities in the context of higher education.

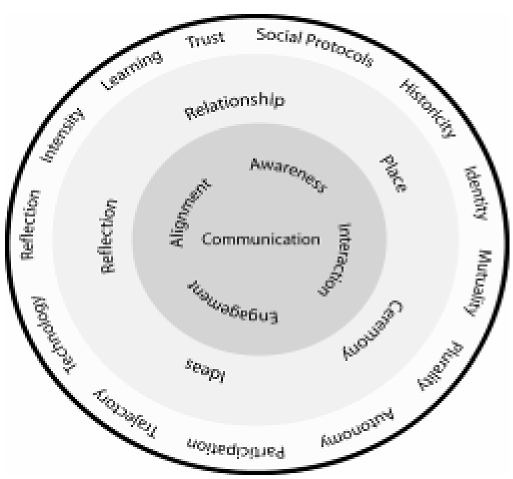


Figure 2-2. A model of virtual learning community [Schwier, 2007]

Schwier [2007] presents these elements of virtual learning communities for educators as a framework to think about and do things purposefully to foster community growth in online learning environments. By considering each of the elements of community, he suggests that it enables educators to derive instructional strategies that are consistent with the elements [Schwier, 2007]. He further adds that these elements help researchers examine whether communities form online and the various ways in which they can be supported.

2.9.2 Distributed communities of practice

Another context for studying social capital in this thesis is distributed communities of practice. A DCoP describes a group of geographically dispersed professionals in different fields who share common practices and interests in a particular area of concern, and whose activities can be enriched and mediated by information and communication technologies [Daniel, Sarkar & O'Brien, 2004]. A distributed community of practice (DCoP) can be regarded as a formalized knowledge network, serving as a vehicle for exchange of data, information and creation of knowledge [Daniel, Sarkar & O'Brien, 2004; Lave & Wenger, 1991]. What holds members together in a DCoP is a common sense of purpose and an authentic need to know what each other knows and to share that information.

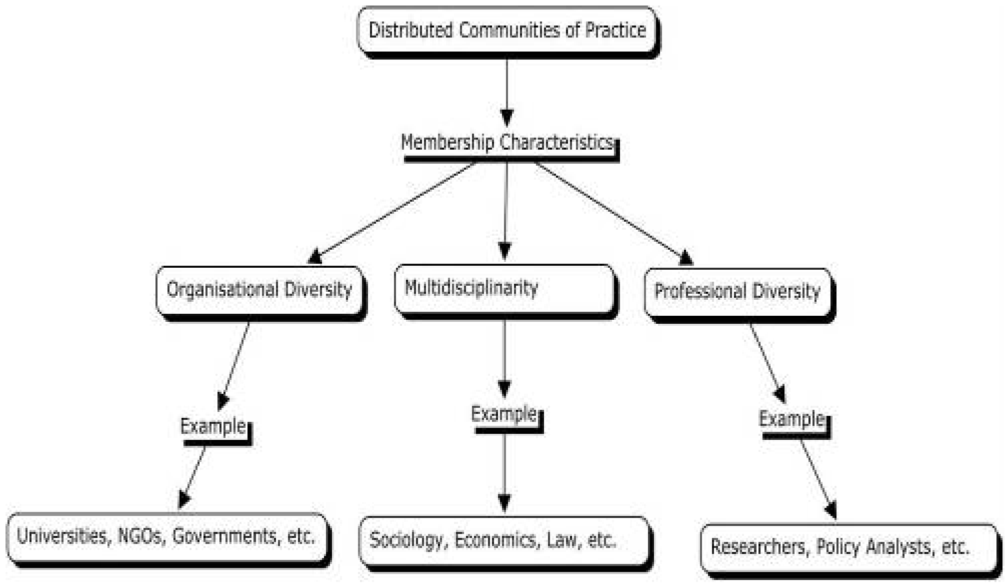


Figure 2-3. Main features of a distributed community of practice

In a DCoP individuals are characterized by diverse relationships, drawing membership from several domains and from various human and organizational cultures (see Figure 2-3). A successful DCoP is organized around the needs of its members and as such, DCoPs exhibit a wide range of sizes, structures, and means of communication.

Fundamentally, a DCoP connects professionals with similar interests who are often drawn from different training and professional backgrounds, and who are distributed in terms of time and space. For a DCoP to evolve, it requires individuals who are geographically and organizationally and culturally distributed to become aware of each other and build connections among members. Such individuals normally share common interests and are interested in connecting to others through the use of information and communication technologies.

Table 2-2. Virtual learning communities and distributed communities of practice

Virtual learning communities (VLCs)	Distributed communities of practice (DCoPs)
• Membership is explicit and identities are generally known	• Membership may or may not be explicit
• Presences of an instructor	• Facilitator, coordinator or a system
• Participation is often required	• Participation is mainly voluntary
• Explicit set of social protocols for interaction	• Implicit and implied set of social protocols for interactions
• Formal learning goals	• Informal learning goals
• Possibly diverse backgrounds	• Common subject-matter
• Low shared understanding of domain	• High shared understanding of domain
• Loose sense of professionalism	• Strong sense of professional identity
• Strict distribution of responsibilities	• No formal distribution of responsibilities
• Easily disbanded once established	• Less easily disbanded once established
• Low level of trust	• Reasonable level of trust
• Life span determined by extent in which goals are achieved	• Life span determined by the instrumental/expressive value the community provides to its members
• Pre-planned activities and fixed goals	• A joint enterprise as understood and continually renegotiated by its members

Table 2-2 compares VLCs to DCoPs. The question of what is a theoretically appropriate level for analyzing the effects of social capital on either kind of virtual community, whether a VLC or a DCoP, ought not to be couched in terms of a dichotomy (between the individual level and the collective level)—rather, it should be analyzed and understood through a multi-level, multi-dimensional and multivariate analytical framework. Further, there are benefits to conceptualizing social capital as a contextual construct within a clearly defined virtual community, while maintaining its general variables at the global level.

2.10 Chapter Summary

Current literature on social capital shows no consensus on the definition of social capital. However, the various definitions of the construct can be categorized into structural and content dimensions. Structural dimensions of social capital can be studied using social network approaches aimed at understanding social and structural features of a community. The content dimension can be understood through content analysis by identifying and categorizing variables such as trust, shared understanding, etc., as proxies for understanding community interaction. Chapter 3 presents an empirical investigation of social capital within the context of virtual learning communities, informal virtual communities and distributed communities of practice using social network and content analysis.

Chapter 3

3.0 Empirical analysis of social capital in virtual communities

3.1 Overview

This chapter summarizes results of three empirical studies conducted within three kinds of virtual communities, to further explore key variables of social capital identified in Chapter 2. The chapter also sets the foundation for identifying fundamental variables of social capital in virtual communities which constitute a model of social capital.

3.2 Introduction

This chapter presents a summary of three studies that built upon a significant on-going program of research into the nature of social capital in virtual communities. This on-going research looked into a diverse set of issues, including exploring the fundamental elements of virtual learning communities [Schwier & Daniel, 2006], extracting a synthesis of patterns of interactions in video-mediated virtual communities [Daniel & Poon, 2006], understanding the process of learning in virtual learning communities [Daniel, Schwier & Ross, 2006; Daniel & Schwier, 2006], exploring social capital in virtual learning communities [Daniel, McCalla & Zapata-Revera, 2003; Daniel, McCalla & Zapata-Revera, 2004], and isolating issues critical to the formation and sustainability of distributed communities of practice (DCoPs) [Daniel, Sarkar & O'Brien, 2004; Daniel, O'Brien & Sarkar, 2006].

The three studies that are the focus of this chapter were conducted in three contexts: a formal virtual learning community, a distributed community of practice, and an informal virtual community. The goals and purposes of the studies are summarized and illustrated in Figure 3-1.

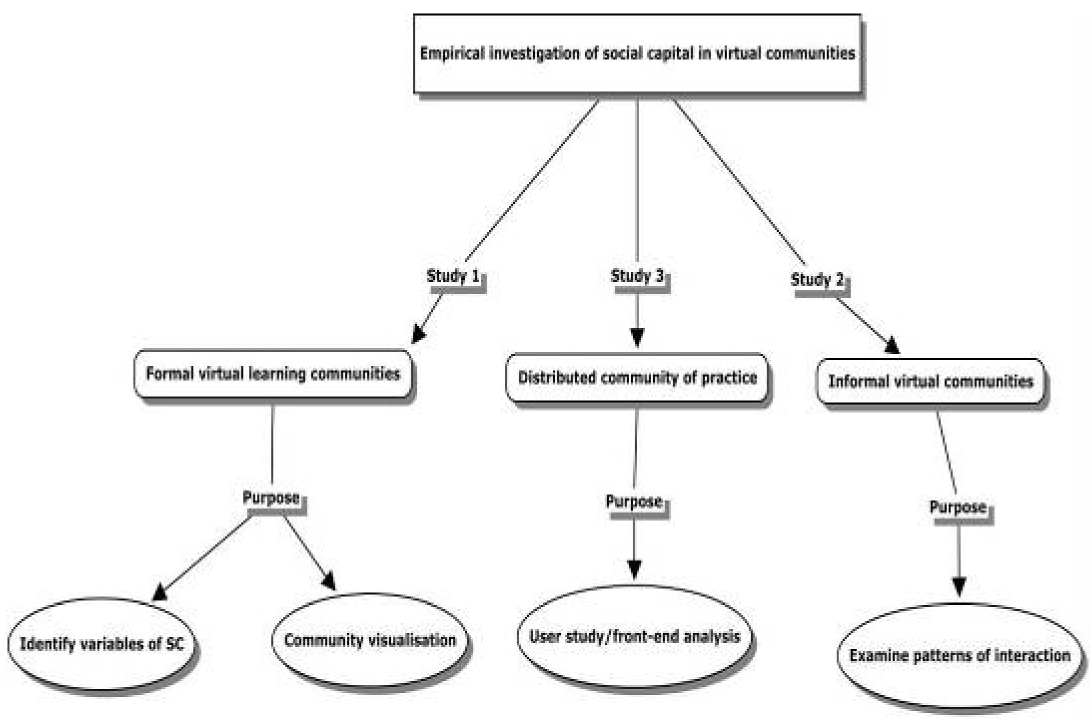


Figure 3-1. Investigation of social capital in virtual communities

3.3 Study 1: Social capital variables in a virtual learning community

3.3.1 Purpose and goals of the study

Study 1 was aimed at visualizing interactions in a virtual learning community using social network analysis and identifying variables of social capital that would be of interest to the modelling process based on content analysis approach. The social network approach and content analysis approaches employed are described in details in section 3.3.2.1 and 3.3.2.2 of this Chapter. The data analyzed for study 1 were drawn from virtual learning communities that emerged out of interactions in five graduate courses in Educational Communications and Technology at a western Canadian university. The courses were blended online and face-to-face seminars on the theoretical and philosophical foundations of educational technology and the principles and practices of instructional design. Each course spanned an entire semester or academic year.

3.3.2 Research procedures and methodology

3.3.2.1 Social network analysis

Social network analysis (SNA) techniques were used to visualize the patterns of interactions among participants in data on the virtual learning community. SNA is the study of mathematical models for interactions among people, organizations and groups. According to SNA theory, social relationships are viewed in terms of nodes and ties. Nodes are individual actors within the network, and ties represent the flow of relationships between the actors. The relationships defined by linkages among units/nodes are a fundamental component of SNA [Wasserman & Faust, 1994].

The SNA approach has become a popular means of investigating social networks [Burt, 1980; Freeman, 2000; Wellman & Haythornthwaite, 2002]. The SNA approach also provides the possibility of both a visual and a mathematical analysis of human relationships. In SNA social networks are described using a graph [Robinson & Foulds, 1980]. The graph is a directed graph with arrows indicating interaction and engagement between nodes (individuals) in the community.

3.3.2.2 Content analysis approach

The analysis of the presence of social capital variables in virtual learning communities involved analysis of online interaction transcripts using content analysis. . Content analysis is employed regularly in many domains to determine the presence of words, concepts, and patterns within a large body of texts or sets of texts [Rourke, Andersen & Archer, 2001; Soller, 2001; Soller & Lesgold, 2003; Stemler, 2001]. For this research, For the content analysis of the transcripts were done using Atlas ti™[1] software. A pre-determined coding scheme was used to guide the analysis (see figure 3-2).

The codes for study study 1 were primarily based on the variables of social capital discussed in Chapter 2. Grounded theory was also used throughout the coding processes to look for emergent variables, especially those that did not necessarily relate to instances

[1]ATLAS.ti [http://www.atlasti.com/] is a workbench for qualitative analysis of large bodies of textual, graphical, audio and video data. It offers a variety of tools for accomplishing the tasks associated with any systematic approach to "soft" data—material which cannot be analyzed by formal, statistical approaches in meaningful ways.

of social capital. According to Strauss and Corbin [1990] grounded theory is relevant and useful for the analysis of complex phenomena where little is known, as is the case in the study of SC.

Further, grounded theory is relevant to the study of SC in virtual communities, because of the methodology's flexibility which is required to cope with complex data and the need for continual cross referencing. In this research, manually coding of the data was done by reading and re-reading the chosen sample of the transcripts and noting occurrences of social capital or emergent variables. In grounded theory, codes are not necessarily independent or separately describable. They may overlap and contain many analysis units. However, physical limits are set on the meaning of data based on the context (Figure 3-2 shows the coding scheme and the unit of analysis).

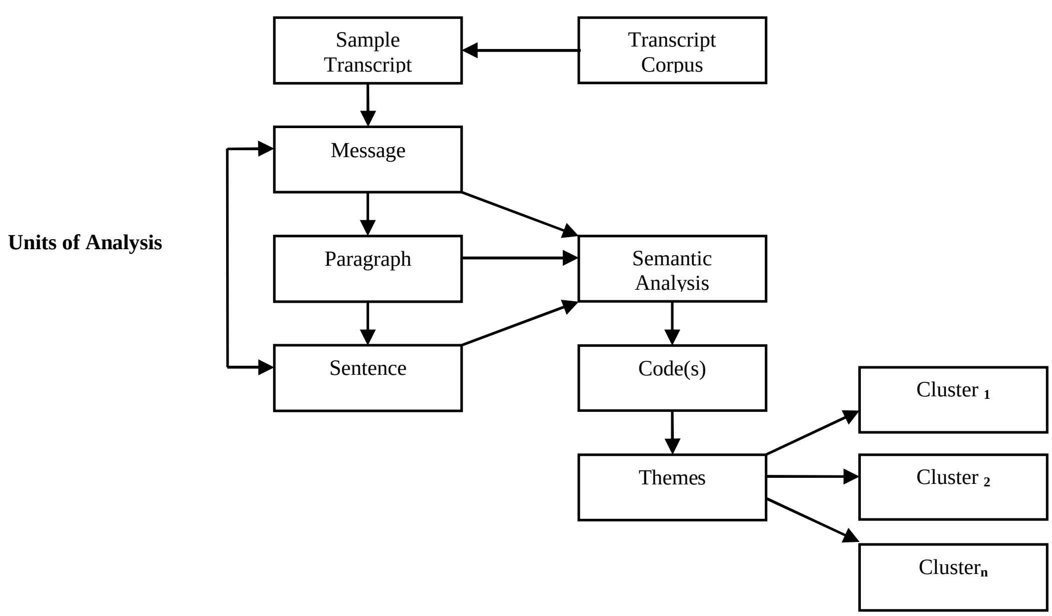


Figure 3-2. The coding scheme and unit of analysis

3.4 Results

3.4.1 Community visualization of interactions

In order to examine, understand and visualize the patterns of interaction among participants in study 1, interactions were codified into a two dimensional matrix. A matrix of a network of size ***n*** is a square matrix (**n x n**) whose elements represent ties (links) among individuals or agents in a given network. UCINET 6 software [Borgatti, & Freeman, 2002] was used to construct the network graph, which consisted of 15 actors/nodes (N=15) with connections indicating the flow of interactions or information flow [see Figure 3-3].

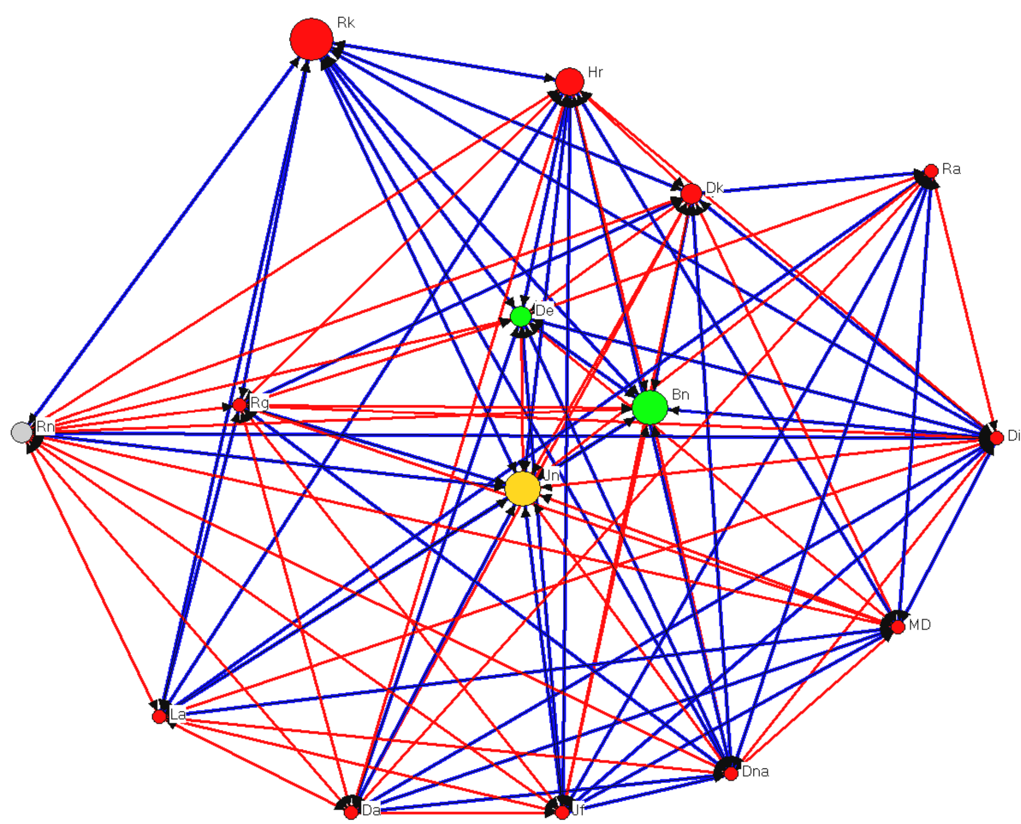


Figure 3-3. Community visualization

In figure 3-3 arrows in the graph indicate engagement between nodes (individuals) in the community. A single-edge link suggests one-way communication (when **A** sends mail or message to **B** but **B** does not respond to **A**) while a double-edge link suggests two-way communications. In order to determine individuals' centrality in the network, Freemen's indegree and outdegree measures were used. In this analysis, indegree reveals the number of individuals who have read messages in the community. Outdegree measures the number of messages an individual has sent to all other individuals in the community. Table 3-1 summarizes the results of the in-degree and out-degree measures.

Table 3-1. Degrees of connectivity among individuals in the network

Actor	**Outdegree**	**Proportions**	**Indegree**	**Proportions**
Rk	109	0.9	18	0.03
Dm	24	0.04	12	0.02
Bn	67	0.11	79	0.13
Dna	25	0.04	39	0.06
De	54	0.09	56	0.09
Di	24	0.04	35	0.05
Dk	54	0.09	51	0.08
Dn	11	0.01	29	0.04
Hr	57	0.09	43	0.07
Jf	41	0.07	38	0.06
Jn	59	0.1	74	0.12
La	13	0.02	31	0.05
Rg	16	0.02	26	0.04
Ra	21	0.03	29	0.04
Rn	7	0.01	33	0.06

The degree of centrality in a social network theory is the most intuitive network centrality measure. The centrality of an individual is simply the number of people to whom that person is directly tied or connected. For example a node with a high degree of centrality in a social network has a high proportion of connectivity with other nodes in the network, suggesting that person is more central to the network.

The total number of messages a person has sent to members of the community shows their outdegree of centrality. For example, in Table 3-1 Rn has the lowest outdegree of centrality, meaning that s/he sent out only 7 messages compared to Rk who has a high outdegree centrality (109), with a bigger node in the graph colored red.

Indegree, on the other hand, shows the number of messages a person has received from other members of the community. In Table 3-1, Bn has the highest indegree of centrality (79), with a node colored green in the network, followed by Jn (74), (see node in the graph colored yellow) compared to DM who has only 12 (which shows that s/he has only received a total of 12 messages from others in the community). Figure 3-4 shows the proportions of the distribution of indegree and outdegree measures among all the members of the network.

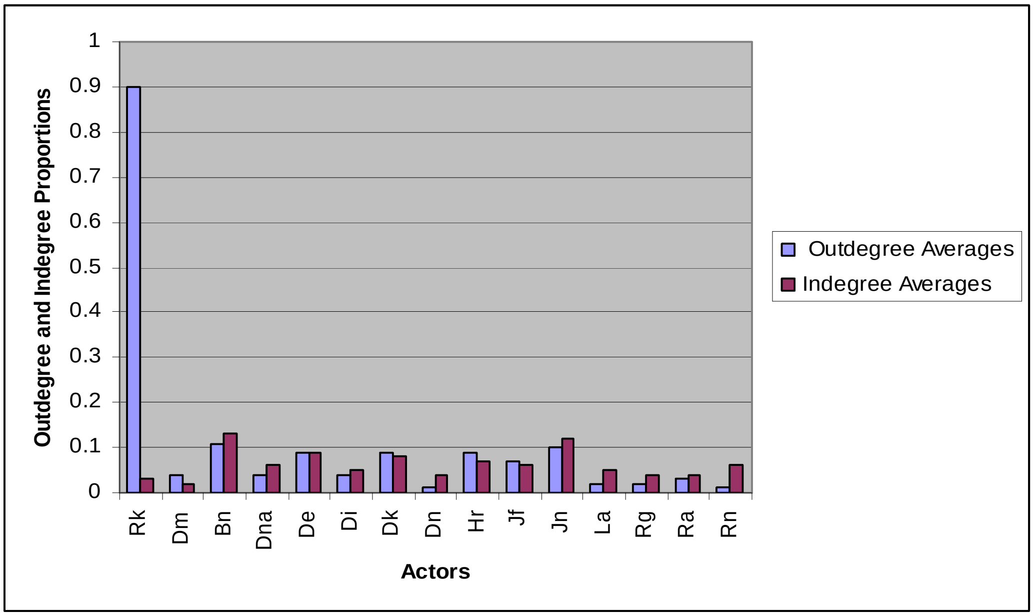


Figure 3-4. Distribution of indegree and outdegree of engagement

In Figure 3-4, Rk displays a high outdegree of centrality. A high outdegree of centrality in the network can also imply that an actor can gain access to more information or knowledge than those who have a low outdegree. It can also suggest power and control and ability to gain prestige through exposure of oneself. It can mean that an actor has the possibility of influencing other actors in the network through multiple channels of communication. In other words, Rk's position is regarded as the most influential in the network.

In contrast, peripheral actors maintain few or no connections with others and thus are located at the margins of the network. For instance, Rn who has a relatively low proportion of outdegree centrality can be considered a spectator or "lurker". However, lurkers in social network terms are not necessarily unimportant. An individual who is a recipient of many messages, but sends out very few, may still have "prestige" by the very fact that many people want to send him/her messages.

3.4.2 Social capital and emergent variables

Several variables of social capital and other emergent variables were identified in the online interaction transcripts. The results of the analysis are summarized and shown in Figure 3-5.

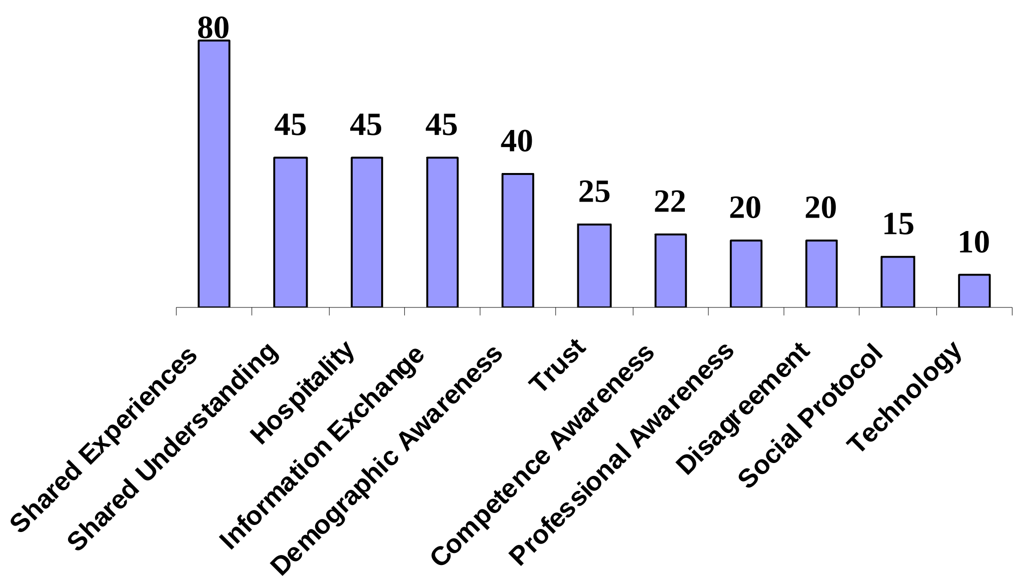


Figure 3-5. Frequency of the observed indicators of social capital in the transcripts

Figure 3-5 shows frequencies of the occurrences of the variables of social capital such as shared understanding, demographic awareness, trust, competence awareness, and social protocols. These results might reflect some of the variables identified in Chapter 2 but interpretation might be limited to the nature of this community, which was highly formalized, with clear goals and established social protocols. The variations among the variables do not generally describe the amount of social capital in the community, but they indicate a gross measure of some the variables of social capital in this community. Selected examples of the variables in Figure 3-5 are illustrated qualitatively in Table 3-2.

Table 3-2. Example of qualitative quotations from the transcripts

Instances of Variable	Example from Transcripts
Professional awareness	*"I am a full time teacher at…..High School in…..where I teach Physics, coach volleyball, organize and…."* *"I belong to my school's technology/computer committee. In this community there are seven individuals working together to enhance the technology program at the school, coordinate the purchase of hard/soft ware, provide training for staff on various software, set report card deadlines, organize the printing of report cards, place heat calls, take care of password changes, trouble-shooting, and just about anything at all dealing with computers at……"*
Demographic awareness	*"My name is …... I am a dad and husband, I teach computer technology courses and various other things (biology and science, mostly) at the high school in… I have also worked as a technology coordinator for the …School Division during the introduction of a large-scale thin client computer platform."*
Capability awareness	*"I have been a technology coordinator for our school for 12 years and have represented our school and school division on various committees during that time."*
Technology	*"I'd love to have a spell check in WebCT ... and I'm sure people who read my posts wish for the same thing. Plus, I'd like to be able to save a message and not post it immediately. This way if I'm unsure of my thought, I can step back for awhile and not have to start again from scratch."* *"Well, I have been vocal about the problems I have with my G4 Power book. After talking with Marlene today at the conference, she has the same problems with her G4 Power book. Funny, she said Mac users usually aren't vocal about any problems."*
Hospitality	*"Thank you everyone for your warm welcome. I am going to work on sending a video back! Such a nice touch... it is great to out faces to the postings."* *"Apologies for the extremely late posting. I'm not sure why I had the brain lapse, but thanks to Marlene for reminding me I'm in the class).Hope you're having a*

	great face-to-face meeting today. See you online!"
Competence awareness	*"I too think your English is fine. Yes, I can tell you are from… but so what? I will tell you a story I already told … about my experience with accents. When I was little, my parents spoke to me in Dutch (Flemish). Before I started school they taught me English but I spoke with a Dutch accent……"*
Shared understanding	*"I agree with both of you about the dangers of misconceptions and inaccuracies in any field......"* *"You are absolutely right about what you said in terms of ….reminding us to note cultural differences. I think that it is important for us to try to remember the more subtle differences that come with the "mosaic" that is this class."*
Information exchange	*"Virtual learning communities are very new to me and have been a huge shift in the way that I work and think as a student, and as an instructor. There are many losses, I think, that are hard to compensate for in a virtual learning community (all the ones you mentioned)."* *"I found the listings for my great grandmother and her mother and sister when they came through Ellis Island in the late 1800s. At the same time I also discovered that the U.S. government posts the social security numbers of people who have been dead at least a year…"*
Social protocols	*"Describe the learning community of practice to which you belong. What's special about your community? What do you think makes it a community of practice? What have you learned about the other members? What have you learned from them...?"* *"Post one commentary of approximately 200 words based on the questions below in the bulletin board discussion, Motivation, by Thursday. Post one response of approximately 100 words to the issues addressed by another student in the bulletin board discussion, Motivation, by Sunday"*.
Trust	*"I have already mentioned that I believe that trust is the key element I am trying to establish with students. They need to trust that I care, that I understand, and that I will attempt to work to create a fun and interesting learning environment."* *"Trust and acceptance (irrespective of the level of French an individual has); reassurance that what's important is that you improve your French speaking abilities (irrespective of where you're starting from) not that you get 98% on a test."*

3.4.3 Sharing experiences

Among the variables presented in Figure 3-6, sharing experiences has the highest frequency of occurrence. The sharing of experiences in virtual learning communities results in effective interactions that are likely to influence the process of teaching [Daniel & Schwier, 2007]. Sharing experiences can occur through sharing resources and information or telling others in the community about one's experiences or problems. It can be argued that sharing experiences is a key feature of developing SC in virtual communities. For instance, when people share their experiences with others, they express a sense of belonging to a community, and feel they are contributing useful knowledge that can benefit others.

Furthermore, sharing experiences in VLCs can be regarded as members' active involvement and personal commitments to others in their community; it involves exposing one's hidden (tacit) knowledge. Sharing experiences can also help people establish a level of shared understanding since it requires continuous interactions where individuals can get to know each other and possibly identify personal interests or build trusting relationships [Daniel, McCalla, & Schwier, 2002].

3.4.4 Shared understanding

Shared understanding enables people in a community to develop common goals, beliefs, values, and principles that will in turn allow them to work together as a community and build strong social capital. In a community where individuals have little awareness of each other, however, shared understanding is difficult to develop, as it needs to evolve over time as individuals spend time together and learn about each other. In a virtual learning community where individuals are required to engage in free and honest discourse throughout the learning process, having shared understanding can provide a basic structure within which a community can smoothly operate and can help members to productively engage in free and fair discourse based on mutual respect.

Overall, it can be argued that shared understanding nurtures SC when individuals share common goals and are willing to work together toward the attainment of common goals. It also allows people to understand each other, and use the same frame of reference in discourse. Further, shared understanding can strengthen SC when individuals agree on common terms, activities and goals in a community.

3.4.5 Trust

Although trust is a key variable and vital for developing SC as discussed in Chapter 2, in this study it was observed comparatively few times in the transcripts. This is attributed to the fact that indicators of trust may not be directly observed in data of this kind; references to trust are only mentioned obliquely in conversations.

3.4.6 Awareness

Results from the analysis of the data further suggested a strong link between awareness and trust. Participants mentioned that they trust people they know (awareness). However, in a formal virtual learning community, awareness can be situated in different contexts and it evolves over time. As one respondent pointed out in the transcripts:

"I find that the social capital in the online course that I am teaching is in the early phases, where we are trying to build it. Most of the students do not know each other, but in just one week of the course, have figured out how to get in touch with each other and help each other out. They email each other for questions and arrange to meet in the chat room. They are just now building these relationships that will form a community".

While the level of individuals' awareness and its relation to trusting relationships in terrestrial communities can be easily observable, little is known about how the level of awareness in virtual communities and how it can affect the level of trust. Building trust in virtual learning communities that can nurture SC requires more research.

3.5 Conclusion and summary of study 1

Study 1 has explored the nature of social capital in a formal virtual learning community through examination of members' social interaction and the content of the messages exchanged. Results from study 1 helped to further the exploration of the structural and the content dimensions of social capital. In addition, the content analysis revealed messages exchanged by individuals that can labelled as indicators of social capital. Congruent with other previous research [Daniel, McCalla & Schwier, 2005], social capital can have various indicators. As the results show some of these indicators include sharing experiences, shared understanding, various forms of awareness and trust.

3.6 Study 2: Analysis of online interaction in informal virtual communities

3.6.1 Purpose and goals of the study

Informal virtual or "open virtual communities" are widespread in the Internet. Unlike formal virtual communities, which are mainly developed around formal courses in educational institutions or corporate settings, informal virtual communities are those online communities where membership is voluntary and the communities are focused specifically on information exchange and implicit learning. The purpose of study 2 is to examine indicators of social capital in an informal virtual community. The goal is to understand the thematic exchange of messages as well as the density of interactions.

3.6.2 Research procedures and methodology

The data reported in this study were drawn from a video-mediated virtual community called "Café Americano," a community that is primarily social rather than learning oriented part of [http://www.cuworld.com/]. Community members interacted regularly—sometimes on a 24 hour basis—with members checking in and out according to their needs. Social network analysis as described earlier in this Chapter was used to map out interactions among individuals in the community. Content analysis was employed to categorize themes of interaction and indicators of social capital. The same scheme of content analysis presented Figure 3-2 was employed.

3.6.3 Results

3.6.3.1 Community visualization of interactions

UCINET 6 (Borgatti, & Freeman, 2002) software was used to generate the network (see Figure 3-7). There were 23 actors/nodes (N=23) with connections indicating the flow of interactions, which subsequently determined community structure as well as patterns of discourse. Red links indicate reciprocal relationships while blue links indicate one-way flow of information.

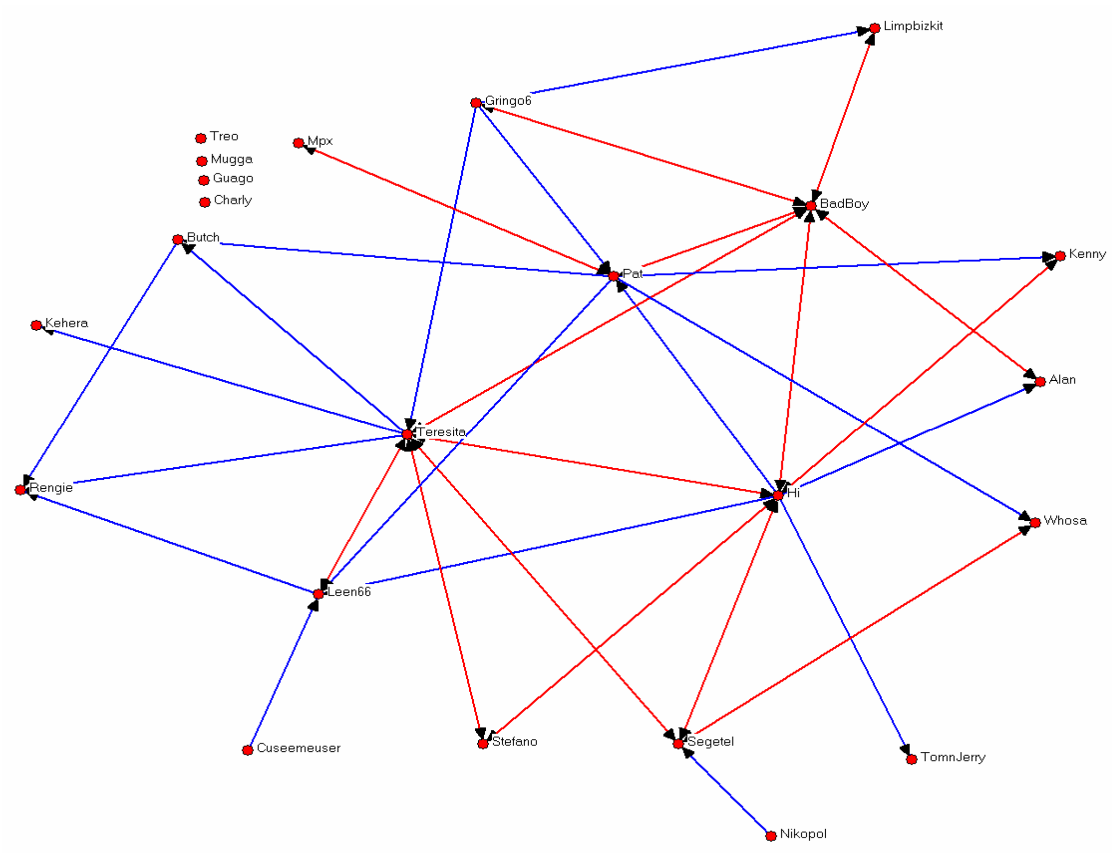


Figure 3-6. Flow of engagement in a video-mediated virtual community

To determine whether a community formed out of the interactions, a measure of group density was calculated. Density is a measure of how connected individuals are to others in a group. A higher degree of connection reveals possible existence of a community. Fahy [2001] suggests that a group's density is "the ratio of the actual number of connections observed, to the total potential number of possible connections." It is calculated by using the following formula: Density = 2*a*/N (N-1), where "*a*" is the number of observed interactions between participants, and "N" is the total number of participants.

Fahy [2001] cautions however, that the measure of density is sensitive to the size of the network, so larger groups will likely exhibit lower density ratios than smaller groups. In order to identify the alignment of sub-groups (cliques) within the network, a fragmentation index was calculated. Fragmentation in social network measures the extent to which a whole network is segmented into smaller and more cohesive subgroups within which interaction is particularly intense. The degree of fragmentation is quantified by measuring the number of components within a network.

The calculations revealed a density ratio of .67, suggesting that 67% of all possible connections were made, i.e. Density = 2(35)/23(22) = 0.67 with fragmentation of 0.324[2]. Although there is no baseline data to make judgments about the existence of community at this point, the density level suggests a reasonably strong connection between community members, regardless of the number of reciprocal relationships.

---

[2] Indicates the proportion of participants who cannot reach each other in the community

A reciprocity measure aimed at understanding the rate of mutual interdependency between two or more nodes in the network was employed. The overall reciprocity value is the same as in a dyad-based model, i.e., Num (Xij>0 and Xji>0)/Num (Xij>0 or Xji>0) reciprocity is 0.4545, indicating a fair number of ties (expressed through communication among individuals in the community) in the community. Though the number of ties in a network does not automatically suggest the existence of a community, it indicates a fairly active pattern of connections among members during discourse.

Also, present were prominent individuals with higher levels of reciprocal relationships within this community. For instance, Badboy had the highest level of reciprocal relationships in the community followed by Terresita (5) and Hi (5) respectively. It follows that Badboy has one of the most strategic positions in the community, connecting with others such as Limpbizkit, Alan and Gring06. On the other hand, Hi and Segetal are both connected to two important individuals in the community, namely Nikopol and Tomnjerry. Though Nikopol and Tomnjerry have few connections, they occupy critical positions in the social network in that they are hubs by which new information can flow to and from other communities and also help translate that new information to the community members. In other words they act as “diplomats” in the community [McCalla, 2000].

Some individuals are outliers. Such individuals are members of the community but are not directly connected to others. In virtual communities they are sometimes referred to as “lurkers”. These include participants such as Treo, Mugga, Guago and Charly, though it is also possible that they are lurking because they were absent during most of the interactions, calling into question whether they were participants in any real sense.

3.6.3.2 Social capital and emergent variables

Analysis of the content of interaction in study 2 suggests that people gather in virtual communities for a variety of reasons and they often engage in a variety of themes, ranging from social issues to economic discourse.

Though it is difficult to speculate about what motivates people to join open virtual communities and engage them in discourse of specific themes, it is possible to conclude that most of the reasons are social. For instance, individuals often join open virtual communities to socialize or look for information or knowledge in relation to some particular task. In such a case, open virtual communities serve as spaces for supplementing terrestrial communities by providing a social interaction milieu. A summary of the content analysis of the interactions is presented in figure 3-7.

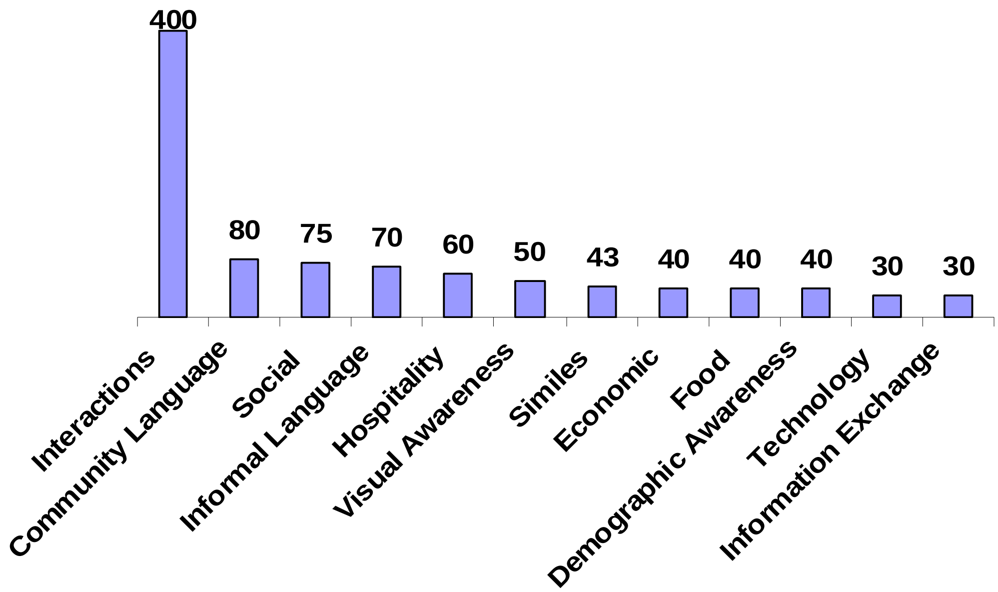


Figure 3-7. Frequency of observed discourse themes in the transcripts

The results enable us to understand gross occurrences of discourse themes and understand the nature of issues that are emergent in these communities and to develop theoretical models of interactions to understand how social interactions affect knowledge and information flow in different virtual communities.

3.7 Conclusion and summary of study 2

The Social Network Analysis approach provides various ways to identify key individuals and their roles in transmitting information in informal virtual communities. However, it is not enough to study network properties of social network; one should also be able to analyze the content of engagement in which a network is formed.

Content analysis of social interactions within the framework of social resources suggests a structural dimension of social capital described in Chapter 2. A social network view of social capital in the study considers the density of social networks that people are involved in; the extent to which they are engaged with others in informal, social activities; and their membership in groups and associations. Further, the social capital examined in this study took into consideration the context of a social network as well as the content exchanged during interaction.

3.8 Study 3: User study for building a distributed community of practice

3.8.1 Purpose and goals of the study

The purpose of study 3 was to examine the motivations a diverse group of people might have for creating a distributed community of practice (DCoP) and to build a strong social capital useful for information sharing across Canada. A group of people were surveyed to find out what they felt was important to include in the development of a DCoP on the topic of governance and international development. Some of the results of the study were used to inform the model of social capital presented in Chapter 4.

This study was one part of a larger program of research looking into building distributed communities of practice (DCoPs). The DCoP program of research was aimed at improving awareness, research and sharing data and knowledge in the field of governance and international development in Canada [see for example, Daniel, Sarkar & O'Brien, 2006; Daniel, Sarkar & O'Brien, 2005; Daniel, Sarkar & O'Brien, 2004].

The research employed a sociotechnical approach to elicit initial information from participants to inform the building of the community. The sociotechnical approach offers useful insights into various ways of blending social and technical factors that helped in the design and development of tools for building community. Further, a sociotechnical approach takes into account participatory design and user-centred dimensions for building software applications and interaction processes. The research protocol involved the participation of potential users throughout the analysis, design, and implementation process.

3.8.2 Research procedures and methodology

The research procedure involved identifying potential technologies for supporting online communities. In addition, a profile list of potential participants mainly stakeholders from academia, government and the non- and for-profit sector was created. A survey was then administered to 200 individuals, randomly drawn from organizations identified as working in the field of international development and governance, including government, non-governmental organizations, private consulting and academic research centres. The survey instrument was divided into three sections:

- an assessment of existing communication/networking mechanisms among participants;

— an assessment of the level of awareness of work undertaken by participants and their affiliated organizations and,

— participants' perceived value of a DCoP and what services would contribute to its potential value.

Following the analysis of the preliminary analysis of the data, design features for the community together with proposal for relevant tools were identified. The results were then use to inform questions administered to self-selected groups via telephone interview. The goal of the interview was to elicit further information regarding individuals' preferences for content of the community and the suggested tools and interaction processes.

3.8.3 Results

Overall response rate to the online survey was 25%. Of those who responded, 38% were university-based, 23% from provincial and federal government institutions, 30% from non-governmental and research organizations and 9% from private consulting firms. The respondents were distributed across Canada: 45% from western Canada, 53% from central Canada and 2% from the eastern part of Canada.

The results revealed that 90% of the respondents were interested in influencing, contributing to, or participating in the policy-making process. In addition, over 80% of respondents indicated that it was important for them to keep current on new developments in research and practice. Depending on their organizational affiliation, 50%

to 80% of the respondents were interested in building collaborative partnerships for research and technical assistance.

Participants identified the potential benefits of a Canadian-based distributed community of practice that can cat as a framework for supporting their interest in keeping abreast of current research and practice in governance and international development. In terms of collaboration, a large number of the respondents viewed the DCoP as a potential mechanism to facilitate information exchange and knowledge sharing among members and source of social capital, manifesting in both content as well as the structural dimensions.

3.8.3.1 Social capital and awareness issues

Congruent with recent research, findings from the study supported the idea that a DCoP develops when individuals realize the potential benefit of building social capital through sharing knowledge, insights and experiences with each other and how sharing can enhance their practices and performances [Resnick, 2004]. Further, the results of the study showed low levels of individuals' awareness of contemporary research and practice in the field of governance and international development. At the same time participants discussed about the specialized nature of their work and the limited number of organizations active in the field, they also reported that they were largely unaware of contributions that their counterparts have made. These results highlight the importance of awareness in building social relations in promoting social capital.

Although establishing a benchmark standard for awareness is problematic, the results indicated a considerable lack of awareness among researchers and practitioners working on governance and international development in Canada. As the majority of the participants described current knowledge on governance and development as fragmented and that there was a serious lack of awareness among people working on similar issues across provinces and between organizations.

3.8.4 Conclusion and summary of study 3

The notion of a DCoP is an important framework for describing a diverse and distributed group of people who are interested in a shared area of activity. The study has identified many variables that are critical to building a distributed community of practice. Some of these include various forms of awareness that can enhance information sharing and building social capital of this group.

3.9 Chapter summary

Chapter 3 has described and discussed three studies aimed broadly at understanding social capital and related issues in virtual communities, using a variety of methods, and across three different contexts. The first study explored social capital through visualization of online interactions in a formal online learning environment. The second study explored social structure of an informal virtual community and examined the different kinds of themes found in a typical informal virtual community. The third study was situated within a broader study aimed at examining fundamental issues critical to building a distributed community of practice and fundamental social capital that can enhance information and knowledge sharing.

The results of the three studies reported in this Chapter helps extending understanding of the fundamental variables critical to social capital in virtual communities. These results also confirmed the existence of indicators of social capital in three different online communities, and thus motivate the need for building a computational model of social capital in these communities. Chapter 4 will describe Bayesian Belief Network techniques that will be used for building a model of social capital.

Chapter 4

4.0 Bayesian Belief Network Modelling

4.1 Overview

The multivariate, multidimensional and imprecise nature of social capital requires understanding the relationships inherent among its key variables and how they interact within a particular virtual community's context. This chapter describes methodologies, in particular Bayesian belief network techniques, for modeling social capital in three kinds of virtual communities.

4.2 Introduction

In artificial intelligence in education (AIED) models are used to capture characteristics of learners and these models can be used by tools to support learning [McCalla, 2000]. Baker [2000] has summarized three major uses of models within AIED: models as scientific tools for understanding learning problems; models as components of educational systems; and models as educational artifacts. He has further observed that the future of artificial intelligence in education (AIED) would involve building models to support learners in learning communities and to help educators manage learning under distributed circumstances.

4.3 Process of building computational models

The process of building a computational model is an iterative one, involving organizing data, establishing logical relationships among the data, and coming up with a knowledge representation scheme that captures these relationships (see Figure 4-1).

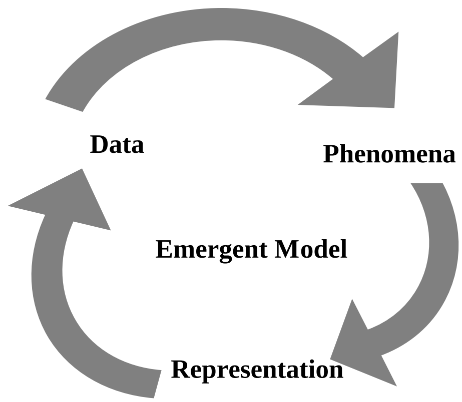


Figure 4-1. Modeling process

A fundamental assumption underlying most of the model building process is that data are available which a researcher can use to infer logical relationships and draw logical and concrete conclusions from the model. There are modelling approaches that do not allow the introduction of prior knowledge during the modeling process. These approaches normally prevent the introduction of extraneous data to avoid skewing the experimental results. However, there are times when prior knowledge would make a useful contribution to the modeling and evaluation processes and the overall observation of the behaviour of a model.

A Bayesian belief network (BBN) provides an opportunity for building simple but robust tools for analyzing and understanding complex systems using prior knowledge. A BBN defines various events, the dependencies between them, and the conditional probabilities involved in those dependencies. A BBN can use this information to calculate the probabilities of various possible causes being the actual cause of an event.

4.4 Bayesian belief networks

Bayesian belief networks (BBNs) are graphs composed of nodes and directional arrows [Pearl, 1988]. Nodes in BBNs represent variables and directed edges (arrows) between pairs of nodes indicate relationships or dependencies between variables. BBNs offer a mathematically rigorous way to model a complex environment. Bayesian models are flexible, able to mature as knowledge about the system grows, and are computationally efficient [Druzdzel & Gaag, 2000; Russell & Norvig, 1995].

Research shows that BBN techniques have significant power to support the use of probabilistic inference and to update and revise belief values [Pearl, 1988]. In addition, BBNs can permit qualitative inferences without the computational inefficiencies of traditional joint probability determinations [Niedermayer, 1998]. Furthermore, the causal information encoded among variables in BBNs facilitates the analysis of actions, sequences of events, observations, consequences, and expected utility [Pearl, 1988].

Due to their robustness in modelling and describing uncertainty, BBN techniques are now being used in a variety of domains. For instance they are used for diagnostic systems

[Pradhan, Provan, Middleton, & Henrion, 1994; Niedermayer, 1998], student modeling [Conati, Gertner, & VanLehn, 2002; Reye, 2004; VanLehn et al. 1998; Vomlel, 2004; Zapata-Rivera, 2002; Zapata-Rivera & Greer, 2004], troubleshooting of malfunctioning systems [Jensen, and Liang, 1994], and as intelligent help assistants in Microsoft Office products [Heckerman and Horvitz, 1998].

The modeling process in BBNs requires capturing domain concepts, variables and their associated prior probability values, as well as building a graphical representation of the variables of the domain being modelled. The role of graphs in probabilistic modelling in BBNs provides a convenient means of expressing substantial assumptions, and graphs also facilitate economical representation of a joint probability function to enhance making efficient inferences from observations.

In choosing a probabilistic approach to modelling, BBNs offer a number of advantages over other methods for the following reasons:

- BBN models are powerful tools both for graphically representing the relationships among variables and for dealing with uncertainties in expert systems.
- The graphical structure of BBNs provides a visual method of relating relationships among variables in a simple way.
- In BBNs, a network can be easily refined (i.e. additional variables can be easily added and mapping from the mathematics to common understanding or reference points could be quickly done).

- The BBN approach allows for evidence to be entered into the network, and updating the network to propagate the probabilities to each node; the resulting probabilities tend to reflect common sense notions including effects such as “explaining away” and “pooling evidence.”
- BBNs offer an interactive graphical modelling mechanism that researchers can use to understand the behaviour of a system or situation, (e.g., it is possible to add evidence/observe variables and propagate this information throughout the whole graphical model to see/inspect the effects on particular variables of interest).
- The fact that BBN has qualitative and quantitative elements gives it many advantages over other methods.

4.5 Building Bayesian belief networks

The construction of a BBN consists of several phases which can generally be reduced to three fundamental steps. The first step involves identifying and defining the problem domain, followed by the identification of the relevant variables constituting the problem being modelled. The second step is to determine the relationships among the variables and establish the graphical structure of the model. The third step is to compute conditional probability values for each variable in the model.

The phases and associated procedures for building Bayesian belief models are graphically described in Figure 4-2. It is quite common that the first two steps concentrate mainly on defining the problem domain with a goal of expressing the problem in its simplest form. This is often done to reduce the number of probability values in the conditional probability table, which is done in the last phase. The last phase is the most difficult one, requiring sophisticated knowledge engineering techniques.

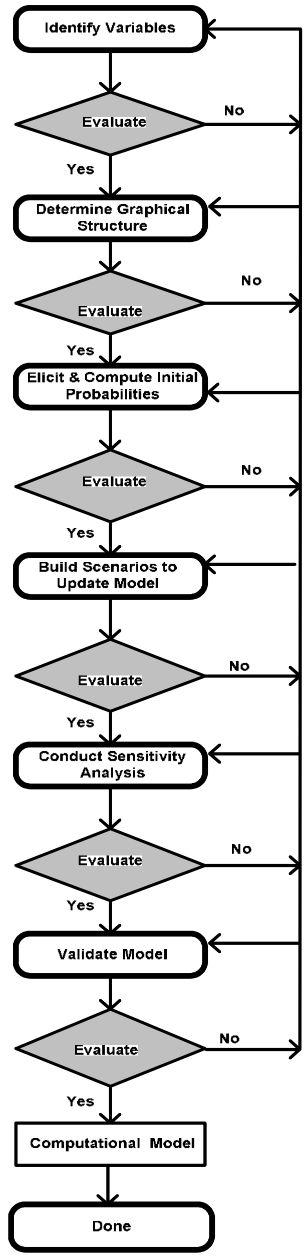


Figure 4-2. Phases and procedures in building BBN models

In the traditional Bayesian network approach, the process of capturing knowledge within a domain normally involves asking the experts to identify the most likely variables constituting the domain to be modelled. In the case of this research, expert and literature were interrogated to identify variables, and original studies were also conducted to identify key variables (see Chapter 3).

In a BBN model, there are different types of variables, For instance, query or objective variables are those variables that are to be the output of the network, the variables the end-user wants to know about. Evidence variables or observation variables (sometimes referred to as controlling variables) are the inputs to the network, the observables in the environment being modelled. There are also contexts or intermediary variables that link the query variables and the evidence variables. The last group of variables is called controllable or intervention variables. This set of variables could potentially be used as an intervention to insert information into the modelling process when needed. Once the various variables of interest are identified, they are connected via causal relationships.

This leads to the second step, which is to establish a graphical representation of variables identified. In constructing the graphical representation, it is necessary to specify the parameters of the model and keep the causal relationship between variables tractable. There are four main kinds of relationships in a Bayesian Network: independent, dependent, conditionally independent and marginally independent. The different kinds of relationships are described [Pearl, 1988]

There are many ways one can determine the causal relationships among the variables. These include asking experts questions such as: what can cause variable **x** to take on state **t**? For instance, what can cause the grass in the lawn to be wet? Others involved using one's expert knowledge to analyze a particular domain and identify variables of interest, doing a review of existing knowledge and identifying relevant variables on domain of interest (similar to the literature review described in Chapter2), and running confirmatory studies (see Chapter 3). The third step of the modeling process involves assigning prior probabilities to each of the variables in a model and conditional probabilities for each. Variables in a Bayesian model are expected to be mutually exclusive and exhaustive [Pearl, 1988].

In the case of discrete variables that can assume binary values, the number of prior probability values needed to determine the joint probability distribution (JPD) in a model is 2^n, assuming binary values for each variable or node, as is the case in the model presented in this thesis. For example, if there are 10 variables in a model, then their joint probability distribution has 2^{10} =1024 probability values. In discrete variables probabilities can often be presented in a conditional probability table (CPT). CPT (see tables in Figure 4-4 lists the probability that the child node takes on each of its different values for each combination of values of its parents.

Developing a conditional probability table is the most difficult part of the modelling process. It involves specifying initial probability values for each node in the network given the values of its parents based on Bayesian reasoning, and for each possible instantiation [3] of the parents' probability values there is a probability distribution. This implies that the probability elicitation process is exponential in the number of parent variables. However, the simpler a graph is, the easier is the elicitation process.

4.5.1 Generating variables and their values

Initial probability values for a Bayesian model come from many sources to consider, depending on the problem being modeled and the availability of data. The common three possible sources for obtaining domain variables and their initial probability values discussed in literature are domain experts, experimental data, and literature in the domain being modeled [Druzdzel & Van der Gaag, 2001; Haddaway, 1999].

Eliciting variables and prior probability values from experts is the most common practice. This often involves asking domain experts about the most fundamental variables within the system being modeled and finding out from them the causal relationships among the variables. For instance, determining the probability that variable 'A' takes a certain state given its parent's variable values can be done using frequency assessment. In other situations, qualitative assessments are done instead, using terms such as the probability of 'A' happening given the state of a parent B is unlikely, probable, high etc. Computational tools such as Verbal Elicitor (VE) which allows entry of probability values in ordinary English. For example, a domain expert selects a verbal cue such as "unlikely" or "almost certain." The probabilities are then set manually or optimised to minimise probabilistic incoherency. VE can also be used to help map verbal terms to sets of probabilities.

[3] Instantiation in Bayesian belief is the process of assigning probability values to a variable's particular state.

There are a number of problems in eliciting domain variables and their initial probabilities using systems such as VE. In some domains, sometimes domain experts do not have the time to go through the elicitation process, but even though they are willing to work with knowledge engineers, there can still be possible biases and inaccuracies in the probability values. One way to eliminate human errors in obtaining accurate probabilities is to use experimental data.

One of the goals for using experimental data in a Bayesian model is to train the model; the whole process can be automated using any of the Bayesian tools (Netica, Hugin etc. see appendix L). But experimental data sources have their own limitations, including noise in the data collected; missing values and sometimes a mismatch of the values in the model leading to wrong predictions.

4.5.2 An example of a simple scenario

To fully illustrate how variables causally relate to each other in a model and their initial probabilities, a simple scenario on how to build a model is provided. Imagine a scenario in which we are interested in understanding how different variables can affect the level of trust in a virtual learning community. Suppose we know through empirical evidence, intuition, literature, observation or experiences that interaction in all of its forms is necessary for building trust in any environment. Suppose we also know that people do not just develop trust with strangers, they have to know different aspects of the people they are interacting with (for example they have to know where they are located, what they look like, what they are interested in, what they know and can do, where they work, their good and bad habits etc.), in short people have to be aware of others in order to trust them.

There are situations whereby people form cliques with only few individuals within their community. Those cliques are often made up of individuals who have strong ties with each other, sharing common interests, goals, professions, etc (e.g. in an academic community, people with similar research interests are more likely to be drawn closely together because they can understand each other). Strong ties between individuals are maintained by shared understanding and shared understanding can nurture trust. Based on this scenario the possible variables for the domain are interactions, awareness, shared understanding and trust. These are defined and given probable states in Table 4-1.

Table 4-1. Example of few variables of social capital

Variable	**Definition**	**States**
Interaction	A mutual or reciprocal action between two or more agents determined by the number of messages sent and received	High/Low
Awareness	The ability to acquire and retain knowledge about situations, people and environment	High/Low
Shared Understanding	A mutual agreement/consensus between two or more agents about the meaning of an object	
Trust	A particular level of certainty or confidence with which an agent use to assess the action of another agent	High/Low

The variables in the table are discrete and each variable is given two states: high and low. In a BBN model each variable is deliberately associated with those variables that lie under its influence. For example, interaction influences awareness and shared understanding. In turn, the two variables have direct influence on the variable trust. In addition, each variable in a BBN is described by a probability distribution conditional on its direct predecessors (parents).

The relationship between a parent and a child is determined by the direction of an arrow, linking parent to child in the BBN graphical representation. From our example, if there is an arrow (directed edge) from interaction to awareness, then interaction is said to be a parent of awareness. In other words, interaction has a direct influence on awareness. Nodes with no predecessors are described by prior probability distributions and are either independent or conditionally independent.

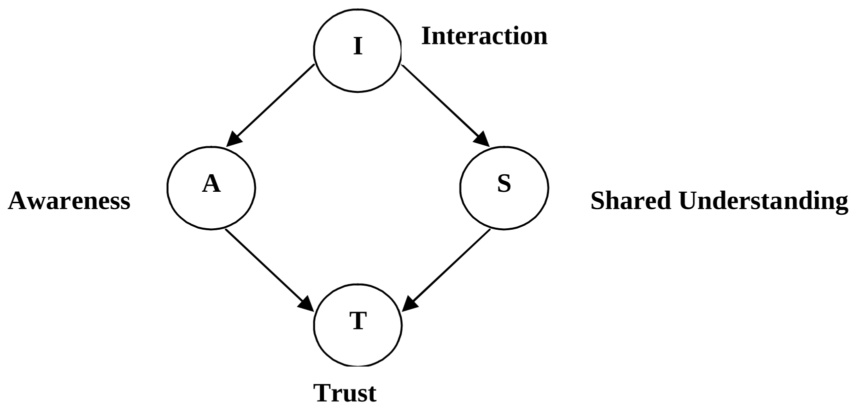


Figure 4-3 (a). Graphical model

P(I=Low)	P(I=High)
0.5	0.5

I	P(A=Low)	P(A=High)
Low	0.5	0.5
High	0.9	0.1

I	P(S=Low)	P(S=High)
Low	0.8	0.2
High	0.2	0.8

A	S	P(T=Low)	P(T=High)
Low	**Low**	1.0	0.0
High	**Low**	0.1	0.9
Low	**High**	0.1	0.9
High	**High**	0.01	0.099

Figure 4-3(b). Initial probabilities for example in Figure 4-3

In the Figure 4-3(b) the event "trust is high" (T=High) has two possible causes: either awareness is high (A=High) or there is high level of shared understanding (S=High), since in the graph there are direct dependencies between trust and awareness as well as shared understanding. The strength of this relationship is quantitatively shown in Figure 4-4 and the dependencies (causal relationships) in the variables are extracted based on the description of the scenario. Imagine a situation where individuals might be aware of each others' skills and knowledge in a typical virtual learning community, but they might not necessarily have shared understanding. For example, we see that P (Trust=High | Awareness=High, Shared understanding=low) = 0.9 (second row), and hence, P (Trust=Low | Awareness=High, Shared understanding=Low) = 1 - 0.9 = 0.1, and each row in the table must sum to 1. Since the root variable (interaction) has no parents, its CPT specifies the prior probability that it is high or low (in this case, 0.5), i.e. all states are equally probable.

4.5.3 Querying the model

The mechanism for drawing conclusions in BBNs is based on propagation of probabilities through the network. As evidence is entered into the model through the observable variables, the effects of this evidence can be propagated using the rules of Bayesian probability through to the output variables. This is termed "querying the BBN". It is sometimes the case that a BBN contains many variables each of which can be relevant for some kind of reasoning but rarely are all variables relevant for all kinds of reasoning at once. Therefore, it is often necessary to identify a subset of the model that is relevant for reasoning in a particular situation. Such a decision can be made based on some qualitative inferences from real world data using scenarios to query the relevant part of the network [Daniel, Zapata-Rivera & McCalla, 2005; Zapata-Rivera, 2002].

One way of using a BBN is to develop detailed scenarios that can be used to query the model. A scenario refers to a written synopsis of inferences drawn from observed phenomena or empirical data. Druzdzell and Suemondt [1994] suggest that one way of querying a network is to instantiate variables to their observed values. Some evidence suggests the presence of other evidence (e.g., when a computer boots it implies it is on, which will also indicate there is electricity or the battery is filled up). Lin and Druzdzel [1998] use a reduction method through variables instantiation rendering some variables as d-separated and hence, can reduce computational complexity.

Drawing from the scenario described above it can be concluded that interaction can increase the ability of people to become aware of each other. In addition, awareness can lead to trusting relationships and trust can also be built among close friends who have developed shared understanding. In other words, there is a strong correlation between awareness and shared understanding i.e., if awareness increases, shared understanding is likely to increase (case of positive outcomes). However, if it is not known whether awareness can lead to shared understanding (given interaction), then awareness becomes conditionally independent (see Figure 4-3 (a)) of shared understanding (given interaction).

Since it is necessary to construct accurate models, it is also important that the data used for training the network are reliable and that the model is stable and capable of predicting and reflecting real world situations. Further, since any measurement often has an element of imprecision associated with it, it is expected that probabilities of events obtained through measurement cannot always be precise. In such cases reliance on approximation of probabilities is important.

Even in circumstances where prior probability values are accurate, the number of prior probability values can grow exponentially, as new variables are added to the network. In general, the challenges that have prevented the wider use of BBN approach in many domains can be summarized as follows:

- Building BBN models requires a considerable knowledge engineering effort, in which the most difficult part is to obtain numerical parameters for the model and apply them in complex and ill-defined situations, which are the kinds of problems social scientists are attempting to address.
- Constructing a realistic and consistent graph often requires collaboration between knowledge engineers and subject matter experts, which in most cases is hard to establish.
- Combining knowledge from various sources such as textbooks, reports, and statistical data to build models can be susceptible to gross statistical errors.
- The process of eliciting conditional probability values for all possible nodes in a BBN is cumbersome.

- The structure of a BBN for a domain is the result of domain specifications. However, in situations where domain knowledge is not available or insufficient or inaccurate, the model's outcomes are bound to be in error.
- Data used for eliciting prior probabilities might have been drawn from subpopulations and might contain statistical errors which can render the BBN model invalid.
- Acquiring knowledge from subject matter experts can be subjective.
- Further, where an expert's knowledge is used, a challenge lies in translating qualitative knowledge into quantitative values.

4.6 Qualitative Bayesian network

The qualitative Bayesian network approach was introduced to address some of the difficulties in building models that mainly depend on quantitative data. Building BBN models from quantitative data presupposes that relationships among variables or concepts of interests are known and can be correlated, causally related or they can relate to each other independently.

Wellman [1999b] introduced the qualitative abstraction of BBNs known as qualitative Bayesian networks (QBN) to help overcome some of the problems of building a quantitative BBN. Instead of numerical probability distributions, a QBN uses the concept of positive and negative influences between variables. It assumes an ordering relationship between the variables. For example, **X** has a positive **(+)** influence on **Z**, if choosing a high probability value of **X** produces higher probability values of **Z**. In a similar way a negative influence between two variables is defined. Further, Druzdzell and Henrion [1993] proposed qualitative belief propagation as an efficient algorithm for reasoning in QBN. The algorithm builds on research into the studies of verbal protocols of human subjects solving problems involving uncertainty. In qualitative propagation each variable in a network is provided a sign either positive **(+)** or negative **(-)**. The effect of an observation **e** on the **n** variables in a network propagates the sign throughout the network. The qualitative propagation algorithm is handy in situations where hard data are not available or are difficult to obtained [Druzdzell, 1996]. In other words, QBN can supplement or replace quantitative approaches for obtaining hard data.

Eliciting probabilities from experts has its own drawbacks, even in QBN approaches. It has been found that experts can exhibit problems such as overconfidence; probability estimates can be adjusted up and down based on an initial estimate (anchoring problem); there can be disagreement among experts; high probability values are often assigned to easy to remember events (availability problem) [Morgan & Henrion, 1990]. All these issues can affect the quality of the probabilities elicited. To help overcome these problems, in QBN researchers use simple probability distributions to initialize models. e.g., NOISY-OR and NOISY-AND distributions [Conati et at. 2002], and use numerical and verbal anchors [Renooij & Witteman, 1999; Van der Gaal, L. Renooij, S., Witteman, Alema & Taal, 1999;], and can deploy visualization tools available in many BBN authoring tools.

The methodology described in this thesis uses both a qualitative and quantitative approach to eliciting knowledge from experts (i.e., structure and initial prior and conditional probabilities) based on the descriptions of the strength of the relationship among variables in a network [Daniel, Zapata-Rivera & McCalla, 2003]. This approach takes into account the number of states of a variable, the number of immediate parents a child variable relates to, the degree of strength (e.g., strong, medium, weak) and the kind of relationship/influence (e.g., positive or negative) to produce initial prior and conditional probability values. Once an initial model is developed, scenarios grounded on empirical analysis are used to refine and document the network.

In contrast to QBN methodology, which makes use of its own qualitative propagation algorithms, the methodology in the thesis uses standard Bayesian propagation algorithms, albeit on data that is more qualitative than it is quantitative. The methodology is described in detail in Chapter 5 with the help of an example of a model of social capital in virtual communities. Further, through inductive reasoning, the methodology enables us to refute, refine, or consolidate hypotheses and prior knowledge about a given situation under study, potentially filling in any missing information. In addition, the initial probabilities can be refined as data becomes available.

4.7 Updating Bayesian models using scenarios

Constructing and updating a model of social capital in virtual learning communities is a complex task since there are numerous underlying variables that are not necessarily obvious. One way to facilitate model construction and updating is to develop scenarios illustrating various events, based on either directly obtained evidence or an expert's knowledge. A scenario can generally be described as a set of written stories or synopsis of acts in stories built around carefully constructed events.

In a scientific and technical sense a scenario describes a vision of the future state of a system. Such a description can be based on current assessment of the system, of the variables and assumptions, and the likely interaction between system variables in the progression from current conditions to a future state [Collion, 1989]. Scenarios provide simple, intuitive, examples based upon descriptions of the patterns of interactions between two or more variables of interest. They can be developed based on observation of interactions among people in a virtual community.

4.7.1 A scenario-based modeling approach

In this thesis, scenario-based modeling is essentially a set of procedures for describing specific sequences of behaviours within a model that illustrate actual interactions within a learning community. The goal is to understand and explain the interactions of variables or a set of events within a model and how these might possibly influence the direction of interaction patterns, and subsequently their influence on the level of social capital measured independently within that community. This means that a single scenario might describe a possible set of interactions as they occurred within a community, and when it is used for querying the model, possible alternative explanations are provided to describe the current and future behaviours of a model.

When several scenarios are used together to describe possible outcomes of events within a model, they can exceed the power of predictions based on a single hypothesis or a set of propositions drawn from a single data set. While a hypothesis normally refers to a set of unproven ideas, beliefs, and arguments, a scenario can describe proven states of events, which can be used to understand future changes within a model.

Further, the outcomes of the events might be used to generate a set of hypotheses. These hypotheses can then be used to understand a specific situation within the model. Moreover, the results of a scenario and hypothesis can be combined to further refine the consistency and accuracy of a model. However, for a scenario-based approach to be useful the scenarios created within any particular evidence or data sets must be plausible and internally consistent. Scenarios in Bayesian modeling of social capital provide alternative explanations to the effects of particular changes in variables and their effects on a particular community.

The use of a scenario-based approach to query a model also offers a common vocabulary and an effective basis for communicating complex and sometimes paradoxical conditions. In the context of this research, this scenario-based querying provides an opportunity for incorporating strategies from qualitative perspectives and to avoid potential for sharp discontinuities that most quantitative approaches encounter. In addition, a scenario-based approach is also likely to be useful in this research because of the three studies you mentioned in Chapter 3, which gave insights into actual interactions in real virtual communities.

4.8 Chapter summary

This chapter presented and discussed Bayesian belief networks as an approach for building computational models. Bayesian networks are models for representing uncertainty in our knowledge. Uncertainty arises in a variety of situations such as uncertainty inherent in the domain being modelled, uncertainty in the experts concerning their own knowledge, uncertainty in the knowledge engineer trying to translate the knowledge, and just plain uncertainty as to the accuracy and actual availability of knowledge within a domain.

A Bayesian belief network uses probability theory to manage uncertainty by explicitly representing the conditional dependencies between the different knowledge components. This provides an intuitive graphical visualization of the knowledge including the interactions among the various sources of uncertainty. A Bayesian model uses Bayesian statistical rules to calculate conditional dependencies among the variables in the network. This allows probabilistically sound propagation of evidence through the network that can be used for making inferences of various sorts about the implications and effects of various actions and events on the model.

Chapter 5

5.0 A Bayesian Belief Network Model of Social Capital in Virtual Communities

5.1 Overview

This chapter presents a Bayesian belief network computational model of social capital (SC). The construction of the model was informed by a synthesis of the literature on social capital as described in Chapter 2, and results of the empirical exploration of social capital variables and issues presented in Chapter 3. The computational model presented here is a reasoning tool, meant to help researchers and practitioners concerned with social issues in virtual communities to understand fundamental variables that constitute SC and how they influence one another. The model also is intended to provide them with a basis from which they have the opportunity to explore how to support productive social interactions critical to knowledge sharing and learning in online learning environments.

5.2 Modelling social capital in virtual communities

Current research on social capital suggests that there is no single variable constituting social capital, but rather, social capital is a composite of different variables, each of which can be interpreted independently [Daniel, McCalla & Schwier, 2005]. In this thesis, social capital in virtual communities is defined as a common social resource that facilitates information exchange, knowledge sharing, and knowledge construction through continuous interaction, built on trust, shared understanding and various forms of awareness. Table 5-1 describes and defines various variables of social capital and their associated Bayesian states. The variables were extracted from the three experiments described in Chapter 3 and are extension of the table 4-1 presented in Chapter 4. These variables are considered relevant within the context of virtual communities

As described earlier, the second step in building a model of SC is to map the identified variables in the first step into a graphical structure that captures the influences of the variables on one another. The basis for developing the logical relationships of the variables and their relevent influences can be extracted from current research into social capital and our work on social capital in virtual communities as discussed in Chapter 3. For instance, in virtual learning communities people's attitudes can strongly influence the level of their awareness of various issues, which in turn can influence trust. Further, since awareness can contribute to both trust and distrust, the strength of the relationships can be medium positive, medium weak, etc. depending on the kind of awareness. Further, from a domain's expert's point of view and synthesis of the literature described in Chapter 2, demographic awareness has a positive and medium effect on trust meaning that it is more likely that people will trust others regardless of their demographic backgrounds.

Table 5-1. Social capital variables and their definitions

Variable Name	Variable Definition	Variable States
Interaction	A mutual or reciprocal action between two or more agents determined by the number of messages sent and received	Positive/Negative
Attitudes	Individuals' general perception about each other and others' actions within a particular community	Positive/Negative
Shared Understanding	A mutual agreement/consensus between two or more agents about the meaning of an object or idea	High/Low
Awareness	Knowledge of people, tasks, or environment and or all of the above	Present/Absent
Demographic Awareness	Knowledge of an individual: country of origin, language, gender, age, and location	Present/Absent
Professional Awareness	Knowledge of people's background training, affiliation etc.	Present/Absent
Competence Awareness	Knowledge about an individual's capabilities, competencies, and skills within their domain of training	Present/Absent
Capability Awareness	Knowledge of people's competences and skills in regards to performing a particular task	Present/Absent
Social protocols	The mutually agreed upon, acceptable and unacceptable ways of behaviour in a community	Present/Absent
Trust	The level of certainty or confidence with which an agent assesses the action of another agent.	High/Low

This type of qualitative reasoning results in the BBN model shown in Figure 5-1. In the model, those nodes that contribute to higher nodes align themselves in "child-to-parent" relationships. For example, trust is the child of shared understanding and four forms of awareness and social protocols, which are in turn children of community type, interaction and attitudes.

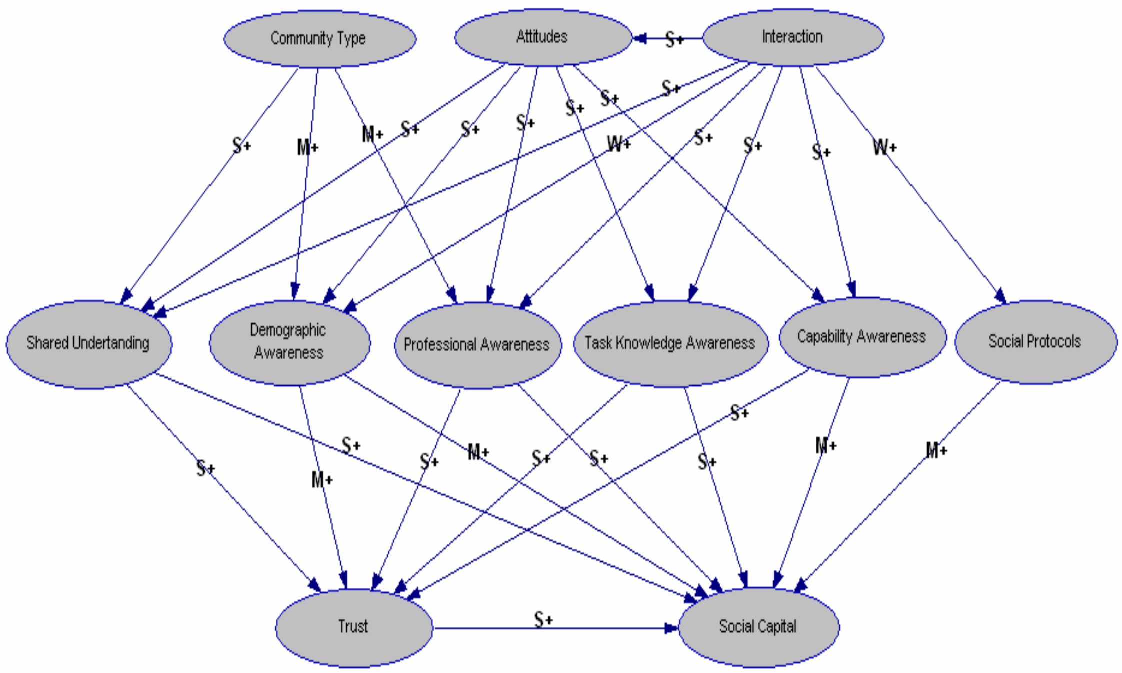


Figure 5-1. A complete model of social capital in virtual communities

The Bayesian belief network graph shown in Figure 5-1 applies to all forms of virtual communities (VLCs and DCoPs) described in the thesis. The graph topology is limited to the definitions of the various variables of social capital and the reasoning involved in conceptualising social capital within the contexts described. As suggested before, the third stage of modelling with a BBN is to obtain initial probability values to populate the network. Initial probabilities can be obtained from various sources including the author's expert knowledge of virtual communities (drawn in part from the three studies in Chapter 3) and current research on social capital (see Chapter 2).

5.2.1 Conditional probability tables

In a Bayesian model every node has a conditional probability table (CPT) associated with it. Conditional probabilities represent likelihoods based on prior information or past experience. In other words, for each parent variable and each possible state of that parent variable, there is a row in the CPT that describes the likelihood that the child node will be in some state. In a Bayesian network, every stage of situation assessment requires assigning initial probabilities to the hypotheses. These initial probabilities are normally obtained from knowledge of the prevailing situation. However, converting a state of knowledge to probability assignment is a problem that lies at the heart of Bayesian probability theory.

In addition, the number of probability distributions required to populate a CPT in any given Bayesian network grows exponentially with the number of parent-nodes associated with that table. For instance, if a table is to be populated through knowledge elicited from a domain expert then the magnitude of the task forms a considerable cognitive barrier and can be a computationally hard problem. One way to simplify this complexity is to assign binary states to the variables in the model (see Table 5-1), although it is also possible that the variables in the model can have more than two states. Each probability value describes strength of relationships and the letters S (strong), M (medium), and W (weak) represent different degrees of influence among the variables in the model are [Daniel, Zapata-Rivera & McCalla, 2003]. The signs + and - represent positive and negative relationships among the variables.

For the SC model presented in the thesis, the conditional probability values were obtained by adding weights to the values of the variables depending on the number of parents and the strength of the relationship between particular parents and children. For example, Attitudes and Interaction have positive and strong (S+) relationships with Knowledge Awareness. In numerical terms, evidence of positive interactions and positive attitudes will produce a conditional probability value for Knowledge Awareness of 0.98 (where the threshold value for strong = 0.98). The weights were obtained by subtracting a base value (1 / number of states, 0.5 in this case) from the threshold value associated to the degree of influence and dividing the result by the number of parents (i.e. (0.98 - 0.5) / 2 = 0.48 / 2 = 0.24), which follows from the fact that in the graph Knowledge Awareness is a child of both Interaction and Attitudes.

Table 5-2 shows the threshold values and weights used in this example. Using this approach, it is possible to generate conditional probability tables (CPTs) for each node (variable) regardless of the number of parents. These threshold values can later be adjusted based on expert opinion.

Table 5-2. Threshold values and weights with two parents

Degree of influence	**Thresholds**	**Weights**
Strong	0.98	(0.98-0.5) / 2 = 0.48 / 2 = 0.24
Medium	0.8	(0.8-0.5) / 2 =0.3 / 2 = 0.15
Weak	0.6	(0.6-0.5) / 2 =0.1 / 2 = 0.05

This process often depends on how initial knowledge is elicited and what decisions are made to process the knowledge into initial probabilities. For instance, subject matter experts could be consulted to obtain the initial probabilities in this example, and then this knowledge would be translated into the threshold weighted values as described in Table 5-2 depending on the degree of influence among the variables (i.e. evidence coming from one of the parent's states). A decision about this degree of influence can also be obtained from the subject matter experts in a particular domain. However, when experts define the degrees of influence for more than one of the parents' states, adding weights could result in ties, which could generate an inconsistent CPT. In such cases, one could ask the expert which parent should be used, or has the highest degree of influence depending on the case under investigation.

5.2.2 Example of computation of conditional probability values

As discussed earlier in this Chapter, various forms of awareness are critical to interaction that can stimulate positive SC in virtual communities. According to the structure of the BBN (see Figure 5-1), Task Knowledge Awareness is influenced by two parents: Interaction and Attitudes.

Table 5-3. Conditional probability table for Task Knowledge Awareness given two parents

	Attitudes	**Positive**		**Negative**	
	Interaction	**Positive**	**Negative**	**Positive**	**Negative**
TaskKnowledge Awareness	High	0.98	0.74	0.74	0.5
	Low	0.02	0.26	0.26	0.5

Combining the Bayesian laws of computation described in Chapter 4, the initial probabilities for task knowledge awareness given different states of interactions and attitudes can be calculated as follows:

- P (TaskKnowledgeAwareness= high | Attitudes= positive & Interaction= positive) = 0.5 + 0.24 + 0.24 = 0.98
- P(TaskKnowledgeAwareness= low| Attitudes= positive & Interaction= positive) = 1 - 0.98 = 0.02
- P (TaskKnowledgeAwareness= high| Attitudes= positive & Interaction= negative) = 0.5 + 0.24 = 0.74
- P (TaskKnowledgeAwareness= low | Attitudes=positive & Interaction= negative) = 1 - 0.74 = 0.26
- P (TaskKnowledgeAwareness= high | Attitudes= negative & Interaction= positive) = 0.5 + 0.24 = 0.74
- P (TaskKnowledgeAwareness= low | Attitudes= negative & Interaction= positive) = 1 - 0.74 =0.26
- P (TaskKnowledgeAwareness= high | Attitudes= negative & Interaction= negative) = 0.5
- P (TaskKnowledgeAwareness= low |Attitudes= negative & Interaction= negative)=1-0.5=0.5

Experts could be asked for a threshold value or one could provide experts several possibilities and let them decide for a relevant threshold. Since the expert has not provided any information about what to do when there is evidence of Attitudes = negative and Interaction = negative, a value of 0.5 has been arbitrarily assigned. This is largely hypothetical in any event, especially in virtual communities, in that interaction is prerequisite for the existence of a community.

However, one expects to get a high conditional probability value of TaskKnowledgeAwareness = negative when Attitudes = negative and Interaction = negative, so a possible alternative for the last column would be to use P (TaskKnowledgeAwareness = positive | Attitudes = negative & Interaction = negative) = 0.02 and P (TaskKnowledgeAwareness = negative | Attitudes = negative & Interaction = negative) = 0.98 assuming that a positive strong relationship also occurs when Attitudes = negative and Interaction = negative. Table 5-4 shows this possible conditional probability table.

Table 5-4. Conditional probability table of a variable with two parents with positive strong relationships

	Attitudes	**Positive**		**Negative**	
	Interaction	**Positive**	**Negative**	**Positive**	**Negative**
TaskKnowledge Awareness	High	0.98	0.74	0.74	0.02
	Low	0.02	0.26	0.26	0.98

5.2.3 Case scenarios and model updating

In this section, a number of scenarios are described based on an expert's opinion and knowledge of the operations of virtual communities. The case scenarios described in the next sections were taken from real communities which were similar to those described in Chapter 3, in which the author was a participant observer for a period of two years. However, the description of the communities is not based on formal experimental study, but rather the scenarios are shown here to illustrate the process of updating an initial

Bayesian model using various kinds of evidence. It is likely that the results of the model predictions could change in the face of further empirical evidence. Although, the scenarios presented in this chapter are not empirically documented, the scenarios themselves demonstrate real social phenomena in virtual communities and were actual situations observed within each case study.

5.2.3.1 Case 1: A formal learning community

Community A was a formal virtual learning community of graduate students learning fundamental concepts and philosophies of E-Learning. The members of this community were drawn from diverse cultural backgrounds and different professional training. In particular, participants were practising teachers teaching in different domains at secondary and primary school levels. Some individuals in the community had extensive experiences with educational technologies, while others were novices but had extensive experience in classroom pedagogy. These individuals were not exposed to each other before and thus were not aware of each other's talents and experiences.

Since the community was a formal one, there was a formalized discourse structure and the social protocols for interactions were explained to participants in advance. The special protocols required various forms of interaction including posting messages, critiquing others, providing feedback to others' postings, asking for clarifications etc. As the interactions progressed in this community, intense disagreements were observed in the community. Individuals began to disagree more on the issues under discussion and there was little shared understanding among the participants in most of the discourse.

5.2.3.2 Case 2: A Distributed community of practice

Community B was a distributed community of practice for software engineers who gathered to discuss issues around software development. The main goals of the community were to facilitate exchange of information, and to provide knowledge and peer-support to the members of the community. Members of this community shared common concerns. Skill level varied widely: some members were highly experienced software developers and others were novices. Participants were drawn from all over the world (Europe, North America, and Africa) and were affiliated with different organisations, including researchers at universities and software organisations and various support groups.

After a three-month period of interaction, individuals were exposed to each other long enough to start exchanging personal information among themselves. It was also observed that individuals offered a lot of help to each other throughout their interactions. Though no formal social protocols were explained to the participants, members interacted as if there were social protocols guiding their interactions. Further, there were no visible roles of community leaders.

5.2.3.3 Case 3: An informal virtual community

Community C consisted of a group of individuals learning fundamentals of programming in Java. It was an open community whose members were geographically distributed and had diverse demographic backgrounds and professional cultures. They did not personally know each other; they used different aliases from time to time while interacting in the community. Diverse programming experiences, skills and knowledge were also observed among the participants. It was interesting to observe that though these individuals did not know each other in advance, they were willing to offer help and to support each other in learning Java. Though there were no formal social protocols of interaction, individuals interacted as if there were clear set social protocols to be followed in the community.

5.2.4 Procedures for model updating

In order to test and update the initial Bayesian model of SC, each of the above case scenarios was analysed looking for evidence regarding the impact of individual variables in the model. Once a piece of evidence was added to the model, typically through tweaking a state of a variable (i.e. observing a particular state of a variable) or a process commonly known as variable initialisation, the model was updated and the results propagated to the rest of the variables in the Bayesian model. This process generates a set of new marginal probabilities for the variables in the model. In the three case scenarios, the goal was to observe changes in probability values for trust and social capital.

This phase of a model development helps experts to further examine the model and refine it based on their knowledge of the domain and the accuracy of predictions made by the model when compared to what actually seems to have occurred in the scenario. The Bayesian model therefore serves as an interactive tool that enables experts to create a probabilistic model, simulate scenarios and reflect on the results of the predictions.

5.2.4.1 Community A: Scenario one

Community A is a virtual learning community (Community Type = VLC.) Based on the case description Shared Understanding is set to low = (0.09) and Professional Knowledge Awareness is set to does not exist = (0.09). Individuals in this community are familiar with their geographical diversity and so Demographic Cultural Awareness is set to exists (= 0.8). There are well-established formal social protocols set previously by the instructor, Social Protocols were therefore set to known = (0.7). Figure 5-2 shows the Bayesian model after the evidence from community A has been added (shaded nodes) and the results of the posterior probabilities.

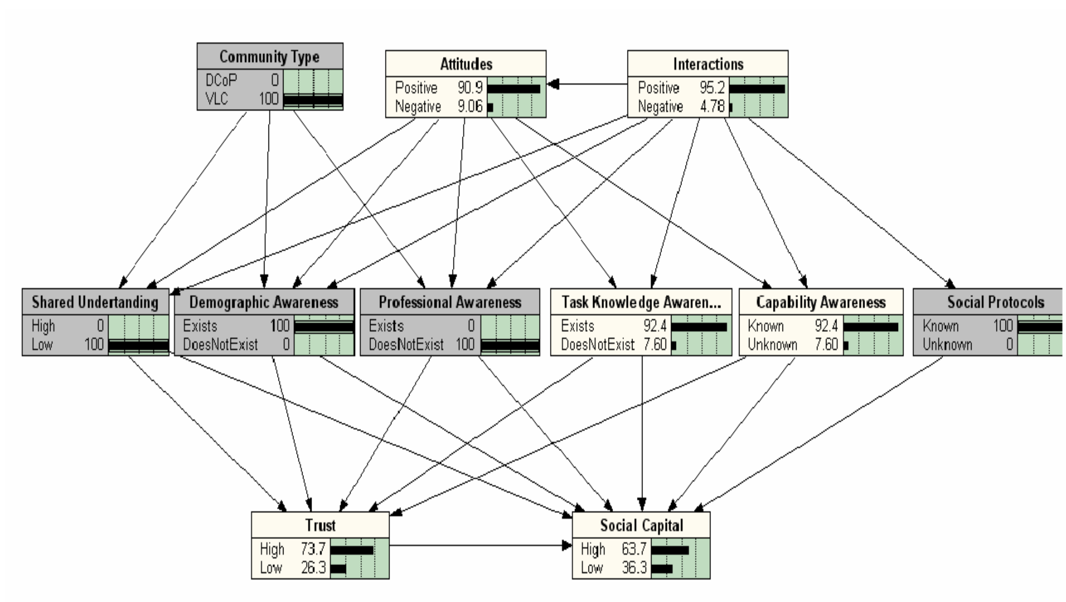


Figure 5-2. A Bayesian model of SC updated with evidence from community A

The highest level of trust (P (Trust=*high*) =0.737) and a corresponding probability level of SC (P (SC=*high*) =0.637) are predicted. These values are relatively low. Several explanations can be provided for the drop in the levels of SC and trust. First, there was a negative interaction in the community and lack of shared understanding in the community. The lack of shared understanding possibly affected the level of trust and subsequently social capital. It is also possible that negative interactions and attitudes further affected the levels of task knowledge awareness and individual capability awareness. It could also be inferred that experiences of more knowledgeable individuals in the community were more likely to have been ignored, making individuals less co-operative, since there competence and skills were not observed.

5.2.4.2 Community B: Scenario two

The variables observed in this case include: Community Type, which has been set to community of practice (DCoP) *(P=1.00)*; and Professional Awareness, which was set to the state *exists(P=1.00)*, since after interaction, it was observed that individuals in that community became aware of their individual talents and skills. Individual Capability Awareness and Task Knowledge Awareness were set to *exists states (P=1.00)* and (*P*=1.00) respectively. Individuals in this community shared common concerns and frame of reference, and so Shared Understanding was set to *high(P=1.00)*. Figure 5-3 shows the Bayesian model after the evidence from community B has been added (shaded nodes) and propagated through the model.

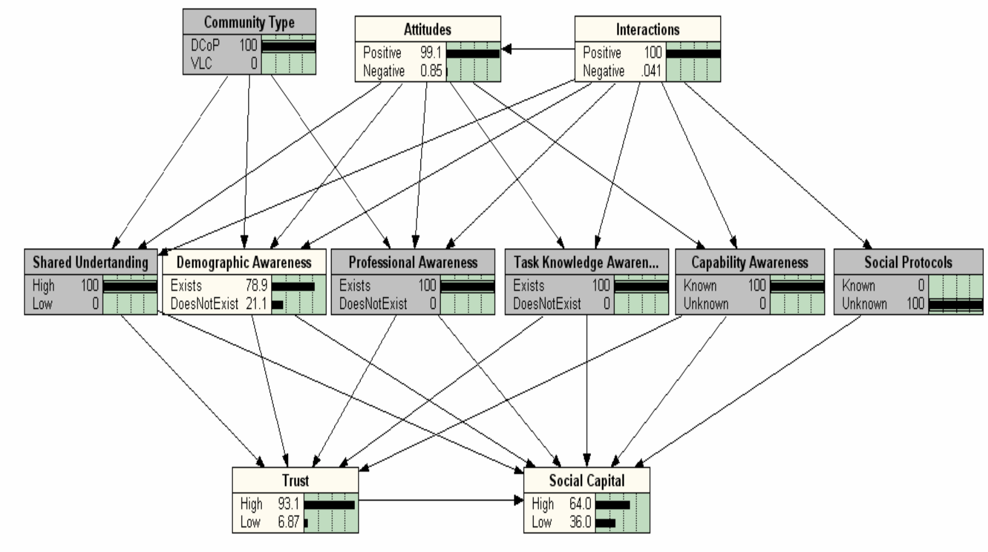


Figure 5-3. A Bayesian model of SC updated with evidence from community B

Propagating this set of evidence, high levels of trust and SC (P (Trust=*high*) =0.93 and P (SC=*high*) =0.64) were observed. Given the evidence, it was also observed that Interaction and Attitudes in the model were positive which have positively influenced Demographic Cultural Awareness and Social Protocols. Along with the presence of Shared Understanding the high degrees of different kinds of awareness and knowledge of social protocols in this community have resulted in high levels of trust and SC.

In spite of the evidence, Demographic Cultural Awareness has little influence on the level of trust in this kind of a community and subsequently, it has not significantly affected SC. This can be explained by the fact that professionals in most cases are likely to cherish their professional identity more than their demographic backgrounds. This is in line with a previous study, which suggested most people in distributed communities of practice mainly build and maintain social relations based on common concerns other than geographical distribution [Daniel, O'Brien & Sarkar, 2003].

5.2.5 Community C: Scenario three

The variables extracted from this case scenario include Community Type (*VLC*), Shared Understanding, Professional Cultural Awareness, Demographic Cultural Awareness, individual Capability Awareness and Task Awareness, all set to exists and each with probability values of (P=1.00). Figure 5-4 shows the Bayesian model after the evidence from community C has been added (shaded nodes) and propagated through the model.

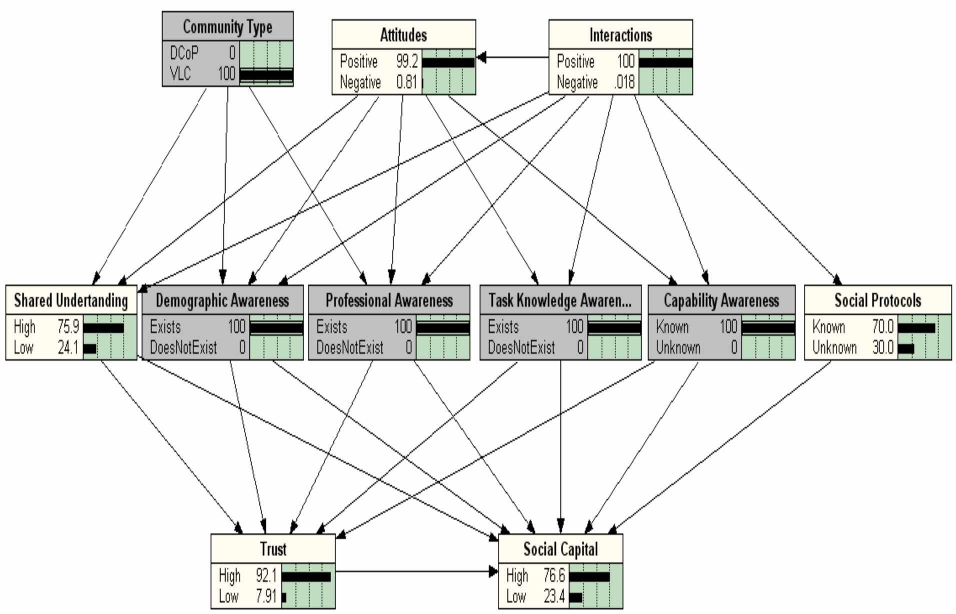


Figure 5-4. A Bayesian model of SC with added evidence from community C

In community C, high levels of trust and SC (P (Trust=high) =0.921 and P (SC=high) =0.766) were observed after the propagation of the evidence. These high levels of trust and SC can be attributed to the fact that the community was based on an explicit and focused domain. Though members might conceal their identities, they were willing to positively interact and participate in order to learn the domain. Further, increase in the levels of trust and social capital can also be attributed to the presence of shared understanding. In other words, people in that community got along well and understood each other well enough. They used the same frame of reference and the common goals of learning in a domain (Java programming language).

5.3 Chapter summary

Bayesian belief network modeling can model a situation involving uncertainty. In the social sciences and humanities and in many other fields, uncertainty may arise due to complexity, imprecision, domain knowledge gaps, or volatility of knowledge.

Overall model predictions suggest that different forms of awareness and shared understanding and trust can have significant influence on the level of social capital in a virtual community. Although the scenarios presented in this Chapter are inadequate to draw comprehensive final conclusions about causal links between these variables, and an overall level of social capital in a virtual community, the predictions provide a starting point for understanding social capital in virtual communities. These variables are verified in empirical work presented in Chapter 6.

Chapter 6

6.0 Empirical Verification of the Model

6.1 Overview

The last step of model development is to conduct model validation. Validation is often carried out to determine whether the model is theoretically and practically useful. Validation is done through sensitivity analysis. In this Chapter an empirical study is described conducted to validate the model and further explore some of the issues raised by the model predictions.

6.2 Introduction

Model validation involves the evaluation of the accuracy of a computational prediction with respect to experimental data [Hemez & Doebling 2003]. Building a computational model is always an iterative process. The process of validation is intended to remove barriers and objections to the usefulness of model. Validation is meant to establish an argument that the model produces sound insights and sound data based on a wide range of tests and criteria that “stands in” for comparing model results to data from empirical work. Unlike other mathematical models, for which there are well-established procedures for model validation, no such guidelines exist for modeling social systems.

In building computational models of social systems using Bayesian belief networks, two approaches can be used: data-driven model building, normally involving building models grounded in empirical data; and knowledge-driven modeling, involving building models from knowledge often elicited from experts. In the latter case, validation requires empirical data that are used to validate the expert's claims embedded in the initial computational model and then to make necessary model revisions.

Knowledge-driven Bayesian computational models are descriptive and exploratory in nature. They are intended to describe a social phenomenon and to explore issues or hypotheses that can be used to further investigate the model and tune it over time to practical scenarios. What is presented in this research is a knowledge-driven model meant to uncover the most critical variables of social capital and the underlying issues that can be further investigated.

One major task of the validation process is to establish conceptual validity through sensitivity analysis. Conceptual model validation is established by determining that the assumptions underlying the conceptual model are appropriate. Such validation assures that model's representation of the problem and the model's structure, logic, and mathematical and causal relationships are "reasonable" for the intended purpose of the model.

6.3 Sensitivity analysis (SA)

Sensitivity analysis is a mathematical technique for investigating the effects of inaccuracies in the parameters of a mathematical model. It analyses how variation in the output of a model (numerical or otherwise) can be apportioned qualitatively or quantitatively to different sources of data [Morgan & Henrion, 1990]. The process of conducting sensitivity analysis includes:

- defining the model with all its input and output variables;
- assigning probability density functions to each input parameter;
- generating an input matrix through an appropriate random sampling method and evaluating the output; and,
- assessing the influences or relative importance of each input parameters on the output variable.

In a Bayesian network, sensitivity analysis helps to determine the spread of probability distribution of a particular variable and how it influences other variables. In other words, sensitivity analysis is conducted to know how sensitive a variable's value is to the other variables in the model. If it is very sensitive, we may want to know the state of that variable, and then invest more effort in determining the values of all the variables that substantially influences it.

There are many ways of conducting sensitivity analysis; the ones commonly used in Bayesian models are variance and entropy reduction. This thesis employs entropy reduction, since entropy reduction will help in determining those variables that are highly sensitive to social capital.

6.3.1 The notion of entropy

Entropy is a mathematical concept used to measure changes in density of a natural or social phenomenon. It is a term widely applied in thermodynamics, physics, chemistry etc. From a statistical perspective, entropy is a measure of uncertainty of a particular event associated with a probability distribution of a possible event (see information theory entropy or Shannon Entropy for further discussion of entropy as describe in [http://mtm.ufsc.br/~taneja/book/node1.html]).

The notion of entropy and how it works is best illustrated with a simple scenario from probability theory. Consider a box containing many colored balls from which we are considering drawing balls. If no single color predominates in the box, then our uncertainty about the color of the ball to be drawn is maximal and the entropy is high. On the other hand, if the box contains black colored balls more than other colors, then there is more certainty about the color of a drawn ball, and the entropy is lower. Intuitively, the second case would be preferable, because it is possible to place bets on black and win. In fact, in the extreme in which every ball is black, the entropy would be zero, and we would win every time.

In this scenario, entropy measures the average amount of information associated with a drawing a ball from the box of balls. Essentially, in the third case, the color of the ball is a certainty, and there is no information conveyed by knowing the color of a drawn ball. In the first case, knowing the color of previously drawn balls tells a gambler a lot about how to place a bet.

In mathematics, entropy can be expressed as a discrete random variable **X** which consists of several events **x**, which occur with probability **P (x)** the entropy of an event **X** is given by **H(X)**. **T**here are two basic ways in which entropy can change:

- If the total number of events in **X** increases, the entropy of **X** will increase. This is because entropy is defined as a summation of the values given by a function based on the probabilities of **X**.
- If the distribution of **X** becomes more uniform, entropy will also increase, since any change toward equalization of the probabilities increases H.

6.3.2 Conditional entropy

A more complex idea is the concept of conditional entropy. The conditional entropy **H (Y|X)** measures how much entropy of a random variable **Y** is remaining if we have already learned the value of a second random variable say **X**. An easier way to explain conditional entropy is to first understand joint entropy. Joint entropy determines how much entropy is contained in a joint system of two random variables (**X, Y**). Conditional entropy can be expressed as: **H (X|Y) =H (X)-H(Y)** i.e. given a random variable **X**, the entropy **H(X)** describes an uncertainty about the value of **X**. If **X** consists of several events $\boldsymbol{x....x_n}$, in which each variable occurs with probability $\mathbf{p_x}$, then the entropy of **X** is given by:

$$H(X) = -\sum_{x} p_x \log(p_x)$$

Moreover, given two discrete random variables **X** with support $\mathcal{X}$ and **Y** with support $\mathcal{Y}$, the conditional entropy of **Y** given **X** is defined as:

$$
\begin{aligned}
H(Y|X) &\stackrel{\text{def}}{=} \sum_{x\in\mathcal{X}} p(x)\, H(Y|X=x) \\
&= -\sum_{x\in\mathcal{X}} p(x) \sum_{y\in\mathcal{Y}} p(y|x)\ \log\ p(y|x) \\
&= -\sum_{x\in\mathcal{X}} \sum_{y\in\mathcal{Y}} p(x,y)\ \log\ p(y|x) \\
&= -E_{p(x,y)} \log\ p(Y|X).
\end{aligned}
$$

From this definition and Bayes' theorem, a chain rule for conditional entropy is given by:

$$H(Y|X) = H(X,Y) - H(X).$$

This also implies that:

$$
\begin{aligned}
H(Y|X) &= -E_{p(x,y)} \log\ p(Y|X) \\
&= -E_{p(x,y)} \log \left(\frac{p(X,Y)}{p(X)} \right) \\
&= -E_{p(x,y)} (\log p(X,Y) - \log p(X)) \\
&= -E_{p(x,y)} \log p(X,Y) + E_{p(x)} \log p(X) \\
&= H(X,Y) - H(X).
\end{aligned}
$$

Intuitively, this suggest that if we learn the value of **X**, we have gained **H(X)** bits of information, and the system has **H(Y | X)** bits remaining. **H(Y | X)** = **0** if and only if the value of **Y** is completely determined by the value of **X**. Conversely, **H(Y | X)** = **H(Y)** if and only if **Y** and **X** are independent random variables.

A sensitivity analysis of each variable to social capital and social capital to itself was conducted using Netica software [http://www.norsy.com]. The goal was to measure the degree to which findings at the Social Capital node can influence findings at another node, given a set of evidence (scenarios). The results of the sensitivity analysis are presented in the form of mutual information (entropy reduction) and the expected reduction of real variance (Figure 6-1 provides a summary of the probability distribution of the variables measured). A full report of this analysis is provided in appendix **A.**

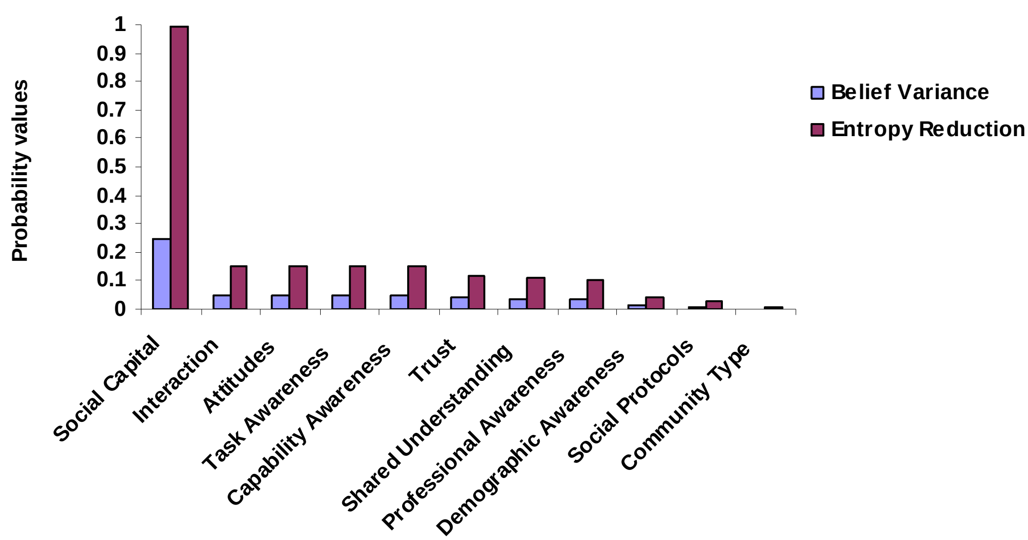


Figure 6-1. Summary of sensitivity analysis of individual variables

The results of the sensitivity analysis reveal that the variables with a weak degree of influence on social capital showed low entropy reduction values. Meanwhile, those with relatively strong and medium degrees of influence show high entropy reduction values (see figure 6-1). For instance, Interaction, Attitude, Trust, Capability Awareness and Task Awareness are relatively sensitive to social capital compared to Professional Awareness, Demographic Awareness, Social Protocols and Shared Understanding.

In general terms, however, the sensitivity analysis of the model suggests that social capital is sensitive to a number of variables and even more so to variables that are in strong paths (strong positive paths in the model—see Figure 5-1). The results of the sensitivity analysis show at least three relatively high levels of entropy reduction for three of five variables: Interaction and Attitudes with the same entropy reduction of (0.1533), Capability Awareness with entropy reduction of (0.1494), Shared Understanding at (0.1112) and Trust at (0.1175).

Thus, higher values of entropy reduction tend to correspond to variables in strong paths which generally suggests that the qualitative reasoning used for deriving the initial probabilities presented in the model are reasonable. The results of the sensitivity analysis also seem to suggest that different variables can affect social capital at different levels; however, at this point it is not possible to speculate further on the results since more studies are required to determine more about the actual effects of individual variables on social capital.

Nonetheless, the results of the sensitivity analysis can be used to improve the model by changing the threshold probabilities in Table 5-2. Further, drawing from the results it is possible that the individual variations in probability values could be caused by the partial knowledge of domain experts initially used for building the model as well as assumptions made during the development of the model, both of which are common problems inherent in the development of any Bayesian model.

6.4 Survey Research

As shown in Chapter 5, variables such as Trust, Capability Awareness and Task Awareness were observed to be relatively sensitive to social capital compared to Professional Awareness, Demographic Awareness, Social Protocols and Shared Understanding. The results of the model predictions and the sensitivity analysis let into a design of a follow up survey study.

In addition to the model predictions and the results of the sensitivity analysis, other issues independent of the fundamental variables of social capital were also explored in the survey study; these include participants' sense of community in an online environment which seemed to play a critical role to further our understanding of the operation of social capital in virtual communities. The main questions pursued in the study were:

1. What are participants' experiences and perceptions about sense of community in an online learning environment?
2. Are the model's predictions similar to participants' experiences in virtual communities?

6.4.1 Experimental set-up and procedures

A survey instrument with 30 items (see appendix D) was administered to nine graduate students (n=9), who have participated in a six credit graduate course on theory and philosophy of educational technology. The sample was randomly chosen from the population of 15 students who had taken the class. All participants were enrolled in a six credit graduate theory course during the year 2004-2005.

The survey questionnaire was divided into three parts. Part 1 sought to find out the backgrounds of the participants; the goal was to understand their demographic information. Part 2 explored participants' interaction patterns and whether or not they formed any kind of social networking or sense of community. The indicators meant to solicit the sense of a community within the group were based on the original instrument developed by Chavis [1986]. The third part of the instrument was to explore further the prevalence of the social capital predicted by the model discussed in Chapter 5.

6.4.2 Sense of community index

A sense of a community emerges when people interact in a cohesive manner, continually reflecting upon the work of the group while respecting the differences individual members bring to the group [Graves, 1992]. It is a result of interaction and deliberation among members of a community brought together by similar interests and common goals [Westheimer and Kahne, 1993]. Rovai [2002] has extended the notion of the sense of community to online learning environments. He suggests that a virtual classroom has the potential of building and sustaining the sense of a community.

The literature suggests that a consensus definition of the concept of "sense of community" is lacking, and this is attributed to the fact that a sense of a community can be context dependent and unique to each community [Sarason, 1986]. McMillan and Chavis [1986], however, define sense of community as a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared understanding among the members and that their needs will be met through their commitment to be together.

McMillan and Chavis [1986] have developed the sense of a community index around an individual's feelings of membership, identity, belonging, and attachment with a group. Their descriptive framework of sense of a community has been widely accepted because of its theoretical base and its qualitative empirical support. This framework has four dimensions:

- **Feelings of membership**: feelings of belonging to, and identifying with, the community.
- **Feelings of influence**: feelings of having influence on, and being influenced by, the community.
- **Integration and fulfillment of needs**: feelings of being supported by others in the community while also supporting them.

- **Shared emotional connection**: feelings of relationships, shared history, and a "spirit" of community and togetherness.

The modified version of the sense of community index [in McMillan and Chavis [1986] is based on 11 dimensions to sense of community in an online environment, some expressed in terms of some of the variables of social capital presented in Chapter 5:

— **presence of a community-**sense of community

— **common identity-**professional background

— **awareness-**prior knowledge of people before joining the community

— **participation-**frequency of contribution to discourse

— **sharing resources-**frequency of sharing personal experiences and class related resources

— **social network with individuals-**establishing contacts outside class activities

— **social protocols-**presences of rules guiding interaction in the community

— **help seeking behavior-**sources of help

— **shared values and goals-**collective values and goals

— **help**-frequency of peer-support

— **trust-**trusting others based on several aspects, such as task, competence and abilities

6.5 Results

6.5.1 Background of Participants

There was a 100% response rate to the survey. Of those who responded, 56% were female and 44% male. The majority of the participants [about 90%] mentioned English as their first language and 10 % indicated other languages. Although the majority of the participants identified themselves as teachers, with degrees in education, others have other degrees in different domains in the social sciences and humanities as well as natural sciences including Anthropology, Liberal Arts, Philosophy, Computer Science, and Genetic Biology. It was one of the program requirements that in order to enroll into the graduate program in educational and communications technology, one had to be either a trained teacher or to have had at least a degree in education.

Diversity in training was observed in the wide range of participants' occupations, including schoolteachers 56%, instructional designers 11% and others such as technology-co-coordinators, administrators, and private consultants 11%. Though a considerable diversity of professional affiliations was observed, most of the participants in the study shared common background training and there was no discernable difference between men and women in the sample.

6.5.2 Social networking

As discussed in chapter two, virtual communities are often comprised of people with shared identity or interests coming together for a shared purpose. This shared interest or intent offers a strong forum for members of the community to build relationships and affiliations out of which they can socially network with each other, learn from one another and make an impact on their work or practice.

The nature of networking within a particular community is of fundamental importance when making judgments about the community and the extent to which people can engage in productive interaction and flourish within it. In virtual learning environments, when we think of individuals and their information seeking behaviours, it is quite natural that we think of physical media such as books, documents, web sites, databases, knowledge repositories and formal course content. However, in virtual learning environments, it is reasonable to suggest that a significant component of learners' information and knowledge needs consist of the relationships they can tap for various kinds of information and knowledge from peers.

Due to the complexity of information today, people have insufficient time to go through vast amounts of information to find a solution for solving a specific problem, and even when some are willing, they are often not well equipped or lack the time to conduct comprehensive searches. So people commonly turn to their peers for information and knowledge needs, with the hope they are given digested information to address their own information needs.

Improving the ways people can connect to each other to acquire useful information and knowledge is central to the notion of social capital in virtual communities. Social capital can help determine the advantage created by a person's location in a structure of relationships. It explains how some people gain more success in a particular setting through their superior connections to other people.

The existence of social capital in virtual communities, as it is described in most studies of temporal communities, depends on the development of social relationships that are built on social connections (a social network) when those social connections are useful for acquiring information and knowledge. Connections are also potential sources of peer-support in a community. Putnam [1993] defines “civic engagement” as participation in organized community activities such as bowling leagues and choirs. When looking at virtual communities, such groups can be equated to community activities organized around specific themes or topics which typically define social groups in cyberspace.

This thesis also has examined the extent to which participations were connected to each other through participation in the community, and the issues they engaged in discourse with others. When asked about their engagement in discourse, 56% regularly participated in discourse related to class materials and 44% were engaged in discourse not related to class material.

In addition, when asked whether they participated in other social activities outside class, results show that individuals seldom engaged each other socially outside of class activities during the course and after its completion. Figure 6-2 summarizes participants’ extent and frequencies of personal connections with peers outside class activities.

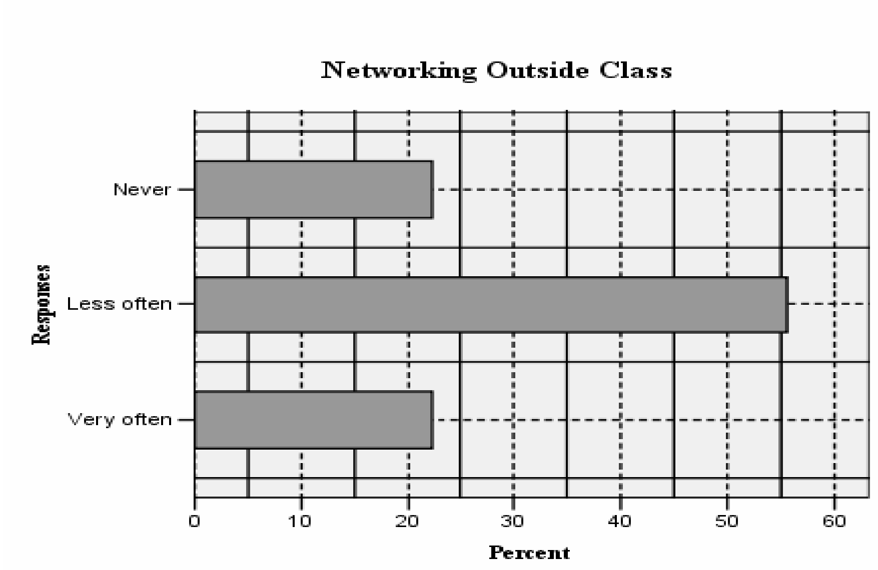


Figure 6-2. Extent of personal connection with peers outside class

Perhaps one of the reasons why individuals did not see the need to develop a strong social network outside class or after the completion of the course is due to the fact that most of them considered their community to be more of a professional one, as indicated by one of the participants:

> *"I would think it was an academic community and the reason I say that, and this ……it is because it developed within the parameters of ……. very much so…..When the class ended, there were a couple of us that attempted to continue the social aspect of it and it didn't happen. So I wouldn't call it a social community, certainly not. Professional in that I know that I can call on any one of those people again, but it would be sporadic and it would be only in times of need. So is that a social community? I don't think so. They would be people I could network with if I needed them professionally".*

"I felt it was an academic learning community. It functioned that way. I felt that it worked well and I had a chance to see it that way. So I saw it that way. I also saw it as a professional community but somewhat differently because I am new at it [SIC]. I also felt like I was professionally developing my understanding of what a virtual learning community is. So I was constantly sort of trying to figure out what is happening in this virtual ... what are we experiencing. And so, I know that there was a moment when communicating, where I remember you posted something about will this last a long time. And my response was "I don't think so." Not that I was saying that I don't care about people it's just that I don't ... I didn't come into this and I don't actually want it to feel that I have to stay in contact with all of these people because I didn't join the program to be friends with everyone for the rest of my life. There's a few that might last".

It was interesting to observe that most individuals mentioned that they did not often maintain any social connection outside of class, yet they felt a strong sense of a community among themselves built around professional purpose.

6.5.3 Sense of Community among the participants

Findings suggest that there was evidence of a strong sense of community among the participants indicated by the feeling of togetherness. The feeling of togetherness denotes recognition of membership in a community and the feeling of friendship among peers, cohesion and bonding among participants as they work, collaborate and learn together as a community, and regularly participate in community social rituals (such as lunch together).

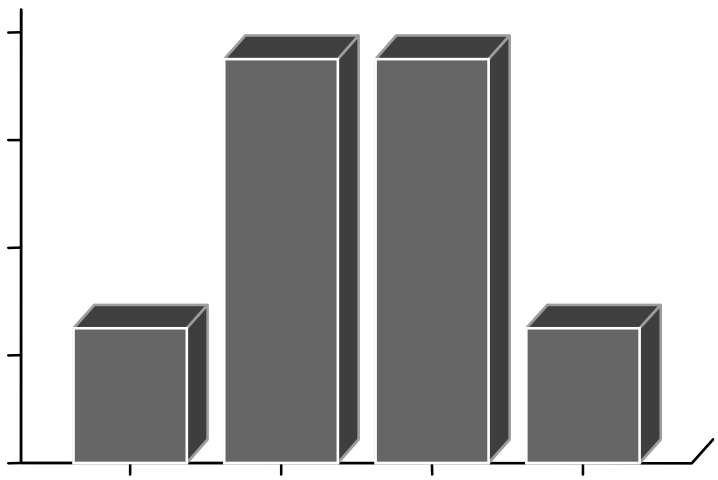


Figure 6-3. Participants feeling of togetherness in the community

The feeling of togetherness in the community enables participants to personally connect to each other, and to openly and respectfully challenge each other's ideas without fear of negative sanctions and exclusion from the community. The feeling of togetherness in the group is an important indicator of community, and it is also an important element of a community identity.

6.5.4 Common identity

In virtual learning communities, community boundary is normally defined along common goals and social protocols. A shared interest, which can hold members of a virtual learning community together, can create a strong feeling of a common identity. Identity plays an inherent role in defining members' participation in a community and it can affect how people network with each other and with whom they choose to exchange information and share knowledge. A community's identity is largely formed by the community's history or heritage including members' shared goals and shared values [Barab & Duff, 2000].

A group identity can influence the way individuals contribute to their community. For example, effective communication can be enhanced, if one knows the identity of those with whom one is communicating. This can also foster trust and social capital of the community [Daniel, McCalla & Schwier, 2005].

A recent study has revealed that a stronger group identity can lead to a greater attribution of similarity when members are physically at a distance [Blanchard & Horan, 2000]. Consistent with this finding, results of the study presented here seem to suggest that shared group identity played a key role in shaping and fostering a sense of a community. Results revealed that 64% of the individuals mentioned that they felt strongly as a community, and 36% reported neutral feelings. They also revealed that group identity was primarily socially constructed around shared professional and learning goals rather than social aspects. As one participant indicated:

> *"I think we have a common identity. I think we all had a focus in educational technology. We had common interests I suppose. We were all just working towards that. For me, I was just looking at interdependence here and mutuality stood out as well.*

Identifying with a group whether virtual or not, implies interdependence, attachments, and to a greater extent, a feeling of togetherness. Such feelings can also be influenced by what people have in common. It is not uncommon to realize that as people interact or grow up with certain groups of people—they experience a feeling of togetherness and they are often more likely to identify with the group. In professional life, however, people are more inclined to identify with those with whom they share the same experiences or who are trained in the same profession. In other words, professionals often seem to associate more with those with whom they easily identify. It is also within those groups they can easily build trust and feel as if they are part of a community.

6.5.5 Shared Understanding

Drawing on the results of our study, it is possible to conclude that people join communities when they share goals and values with others in the community. Similarity in backgrounds, interests and goals among participants enable them to share common experiences, swap stories and learn from each other as they interact as a community.

Participants were asked whether they believed most people in the community shared common goals and values. Findings showed that most of the participants believed they had common goals and shared values. Figures 6-4 and figure 6-5 summarize the results of the responses.

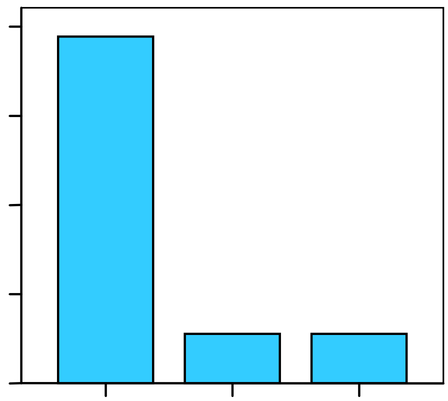


Figure 6-4. Shared goals

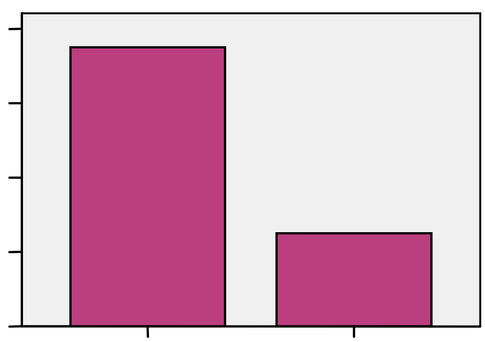


Figure 6-5. Shared values

Although there were shared goals and values within the group, participants also exhibited diversity and multiple perspectives during discourse on issues critical to their community, but they were willing to collaborate with other members of the community to achieve common goals. Participants demonstrated multiple perspectives by sharing personal experiences.

> *“There was certainly a common goal among the group. While we were in that community, we did diverge from the common goal and that was nice. We did so, but in an academic way, whether it was philosophy or a different epistemology or whatever it happened to be. There would be strands in the discussion that would take off into another academic area. I didn't ... there wasn't a lot of chitchat and when it was there I have to admit that I did not take part in it that much. So I guess from my point of view, it's ... I was trying to establish ..."We're here for a reason. Let's just get this done." But at the same time, I did go off on the tangents as well ... the academic tangent.”*

It is also likely that when people share common goals and values, they develop a sense of trust, which is critical to the process of learning in virtual learning communities. Further, shared goals and values can enhance shared understanding. Even though sharing experiences is critical to generating tacit knowledge, it is informal and typically voluntary, as discussed in Chapter 2. Individuals typically need to be highly motivated to share their personal life experiences and participate socially with others in the community.

6.5.6 Participation and social protocols

In virtual learning communities, effective participation requires the presence of either explicit or implicit social control mechanisms (social protocols of interaction). Social protocols provide a form of informal social control that obviates the necessity for more formal, institutionalized legal sanctions. Social norms are generally unwritten but commonly understood formulae for both determining what patterns of behaviour is expected in a given social context, and for defining what forms of behaviour are valued or socially approved.

Typically, in virtual communities, social protocols are set by the moderator/instructor of the class in the case of formal virtual learning communities, and over time, vibrant learning communities shape social engagement protocols to meet the context and preferences of the participants. Participants were asked whether they were aware of social protocols in the community and whether or not these were linked to any expectations. Approximately 67% of the participants indicated that they were aware of the presence of social protocols while 33% reported that they were not aware of any social protocols. Participants also mentioned that there were clear expectations from the instructor about the content of the course 78%, while 22% felt there were either no clear expectations connected to participation or they were not sure.

When inquiring about the presence of social protocols in the community, we were aware that people can respond differently to protocols or rules of engagement in a formal learning environment. Such reaction could possibly influence the way in which people participate and respond to the question. Social protocols and how they had affected interactions in the community were explored. Approximately 45% reported that social protocols had influenced their participation in discourse to the community to a great extent, while 55% mentioned social protocols had little or no influence on their participation in the community.

6.5.7 Peer-support and reciprocity

One of the most important binding factors for enhancing peer-to-peer support in a virtual community is reciprocity. Reciprocity connotes a mutual and shared interchange of favours or privileges, especially the exchange of information, knowledge and experiences among individuals. Rheingold [1993] has noted that in virtual communities, information is the primary commodity that is exchanged. Participants request information or ask questions and other members provide answers or information either directly to the group or in private correspondence. This is one of the factors that encourage individuals to join virtual communities.

In studying the thesis, reciprocity was assessed by asking participants about the frequency of sharing class-related resources among their peers. Approximately 56% indicated that they frequently shared resources with others in the community, while 44% mentioned they did not frequently share resources with their peers. The participants in a virtual learning community can inform our understanding of the social connection and engagement. Approximately 78% mentioned the instructor of the class as the main source of help and support. While 11% sought help from their friends in the class and 11%

sought help from outside sources, including people who had previously taken the course. These results describe the nature of information and help seeking behaviours among the group, which also suggest their reciprocal relationships and peer-support.

The act of peer-support in a virtual community can be treated as a reinforcement of members' sense of belonging to a community and their duty to reciprocate in relationships with others. Hence, a community with high rates of reciprocity among its members suggests a high level of social networking, which is also an element of social capital [Putnam, 1993]. Since participation in communities is primarily voluntarily, it is expected that reciprocal relationships are not obligatory, as participants in this study suggest:

> *"If <name>helps me with something, he's not doing it because he wants something back, but the expectation is that if he's going to need help in the future, me or somebody else in the community is going to provide it."*

> *"Well, participation in a community shouldn't have to force being in contact with people. It should just come naturally. It shouldn't be, "Oh, you know I haven't written to them in a few weeks. If this community is going to make it I have to write to people."*

The kinds of reciprocal relationships described in the community presented in this study are similar to generalized reciprocity, which is responsible for generating social capital

[Putnam, 2000]. In other words, reciprocity implies that the an individual provides a favour to others, or acts for the benefit of others at a personal cost, but in the general expectation that this kindness will be returned at some undefined time in the future in case of need. And so, in a community where reciprocity is strong, people care for each others' interests.

6.5.8 Autonomy and social resilience

When participation in a community is voluntary and people are free to participate whenever they can, there is a greater sense of autonomy within the community. Schwier [2001] defined autonomy as the ability of individual to have the capacity and authority to conduct discourse freely, or withdraw from discourse without penalty. An individual's autonomy is a critical value that influences participation in a community.

> *"My main value in this community is autonomy in learning - I am in control of what I choose to learn. Others, even the instructor, have little control over that autonomy. On the other hand, it is important for me to show respect and caring towards everyone else in the community. This means valuing difference".*

Autonomy implies that people can engage in discourse more freely and meaningfully. But it is also important to note that in formal virtual learning communities, where there are clear sets of expectations and goals to reach, social protocols, whether explicit or not, can guide individuals toward achieving goals and provide a context for amicable discourse. In some situations, high autonomy can encourage lurking.

As discussed in Chapter 4, lurking without proper social protocols presents an interesting but often unresolved social problem. Lurking without social protocols occurs when members of a virtual community read messages but seldom engage in any reciprocal relationships or directly participate and contribute to the community. Some members do not consider themselves to be lurkers even though they grossly violate the social protocols or expectations of reciprocity in the community.

Results showed instances where individuals proudly labeled themselves as lurkers, and announced to the group that they would not participate regularly. They treated their reluctance to participate actively as a personality characteristic, similar to being shy in large groups. But reticence in a virtual community creates an even stronger opportunity for the individual to become isolated. If members fail to participate in a virtual group, they essentially disappear from the community, but they sometimes leave a residue of concern or resentment about their silence.

In some virtual learning communities individuals' interests are not easily aligned with community interests, and it can be complicated if there is a considerable diversity among members of the community. An effective way to promote a sense of community in the face of diversity is to inculcate in the community a sense of social resilience. We define social resilience in a virtual learning community as an individual's ability to adapt and readily adjust to changes brought about by being a member of a diverse group.

In this study, diversity in knowledge and skills among participants in the community was viewed as a positive contribution to the knowledge base of the community and a potential conduit for high quality discourse and social networking. Participants in the study mentioned that the quality of discourse was enhanced because of the diverse range of issues that were addressed in the community. In most cases the issues seemed to have covered individuals' interests and were all attributed to the diversity in members' views.

In addition, participants stated that everybody was knowledgeable in some specific knowledge domains. Others felt that some people had more technical skills than others. There were also personal attributes which participants indicated were important in fostering a greater sense of community including:

- motivation to learn course material;
- demonstration of maturity and motive;
- openness to diverse views and expression of courtesy to peers;
- mutual respect and shared understanding;
- shared experiences and new observations and insights;
- freedom of discourse;
- deep reflection about content and views learned from others;
- expression of personal views without fear of negative feedback from peers and instructor;

- intellectual curiosity and firm goal orientation;
- diversity in individuals' backgrounds;
- willingness to collaborate with peers;
- positive work ethic;
- willingness to freely engage in intellectual discourse with peers and openness to diversity;
- treating negative feedback as a reflective view for personal check-and-balance but not as personal failures or attacks;
- establishment of relaxed community rituals (e.g. common lunch) where each individual is treated as equal, one and a colleague;
- frequent face-to-face community meetings so that members can establish new rapport and maintain old one with others in the community;
- humour, organization, attentiveness and rigor in open discourse in the community.

6.5.9 Level of trust and awareness

It seems there is some form of correlation between trust and awareness. As Devis [2003] puts it; "to trust someone, we need to know who we are dealing with, which means thinking back to how they behaved before" [p.18]. In virtual communities, trust is mainly dependent on different forms of awareness. For example, awareness about the presence of individuals in the community, awareness of individuals' demographic backgrounds, awareness of individuals' capabilities and skills in performing specific tasks and awareness of personal or professional affiliations can all promote trust.

Participants were first assessed on their levels of awareness of other group members before joining the course. Results indicated that they had little prior awareness (56% suggested they knew nobody while 44% knew a few of the people in the class). In asking about prior awareness, we were aware of the fact that awareness takes a long time to develop.

Awareness can develop as participants get to know each other by working and learning together and interacting socially. Results from the focus group also confirmed this line of thinking as one member commented:

> *"I think that's natural that in any environment in the beginning—you don't know that you're talking to or not quite sure what they're talking about. I think you just feel more comfortable as the year went on. I certainly did; anyway, especially in a different ... you know people would try to include me. The welcome video that everybody shot, that was really helpful."*

In virtual communities, awareness can be linked to trust. However, as indicated earlier there are several kinds of awareness, which can differently influence trust [Daniel, McCalla & Schwier, 2005]. In previous work we concentrated on different kinds of knowledge and demographic awareness in influencing social capital. See Daniel, McCalla, and Schwier [2002] Daniel, McCalla, and Schwier [2005] and Daniel, Schwier, and McCalla [2003] for a comprehensive discussion of different forms of knowledge and demographic awareness in virtual communities.

6.5.10 Knowledge awareness

Discourse is the means to the formation of social relationships in any environment but discourse in a virtual community is very different from face to face, in that participants are separated from one another physically and temporally, and so they significantly lack many pieces of information that are traditionally used in developing the social knowledge that forms the basis for social interaction in terrestrial communities. For example, it is sometimes difficult to know others' gender, socioeconomic and cultural status, even though such knowledge can provide clues about that person's identity and personality.

In addition, facial expressions and body language provide valuable information about another's immediate state of mind. Moreover, in a physical face-to-face encounter, another's presence is self-evident, the comments they make are unambiguously theirs, and the identity they can project is somewhat constrained by these factors. In stark contrast to this, online people are physically separated and can have multiple identities. They can often see others without being seen themselves, and can, to some degree, take on personas with characteristics very different from their own, and be a different age, race, gender, sexuality, and so on. This makes it possible not only to experiment and be free from some conditions of one's life, but it also frees people to do things that would incur social sanctions otherwise.

For a productive discourse to take place in virtual communities and for social relations to form among individuals, it is necessary to foster knowledge awareness among the participants. Knowledge awareness is information about other learners' activities and knowledge—what individuals know (competence awareness) and what they can do (capability awareness). Knowledge awareness allows a better understanding of shared knowledge, since it provides information about the knowledge of the community.

Knowledge awareness can also breed trust in a community. Knowledge awareness is an important component of social capital in virtual communities [Daniel, McCalla & Schwier, 2005] and it plays a major part in how the learning environment creates collaborative opportunities naturally and efficiently [Ogata & Yano, 2000]. In one of the questions, participants were asked about possible context(s) in which they could trust their peers in the community. Results revealed that people are more likely to trust others in the community based on various forms of awareness about those individuals (see Figure 6-6).

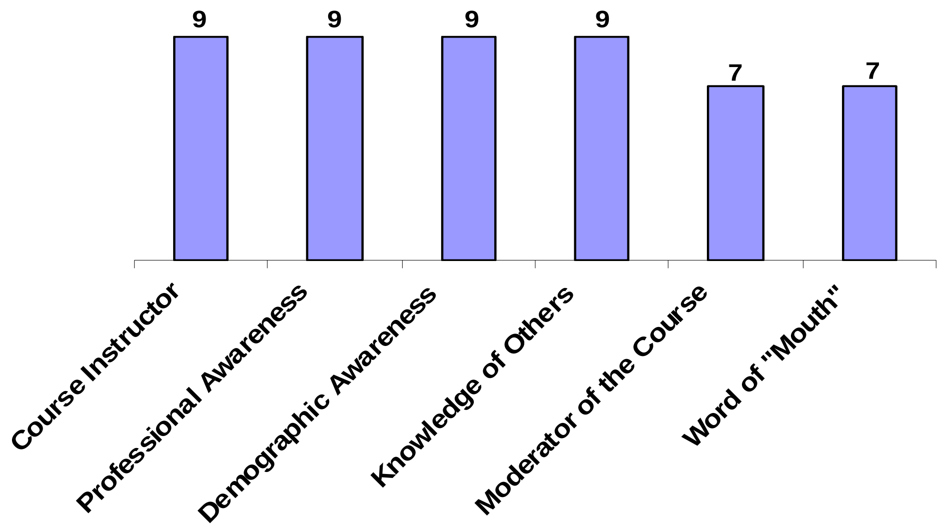


Figure 6-6. Context based trust

Most of the participants reported that they can trust their peers when it comes to capabilities and the quality of intellectual discourse. Others based their level of trust on similarity of prior training and their knowledge of a domain; this is similar to professional awareness mentioned earlier in the thesis.

Trusting people based on similarity of training is in line with studies that show that when people meet each other for the first time they develop mental models of each other and the content of their discussion [Norman, 1996]. Their opinions are influenced partly by such things as age, gender, physical appearance and the context of the meeting. Mental models tend to be developed very quickly but can be remarkably powerful and resistant to change, even when evidence suggests they are not completely correct [Wallace & Boylan, 2001]. So another feature of reduced social presence, particularly in low bandwidth environments, is that the ways people form impressions of each other is different, and this can have positive or negative effects depending on the context. Conversely, there are times when not being able to see the person with whom you converse and knowing you may never meet them can be a positive feature of these environments, because people are encouraged to disclose more about themselves online [Lea, O'Shea, Fung, & Spears, 1992].

Furthermore, when people discover they have similar problems, opinions or experiences they may feel closer, more trusting and be prepared to reveal even more. We asked how likely individuals were willing to trust others based on their awareness of others' demographic backgrounds. Little or no difference in their levels of trust was reported by participants.

In an attempt to understand whether trust in others can be based on similarity in profession, we asked to what extent individuals' trust in others was based on their professional affiliation. The majority of participants indicated that their trust level based upon professional affiliation of others was neither great nor small.

6.5.11 Overall level of trust at the end of the class

In any community, trust is the confidence and expectations that people will act in a consistent, honest and appropriate way. More accurately, trust entails that people are more reliable and trustworthy. Closely linked to the norms of reciprocity and networks of civic engagement [Putnam, 1993; Coleman, 1990], trust allows people to collaborate and to work together as a community.

Trust is a dynamic phenomenon, one that evolves, mutates and regenerates. In other words, it seems under favorable conditions, people can develop trusting relationships with others and such relationships can be maintained or destroyed. In a situation where individuals are strangers, it often takes a longer period of time with favourable interactions to develop trust. At the same time continuous and negative interactions can help destroy one's trust on others.

In general, in virtual communities where individuals are often strangers and interact anonymously with each other, the notion of trust is even more relevant but difficult to achieve. Further, it can be slow to develop, due to the absence of common social cues in virtual environments. Since trust is a fundamental determinant of social capital, participants were queried regarding their overall perception of the level of trust in the community at the end of the class, and whether or not over the course of time the level of trust among people in the class had gotten better, worse, or stayed about the same. Results revealed that the level of trust was perceived to have remained almost the same from beginning to end.

Several factors might have indirectly contributed to this including the nature of this community and individual differences, presence of social protocols, and professional backgrounds of the community members, common identity and shared values, different forms of awareness and the level of intellectual maturity among the members. Though each of these factors can differently influence the overall level of trust in a community, their dominant prevalence can suggest an acceptable level of trust.

6.6 Discussion

In a traditional classroom, learning communities can easily be visible to the instructor and students can easily make connections with peers due to the availability of rich visible social cues. Instructors can also easily nurture the sense of a community among students with little difficulty. In virtual learning communities however, where learners are often isolated from each other and the instructor, developing a sense of a community, though critical, can be difficult.

The sense of isolation among learners in online environments can be minimized if forethought is given to the development of the online milieu that can foster a sense of a community among learners. Results in this study reveal that trust and awareness are fundamental variables in promoting a sense of a community. These findings are in line with some of the model predictions based on the scenarios described in Chapter 5. In other words, for a sense of a community to fully develop, individuals need to trust each other and work together as a community. People trust each other when they know each other. Another factor is the durability of a social network in enhancing trust and awareness. In many situations, trust evolves over a period of time and with repeated interactions. Through interactions people establish history of interaction and reputation. People become aware of others, they get to know what others know and can do and subsequently, they can demonstrate they are trustworthy.

In virtual learning communities, trust and awareness are critical to knowledge sharing. People share knowledge with those whom they know and feel is trustworthy, and who will not use their knowledge inappropriately, and who are willing to share with others in the future. Trust can also encourage knowledge sharing when people are aware that they share common goals and common values.

When people do not share common goals and values, a sense of a community is not likely to develop, and the self-interest of high status people is likely to predominate. In other words, people who feel they possess more power are likely to use it inappropriately.

In terms of knowledge sharing, especially tacit knowledge, if the recipient of knowledge is not aware or convinced that the source is competent and trustworthy, it is unlikely that knowledge from that particular individual will be accepted [Huber, 1991]. On the other hand, if the owner of the knowledge is not confident or does not trust the seeker of the knowledge to reciprocate in the near future, they may choose to hoard their valuable knowledge. Even sharing explicit knowledge, in this instance, depends on the willingness of the individual to use the technology and participate in the community. Further, in a virtual learning community a sense of a community can be sustained through the maintenance of proper social protocols, capable of enhancing reciprocal relationships.

6.7 Chapter summary

This chapter has presented a sensitivity analysis of the Bayes net model of social capital presented in the last chapter. It showed that social capital is sensitive to various constituent variables at different levels of analysis. The variance of various variables of the in this analysis is also dependent on the type of the virtual community in which analysis is carried out.

Chapter 6 has also presented a study that sheds further light on the model of social capital. This study surveyed students' experiences and their sense of community in a virtual learning environment and explored key issues predicted by the model. In summary the following can be concluded from the results:

- Diversity in professional cultural affiliation was observed, though there were few differences in prior educational background among the participants.
- Participants exhibited a strong sense of community among participants based on shared identity and shared values.
- Participants demonstrated shared interests and shared understanding in the community.
- Participants were engaged in productive intellectual discourse with others and felt they were autonomous and fairly treated by others.
- Diversity in knowledge and skills was considered a positive characteristic of the community and stimulated continuity of discourse among members.
- The strong spirit of reciprocity among the participants suggested the presence of mutual interdependency, trust and shared understanding.

— Though there was little social networking among individuals outside the formal settings, the pursuit of common goals and common identity helped clearly defined the boundary of the community.

— Trust and shared understanding encouraged individuals to freely share personal experiences and insights with others in the community.

— In line with the prediction of the model, the extent to which individuals trusted others based on demographic and linguistic backgrounds was not significant in this community.

— Participants reported that they increasingly trusted those who seemed to have more knowledge of the domain and were capable performing certain technical tasks.

— In this community participants indicated that they trusted those with whom they shared the same profession.

— The level of trust among participants in the community remained the same and this was perhaps attributed to the high level of various forms of awareness in the group.

Chapter Seven

7.0 Thesis summary, contributions, limitations and future research

7.1 Summary

Social capital is an evolving concept, one that includes constructs such as social networks, trust, reciprocity, shared understanding, and social protocols. The fundamental principle behind social capital—whether in terrestrial or virtual communities—is that value can be derived from social relationships and the extent to which people are embedded within social networks and communities can help to enhance the lives of others.

The motivation to explore social capital in virtual communities in the thesis was inspired by the belief that the notion of social capital holds great potential for understanding social and learning issues in virtual communities. Among other benefits, social capital enables individuals to collaborate and learn together as a community. Social capital can also act as a pipeline and a filter for processing and transmitting information and knowledge. Further, it seems higher and positive social capital can manifest itself in a virtual community of people who engage in reciprocal relationships, through sharing data, personal experiences and knowledge.

While it is too soon to conclude that using the notion of social capital is an accurate analytical "paradigm" for addressing social and learning issues in virtual communities, it is fair to suggest that with the proliferation of social software applications, there is a growing interest about the importance of social relationships in virtual communities, social capital seems to be appropriate and can occupy a central position as an analytical paradigm in understanding social issues in many social software support tools for virtual communities. However, the real usefulness of social capital will depend on understanding precisely what constitutes social capital and how it operates in virtual communities and this thesis provide the first directions to achieve these goals.

7.2 Research contributions

A contribution of the research from the last five years of studies reported in this thesis has been the continued development and deployment of integrated methodologies to explore social capital and virtual communities with the goal of developing a computational model of social capital.

The conceptualization of social capital in virtual communities as a common social resource that facilitates information exchange, knowledge sharing, and knowledge construction through continuous interaction, built on trust and maintained through shared understanding represents an important theoretical departure from what constitutes social capital in terrestrial communities. This fresh conceptualization is useful for the discussion about and inquiry into social capital in virtual communities. In general there are two major contributions of the thesis: (i) modeling social capital in virtual communities and (ii) deployment of coherent integrated methods for studying social capital.

7.2.1 Modelling social capital in virtual communities

The first contribution of this thesis is its detailed exploration of social capital in virtual communities and the identification of the key variables that constitute SC in virtual communities. However, we are only at the beginning of understanding how to model social capital using the proposed sets of approaches and so there is no claim made that the variables presented in the thesis represent a definitive set of variables for SC outside the communities studied in the thesis.

7.2.2 Use of Bayesian belief network

Another contribution is the use of a Bayesian belief network for exploring and analyzing social capital within the contexts of virtual communities. The Bayesian belief network methodology has an intentional component flowing from definition to analysis to prediction, so that the methods separately have some intuitive and practical appeal and they can contribute to the coherent nature of the studies throughout the whole process.

Further, the use of various approaches presented in the thesis has provided important insights into analysis of the nature of social capital in virtual communities. For example, the review of the literature helped to identify the most critical variables of social capital. The use of content analysis determined the actual interaction patterns prevalent in virtual communities and the trends that showed variables of social capital. The employment of social network techniques enabled the visualization of the interaction and discourse themes. Moreover, the research led to a Bayesian belief network capturing the influences between identified variables of social capital. This BBN is the first model of social capital in virtual communities, and as such is a major contribution of this thesis. Although only the first attempt, the model seems plausible at least in general terms, as evidenced by sensitivity analysis and a study of members of a virtual learning community.

7.3 Thesis limitations

Modelling a nebulous notion such as social capital can be challenging and the methods used can impose limitations. The Bayesian belief network approach applied in the thesis, although providing a novel way to understand how the various variables of SC can interact though the variables identified, can be replete with assumptions (about variables, values, influences, and conditional probabilities) that may undermine the model's usefulness.

The thesis has addressed two general challenges: conceptual and analytical. The conceptual challenge has to do with methods used for analyzing social capital. The analytical challenge deals with the development and use of computational techniques to build models of complex social phenomenon. In addressing these challenges the thesis provided a starting point for discourse and illustrated that much work still needs to be done to develop a deeper understanding of what constitutes social capital in virtual communities and how key variables interact with each other. And finally, we are now closer to having a predictive understanding of the dynamics of social capital in virtual communities and how it can be supported. The thesis has raised methodological, theoretical, and practical issues that can be addressed in future research.

7.4 Future research directions

This thesis is the first to raise concerns about social capital and its application in virtual communities. Critical issues that need to be pursued by future research include an investigation of the relationships among the constituent variables of social capital in the computational model discussed in the thesis and how the model reacts to new authentic scenarios. Further, the results of the sensitivity analysis can be used to refine and improve the model.

The model presented in this thesis is a first step toward discussion of social capital in virtual communities. Further testing of the model will require that theory development and measurement should be inextricably linked. One informs the other in an iterative process that balances pragmatism against the need for theoretically justifiable and useful questions.

The development of the Bayesian framework presented in the thesis was largely motivated by the need to provide a sound theoretical foundation to make social capital a scientifically useful construct in the context of virtual communities and one in which solid, meaningful and precise measurements may be taken. Results from studies carried out in the thesis indicated that various forms of awareness, shared understanding, and social protocols are critical components of social capital in virtual communities. However, there is need to conduct further experiments to explore how these variables relate to each other. For example, future research needs to investigate the link between social capital taken as a whole and how its constituent variables can affect its operation. One example is investigating empirically how adherence to social protocols can contribute to productive social relationships or how various forms of awareness in virtual communities can affect the amount of social capital.

In addition, since the elicitation of the causal relationships of variables of social capital might be subjectively influenced by the knowledge of an expert, future research needs to be directed at distinguishing causation and correlation among social capital variables in the model. In other words, it is necessary to understand the process involved in building social capital in virtual communities, how it works and how to differentiate productive from unproductive social capital in a particular virtual community and for the benefit of the larger learning system.

It is also possible that a stock of social capital can vary and differ between virtual community types. Therefore, future studies need to be directed at understanding why social capital is successful in some virtual communities and not in others, and to investigate the particular contextual issues critical to the success of social capital in these communities. For instance, studies can examine whether an individual’s characteristics in a virtual community such as knowledge competence, level of education, history of past interaction with others, common identity, and shared interests can help in increasing SC in virtual community.

In current research writings, there is a growing confusion between social capital as input leading to better outcomes and social capital as an outcome. Further, the distinction between the value of social capital and community is blurred. What can be attributed as positive outcomes of community are sometimes referred to as social capital, resulting in conceptual confusion, and theoretical misrepresentation of the concept itself and how it can be used to achieve certain positive community outcomes, such as togetherness, collaboration, learning, civic engagement, and participation in community activities.

Similarly, different variables of social capital such as the levels of trust within a community may be critical for determining outcomes of social capital in a community. Further, social capital can be influenced by cultural or collective social protocols in a community. There are currently few studies directed at understanding these important issues. However, the techniques explored in this thesis, and the model of social capital developed, should provide a framework in which these and other issues can at least be more successfully investigated than they could have been before this research was carried out.

References

Baker, M. (2000). The roles of models in artificial intelligence and education research: A perspective view. *International Journal of Artificial Intelligence in Education, 11*, 123-143.

Barab, S. A., & Duffy, T. M. (2000). From practice fields to communities of practice. In D. Jonassen & S. Land (Eds.), *Theoretical foundations of learning environments*. Mahwah NJ: Lawrence Erlbaum Associates. Retrieved July 3, 2007 from http://crlt.indiana.edu/publications/complete.pdf.

Bielaczyc, K., & Collins, A. (1999) Learning communities in classrooms: A reconceptualization of educational practice. In C.M. Reigeluth (Ed.): *Instructional-design theories and models: A new paradigm of instructional theory* (pp. 269-292). Mahwah NJ: Lawrence Erlbaum Associates.

Blanchard, A., & Horan, T. (2000). Virtual communities and social capital. In E. Lesser (Ed), *Knowledge and social capital* (pp. 159-178). Boston: Butterworth-Heinemann.

Borgatti, E., & Freeman (2002). *UCINet 6 Network analysis software. Analytic technologies*. Retrieved July, 3, 2007 from http://www.analytictech.com/downloaduc6.htm.

Bourdieu, P. (1996). On the family as a realized category. *Theory, Culture and Society, 13*(1), 19-26.

Burt, R. S. (1992) *Structural holes: The social structure of competition.* Cambridge, Massachusetts: Harvard University Press.

Chua, A. (2002). The influence of social interaction on knowledge creation. *Journal of Intellectual Capital, 3,* 375-392.

Cohen, D., & Prusak, L. (2001). *In good company: How social capital makes organizations work*. Massachusetts: Harvard Business School Press.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology, 94*, 95-120.

Collion, M. H. (1989). Strategic planning for national agricultural research systems: An overview. *Working Paper 26*. Retrieved July 3 from http://www.ifpri.org/divs/isnar.htm.

Conati, C., Gertner, A., & VanLehn, K. (2002). Using bayesian networks to manage uncertainty in student modeling. *User Modeling and User-Adapted Interaction, 12* (4), 371–417.

Cooper, G.F., & Herskovits, E. (1992). A Bayesian method for the induction of probabilistic networks from data. *Machine Learning, 9* (4), 309-347.

Cote, S., & Healy, T. (2001). *The well-being of nations. The role of human and social capital*. Paris: Organisation for Economic Co-operation and Development.

Daniel, B.K., Schwier, R. A., & McCalla, G. I. (2003). Social capital in virtual learning communities and distributed communities of practice. *Canadian Journal of Learning and Technology, (29)*3, 113-139.

Daniel, B.K., & Poon, N. (2006, July). Social network techniques and content analysis of interactions in a video-mediated virtual community. *Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies*, Kerkrade, Netherlands.

Daniel, B.K., Zapata-Rivera, D. J., & McCalla, G. I. (2003). A Bayesian computational model of social capital. In M. Huysman, E. Wenger, & V.Wulf, (Eds.). *Communities and technologies* (pp. 287-305). London: Kluwer Publishers.

Daniel, B.K., McCalla, G.I., & Schwier, R.A. (2005, July). Data mining and modeling social capital in virtual learning communities. *Proceedings of the 12th International Conference on Artificial Intelligence in Education*, Amsterdam.

Daniel, B.K., O' Brien, D. & Sarkar, A. (2003). A design approach for Canadian distributed community of practice on governance and international development: A preliminary report. In Verburg, R.M., & De Ridder, J.A. (Eds.), *Knowledge sharing under distributed circumstances* (pp. 19-24). Enschede: Ipskamps.

Daniel, B.K., Poon, N., & Sarkar, A. (2005, June). Analysis of patterns of interactions in video-chat supported virtual communities to model social capital. *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications (ED-MEDIA 2005), Montreal, Canada.*

Daniel, B.K., Sarkar, A., & O'Brien, D. (2006). User-centred design for online learning communities: A sociotechnical approach for the design of a distributed community of practice. In N. Lambropoulos, & P. Zaphiris (Eds). *User- evaluation and online communities* (pp. 54-70). Hershey: Idea Group

Daniel, B.K., Sarkar, A., & O'Brien, D. (2004, June). A participatory design approach for a distributed community of practice on governance and international development. *Proceedings of Ed-Media World Conference on Educational Multimedia, Hypermedia and Educational Telecommunications. Lugano, Switzerland.*

Daniel, B.K., Schwier, R.A., & McCalla, G.I. (2003). Social capital in virtual learning communities and distributed communities of practice. *Canadian Journal of Learning and Technology, 29*(3), 113-139.

Daniel, B.K., Schwier, R.A., & Ross, H. (2005, October). Intentional and incidental discourse variables in a virtual learning community. *Proceedings of E-Learn 2005--World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education,* Vancouver, British Columbia, Canada.

Daniel, B.K., Zapata-Rivera, J.D & McCalla, G.I. (2005, November). Computational framework for constructing Bayesian belief network models from incomplete, inconsistent and imprecise data in E-Learning (Poster). *The second LORNET International Annual Conference, I2LOR-2005,* Vancouver, Canada

Daniel, B.K., Zapata-Rivera, J.D., & McCalla, G.I. (in press). A Bayesian Belief Network approach for modelling complex domains. In A. Mittal, A. Kassim, & T. Tan (Eds.). *Bayesian network technologies: Applications and graphical models* (pp. 13-41). Hershey, PA: IGI Publishing .

Daniel. B.K., Schwier, R.A., & Ross, H. (in press). Synthesis of the process of learning through discourse in a formal virtual learning community. *Journal of Interactive Learning Research, 18*(4), 461-477.

Davis, W. (2003). *You don't know me but social capital and social software*. Retrieved July 3, 2007 from http://www.theworkfoundation.com/Assets/PDFs/you_dontknowme.pdf.

Druzdzel, M.J., & Henrion, M (1993). Efficient reasoning in qualitative probabilistic networks. *Proceedings of the 11th National Conference on Artificial Intelligence,* (pp. 548-553).

Druzdzel, M.J., & Gaag, L. C (2000). Building probabilistic networks: Where do the numbers come from? Guest editor's introduction. *Data Engineering, 12(4), 481-486.*

Druzdzel, M.J., & Suermondt, H.J. (1994). Relevance in probabilistic models: "Backyards" in a "small world". In R. Greiner & D. Subramanian (Eds.), *Proceedings of the American Asssociation for Artificial Intelligence*. *AAAI Fall Symposium on Relevance (pp. 60-63)*.

Fahy, P.J., Crawford, G., & Ally, M. (2001). Patterns of interaction in a computer conference transcript. *International Review of Research in Open and Distance Learning, 2*(1). Retrieved July 3, 2007 from http://www.irrodl.org/content/v2.1/fahy.html.

Falk, I.H., & Harrison, L. (2000). Indicators of social capital: Social capital as the product of local interactive learning processes. Learning communities. *International Journal of Adult and Vocational Learning, 1,* 39-60. Retrieved July 3, 2007, from http://www.research.utas.edu.au/reports/2000/.

Franke, S. (2005). Measuring social capital within the context of public policy research, development and evaluation. *Policy Research Initiative*. Retrieved July 3, 2007 from http://www.policyresearch.gc.ca/page.asp?pagenm=v8n1_art_12.

Freemen, L.C. (2004). *The development of social network analysis: A study in the sociology of science*. Vancouver: Empirical Press.

Fukuyama, F. (1999, November). Social capital and civil society. *Paper presented at the Conference on Second Generation Reforms IMF Headquarters, Washington, D.C.*

Gittell, R., & Vidal, A. (1998). *Community organizing. Building social capital as a development strategy*. London: Sage Publications.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78*(6), 1360-1380.

Graves, L.N. (1992). Cooperative learning communities: Context for a new vision of education and society. *Journal of Education, 174*(2), p. 57-79.

Haddaway, P. (1999). An overview of some recent developments in Bayesian problem solving techniques. *Artificial Intelligence Magazine, (20)*2, 11-19.

Halpern, D. (2001). Moral values, social trust and inequality - Can values explain crime? *British Journal of Criminology 41*, 236-251.

Hanifan, L. J. (1916). The rural school community centre. *Annuals of the American Academy of Political and Social Science, 67*, 130-138.

Heckerman, D., & Horwitz, E. (1998). Inferring informational goals from free-text queries: A Bayesian approach. *Procceedings of the 14th Conf on Uncertainty in AI* (pp. 230-238).

Hemez, F. M., & Doebling, S. W., (2003). From shock response spectrum to temporal moments and vice-versa. *Proceedings of the 21st International Modal Analysis Conference*, Kissimmee, FL.

Huber, G.P. (1991). Organizational learning*:* The contributing processes and the literatures. *Organization Science, 2*, 88-115.

Huysman, M.H. (2004). Traps and challenges for knowledge sharing in practice, *Journal of Knowledge and process management*. Retrieved July 3, 2007 from http://www.sapdesignguild.org/editions/edition5/km_mh.asp.

Ichiro, K., Kim, D., Coutts, A., & Subramanian, S.V. (2004). Commentary: Reconciling the three accounts of social capital. *International Journal of Epidemiolog, 33*, 1–9

Inglehart, R. (1997). *Modernization and postmodernization: Cultural, economic, and political change in 43 societies.* Princeton: Princeton University Press.

Jensen, F. and Liang, J. (1994) "drHugin: A system for value of information in Bayesian networks. *Proceedings of the Fifth International Conference on Information Processing and Management of Uncertainty in Knowledge - Based Systems (IPMU), Paris, France,* (pp. 178-183).

Lave, J., & Wenger, E. (1991*). Situated learning: Legitimate peripheral participation*. New York: Cambridge University Press.

Lea, M., O'Shea, T., Fung, P., & Spears, R. (1992). `Flaming' in computer-mediated communication: Observations, explanations, implications. In M. Lea (Ed.), *Contexts of computer-mediated communication* (pp. 89-112). London: Harvester-Wheatsheaf.

Lewicki, R. J., McAllister, D. J., & Bies, R. J. (1998). Trust and distrust: New relationships and realities. *Academy of Management Review*, *23*, 438-458.

Lin, N. (2001). *Social capital: A theory of social structure and action*. Cambridge: Cambridge University Press.

Lin, N., & Druzdzel, M.J. (1998). *Relevance-based Incremental belief updating in Bayesian networks*. Retrieved July 3, 2007 from http://citeseer.ist.psu.edu/303827.html.

Loury, G. (1977). A dynamic theory of racial income differences. In P.A. Wallace & A. Le Mund, (Eds.) *Women, minorities, and employment discrimination* (pp. 153-186). Lexington, MA: Lexington Books.

McCalla, G. (2000). The fragmentation of culture, learning, teaching and technology: Implications for artificial intelligence in education research. *International Journal of Artificial Intelligence, 11*(2),177-196.

McMillan, D.W., & Chavis, D.M. (1986). Sense of community: A definition and theory. *American Journal of Community Psychology, 14*(1), 6-23.

Morgan, M., Granger, & Henrion, M.(1990). *Uncertainty.* New York: Cambridge University Press.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital and the organizational advantage. *Academy of Management Review*, *23*(2) 242- 266.

Narayan, D., & Pritchett , L. (1997). *Cents and sociability: Household income and social capital in rural Tanzania*. Washington DC: World Bank, USA.

Niedermayer, D. (1998). *An introduction to Bayesian networks and their contemporary applications*. Retrieved July 3, 2007 from http://www.niedermayer.ca/papers/bayesian/bayes.html.

Norman, D.A. (1996). Cognitive engineering. In D.A. Norman & S.W. Draper (Eds.), *User centered systems design-new persepectives on human-computer interaction (pp.31-61).* Hillsdale: Lawrence Erlbaum.

OECD (2001 Summer). The well-being of nations: The role of human and social capital, Paris. Policy-makers should not have to wait for a couple of decades of detailed research before asking whether attentiveness to social capital might be worth their while. *OECD Observer, No 226/227*, 200.

Ogata, H., & Yano, Y. (2000). Combining knowledge awareness and information filtering in an open-ended collaborative learning environment*. International Journal of Artificial Intelligence in Education, 11*, 33-46*.*

Pearl, J., & Verma, T. (1991). *A theory of inferred causation: Principles of knowledge representation and reasoning, in representation and reasoning*. San Mateo: Morgan Kaufmann.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. San Mateo, CA: Morgan Kaufman Publishers.

Phillipson, C., Allan, G., & Morgan, D. (2004). Introduction in social networks and social exclusion: In C. Phillipson, G. Allan (Eds.), *Sociological and policy perspectives (*pp. 1-6), Aldershot: Ashgate Publishing.

Portes, A. (1998). Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology, 24*, 1-24.

Pradhan, M., Provan, G., Middleton, B., & Henrion. M. (2004). Knowledge engineering for large Belief networks. *Proceedings of the Tenth Conference on Uncertainty in Artificial Intelligence*, Seattle, Washington.

Preece, J. (2002). Supporting community and building social capital. *Communication of the ACM*, *45*(4), 37-39.

Prusak, L., & Cohen, D. (2001). *In good company: How social capital makes organizations work*. Boston, MA: Harvard Business School Press.

Putnam R.D. (2000). *Bowling alone: The collapse and revival of American community*. New York: Simon Schuster.

Putnam R.D. (1993). *Making democracy work: Civic traditions in modern Italy,* Princeton NJ: Princeton University Press.

Rafaeli, S., Ravid, G., & Soroka, V. (2004, January). De-lurking in virtual communities: A social communication network approach to measuring the effects of social capital. *Paper presented at the HICSS 37*, Hawaii.

Renooij, S., & Witteman, C. (1999). Talking probabilities: Communicating probabilistic information with words and numbers. *International Journal of Approximate Reasoning,(2), 169-194.*

Resnick, P. (2002). Beyond bowling together: Sociotechnical capital. In Carroll, J. M. (Ed.). *HCI in the New Millenium* (pp. 247 272). New York: Addison-Wesley.

Resnick, P. (2004). Impersonal sociotechnical capital, ICTs, and collective action among strangers. In W. Dutton, B. Kahin, R. O'Callaghan, & A. Wyckoff (Eds.), *Transforming enterprise*. Retrieved from July 3, 2007 from http://www.si.umich.edu/~presnick/papers/xforment/chapter.pdf.

Reye, J. (2004). Student modeling based on belief networks. *International Journal of Artificial Intelligence in Education, 14,* 63–96.

Rheingold, H. (1993). *The virtual community: Homesteading on the virtual frontier*. New York: Addison-Wesley.

Robinson, D. F., & Foulds, L.R. (1980) *Digraphs: Theory and techniques*. New York: Gordon and Breach.

Robinson, D. (1997). Social capital and policy development. Unpublished report*. Institute of Policy Studies.* Wellington, NZ.

Rourke, L., Anderson, T., Garrison, D.R., & Archer, W. (2001). Methodological issues in the analysis of computer conference transcripts. *International Journal of Artificial Intelligence in Education, 12,* 8-22.

Rovai, A.P. (2002). Building sense of community at a distance. Retrieved July 3, 2007 from http://www.irrodl.org/content/v3.1/rovai.html.

Russell, S., & Norvig, P. (1995). *Solution manual for artificial intelligence: A modern approach.* Englewood Cliffs, NJ: Prentice Hall.

Sarason, S.B. (1986). Commentary: The emergence of a conceptual center. *Journal of Community Psychology*, *14*, 405-407.

Schuller, D., & Namioka, A (1993). *Participatory design: Principles and practices*. Hillsdale, NJ: Erlbaum.

Schwier, R. A. (2001). Catalysts, emphases, and elements of virtual learning communities. Implication for research. *The Quarterly Review of Distance Education, 2*(1), 5-18.

Schwier, R.A., & Dykes, M.E. (2007). The continuing struggle for community and content in blended technology courses in higher education. In M. Bullen, M., & D. Janes (Eds.), *Making the transition to e-learning: Issues and strategies* (pp. 157-172). Hershey, PA: Idea Group.

Schwier, R.A., & Daniel, B.K. (2007). Did we become a community? Multiple methods for identifying community and its constituent elements in formal online learning environments. In N. Lambropoulos, & P. Zaphiris (Eds.), *User- evaluation and online communities* (pp, 29-53). Hershey, PA: Idea Group Publishing.

Sirianni, C., & Friedland, L. (1995). Social capital, civic practices network. Retrieved July 3, 2007 from http://www.cpn.org/sections/tools/models/social_capital.html.

Sobel, J. (2002). Can we trust social capital? *Journal of Economic Literature, 40, 139-154.*

Soller, A., & Lesgold, A. (2003). A Computational approach to analyzing online knowledge sharing interaction. *Proceedings of Artificial Intelligence in Education, 253-260.*

Soller, A.L. (2001) Supporting social interaction in an intelligent collaborative learning system. *International Journal of Artificial Intelligence in Education*, *12*(1), 40-62.

Stemler, S. (2001). *An overview of content analysis. Practical assessment, research & evaluation*, *7*(17). Retrieved July 3, 2007 from http://edresearch.org/pare/getvn.asp?v=7&n=17.

Strauss, A., & Corbin, J. (1997). *Grounded theory in practice*. Thousand Oaks, California: Sage Publications.

Szreter, S. (2002). The state of social capital: Bringing back in power, politics, and history, *Theory and Society*, *5* (31), 573-621.

Van der Gaag, L.C., Renooij, S., Witteman, C., Aleman, B.M.P. & Taal, B.G. (1999). How to elicit many probabilities. *Proceedings of Incertainty in Artificial Intelligence* (pp. 647-654).

VanLehn, K., Niu, Z., Siler, S., & Gertner, A. S. (1998). Student modeling from conversational test data: A Bayesian approach without priors. *ITS'98: Proceedings of the 4th International Conference on Intelligent Tutoring Systems (pp. 434–443).*

Vomlel, J. (2004). Bayesian networks in educational testing. *International Journal of Uncertainty, Fuzziness and Knowledge Based Systems 12*(Supplementary Issue 1), 83–100.

Wallace, A.R., & Boylan, C.R. (2001, December). *Interaction patterns in the extended classroom via satellite technology in the Australian outback.* Paper presented at the Annual meeting of the New Zealand Association for Educational Research, Christchurch, NZ.

Wasserman , S., & Faust, K. (1994). *Social network analysis : Methods and applications*. Cambridge: Cambridge University Press.

Wellman, B., & Haythornthwaite, C. (2002). *The Internet in everyday life*. Oxford, UK: Blackwells.

Wellman, B. (1999). The network community: An Introduction. In B. Wellman (Ed). *Networks in the global village* (pp. 1-48). Boulder: Westview Press.

Wenger, E., & Snyder, W. (2000). Communities of practice: The organizational frontier. *Harvard Business Review,* January-February, 139-145.

Westheimer, J., & Kahne, J. (1993). Building school communities: An experience-based model. *Phi Delta Kappan*, 75(4), 324-328.

Widén-Wulff, G., & Ginman, M. (2004). Explaining knowledge sharing in organizations through the dimensions of social capital. *Journal of Information Science, 30*(5), 448-458.

Woolcock, M. (1998). Social capital and economic development: Toward a theoretical. synthesis and policy framework. *Theory and Society, 27*(2), 151-208.

Woolcock, M. (2001). The place of social capital in understanding social and economic outcomes, *Isuma: Canadian Journal of Policy Research*, *2*(1), 11-17.

World Bank (1999). *Social capital research group*. Retrieved July 3, 2007 from http://www.worldbank.org/poverty/scapital/.

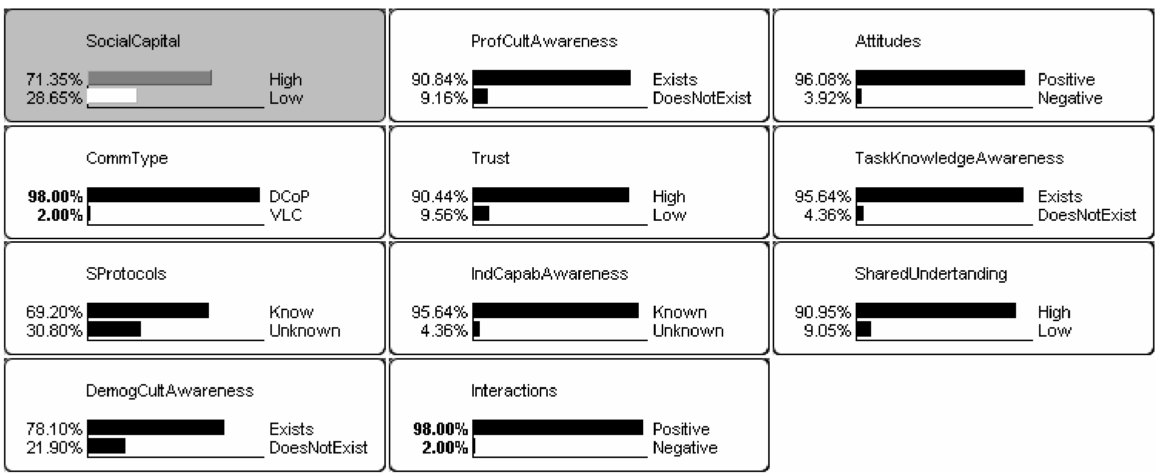
Zapata-Rivera, J.D., & Greer, J. (2004). Interacting with Bayesian student models. *International Journal of Artificial Intelligence in Education, 42*(1), 127-163.

Zapata-Rivera, J.D. (2002). cbCPT: Knowledge engineering support for CPTs in Bayesian networks. *Proceedings of Canadian Conference on AI* (pp. 368-370).

Appendices

Appendix A: View of initial probability values for the social capital model

Appendix **A** shows the probability distribution of the 11 variables of social capital in virtual communities, with evidence that social capital is high [values generated by a Hugin Bayesian Belief Simulator].



Appendix B: Results of the Sensitivity Analysis

Appendix B shows the spread of probabilities obtained from the sensitivity analysis. Each variable was examined with respect to social capital, including social capital to itself. Overall findings are reported in percentages and each sensitivity value is measured in terms of its entropy reduction value.

Probability of new finding = 100 %, of all findings = 100 %.

Sensitivity of '*SocialCapital*' to findings at '*SocialCapital*':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0	0.5423	1	0.4982
Low	0	0.4577	1	0.4982

Entropy reduction = 0.9948 (100 %)
Belief Variance = 0.2482 (100 %)

Sensitivity of 'SocialCapital' to findings at 'Interactions':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3168	0.5423	0.7677	0.2255
Low	0.2323	0.4577	0.6832	0.2255

Entropy reduction = 0.1534 (15.4 %)
Belief Variance = 0.05083 (20.5 %)

Sensitivity of 'SocialCapital' to findings at 'Attitudes':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3169	0.5423	0.7676	0.2254
Low	0.2324	0.4577	0.6831	0.2254

Entropy reduction = 0.1533 (15.4 %)
Belief Variance = 0.05079 (20.5 %)

Sensitivity of 'SocialCapital' to findings at 'TaskKnowledgeAwareness':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3162	0.5423	0.764	0.2239
Low	0.236	0.4577	0.6838	0.2239

Entropy reduction = 0.1511 (15.2 %)
Belief Variance = 0.05012 (20.2 %)

Sensitivity of 'SocialCapital' to findings at 'IndCapabAwareness':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3174	0.5423	0.7628	0.2227
Low	0.2372	0.4577	0.6826	0.2227

Entropy reduction = 0.1494 (15 %)
Belief Variance = 0.04959 (20 %)

Sensitivity of 'SocialCapital' to findings at 'Trust':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3148	0.5423	0.7158	0.1987
Low	0.2842	0.4577	0.6852	0.1987

Entropy reduction = 0.1175 (11.8 %)
Belief Variance = 0.03948 (15.9 %)

Sensitivity of 'SocialCapital' to findings at 'SharedUndertanding':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.315	0.5423	0.7069	0.1934
Low	0.2931	0.4577	0.685	0.1934

Entropy reduction = 0.1112 (11.2 %)
Belief Variance = 0.03742 (15.1 %)

Sensitivity of 'SocialCapital' to findings at 'ProfCultAwareness':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.3279	0.5423	0.7076	0.1883
Low	0.2924	0.4577	0.6721	0.1883

Entropy reduction = 0.1052 (10.6 %)
Belief Variance = 0.03544 (14.3 %)

Sensitivity of 'SocialCapital' to findings at 'DemogCultAwareness':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.4328	0.5423	0.6647	0.1157
Low	0.3353	0.4577	0.5672	0.1157

Entropy reduction = 0.03937 (3.96 %)
Belief Variance = 0.0134 (5.4 %)

Sensitivity of 'SocialCapital' to findings at 'Social Protocols':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.4487	0.5423	0.6359	0.0936
Low	0.3641	0.4577	0.5513	0.0936

Entropy reduction = 0.02562 (2.58 %)
Belief Variance = 0.008761 (3.53 %)

Sensitivity of 'SocialCapital' to findings at 'CommType':

Probability ranges: ***Change***	**Min.**	**Current**	**Max.**	**RMS.**
High	0.4873	0.5423	0.5972	0.05493
Low	0.4028	0.4577	0.5127	0.05493

Entropy reduction = 0.008786 (0.883 %)
Belief Variance = 0.003017 (1.22 %)

Appendix C: Parent-child relationships analysis of variables of social capital model

This table shows the analysis of parent-child relationships, their relative weights and correlations within the social capital model.

Parent	**Child**	**Relative weight**	**Pearson's correlation**
Interactions	Attitudes	1.0000	0.6925
Interactions	IndCapabAwareness	0.1939	0.6449
Interactions	TaskKnowledgeAwareness	0.1939	0.6449
SProtocols	SocialCapital	0.1565	0.1524
Attitudes	IndCapabAwareness	0.1381	0.5700
Attitudes	TaskKnowledgeAwareness	0.1381	0.5700
DemogCultAwareness	SocialCapital	0.1245	0.1419
Interactions	SProtocols	0.0984	0.1213
SharedUnderstanding	Trust	0.0687	0.1164
ProfCultAwareness	Trust	0.0679	0.1201
DemogCultAwareness	Trust	0.0639	0.0979
ProfCultAwareness	SocialCapital	0.0594	0.1116
Trust	SocialCapital	0.0396	0.1094
CommType	SharedUndertanding	0.0375	0.0821
Attitudes	ProfCultAwareness	0.0337	0.1642
IndCapabAwareness	Trust	0.0220	0.1298
TaskKnowledgeAwareness	Trust	0.0220	0.1298
IndCapabAwareness	SocialCapital	0.0216	0.1027
Attitudes	DemogCultAwareness	0.0191	0.0832
CommType	ProfCultAwareness	0.0179	0.0525
Attitudes	SharedUndertanding	0.0150	0.1246
Interactions	SharedUndertanding	0.0122	0.1284
Interactions	ProfCultAwareness	0.0115	0.1562
CommType	DemogCultAwareness	0.0095	0.0353
Interactions	DemogCultAwareness	0.0012	0.0641
TaskKnowledgeAwareness	SocialCapital	0.0000	0.0676
Shared Understanding	SocialCapital	0.0000	0.0218

Appendix D: A sample of a standard sense of community index

I am going to read some statements that people might make about this class. Each time I read one of these statements, please mark it as mostly true or mostly false simply by writing "true" or "false" next to the item.

True = 1 False =0

I. I think my class (deleted) is a good place for me to learn.

2. People in this class do not share the same values.

3. My classmates and I want the same things from this class.

4. I can recognize most of the people who participate in my class.

5. I feel at home in this class.

6. Very few of my classmates know me.

7. I care about what my classmates think of my actions.

8. I have no influence over what this class is like.

9. If there is a problem in this class people who work here can get it solved.

10. It is very important to me to learn in this particular class.

11. People in this class generally don't get along with each other.

12. I expect to know the people in this class for a long time.

Name:

Appendix E: Sample of the survey instrument for the model verification

Survey Questionnaire

Thank you for agreeing to take part in this study. The purpose of the study is to find out more about your experiences interacting with others in one of the online courses you have taken as part of your graduate degree/diploma in [program name]. The goal of this study is to understand the fundamental variables and characteristics of social capital in virtual communities, with the aim of updating a computational model of social capital built to simulate effective interactions in virtual communities.

In this part of the study, I would like you to fill out the following questionnaire. The questionnaire is divided into three parts. Part one asks about your background. Part two is about your participation and part three is about your relationships with others in the class. Your answers to these questions will be anonymous. Neither your instructor nor your colleagues will see your responses. So please, feel free to express your true opinions on the questions. For questions with pre-specified options, place an “X” next to the single choice or (choices) that are appropriate to your situation. I will appreciate if you can answer the questions with a statement (s) that is clear and complete as much as you can.

1. Gender

    [ ] Male

[ ] Female

2. First Language

[ ] English

[ ] Other, please specify---

3. Degree sought/completed

[ ] M.Ed

[ ] M.Sc.

[ ] PhD

[ ] Others, please specify--

4. What is your current practice?

[ ] School teacher

[ ] University lecturer

[ ] Instructional designer

[ ] Corporate learning specialist

[ ] Administrator

[ ] Technology coordinator

[ ] Others, please, specify---

----

5. What is your background training before joining the program? ---------------------------

----

6. How many people did you personally know before taking the class?

   [ ] Few

   [ ] Almost everybody

   [ ] Nobody at all

7. How often did you participate in class related discussions?

   [ ] Very often

   [ ] Less often

   [ ] Never

8. How often did you participate in discussions of issues not related to the class materials?

   [ ] Very often

[ ] Less often

[ ] Never

9. How often did you share class related resources with others in that class?

[ ] Very often

[ ] Less often

[ ] Never

10. How often do you maintain contact with classmates outside class?

[ ] Very often

[ ] Less often

[ ] Never

11. When faced with problems related to the content of the class, who did you sought for help?

    [ ] Instructor of the course

    [ ] Friend(s) in the class with whom I maintained personal contacts

    [ ] Moderator of the course

    [ ] Nobody

    [ ] Others, please, specify--

12. Were there any explicit social protocols guiding participation in that class?

    [ ] Yes

    [ ] No

    [ ] I don't know

13. Were there clear expectations from the instructor in regards to contribution to discussions in the class?

    [ ] Yes

    [ ] No

    [ ] I don't know

14. To what extent do you think established social protocols by the instructor have influenced your participation in that class?

[ ] To a very small extent

[ ] To small extend

[ ] Neither small nor great

[ ] To a great extent

15. Was it likely or unlikely that people who did not participate in the class were either explicitly or implicitly sanctioned?

[ ] Very likely

[ ] Somewhat likely

[ ] Very unlikely

[ ] I don’t know

16. Do you think that people in class shared common values?

[ ] Yes

[ ] No

17. Do you think that people in that class shared common goals?

[ ] Yes

[ ] No

18. In your opinion how well did people in that class help each other on class related issues?

[ ] Always helping

[ ] Helping most of the time

[ ] Rarely helping

[ ] Never helping

19. If an issue discussed in the class did not interest you or related to your class project but of interest to others. How much did you contribute to those kinds of discussion?

[ ] Often contributed to the discussions

[ ] Rarely contributed to the discussions

[ ] Never contributed to the discussions

20. During your interactions with others in the class, how many people did you believe were knowledgeable about the content of the class material? ------------------------------ ---

21. Overall how many people did you think were capable of offering useful help during difficult problems related to the course materials?

22. In general do you agree or disagree with the following questions.

I. Most of people in that class could be trusted

[ ] Agree

[ ] Disagree

II. In that class one had to be alert or someone was more likely to take advantage of others

[ ] Agree

[ ] Disagree

III. Most of the people in that class were willing to offer help when needed

[ ] Agree

[ ] Disagree

IV. In general people in that class did not trust what does say during discussions in the class

[ ] Agree

[ ] Disagree

23. In a scale of 1-5 where 1 means very small extent and 5 means very great extent. How much did you trust people in that class or similar class you might have taken in the past?

	1-To a very small extent
	2-To a small extent
	3-Neither small nor great extent
	4-Toa great extent
	5-To a very great extent
a) People with whom you share professional backgrounds	
b) People with whom you share demographic background	

(e.g. language and gender)	
c) The instructor of the class	
d) Moderator of the class	
e) People who seemed to know a lot about the content of the class materials f) Nobody could be trusted in that class	

24. In your opinion, overall over the course of time in the class, the level of trust among people in the class had gotten better, worse, or stayed about the same

[ ] Gotten better

[ ] Gotten worse

[ ] Stayed about the same

25. In your opinion how strong was the feeling of togetherness in that class?

[ ] Very distant

[ ] Somewhat distant

[ ] Neither distant nor close

[ ] Somewhat close

[ ] Very close

26. There are often differences in background in a graduate class similar to what you have taken; to what extent did such differences characterized your class?

[ ] To a very great extent

[ ] To a great extent

[ ] Neither great nor small extent

[ ] To a small extent

[ ] To a very small extent

27. Did any differences in training, opinion, language led to any problem?

[ ] Yes

[ ] No

If yes, what kinds of problems--

----

28. In your opinion, which of the following differences had or could have caused problems in that class you have taken or similar others

[ ] Differences in professional training

[ ] Differences between men and women

[ ] Differences in ethnic background

[ ] Differences in opinions

[ ] Differences in language

[ ] Differences in educational backgrounds

[ ] Any other differences, please specify---

----

29. Please, list personal or group attributes which in your opinion might have contributed to effective participation in that class

I. ---

II. --

III. --

IV. ---

V. ---

30. Any other comments

Appendix F: List of Bayesian Network Tools

Appendix F lists available BBN tools and resources on the Web some of these are freeware and open source while others are commercial.

Name	**Authors**	**URL/Link**
AgenaRisk	Agena	[http://www.agenarisk.com/]
Analytica	Lumina	[http://www.lumina.com/]
Banjo	Hartemink	[http://www.cs.duke.edu/~amink/software/banjo/]
BayesiaLab	Bayesia Ltd	[http://www.bayesia.com/]
Bayesware Discoverer	Bayesware	[http://www.bayesware.com/]
B-course	U. Helsinki	[http://b-course.hiit.fi/]
Belief net power constructor	Cheng (U.Alberta)	[http://www.cs.ualberta.ca/~jcheng/bnpc.htm]
BNT	Murphy (U.C.Berkeley)	[http://www.cs.ubc.ca/~murphyk/Software/BNT/bnt.html]
BUGS	MRC/Imperial College	[http://www.mrc-bsu.cam.ac.uk/bugs/]
Causal discoverer	Vanderbilt	[http://discover1.mc.vanderbilt.edu/discover/public/]
CoCo+Xlisp	Badsberg (U. Aalborg)	[http://www.math.aau.dk/~jhb/CoCo/information.html]
CIspace	Poole et al. (UBC)	[http://www.cs.ubc.ca/labs/lci/CIspace/]
DBNbox	Roberts et al	[http://www.robots.ox.ac.uk/~parg/software.html]
Deal	Bottcher et al	[http://www.math.aau.dk/novo/deal/[
DeriveIt	DeriveIt LLC	[http://www.deriveit.com/]
Ergo	Noetic systems	[http://www.noeticsystems.com/]
GDAGsim	Wilkinson (U. Newcastle)	[http://www.staff.ncl.ac.uk/d.j.wilkinson/software/gdagsim/]
Genie	U. Pittsburgh	[http://genie.sis.pitt.edu/]
GMTk	Bilmes (UW), Zweig (IBM)	[http://ssli.ee.washington.edu/~bilmes/gmtk/]
gR	Lauritzen et al.	[http://www.ci.tuwien.ac.at/gR/]
Grappa	Green (Bristol)	[http://www.stats.bris.ac.uk/~peter/Grappa/]
Hugin Expert	Hugin	[http://www.hugin.com/]
Java Bayes	Cozman (CMU)	[http://www.cs.cmu.edu/~javabayes/Home/]
MIM	HyperGraph Software	[http://www.hypergraph.dk/]
MSBNx	Microsoft	[http://research.microsoft.com/adapt/MSBNx/]
Netica	Norsys	[http://www.norsys.com/]

Appendix G: List of publications related to this thesis

Book Chapters

1. **Daniel, B.K.**, Sarkar, A. & O'Brien, D. (in press). User-Centred Design for Online Learning Communities: A Sociotechnical Approach for the Design of a Distributed Community of Practice in Tomei, L. (Eds). *Online and Distance Learning: Concepts, Methodologies, Tools, and Applications. Information Science reference*. Hershey: Idea Group.

2. **Daniel, B.K**., Zapata-Rivera, J.D. & McCalla, G.I. (2007). A Bayesian Belief Network Approach for Modelling Complex Domains. In Mittal, A., Kassim, A. & Tan, T. (Eds.). *Bayesian Network Technologies: Applications and Graphical Models*. *Hershey*: Idea Group.

3. Mohan, P. & **Daniel, B.K.** (2007). Caribbean Learning Objects Repositories for Education (CaribLORE): Advanced Technologies for Enhancing Teaching, Learning, and Research. *In New Directions in University Education - Perspectives from the Developing World.* Watson, E.F. & Grant, J. M.A. (eds). Barbados: Learning Resource Centre: The University of the West Indies.

4. Schwier, R.A., & **Daniel, B.K**. (in press). Implications of Virtual Learning Communities for Designing Online Communities of Practice in Higher Education. In C. Kimbel & P. Hildreth (Eds.), *Communities of Practice: Creating Learning Environments for Educators*. Greenwich, CT: Information Age Publishing.

5. **Daniel, B.K**., Sarkar, A. & O’Brien, D. (in press). Theory and Practice of Designing Distributed Communities of Practice: Experience from the Canadian Governance Knowledge Network. In Beaudet, C. Grant-Russell, P. & Starke-Meyerring, D. (Eds.). *Social and Human Sciences Research for a Global Civil*

Society: Research Communication, Public Discourse, and Citizen Engagement. Cambridge: Cambridge Scholar Press.

6. **Daniel, B.K.**, McCalla, G.I. & Schwier, R.A. (2007).) Bayesian Belief Network approach for analysis of intercultural collaboration in virtual communities using social capital theory. In T. Ishida, S.R. Fussell, & P.T.J.M. Vossen, (Eds.). *Intercultural collaboration I: Lecture notes in computer science*. New York: Springer-Verlag.
7. Schwier, R.A., & Daniel, B.K. (2007). Did we become a community? Multiple methods for identifying community and its constituent elements in formal online learning environments. In N. Lambropoulos, & P. Zaphiris (Eds.), *User-evaluation and online communities* (pp. 29-53). Hershey, PA: Idea Group Publishing.
8. **Daniel, B.K.**, Sarkar, A. & O'Brien, D. (2006). User-Centred Design for Online Learning Communities: A Sociotechnical Approach for the Design of a Distributed Community of Practice in Lambropoulos, N., & Zaphiris, P. (Eds). *User- Evaluation and Online Communities, pp. 54-70. Hershey*: Idea Group.
9. **Daniel, B.K.,** Zapata-Rivera, D. J., & McCalla, G. I. (2003). A Bayesian Computational Model of Social Capital in Virtual Communities. In Huysman, M., Wenger, E., and Wulf, V. *Communities and Technologies*, pp.287-305. London: Kluwer Publishers.
10. **Daniel, B.K.,** O’ Brien, D. & Sarkar, A. (2003). A Design Approach for Canadian Distributed Community of Practice on Governance and International Development: A Preliminary Report. In Verburg, R.M. and De Ridder, J.A. (Eds.).

Knowledge sharing under distributed circumstances, (pp.19-24). Enschede: Ipskamps.

Journal Papers

1. **Daniel, B.K**., McCalla, G.I. & Schwier, R.A. (accepted). Soft and hard data patterns of knowledge sharing in a virtual learning community. *International Journal of Advanced Media and Communication (IJAMC).*

2. **Daniel, B.K.** & Schwier, R.A. (accepted). Building a Bayesian Belief Network to Model a Virtual Learning Community. *International Journal of Web Communities.*

3. **Daniel. B.K.**, Schwier, R.A., & Ross, H. (accepted). Synthesis of the process of learning through discourse in a formal virtual learning community. *Journal of Interactive Learning Research (JILR).*

4. Matheos, K., **Daniel, B.K.,** McCalla, G. (2005). Dimensions for Blended learning technology: Learners' Perspectives. Journal of Learning Design, 1(1), pp. 56-76.

5. **Daniel, B.K.**, McCalla, G. Schwier, R. (2003). Social Capital in Virtual Learning Communities and Distributed Communities of Practice. *The Canadian Journal of Learning Technology, 29(3), pp. 113-139.*

6. **Daniel, B.K.** (2000) The Internet, a Wild Weird World (WWW) Making the University Professor a Computer Geek or just Calling for more Competence? Oslo University: *Pedagogik Profil* (1) (2000), pp. 14-20.

Papers in Referred National and International Conferences

1. Daniel, B.K., & Schwier, R.A. (2007). Employing social network techniques to understand community engagement in a formal virtual learning community. To appear in the *Proceedings of World Conference on Educational*

Multimedia, Hypermedia and Telecommunications. Vancouver, Canada, June 25- June 29, 2007

2. **Daniel, B.**K., McCalla, G.I. & Schwier, R.A. (2006). Social Network Analysis: Implications for Information and Knowledge Sharing in Virtual Learning Communities. *The Proceedings of* ***Learning Systems of the Future: Integrating Knowledge and Services***. *LORNET 3rd Annual Scientific e-learning conference on Intelligent Interactive Learning Object Repositories (I^2LOR 2006)* on November 8 to 10, 2006 in Montreal, Quebec.
3. **Daniel, B.K.**, McCalla, G., & Schwier, R. (2006). Bayesian belief network models of trust and social capital for social software systems design. Workshop: Reinventing trust, collaboration and compliance in social systems. CHI 2006, Montreal, April 22-27.
4. Mohan, P., Bucarey, S. & **Daniel, B.K**. (2006) Employing Object-Oriented Design Principles in the Design of Learning Objects in a Software Engineering Course. *The Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies*, July 5-7, 2006 – Kerkrade, Netherlands.
5. Schwier, R.A., & **Daniel, B.K.** (2006). Aggregated approaches to identifying community and its constituent elements in formal blended learning environments. *Proceedings of selected research and development papers from the Annual Conference of the Association for Educational Communications and Technology* (AECT), Dallas, TX.

6. **Daniel, B.K.** & Poon, N. (2006). Social Network Techniques and Content Analysis of Interactions in a Video-Mediated Virtual Community. *The Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies*, July 5-7, 2006 – Kerkrade, Netherlands.
7. Mohan, P. & **Daniel, B.K.** (2006). Towards Object-Oriented Design Patterns for Reusability of Learning Objects. *The Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies*, July 5-7, 2006 – Kerkrade, Netherlands
8. Schwier, R.A., **Daniel, B.K.**, & Ross, H. (2005). The nature of manifest learning in two virtual learning communities. *Paper presented to the annual convention of the Association for Educational Communications and Technology*, Orlando, Florida, October 20, 2005.
9. **Daniel, B.K.**, McCalla, G.I., & Schwier, R.A. (2005). Data mining and modeling social capital in virtual learning communities. *The proceedings of the 12th International Conference on Artificial Intelligence in Education, Amsterdam, 18-22 July.*
10. Daniel, B.K., McCalla, G.I. and Schwier, R.A. (2005a) 'Data mining and modelling social capital in virtual learning communities', The Proceedings of the 12th International Conference on Artificial Intelligence in Education, Amsterdam, 18–22 July, pp.2003–2008.
11. **Daniel, B.K.**, Schwier, R.A., and Ross, H. (2005). Intentional and Incidental Discourse Variables in a Virtual Learning Community. *The proceedings of E-Learn 2005--World Conference on E-Learning in Corporate, Government,*

Healthcare, and Higher Education to be held in Vancouver, Canada, October 24-28, 2005.

12. **Daniel, B.K**., Poon, N., and Sarkar, A. (2005). Analysis of Patterns of Interactions in Video-Chat Supported Virtual Communities to Model Social Capital. *The proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications. ED-MEDIA 2005* -- *Montreal, Canada, June 27- July 2, 2005.*
13. Ross, H., & **Daniel, B.K.** (2005). Technology Enhanced Learning Community: Tribes in the Classroom. *Proceedings of the 3rd Annual Hawaii International Conference on Education Honolulu, Hawaii Jan 4-7, 2005, pp, 3720-3727.*
14. Winter, M., **Daniel, B.K.**, & Brooks, C. (2005). Towards Automatic Discovery of Peer Helpers from a Large Message Board System. *The proceedings of Usage analysis in learning systems workshop of the 12th International Conference on Artificial Intelligence in Education, Amsterdam, 18-22 July (poster).*
15. Mohan, P. & **Daniel, B.K.** (2004). The Learning Objects' Approach: Challenges and Opportunities. *The proceedings of E-Learn 2004* -- *World Conference on E-Learning in Corporate, Government, Healthcare, & Higher Education. November 1-5, Washington, DC.*
16. **Daniel**, B.K. & Poon, N. & Sarkar, A. (Eds) (2004). *Governance Knowledge Network: Building Distributed Communities of Practice for Enhanced*

Research-Policy Interface. Workshop Proceedings of Distributed Communities of Practice. 28th -31st May, 2004

17. **Daniel, B.K**., and Mohan, P. (2004). Re-Engineering the Public University with Reusable Learning Objects Approach. *The proceedings of the International Conference on Education and Information Systems: Technologies and Applications, Orlando, Florida, USA, July 21-25.*

18. **Daniel, B.K.**, Sarkar, A., and O'Brien, D. (2004). A Participatory Design Approach for a Distributed Community of Practice on Governance and International Development. The proceedings of Ed-Media World Conference on Educational Multimedia, Hypermedia and Educational Telecommunications. Lugano, Switzerland June 21st-26th.

19. **Daniel, B. K.,** & Mohan, P. (2004). A Model for Evaluating Learning Objects. In Kinshuk, Looi C.-K., Sutinen E., Sampson D., Aedo I., Uden L. & Kähkönen E. (Eds.), *Proceedings of the 4th IEEE International Conference on Advanced learning Technologies 2004*, Los Alamitos, CA: IEEE Computer Society, 56-60.

20. **Daniel, B.K.**, Matheos, K., McCalla,G. (2004) Blended Learning Approach for Technology Enhanced Learning Environment. *The proceedings of E-Learn 2004 -- World Conference on E-Learning in Corporate, Government, Healthcare, & Higher Education. November 1-5, Washington, DC.*

21. **Daniel, B.K.,** O'Brien, D., and Sarkar, A. (2004). The Cybernetics of Distributed Communities of Practice. *The proceedings of the joint International Conference on Education and Information Systems,*

Technologies and Applications and the International Conference on Cybernetics and Information Technologies, Systems and Applications, Orlando, July 21-25, 2004.

22. **Daniel, B.K.,** & Wu, H. (2003). LearningObject-Markup Language (LOML): A Vocabulary for Defining a Schema for Learning Objects. Proceedings of International Conference on Computers in education, Hong Kong, December 3-7
23. **Daniel, B.K.,** Tang, T., Winoto, P., Sharifi, G., & Niu, X (2003). IDEAL Collaborative Learning System to Support Argumentative Learning. *Proceedings for International Conference in Computers in education, Hong Kong, December 3-7*
24. **Daniel, B.K.**, & Wu, H. (2003). Developing Learning Objects based on Object Oriented Model (OOM). *Proceedings of 3rd IEEE International Conference on Advanced Learning Technologies*. July 9-11, 2003, Athens, Greece.
25. **Daniel, B.K.**, Tang, T., Winoto, P., Sharifi, G., & Niu, X (2003) Intelligent DirEctors for Argumentative Learning (IDEAL). *Proceedings of 3rd IEEE International Conference on Advanced Learning Technologies*. July 9-11, 2003, Athens, Greece.
26. **Daniel, B.K.**, McCalla, G., Schwier, R. (2002). A Process Model for Building Social Capital in Virtual Learning Communities. *Proceedings of the International Conference on Computers in Education (ICCE).* Auckland New Zealand December 2-4 2002: pp. 574-577

27. **Daniel, B.K.** (2000) Engineering Methodology for Educational Webware Development. *The Proceedings of WebNet 2000-World Conference on the WWW and Internet.* San Antonio, Texas; October 30th- November 4th, 2000, pp.871-873

28. **Daniel, B.K.** (1999) Systematic Design and Development of Courseware for Distance Education. Amsterdam: IOS Press.

29. **Daniel, B.K,** & Thune, T, (Eds.) (1999). Cross-Country Reports on Educational Systems. Oslo: Oslo University Press.

Referred Workshops and Posters

1. **Daniel, B.K**., Zapata-Rivera, J.D & McCalla, G.I. (2005). Computational Framework for Constructing Bayesian Belief Network Models from Incomplete, Inconsistent and Imprecise Data in E-Learning (Poster).*The second LORNET International Annual Conference, I2LOR-2005, and November 16 to 18, 2005. Vancouver, Canada.*

2. **Daniel, B.K.**, McCalla, G., and Mohan, P. (2004). Evaluating Learning Objects: Critical Dimensions (Poster). *First annual scientific conference of the LORNET Research Network I2LOR-04-04. Towards the Educational Semantic Web, November 18-19, Université du Québec à Montréal, Montreal (Quebec).*

3. Mohan, P. & **Daniel, B.K.** (2004). A New Distance Education Model for the University of the West Indies: A Learning Objects' Approach. *Workshop proceedings of the IEEE 2nd International Workshop on Technology for Education in Developing Countries 2004 (TEDC 2004). August 30th-September 1st, 2004. Joensuu, Finland.*

4. **Daniel, B.K.** (2000). Rapid Prototyping Methodology for Educational Software Design. 9th- International Conference on World Wide Web, On-line Learning Workshop. May 15th- 2000, Amsterdam-Netherlands.