Network Effects on Learning during Disasters: The Case of Australian Bushfires

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ABSTRACT

Disasters are not just a humanitarian or development problem; disasters are a global challenge that increasingly affects all regions and all parts of society. One of the major disasters that affect Australia is Bushfire. Large areas of land are ravaged every year by bushfires, which also cause property damage and loss of life. In a dynamic environment like bushfire, the largest problems for managers often derive from collaborative problem solving, learning and other problem of coordination between the different organizations. Failure of information sharing or lack off will be the main reason for coordination failure during disasters. Emergency Management Organizations that do not learn from previous mistakes and lack sufficient capacities for self-adaptation make similar mistakes that increase their vulnerability to emergency events. Innovative solutions are needed improve disaster response and improve the performance of response operations. The aim of this research is address this global challenge by using Social Network Analysis to uncover the pattern of people's interactions. The success or failure of the response operations may depend on these patterns.

Understanding factors that enhance or diminish learning levels of individuals and teams is significant for achieving both individual (low level) and organisational (high level) goals. In this study, the effect of social network factors at all levels of analysis (actor level, dyadic level and network level) on learning attitudes of emergency personnel in emergency events is investigated.

Based on social network concepts of structural holes and strength of weak ties, and the social influence model of learning, a conceptual model is developed. To test and validate the model, data was collected from the transcripts of the 2009 Victorian Bushfires Royal Commission reports in conjunction with the 2008 Australian Inter-Service Incident Management System (AIIMS) survey. Secondly, network measures of structural holes (constraint and efficiency), degree centrality, betweenness centrality, tie strength and density were applied for exploring the association with learning from a sample of people working

within Incident Management Teams, combat roles and coordination centres across Australia and New Zealand.

Empirical results suggest that social network factors at all levels of analysis (actor, dyadic and network levels) of emergency personnel play a crucial role in individual and team learning. In particular, network constraint was found to be negatively associated with individual learning whereas tie strength within an incident management team and across teams was found to be positively correlated with team learning.

The findings from this research resonate with results from previous literature. They extend the traditional theory of social networks and learning to include emergency personnel involved in emergency events. For individuals in such non-competitive, dynamic and complex environments, established social network concepts such as structural holes theory still operate. Nevertheless, a crucial outcome is that social network position is a more effective predictor of learning even though the social network structure is still vital. The second vital finding addresses a major gap in the literature concerning understanding social processes that influence learning in a dynamic complex environment.

Furthermore, this study demonstrates that not only does the strength of ties within a team function as a channel of new ideas and information; it is the strength of ties across teams within networks which also enhance learning and adaptability. The results show that increases in actors' involvement within the social emergency management network influence the ability of those actors to engage in learning-related work activity. This means that more highly involved actors are better able to adapt and improvise in complex emergency events.

Methodologically, this research offers a triangulation method that utilises both qualitative and quantitative approaches. The quantitative process comprises both a survey and a content method of data collection and analysis to assist established research approaches in behavioural and social research studies. The final output from this approach is a valid and reliable data collection method that facilitates the collection of both singular attribute and social network information. The data collection method is basically reasonable to apply, and it is time-efficient and simply replicable for further related studies.

The contextual implication from the quantitative and qualitative findings of this research is that when approaches for improving the emergency response at an interpersonal level are contemplated, the importance of social structure, position and relations in the networks of emergency personnel needs to be considered carefully as part of the overall individual and organisation-level goals. With this model of learning-related work activity, based on network connectedness, emergency staff members can strengthen their capacity to be flexible and adaptable. The findings of this study may be appreciated by emergency managers or administrators for developing an emergency practice culture to optimise individual and team learning and adaptability within an emergency management context.

List of Abbreviations

Abbreviation	Meaning
ABS	Australian Bureau of Statistics
AIDS	Acquired Immunodeficiency Syndrome
AFAC	Australia Fire Authorities Council
AIIMS	Australian Inter-Service Incident Management System
BOM	Bureau of Meteorology
CAD	Computer Aided Dispatch
CCS	Centre for Complex Systems
CRC	Co-Operative Research Centres
CFA	Country Fire Authority
DIC	Deputy Incident Controller
DSE	Department of Sustainability and Environment
ESTA	Emergency Services Telecommunications Authority
GSS	General Social Survey
HIV	Human immunodeficiency virus
HRO	High Reliability Organisation
IC	Incident Controller
ICC	Incident Control Centre
ICS	Incident Control System
iECC	integrated Emergency Coordination Centre
IMT	Incident Management Team
IT	Information Technology
LO	Logistics Officer
MGA	Map Grid Australia
MIT	Massachusetts Institute of Technology
NEO	Networked Emergency Organisation
NSW	New South Wales
NIMS	National Incident Management System
OO	Operations Officer
PO	Planning Officer
R&D	Research and Development
RDO	Regional Duty Officer
RECC	Regional Emergency Coordination Centre
SOP	Standard Operating Procedure
SN	Social Network
SNA	Social Network Analysis
SES	State Emergency Service
SDO	State Duty Officer
VBIL	Victorian Bushfire Information Line

Preface

When I graduated from my masters degree in Project Management, I applied to one place, the University of Sydney, to work with one person, Prof. Liaquat Hossain, who motivated me to pursue research exploring emergency response management using social network and learning theories. I am truly thankful to him for his scholarly and academic guidance and supervision, generous funding support and for being a friend. Liaquat has a flair and talent for research supervision and management, a born-natural in idea generation, knowledge sharing and conceptualisation that laid the basis for this work. I also thank Dr Christine Owen for her constructive feedback on my research and support as an associate supervisor. In addition, I sincerely acknowledge the support of the Bushfire CRC and the personnel from the agencies involved in completing the survey. To everyone in my research group (i.e., the Centre for Complex Systems), thank you for your help and support and for providing an open and pleasant environment for research. My acknowledgement and thanks also to Ms. Joan Rosenthal for her excellent editorial skills in improving the readability of the thesis.

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"Glory to Thee, of knowledge We have none, save what Thou Hast taught us: In truth it is Thou Who art perfect in knowledge and wisdom." (Quran, Chapter 2, Verse 32)

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Chapter 1

This chapter provides the introduction, the questions, the objectives and the justification for the research study. It first introduces the concept of learning and its application in diverse disciplines, establishing the point that understanding the factors that affect learning is crucial for enhanced learning. The introduction section concludes with an appraisal of how existing models and frameworks have understood learning, along with a discussion of their limitations. It then briefly discusses the background of the study in terms of different aspects of learning, including the "learning" concept, elements and the social network approach to model learning. That section also provides an overview of the research context. The research questions and objectives are described in the subsequent section. The chapter then reports the significance of this research for theoretical development, methodological enhancement and contextual findings, before providing a basic summary of all subsequent chapters. Subsequent sections in this chapter follow the overview shown in Figure 1.1.

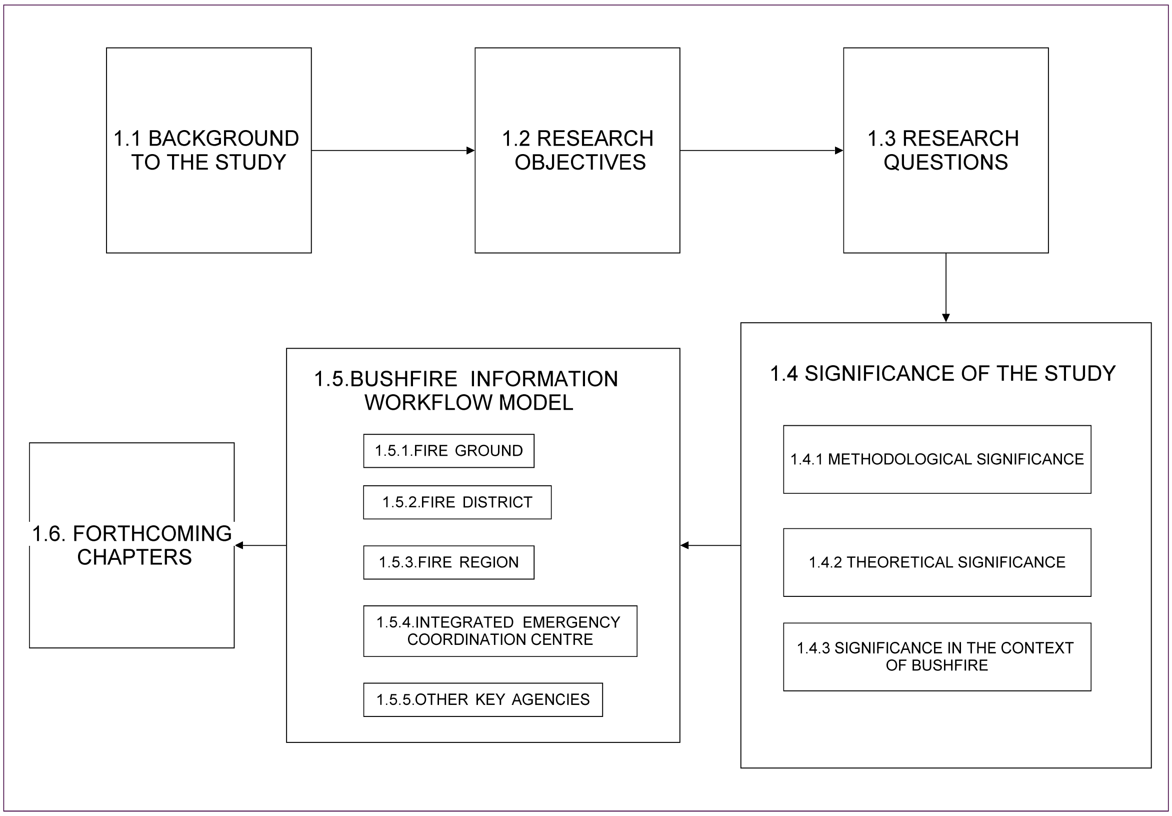


Figure 1.1: Overview of Chapter 1

1. Introduction

In the growing literature of dynamic complex environments such as bushfires, learning has been considered a central issue. It has created long-standing interest in scholars from a wide range of disciplines, including business, computer science, economics, engineering, management science, organisation theory and psychology. Throughout the twentieth century, humans have shifted from the Industrial Age through the Information Age to the Knowledge Age (Weinstein, 2009). The skill to acquire, integrate and execute correct information efficiently will come to be a major ability in the near future. Learning is the answer to accomplishing full potential in order to cope and survive in future. As a matter of fact, the existence of humans in the near future as persons, organisations, and countries will be governed by the ability to learn and the use of what was learned in practical life. Learning can bring individuals, families, organisations and communities any number of benefits, including individual growth and expanded horizons, enhanced employment chances and better career development prospects, an extended range of interests and a wider social life, and the ability to build one's own future (Harun, 2001).

Learning can be socially invigorating while also improving memory and cognitive abilities. The Campaign for Learning is an enterprise promoted by a sponsorship group which considers that all individuals appreciate learning and that lasting learning is every individual's right. This initiative espouses the belief that all individuals need to have the opportunity to learn through their life, supporting the idea of lasting learning. The concept is that everybody should take advantage of the benefit of learning prospects at any stage of life and in any situation.

The website of The Campaign for Learning (http://www.campaign-for-learning.org.uk) shows these statistics in support of continual learning:

"72% of us think we should devote more time to personal development." (http://www.campaign-for-learning.org.uk)
"95% of people think that learning about new things boosts your confidence." (National Adult Learning Survey, DfEE, 1998)

"92% of people think that learning about new things is enjoyable." (National Adult Learning Survey, DfEE, 1998)
"93% of us believe that it's never too late to learn." (http://www.campaign-for-learning.org.uk)
"83% of us believe that 'learning' will become more important in the next millennium." (http://www.campaign-for-learning.org.uk)
"Seven in ten adults (71%) think that learning can lead to a better quality of life." (Attitudes to Learning, Campaign for Learning/MORI, 1996)
"Employers invested £10.6 billion in training in 1993." (The Learning Age, DfEE, 1998)

For organisations too, many organisational theorists have explored the need for learning in different organisational perspectives. Learning is important within organisations and can bring many benefits, including superior performance and competitive advantage, enhanced customer relations, improved quality and innovation. The bottom line is that learning within organisations and at the workplace is vital for individuals, organisations, and even nations to flourish in this century. Learning in the workplace, precisely in the setting of this research study—in the bushfire context—might comprise clear manageable phases such as observing and learning from colleagues or seniors, training during the job, applying emergency guidelines during extreme events, and might include the complex steps of formal learning resulting in certificate qualifications.

1.1. Background to the Study

At this point, a brief background of this dissertation is presented in terms of the concept, methods, and context of the study.

1.1.1. Definition: Learning

In any research, learning is a concept that is extremely challenging to capture and quantify, as it deals with a multitude of factors making it hard to establish internal validity. Researchers have defined learning in different ways. Behaviourists look at learning as an aspect of conditioning and will advocate a system of rewards and targets in education. Educators who embrace cognitive theory believe that the definition of learning as a change in behavior is too narrow and prefer to study the learner rather than the environment, and in particular the complexities of human memory . Humanists emphasize the importance of self-knowledge and relationships in the learning process. Those who advocate constructivism believe that a learner's ability to learn relies to a large extent on what he already knows and understands, and that the acquisition of knowledge should be an individually tailored process of construction.

Learning has been defined and measured in different ways. Child (1977) defined learning as a process “which results in a relatively permanent change in behaviour”. However, a more useful definition is the one put forward by Lovell (1980), “learning is a reasonably permanent change in our potential for performance as the result of our past interaction with the environment”. Another definition presents learning as “a process of gaining or changing insights, outlooks, expectations or thought patterns” (Bigge, 1982). Ramsden (1988) stated that learning should be seen as a “qualitative change in a person’s way of seeing, experiencing, understanding, and conceptualising something in the real world”.

According to Chris Argyris and Donald Schon (1997), learning is defined using the terms, “**single-loop learning**” which is correcting an action to solve or avoid a mistake, while “**double-loop learning**” is correcting also the underlying causes behind the problematic action (Figure 1.2). Underlying causes may be an organization’s norms and policies, individuals’ motives and assumptions, and informal and ingrained practices that block inquiry on these causes. Double-loop learning requires the skills of self-awareness and self-management, and the willingness to candidly inquire into why what went wrong did so, without sliding into defensiveness, blaming others, making excuses, trying to be “nice and positive” to each other, protecting each other’s egos, and other automatic or unconscious patterns of behaviour that block honest feedback, inquiry and learning. Single-loop learning looks at technical or external causes; double-loop learning also looks at cultural, personal or internal causes.

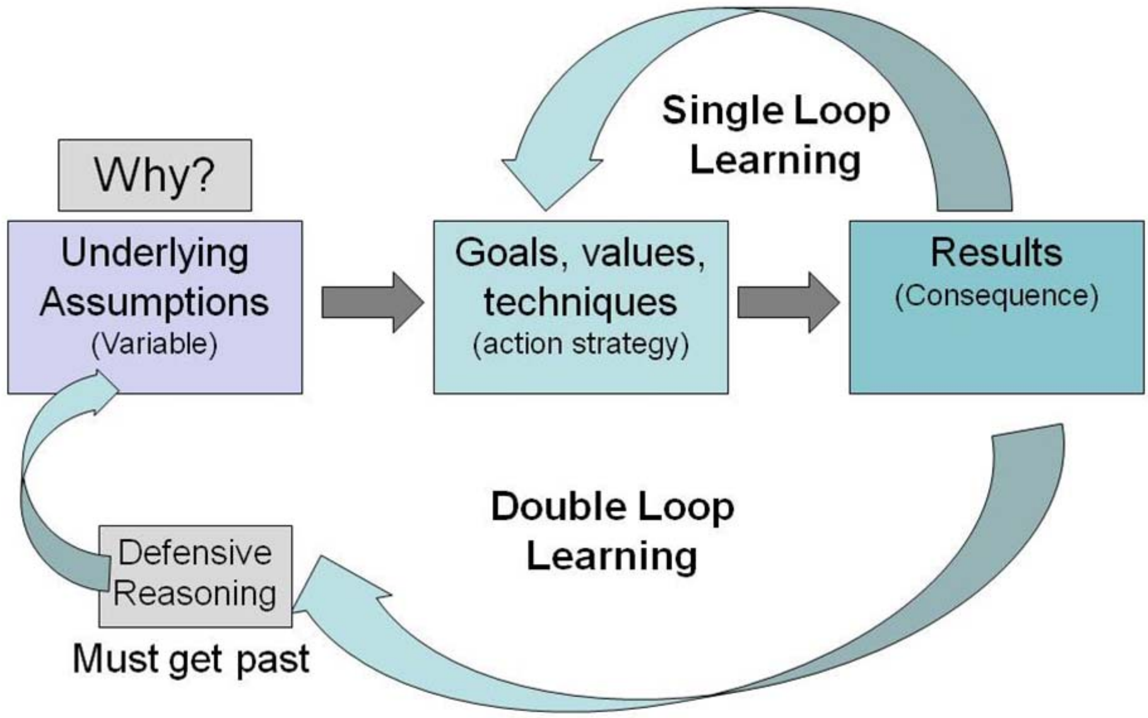


Figure 1.2: Single loop and Double loop learning (Argyris & Scholl, 1997)

Some other definitions for the term *"learning"* proposed by different researchers from a wide range of research backgrounds are as follows:

- Learning is a "permanent change in behaviour brought about by experience" (Orrell et al., 2006).
- Learning is "any process through which experience at one time can alter an individual's behaviour at a future time" (Gray and Trahan, 2006).
- Learning is "acquiring new, or modifying existing knowledge, behaviours, skills, values, or preferences and may involve synthesizing different types of information" (Kazanas, 2004).
- Learning is "the acquisition of knowledge or skills through experience, practice, or study, or by being taught" (Denkl et al., 2010).

To conclude, different definitions and techniques are used for the learning process. Nevertheless, few research studies succeeded to link the learning process with social networks. The vitality of these networks will be discussed in the following section.

1.1.2. Learning and Its Relationship with Networks

Understanding of factors that enhance and diminish learning levels of individuals is a necessity for enhanced learning. Consequently, an emergent body of research in organisational psychology and management has suggested understanding the learning process by decomposing its constructs at task level and contextual level (Lave and Wenger, 1991). Theories from learning research, for example, suggest understanding individual learning by examining the resources available within organisations (Gulati, 1999; Marsick and Watkins, 2003). Others have suggested understanding the learning process by evaluating the influence of rewards connected with any learning activity (Postman, 1962), the availability of information about learning opportunities (McGill et al., 1992; Brown and Brudney, 2003), or the availability of appropriate learning environments (Confessore and Kops, 1998). Such models, however, do not account for the significance of social processes that weave together a rich fabric of human and professional interactions that contribute fundamentally towards learning.

Nevertheless, other researchers have argued and shown that one of the characteristics that seem to be central to constructivist descriptions of the learning process is collaboration (Tam, 2000). The constructivist perception supports the contention that learners learn through collaboration with others. Learners work together as peers, applying their collective knowledge to the resolution of problems. The discussion that results from this collective effort offers learners the prospect of examining and enhancing their understanding in a continuing process (Tam, 2000).

To this end, the growing discipline of social network theory and research has developed, with its essential principle being the connectedness of individuals in social networks (Granovetter, 1985). The originality of these research studies is governed by how they rely on relational and structural properties of actors in a social network to explain individual and group outcomes such as team learning. With the pervasive evolution of information and communication technologies, social network studies now include virtual teams, computer supported cooperative networks and online communities in its realm of clarifying social outcomes. Aligning with the social network perspective of recognising individual outcomes as the consequence of network structure (Borgatti and Foster, 2003; Wagner and Leydesdorff, 2005; Neville et al., 2010), this thesis constructs a theoretical framework for understanding learning in a dynamic, complex environment by exploring its interplay with social network structure.

1.1.3. Social Networks and Learning

A social network approach is followed in this dissertation to investigate the qualities and attributes of network relationships. The basic framework of a social network can be viewed as a set of actors and a set of links between those actors (Wigand, 1988; Hamra et al., 2012a; Hamra et al., 2012c). An actor is a node which represents an entity such as an individual or an organisation in a social network. The creation of a social network is usually linked with the need for an actor to send or receive some sort of information or resources to or from others, thus creating an exchange whereby the actor invests in connections determined by the level of need (Stocker et al., 2002; Kuosa, 2011).

The theory of social networks plays a major part in classifying and measuring informal networking, which operates at a level outside the traditional structure of relations (Burstein and Linger, 2006; Hossain et al., 2012). Previous studies propose that examining social networks is beneficial for detecting network characteristics such as which individual is the most prominent and what kind of relationship exists between individuals (Mullen et al., 1991; Chung et al., 2005). The measures of social networks, such as network centrality or network constraint, are very useful for revealing the patterns of current informal networks (Brandes and Fleischer, 2005). Network centrality, for example, is a structural attribute of actors in a network that determine their relative prominence within that network. The selection of social network approaches and measures to study informal networks predominantly depends on the network under investigation and its associated level of data availability.

Social network analysis (SNA) is the mapping and measuring of interactions among actors (Wigand, 1988; Adam, 2001; Carrington et al., 2005; Liebowitz, 2005), which provides both a mathematical and a visual analysis of network relations (Chan and Liebowitz, 2006). It has been fruitfully applied to assessing the position of actors in the network. The convenience of applying SNA to networks is appreciated across several disciplines because of its capacity to evaluate structural patterns and network behaviour (Brandes and Fleischer, 2005). By exploring a network in terms of nodes and relationships, an assessment of prediction can be made which permits anticipation of events such as the spread of disease or the dissemination of innovation (Borgatti, 2005). As well, SNA allows us to examine a network to obtain insight into how and why information flows within the network, which may in turn have consequences for the learning process. The capacity to make this kind of conjecture and to graphically visualise networks may be particularly valuable for developing a design of patterns for learning.

Network effects on individuals' ability to learn have been acknowledged in studies in communications, social psychology and sociology. In organisations, the complex nature of learning can be seen by the need for employees to share information, delegate and decompose tasks, or coordinate to solve problems. In each case, an informal social network evolves. SNA allows us to investigate and visualize such informal networks in order to understand the interactions and network properties that are linked with a specific outcome of learning. This approach for studying the learning process helps to provide insight into network circumstances such as the level of network involvement for certain actors, the existence of any structural holes, and any other enabling or inhibiting factors that may produce a particular learning outcome.

1.1.4. Overview of Study Context: Bushfires

The quality of learning in dynamic complex environments such as bushfires is affected by a range of factors such as communications skills, education, experience, the use of technology and so on. Keeping such factors constant, learning to a large degree is the outcome of getting the correct available data to complete the mission or to resolve multifaceted difficulties. For instance, obtaining information and identifying individuals with the correct information are essential for learning and improved performance. While knowledge and experience are crucial factors, they are not enough to create superior performance. Faraj and Sproull (2000) contend that knowledge should be organised in order to realise its full potential. This necessitates knowing where expertise is positioned and where expertise is required, and obtaining the desired expertise.

The problem is highlighted during extreme non-routine events such as disasters (Hansson et al., 2011). Grinter et al. (1999) argue that, regardless of the area of expertise and the customised steps in organisational work, the most relevant problem is the position of expertise. Cross and Cummings (2004) argue that individuals who are not aware of the position of expertise elsewhere, and who have relatively few connections covering organisational and geographical boundaries, suffer from limited ability to obtain valuable information for work purposes. Moreover, the literature emphasises the significance of social network theories at all level of analysis (actor, dyadic and network levels). For example, people who have a tendency to remain in closed networks are likely to have similar non-diverse relations and their connections are usually with the same individuals. Such people are less successful in adapting to a dynamic changing environment. The reason for that is that such people receive similar and old information and their effort is thus marked with low-quality learning (Podolny and Baron, 1997; Reagans and Zuckerman, 2001; Ancona and Caldwell, 2007).

The effect of network use in disaster response teams has been sufficiently well documented in disaster research. In dynamic complex environments such as emergencies, SNA has proved useful for understanding the diffusion of information among emergency response organisations. For example, SNA was successful in helping to understand the social processes that occurred throughout the events on September 11 and in the days and weeks that followed in New York City’s massive destruction and social disruption. In other network disaster studies, traditional SNA has been widely used to understand disasters, emergencies, and the spread of human immunodeficiency virus (HIV) disease (Morris, 1994). It is particularly beneficial for distributed groups such as bushfire response teams, who find preservation of ties with peers and communities challenging and expensive. However, although the overall argument from these research studies is that an actor's social relations are established, enabled and sustained in a routine environment, very few studies have considered the connections between emergency personnel and organisations during an unstable and dynamic environment. Aligning with the social network standpoint of recognising individual outcomes as the consequence of network structure (Borgatti and Foster, 2003), this research constructs a theoretical framework for understanding the relationship between social network structure and the learning of individuals and organisations during extreme events.

1.2. Research Questions

This thesis investigates the interplay between social network structure and learning in a dynamic complex environment. Most network studies have focused on networks in very routine and stable situations. But these traditional frameworks for studying social networks are not adequate for research in a non-routine and dynamic environment, such as a disaster (Varda et al., 2009). Based on this, the following questions motivate this research:

1. How can learning in a dynamic complex environment be explored through the emergent patterns of social processes? How can it be evaluated?
2. What is the role of social networks in understanding learning in a dynamic complex environment? Why is the understanding of social network structure and position important for understanding learning in a dynamic complex environment?
3. Is there a relationship between the configuration of social network structures and learning in a dynamic complex environment?
4. How can the properties of social networks within various levels of relations among actors help in modelling the dynamics of learning?

The research questions stated above were tested through the literature review, in chapter 2, against what is already known about Network Effects on Learning during Disasters. Through the literature review, it was found that these research questions have not been answered satisfactorily. However, some of the questions asked in the earlier stage of research, which are not mentioned here, have been answered in the literature and therefore they were modified. This process is continuous until it was found that the above research questions have not been answered adequately in the literature. Therefore, this dissertation will try to find the answers for these questions.

1.3. Research Objectives

The following are the objectives of this research, along with methods to accomplish them:

1. To introduce a social network perspective for understanding the learning and adaptability of individuals and organisations involved in disaster and emergency management.
2. To describe the relationship between social networks and learning in a dynamic environment.
3. To develop a theoretical model to capture abstract concepts outlined in objective 2 through a comprehensive, iterative literature review.
4. To describe the interaction effects of the constructs in the theoretical model.
5. To extend the traditional theory of social networks and learning by understanding the effect of a dynamic environment on the inherent relationship between network structure and learning.
6. To demonstrate the ability of the conceptual model developed to be operationalised in the context of a bushfire, using both content analyses and a data collection survey instrument that achieves both reliability and validity.
7. To improve strategies to enhance the effectiveness of the Australasian Inter-Service Incident Management System (AIIMS) work practices;
8. To improve flows of information between personnel involved in incident responses and their management
9. To generate data that can be transferred into improved training initiatives to enhance the effectiveness of AIIMS.
10. To propose a way for bushfire managers or administrators to evaluate their present organisational practice culture.

1.4. Significance of the Study

The aim of this research study is not to clarify, in theory or in detail, every aspect of individual and team learning and what features affect it. Rather, it offers a unique mechanism for clarifying one of the several effects in individual and team learning from a social network perspective. To do this, a conceptual model is developed to explore the effect of social networks on the learning and adaptability of individuals and teams in Australia during extreme events. In the following section, the significance of the study is outlined at the theoretical, methodological and contextual levels.

1.4.1. Theoretical Significance

At the theoretical level, the unique contribution of this research is that it extends the traditional theory of social networks and learning to include individuals and organisations involved in incident response management by examining the relationship between social network properties and individual/team learning in a dynamic complex environment. It also extends the theory relating to individual and team learning by showing how network structure, position, and ties can be used to empirically measure and validate the key constructs of the social influence model. More significantly, it adds further empirical weight to the social influence model by explaining, with numerical evidence, how network properties such as tie strength are associated with learning. In doing so, it demonstrates how the research model can be applied in the context of bushfires in Australia. It is also effectively the first study in Australia to measure learning for social network communication.

1.4.2. Methodological Significance

Methodologically, this research uses two sources of data to test the conceptual model. The research provides an established, validated and reliable method of deriving social networks from archival data such as journal articles, newspapers, reports, minutes of meetings, and so on, which can be easily applied in a dynamic complex environment. This approach has many advantages, the first being that data analysis is inexpensive as the data are already collected. Second, data are free from certain biases that might put the validity of the primary data collection in question. Finally, the use of this approach enables the researcher to verify the findings based on the primary data. The research also provides a well-established, validated and reliable survey tool which can be easily administered to individuals in a dynamic complex environment. Obviously, in the case of a different domain, survey items pertaining to network and learning would need to be contextually adjusted. The idea behind the analysis, however, remains identical. More importantly, a crucial advantage offered by the survey is its ego-centric nature, such that it is capable of acquiring both relational data and attribute data for richer analysis of individual and team patterns and outcomes in a simple and reasonable manner. As such, the methodology provides a unique, theoretically-motivated way of collecting social network data.

1.4.3. Significance in the Context of Bushfire

For emergency incident organisations, this study is significant in that provides insight into their advice-seeking and professional and social networks in order to explore the dimensions of structure, position and relation that affect their learning attitudes during bushfires. In addition, while many studies exist in the disaster literature (Paton and Johnston, 2001; Paton, 2005; Paton et al., 2008), very few have sought to understand the social processes that influence the uptake and use of learning in disasters. As well, the study offers insights on how social networks play a significant role in the formation of learning attitudes of emergency personnel towards better emergency responses. As detailed in Chapter 5, recommendations about social problems to consider when designing effective and operational practices for enhanced learning are also provided.

At the domain level, the key contribution from this research is the evaluation of the relationship between network structure, network position, network ties and learning attitudes within the context of individuals working in a dynamic complex environment such as bushfire. Such individuals are working under extreme pressure in an unstable and ambiguous environment. In this context, when comparing network structure against network position and ties and their influence on learning, the study (as evidenced in Chapters 4 and 5) suggests that network position is the best predictor for learning. In particular, how individuals are strategically positioned is more crucial than the number of social and professional connections or how close or diverse their connections are. These findings are essential because they emphasise the role of network position, network structure and network ties, rather than individual personality attributes, in improving the learning of emergency personnel during bushfire.

1.5. Bushfire Information Workflow Model

To understand the bushfire information flow, a model based on the information given by the transcripts of 2009 Victorian Royal Commission reports, and specifically the work done by DSE employee John Towt depicting the workflow of the Department of Sustainability and Environment (DSE) emergency management personnel, is provided in Figure 1.3. The chart depicts the flow of information regarding the initial fire notification or the ongoing fire information from the fire ground to the broader community and senior executives of government in the State of Victoria in Australia. The flow of information regarding preparedness, new fires and ongoing fire situations follows the model in Figure 1.3. Each unit has specific tasks to undertake and deliver. Note that the model is indicative in nature and does not comprehensively include all parts of the bushfire emergency management operations.

Before exploring the model, it would be ideal to introduce the major fire agencies in the state of Victoria in Australia, which are the Country Fire Authority (CFA) and the Department of Sustainability and Environment (DSE). The CFA is a volunteer- and community-based fire and emergency services organisation. It delivers fire-fighting and other emergency services to all the state regions within Victoria, Australia. The CFA operates closely with the other emergency services within Victoria, specifically the Department of Sustainability and Environment, State Emergency Service, Ambulance Victoria, Victoria Police and the Metropolitan Fire Brigade, working together with unique ability sets and resources for the benefit and security of all Victorians.

The DSE is the fire service agency that provides fire-fighting and other emergency services to all public land regions within the state of Victoria, Australia. The department has other responsibilities (taken from its website) including: “sustainable water management and supply, sustainable catchment management, services for management and governance of Victoria’s parks, services for biodiversity, conservation, the ecosystem, heritage recreation and tourism, public land and sustainable forest management services, urban and regional strategies and programs, sustainability and Greenhouse Policy, sustainable Cities, regions and heritage conservation, land information, policy frameworks, regulations and services to protect the environment."

It should be noted that the model developed here is based on information flow within the DSE. The workflow model is divided into six areas or sections (fire ground, fire district, fire region, integrated emergency coordination centre, media stakeholder, and other key agencies) which are based on the roles and responsibilities of the individuals and agencies involved in the bushfire and the location of those actors within the fire event. The following sections introduce the individuals and agencies involved in the bushfire and explain how information flows during bushfires.

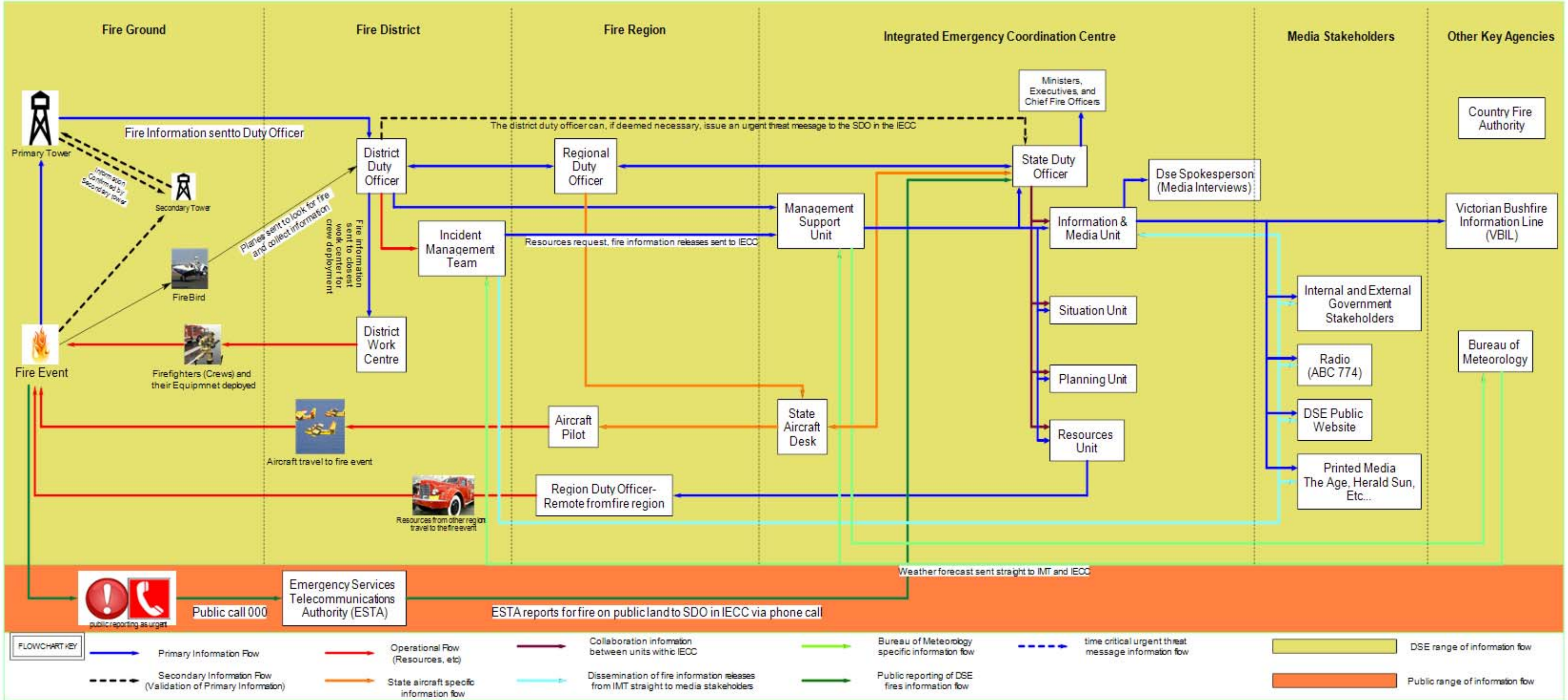


Figure 1.3: The Bushfire Information Workflow Model

1.5.1. Fire Ground

The first phase commences when the *fire event* happens. The authorities must collect realistic information about the fire (i.e., location, time, etc.). This can be done using aerial reconnaissance, lookout tower observation, on-ground investigation, remote sensing and verified public reports.

1.5.1.1. Bushfire detection

Bushfire detection procedures can usually be grouped into *volunteer reporting* and *operational detection systems. Volunteer reporting* includes community reporting of fires by calling triple-0, public aircraft, and agency staff. *Operational detection systems* include aerial patrols, automatic detection systems, electronic lightning detectors and fire towers. The following paragraphs briefly explain these detection processes.

The majority of fire services depend on volunteer reporting of fires. This method depends on community programs that deliver information to the public on communications in the occasion of an emergency. For instance, the public can use the triple-0 number in cases of emergency. Observations of fire occurrences by the community have been a major source of fire incidence information.

A *fire lookout tower* offers cover and protection for an individual recognised as a 'fire lookout' whose responsibility it is to search for bushfires. The fire lookout tower is a small building, usually situated on high ground where emergency staff members can observe and report the smoke from the initial phase of a fire. These towers are part of a network of fire towers. All the towers have radio and telephone facilities and they communicate easily between themselves and with other towers in the wider area. The towers depend on observation of a fire by observers and reporting of observations to fire office.

1.5.1.2. Fire-fighters

Fire-fighters are rescuers comprehensively qualified in fire-fighting, their role being mainly to extinguish dangerous fires that threaten public communities and property and to rescue human beings from hazardous events such as collapsed and burning buildings. The growing complexity of current lifestyles with an upsurge in the scale of threats has generated an increase in the abilities required in fire-fighting expertise and an expansion of fire-fighters' responsibilities. They occasionally deliver emergency medical services. Fire-fighters have become ubiquitous around the world, from rural areas to urban areas, and aboard ships.

1.5.1.3. Aerial fire-fighting

Aerial fire-fighting is the usage of aircraft to fight bushfires. These aircraft are specially designed to fight fires using a range of different technologies. For instance, special chemicals used to combat fires are made from simpler chemicals like water and foams.

1.5.2. Fire District

1.5.2.1. District Duty Officer

The district duty officer is accountable for all preparedness and early response activities in a district. During preparation activities, the district duty officer advises the regional duty officer of changes in district coordination or standby arrangements and sends a summary of resources on standby in the fire district. Moreover, the district duty officer notifies work centre staff (and/or work centre duty officers if applicable) of standby levels. As well, the district duty officer guarantees the effectual management of all district fire lookouts (contact arrangements, starting and finishing arrangements, administration arrangements, etc.). The district duty officer similarly ensures that extra detection preparation (aerial reconnaissance flights, etc.) is in place as required.

When a fire is reported, the district duty officer first determines the location (plots fire from lookout bearings and cross bearings) and then labels the location using the MGA (Map Grid Australia) grid reference or by roads or physical features. In addition, the district duty officer determines whether the fire is on public land (DSE being the control agency) or private property (CFA being the control agency). DSE resources should still be directed to support the CFA if DSE resources can get to the fire first, or considerably support in suppression. Where a fire is on or threatening a State forest, National Park or Protected Public Land, the district duty officer initiates the first attack with suitable staff members and assigns an incident controller, or acts as the initial incident controller as required. The district duty officer may continue as incident controller for very minor emergency incidents. Furthermore, the district duty officer supports, organises and records the deployment of resources. The district duty officer may also arrange for aircraft via the regional duty officer and keep contact with crews at the fire. If more resources are necessary, and these cannot be delivered from within the district, the district duty officer directly requests more resources from the regional duty officer. If there is a possibility for a severe situation to progress, the district duty officer requests an incident management team. The incident management team then replaces the initial attack team. Finally, the district duty officer arranges and transfers situation reports to the regional duty officer and the state duty officer until the status of the fire is safe.

1.5.2.2. Emergency Services Telecommunications Authority (ESTA)

The Emergency Services Telecommunications Authority (ESTA) has governmental right for treating triple-0 calls and providing and handling the delivery of emergency and operational communications for dispatching police, fire and ambulances in Victoria. When an individual calls 000 for an emergency response within Victoria, the phone operator will attach the individual to the appropriate ESTA facility. In this facility, a qualified call taker will gather information from the caller. Using this information, a qualified dispatcher will respond with suitable emergency services (for instance, in an event of a bushfire, a fire agency will be suitable). Many ESTA procedures are standardised across all emergency organisations, and all organisations use an identical computer network. The outcome is comprehensive and rapid information sharing between emergency services.

1.5.2.3. Incident Management Team

Incident management includes executing plans and using emergency staff members and equipment to accomplish the strategic and mission requirements of an emergency event response (AFAC, 2005). Scalable incident management teams are used to guarantee that they can successfully respond to and address possible fluctuations in the instantaneous emergency event environment.

The structure of the incident management team is based on AIIMS and shown in Figure 1.4, whose principles are:

- management of incidents by objective
- one controller of the incident — incident controller
- the delegation of functions depending on the complexity of the incident
- span of control — one person responsible for five people at any one time
- the development of a plan outlining strategies and tactics to combat the incident. (AFAC, 2005)

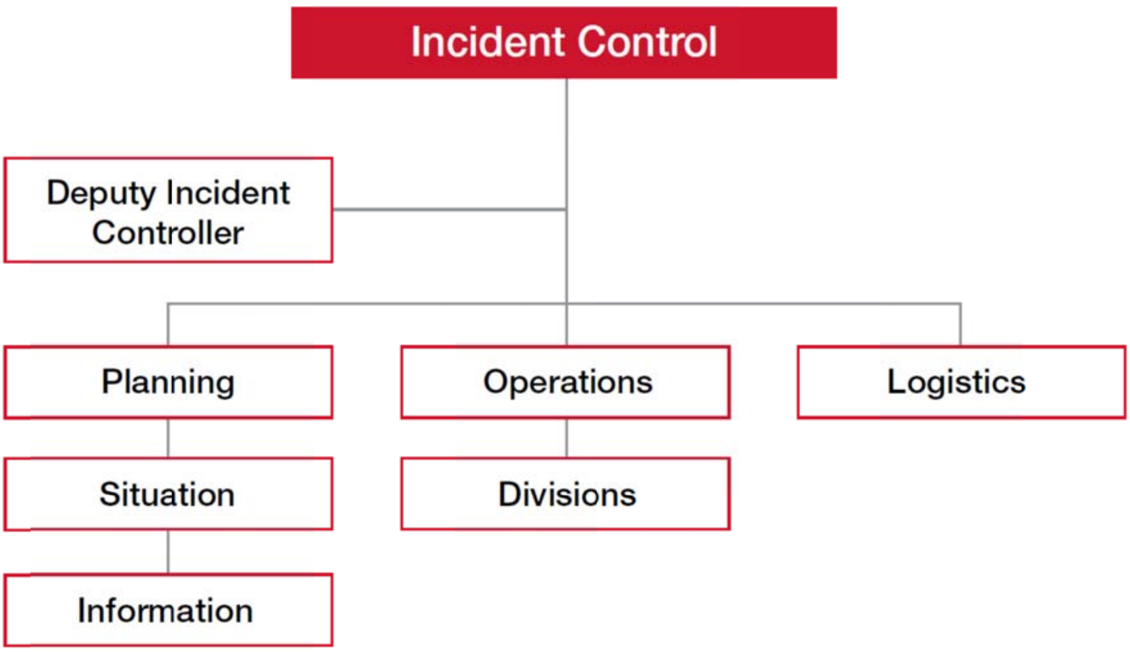


Figure 1.4: Elements of the AIIMS structure referred to in this chapter (Source: Adapted from Exhibit 131 – Mapping Information Flow During Critical Incidents (TEN.033.001.000111)

1.5.3. Fire Region

1.5.3.1. Regional Duty Officer (RDO)

The RDO is a regional contact for crucial operational issues and the key point of contact within the region for many individuals and organisations, including the State Duty Officer, Operations Manager, Brigades and Groups within the region, and Emergency Services (Ambulance, Environmental Protection Authority, Municipalities State Emergency Service, Office of Gas Safety, Police, SES, WorkSafe) (Teague et al., 2009).

The RDO is similarly responsible for organising resources of integrated fire stations and providing expert operational guidance to Incident Controllers at complex incidents. Moreover, the RDO is also responsible for the escalation of resourcing in response to an emergency event when the Regional Emergency Coordination Centre (RECC) is not operational. For instance, the RDO can organise the deployment of an Operations Officer to deliver fire ground support and guidance. The RDO coordinates readiness preparations for the Region, delivers information flow from the ground to the integrated Emergency Coordination Centre (iECC) about ongoing events, and is the main regional contact individual for other organisations.

1.5.4. Integrated Emergency Coordination Centre

The integrated Emergency Coordination Centre (iECC) is a facility that DSE has made available to other emergency management organisations so that they can conduct their state-level emergency coordination roles from a common place. Co-location of these organisations in the iECC during emergency events is valuable since it brings the prospect of enhanced inter-organisational communication and cooperation.

An iECC Panel, including the Chief Officers and a high-ranking operational member of each of the partner organisations, has been established to deliver direction regarding a shared approach to the various organisations' emergency coordination activities in the centre. The main objective of the iECC Panel is to guarantee that each of the organisations is capable of meeting its legal responsibilities, linked to emergency coordination, while functioning from the Centre. The following sections show the major actors involved in the response to bushfires who are located in the iECC.

1.5.4.1. State Duty Officer (SDO)

At the iECC, the role of the DSE State Duty Officer (SDO) is to coordinate Networked Emergency Organisation (NEO) resources. The SDO's role and duties are to coordinate state fire and emergency events, support emergency incidents and activities by the deployment of the state's resources and the delivery of information to stakeholders and the public. In addition, the SDO has regular discussions with DSE RDOs to guarantee adequate state-wide situational awareness of the existing fire load, resource requirements and readiness preparations. Figure 1.5 shows the process map of the DSE SDO.

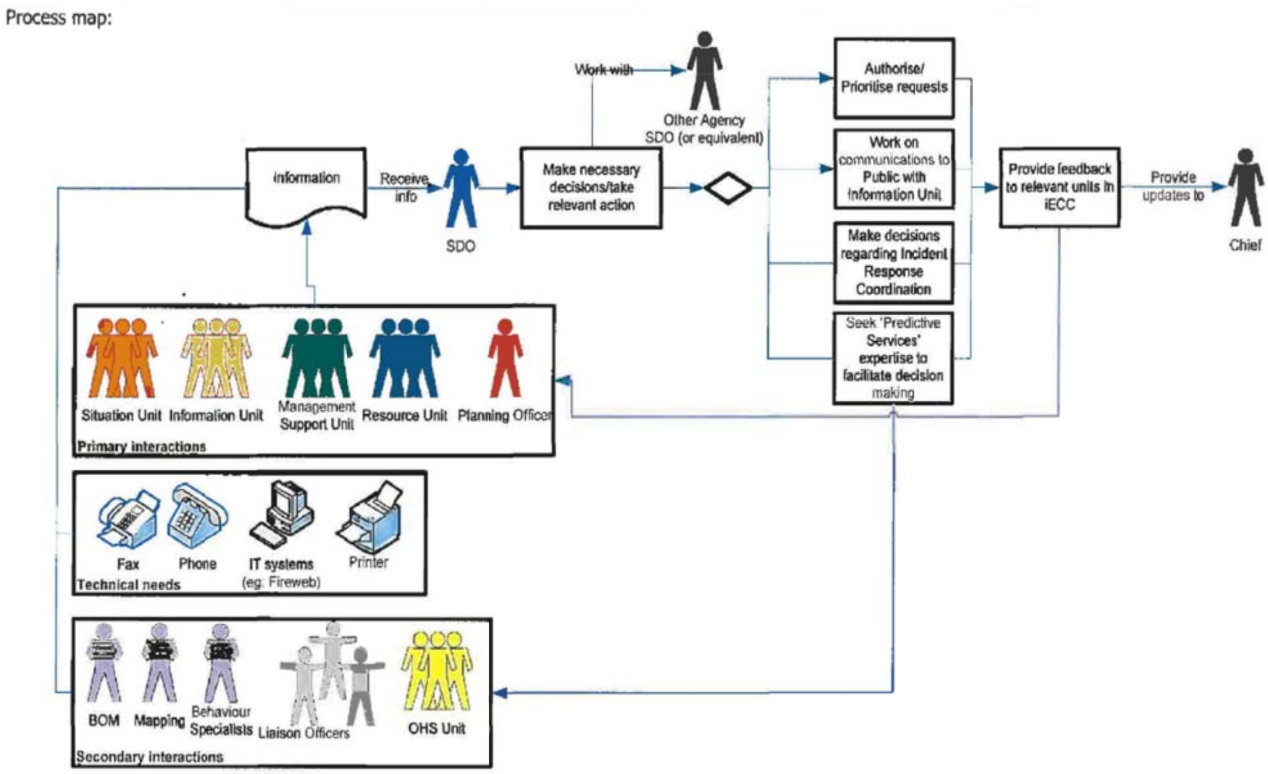


Figure 1.5: Process map of the DSE State Duty Officer (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.4.2. *DSE Management Support Unit*

The purpose of the DSE Management Support Unit is to deliver several methods of support to the key actors within the iECC in order to enable effective operation within the room. This support usually takes the form of obtaining information from numerous sources, determining the suitable audience for that information and facilitating the usage of that information. The primary flow is illustrated in Figure 1.6. Moreover, the division can be responsible for providing forms of administration support, such as taking minutes or supporting the facilities unit in servicing the requirements of the room. The Management Support Unit may likewise fulfil the roles of the Situation Unit in cases where the nature of an emergency incident does not permit a devoted situation unit.

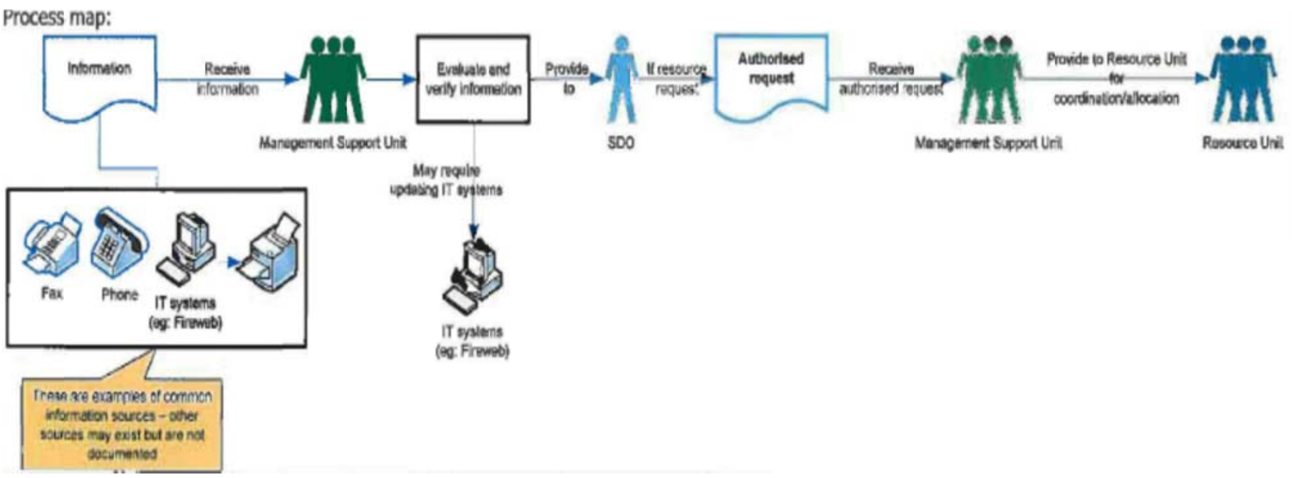


Figure 1.6: Process map of the DSE Management Support Unit (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.4.3. *State Airdesk*

The State Airdesk is a combined DSE/CFA service, responsible for the administration and deployment of aircraft resources during an emergency event. Aircraft requests are generally received through the SDO or through direct request normally by telephone. The request is assessed and decisions concerning priority are made in accordance with the appropriate procedures. Requests are debated with the SDO if they are not in accordance with usual procedures. For line-scan requests (information gathering), the Airdesk will participate with the Situation Unit. When deployment is decided, the aircraft resources are dispatched and the RECC is notified. Figure 1.7 shows the process map of the State Airdesk.

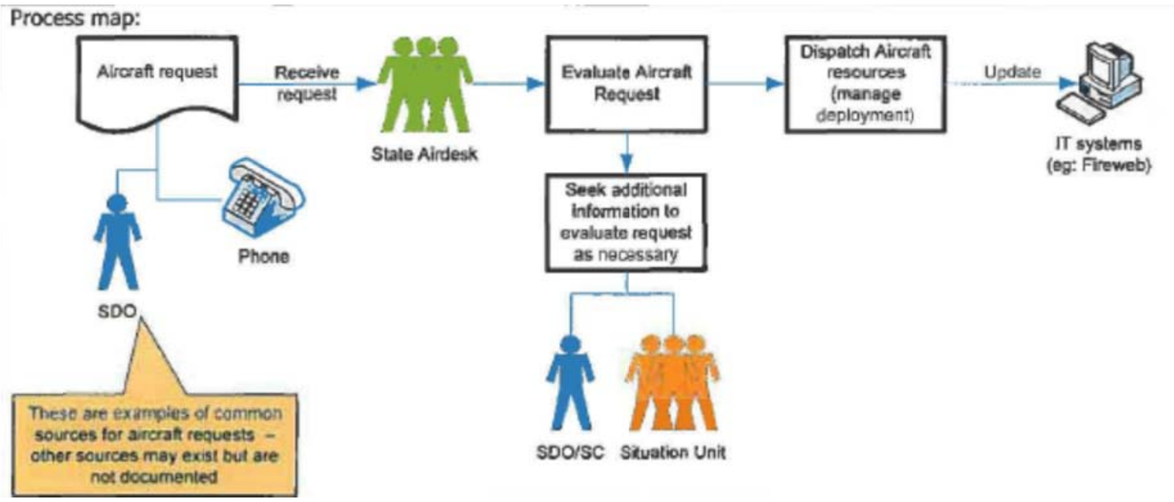


Figure 1.7: Process map of the State Airdesk (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.4.4. DSE Resources Unit

The DSE Resources Unit is responsible for coordinating the deployment of DSE human resources to emergency incidents. This is separate from the Logistics Unit, which is responsible for coordinating the deployment of DSE supplies and equipment (i.e., non-personnel resources). Resource requests are delivered through the Management Support Unit; these requests have been shown and approved by the SDO prior to reception by the Resources Unit. The Resources Unit assesses all resource requests (the SDO might be consulted if several resource requests result in priority conflicts) and coordinates the deployment of the resources to the RECC. The Resources Unit is not informed when the resources arrive at the RECC, but is informed when the resources are released from responsibility. The Resources Unit likewise implements a range of other tasks in the iECC on an as-needs basis, such as iECC shift planning, Strategic Resourcing and Interstate and International resources. Figure 1.8 shows the process map of the DSE Resources Unit.

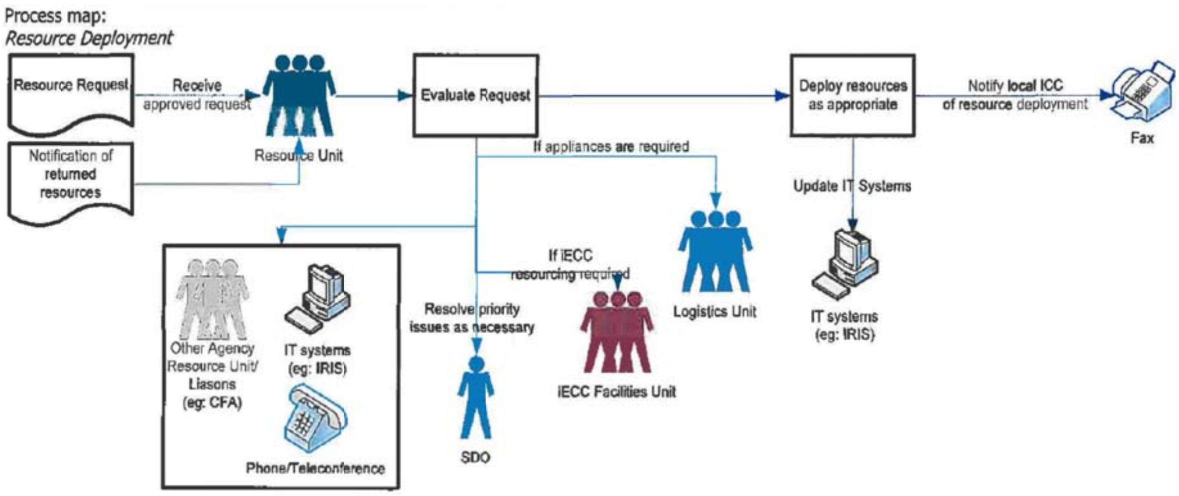


Figure 1.8: Process map of the DSE Resources Unit (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.4.5. DSE Information Unit

The Information Unit is responsible for the reception, verification and distribution of incident-related information to the public (including the media). The Information Unit obtains information from a range of sources and in a variety of manners. It then assesses and authenticates the information with suitable audiences before deciding whether and how it should be made public. The SDO is the most significant source for information verification, and no information is delivered to the public unless the SDO has approved that the content be circulated. The Information Unit has corresponding counterparts in other organisations and works with these other divisions to aim for consistency in the information dispersed. Figure 1.9 shows the process map of the DSE Information Unit.

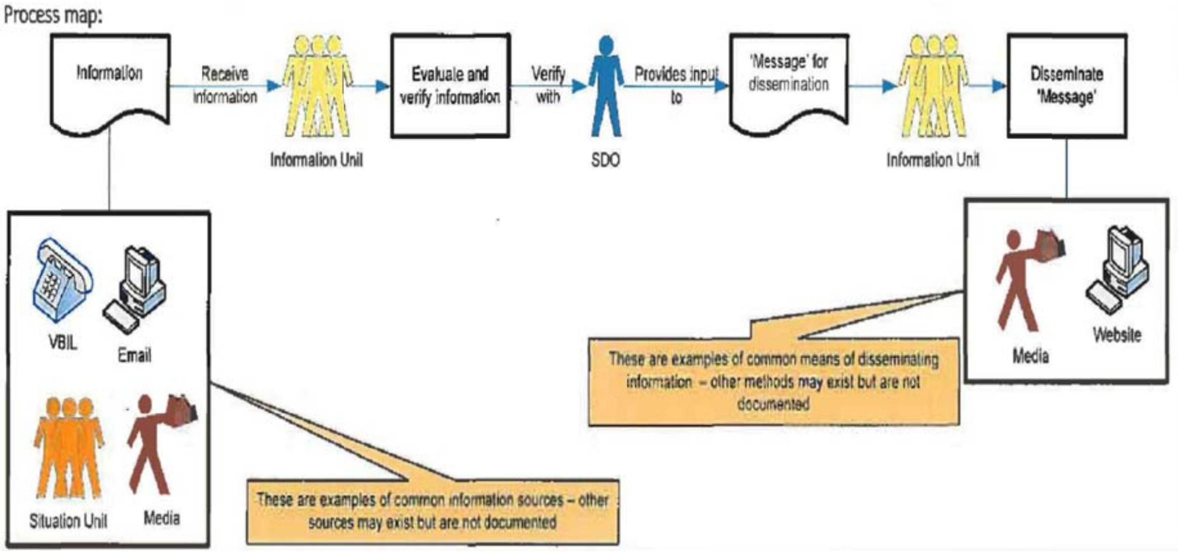


Figure 1.9: Process map of the DSE Information Unit (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.4.6. DSE Situation Unit

The Situation Unit is responsible for capturing, assessing, and understanding incident-related information, and organising updates and reports for the iECC and other departments and organisations (government). The Situation Unit mainly obtains information from 'out in the field'. It then assesses and validates the information with suitable actors before deciding if it should be made accessible to the iECC and/or government. The SDO is the most vital source for information validation, and no information is delivered to the room (or government) unless the SDO has approved. The Situation Unit may participate with other groups (such as the BOM or behaviour specialists) to offer analytical services before making information accessible to the room (or government). The Situation Unit has corresponding counterparts in other organisations and work with these other divisions to aim for uniformity and precision in the information that is used in the iECC to coordinate the response. Figure 1.10 shows the process map of the DSE Situation Unit.

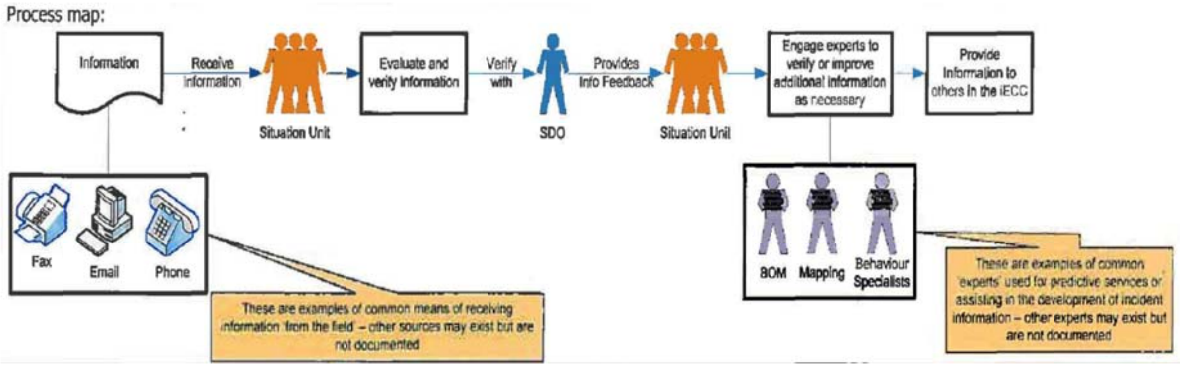


Figure 1.10: Process map of the DSE Situation Unit (taken from evidence WIT.3024.002.0330 which was submitted to the 2009 Victorian Bushfire Royal Commission)

1.5.5. Other key agencies

1.5.5.1. Victorian Bushfire Information Line (VBIL)

The Victorian Bushfire Information Line (VBIL) delivers information throughout bushfire incidents. It similarly offers information to assist householders, landlords and minor businesses in reducing bushfire risk.

1.5.5.2. Bureau of Meteorology

The Bureau of Meteorology (BOM) is the organization within the Australian Government responsible for providing weather services to Australia and adjacent regions. The BOM supplies weather forecasts and cautions to the Australian community. The BOM sends weather images to other agencies and is responsible for supplying warnings in Australia.

1.5.6. Summary of the Bushfire Information Workflow Model

In summary, the flow of information in all bushfire cases follows the model in Figure 1.3. The model shows the full flow of information across the state regarding readiness, new fires and ongoing fire situations on the 'Black Saturday' bushfires. The Black Saturday bushfires were a series of bushfires that were burning across Victoria on Saturday, 7 February 2009. The fires occurred during extreme bushfire-weather conditions and resulted in Australia's highest ever loss of life from a bushfire; 173 people died and 414 were injured as a result of the fires. Each fire agency (DSE and CFA) has its own measures for preparation, response and recovery.

During the Black Saturday bushfires there were 5 DSE Fire Areas and 20 CFA Regions. Each organisation depended on regional centres to coordinate planning, response and recovery for bushfire incidents in their regions. The reporting line flowed from the fire-ground through the Incident Management Team (IMT) to the region, and only then to a person located in the iECC. Once an incident management structure had been established, the IMT reported through the Incident Controller to the RDO at the RECC, or through the DSE Regional Office. Regional coordination "involves the key functions of monitoring and supporting Incident Control Centres (ICCs) and IMTs in the management of incidents, obtaining and coordinating resources for incidents in the region and to support others across the state, and liaising with other agencies as appropriate" (Teague et al., 2009).

During the Black Saturday bushfires there were problems of communication which stalled coordination efforts. A person with major emergency responsibility involved in these events stated, "The flow of information between the iECC and the ICCs (whether directly or through the Regions) on 7 February 2009 fell short of the standard desired". That person admitted that, "in some cases, valuable intelligence received in the iECC (e.g. the linescans and a report of the position of the Kilmore East fire received from the air at about 1530) were not shared down the reporting lines to the IMT. Correspondingly, valuable information available in the ground or in the ICCs did not find its way back through the reporting lines to the iECC. In part, that reflects the massive stress of the day and it is logical that those in the field and ICCs, facing rapidly changing and unstable conditions, absorbed on accomplishing their instant responsibilities rather than on reporting their observations and other information to others."

1.6. Forthcoming Chapters

Before the outlines of the forthcoming chapters, Figure 1.11 shows the framework of this research.

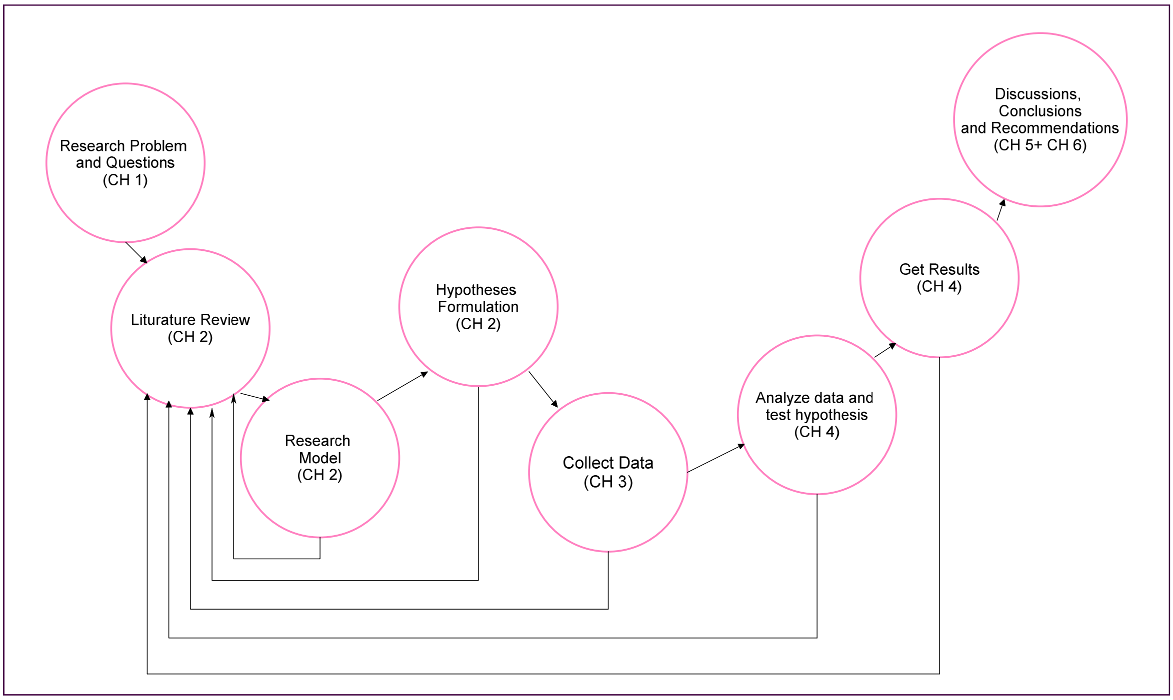


Figure 1.11: Framework of research **(note: The different height positions of the circles do not merit any meaning)**

The forthcoming chapters are structured as follows:

In Chapter 2, a review of literature is presented, exploring the inherent relationship between social network and learning in a dynamic complex environment. It first provides an overview of social networks. Second, in order to develop a model for understanding the relationship between social networks and learning, traditional theories of network structure, structural holes and strength of weak ties are explored, along with their underlying assumptions. The model is discussed within the context of a catastrophic dynamic complex environment where agents must adapt to new situations and overcome possibly unpredictable obstacles or problems. Subsequently, a review of current literature on social networks in dynamic environments is presented, along with the introduction of networks as learning catalysts by bridging and fostering social ties. The effects on learning are discussed, with particular emphasis on the social system effects on learning during a non-routine dynamic complex environment. The chapter concludes by proposing a theoretical model together with hypotheses for understanding the relationship between network structure, position, and learning in a dynamic complex environment.

Chapter 3 provides an outline of the design of the study. It explains the triangulation research methodologies used and the process of collecting social network and learning data using both content analysis and a survey instrument based on theoretical perspectives that inform the conceptual model. The content analysis was based on data collected from the transcripts of the 2009 Victorian Royal Commission reports. In addition, the research framework consisted of a survey that was conducted with a random sample of people from different layers within the AIIMS structure in Australia. The chapter concludes with an overview of the design of network data collection methods, the phases of collecting data and the techniques that were used to collect, store, extract and analyse the data.

In Chapter 4, the outcomes of the qualitative and the quantitative components of the research are stated. A brief summary of the findings is provided, followed by descriptive statistics about the data including tests of normality and a brief discussion of the distribution of each data variable. The initial results of the relationships between the variables are also provided. Then the results inferred from hypothesis testing using parametric techniques such as partial correlation, t-tests and multivariate techniques such as multiple regression models are stated and discussed.

Chapter 5 re-establishes the main objective of this research, which is to understand the influence of social networks on learning in the context of an unstable dynamic complex environment. By restating the motivating research questions from Chapter 2, this chapter systematically synthesises the literature review and the results from the study within the context of a dynamic non-routine complex environment. Specifically, the discussion is organised by: (1) the *actor-level social network* hypotheses, which discusses the influence of individual social network measures such as network efficiency, constraint, degree centrality and betweenness centrality on learning in a dynamic complex environment; (2) the *dyadic-*

level social network hypotheses, which discusses the influence of tie strength on the learning of incident management teams in a dynamic complex environment; and (3) the *network-level social network* hypotheses, which discusses the influence of social network measures for the whole network, such as network density, degree centralisation and betweenness centralisation, on the network learning in a dynamic complex environment. Then the rationality of the theoretical and conceptual model is discussed as a whole, along with key findings.

Finally, in Chapter 6, conclusions, limitations, key findings and implications for future research and practice are presented. The critical outcomes and interpretations of the research study in Chapter 5 translate into a set of implications and recommendations for theory, method, domain, and for emergency management organisations in Australia in particular. In conclusion, the limitations of the study are presented, along with directions for future research.

CHAPTER 2

2. A SOCIAL NETWORKS-BASED MODEL FOR EXPLORING LEARNING IN A DYNAMIC ENVIRONMENT

This chapter provides a literature review of research that explores the inherent relationship between social network and learning in a dynamic complex environment. The chapter first provides an overview of social networks and learning in a dynamic complex environment. The chapter is organised by the levels of analysis (actor level, dyadic level and network level). Second, traditional theories of social network within various levels of relations among actors, such as structural holes and the strength of weak ties, along with their underlying assumptions are investigated in order to support the development of a conceptual model for understanding the relationship between social networks and learning in a dynamic complex environment. In particular, the validity of the assumption that bridges are important is discussed because they span weak ties. Moreover, the brokerage advantage assumption obtained by actors occupying structural holes in the network is discussed. Conventionally, these theories have been applied in a routine and stable environment. However, in this research, the model is applied in a dynamic complex environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles or problems. In the third section, an appraisal of existing literature on learning is presented. Clarification of what is meant by learning, including its types, and justifications for measures of learning are also provided. In the subsequent section, the effect of networks on learning is introduced. In particular, learning by association is discussed, with emphasis on social system effects on learning in a dynamic complex environment. Finally, a conceptual model is proposed together with hypotheses for understanding the relationship between network relations and learning in an unstable dynamic complex environment. Figure 2.1 presents an overview of Chapter 2.

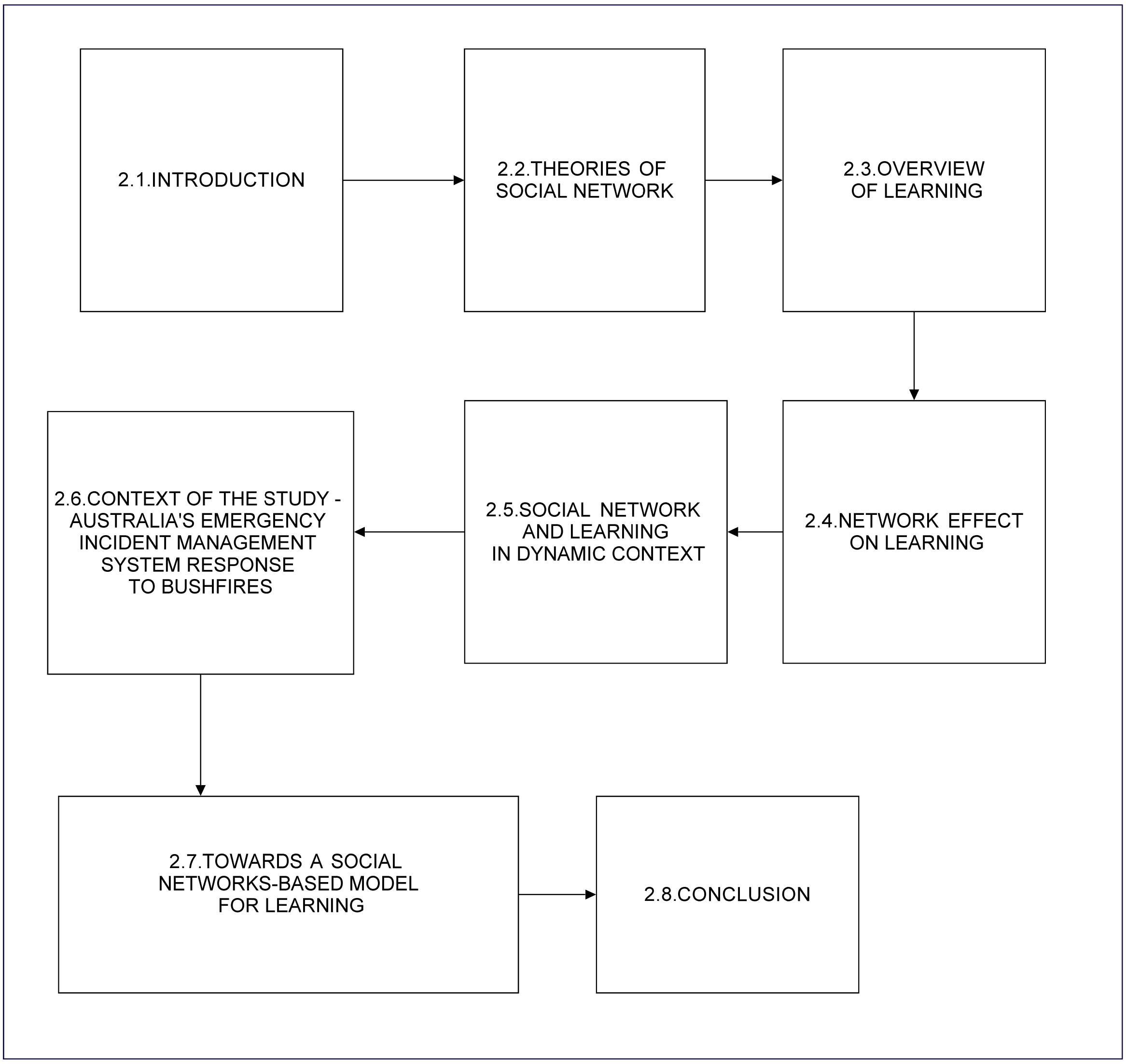


Figure 2.1: Overview of Chapter 2

2.1. Introduction

Social network theorists have explored the significance of social communication and network structures on learning at individual and group levels (Granovetter, 1973; Powell et al., 1996; Kraatz, 1998; Knight and Pye, 2004). However, most network studies have focused on networks in routine and stable situations. Indeed, few studies have been conducted in a dynamic complex environmental context where agents must adapt to new situations and overcome possibly unpredictable problems, such as emergency events. Catastrophic emergencies are best described by surprising and remarkable interruptions to the communication and decision-making capabilities of the emergency response system itself, and failures in coordination and communication (Kapucu and Van Wart, 2006). Overwhelming emergencies are qualitatively and quantitatively different from routine emergencies, and they are more than simply a "very large scale traffic accident" (Quarantelli, 2005). The context of routine emergencies is usually based on stable working relationships with limited environmental uncertainties. Therefore in this research only complex emergency events are considered, because it is established that these events represent a more dynamic environmental emergency management context. Understanding these contexts is therefore important to improve emergency management systems to mitigate the vulnerability of local communities to extreme risk.

Emergency management organisations are expected to react to emergencies by reducing the impact of the incident on communities. One of the crucial mechanisms through which organisations can enhance their effectiveness in response is through learning. In doing that, adaptation can occur, in the context of uncertainty and unpredictability, enabling managers and their organisations to respond to feedback from the environment (Carley and Harrald, 1997; Berkes et al., 2003). However, the challenge of learning in the context of an emergency event as it unfolds is not easy (Comfort et al., 2009). Members of organisations engaged in the emergency therefore need to maximise their ability to learn during incidents in order to reduce the frequency and severity of errors (Blanco et al., 1996).

In this research, the emergency management response to some Australian bushfire incidents is investigated from the social network perspective. Bushfire is a common terminology used exclusively by Australians. It covers grass fires, forest fires and scrub fires (any fire outside the urbanised environment). In the United States, it is called wildfire and in Europe and Asia it is usually called a forest fire (Bento-Gonçalves et al., 2012). Clearly, the theoretical foundations of social network research have developed to a stage where the scope of its application extends to several disciplines. The questions that currently challenge philosophical notions of the relationship between social network theory and learning in a dynamic complex environment are thus:

1. How can learning in a dynamic complex environment be explored through the emergent patterns of social processes? How can it be evaluated?
2. What is the role of social networks in understanding learning in a dynamic complex environment? Why is the understanding of social network structure and position important for understanding learning in a dynamic complex environment?
3. Is there a relationship between the configuration of social network structures and learning in a dynamic complex environment?
4. How can the properties of social networks within various levels of relations among actors help in modelling the dynamics of learning?

To answer the above philosophical questions it is necessary to investigate possible responses by reviewing the literature in the area of *social networks* and *learning* in a *dynamic complex environment*. While there is currently a lack of literature that connects these three concepts in a coherent form, it is vital that they be investigated separately, jointly and holistically in a sequential manner. The following section begins by exploring and investigating some of the original works in the area of social network and learning.

2.2. Theories of Social Networks

To begin with, a social network is essentially a group of nodes or actors and relationships which keep the actors nodes together. Nodes can be persons or collective entities such as divisions, agencies, clans, or even nations. Actors form social networks by exchanging resources with each other (Chung et al., 2005; Pince and Humphreys, 2008). Such resources can be information, advice, goods, communal or monetary support. These types of interaction are referred as the social network *relation*, where actors who keep the relation are assumed to keep a *tie* (Emirbayer, 1997). The strength of a tie might vary from strong to weak, subject to the quantity and kinds of resources they interchange and the regularity and intimacy of the exchange (Marsden, 1990). As well, social ties can consist of multiple relations (as in the case of fire-fighters who have a professional and family relationship with colleagues) and are called *multiplex ties* (Haythornthwaite, 2002).

Lately, social network research studies have gained substantial appreciation in terms of both theory and method and have significantly impacted on research disciplines such as knowledge management, social capital and organisational behaviour (Freeman, 2004). In fact, Borgatti, Everett et al. (2002) note that "the boom in network research is part of a general shift, beginning in the second half of the 20th century, away from the individualist, the essentialist, and the atomistic explanations towards more relational, contextual and systemic understandings".

The fact that social network analysis (SNA) techniques and approaches have been used in different research areas and domains demonstrates the growing and emerging importance of SNA (Otte and Rousseau, 2002). An interesting observation made by Otte and Rousseau is that "in the early 1990s most articles dealt with family and socialisation, while at the end of this period the SNA articles mostly dealt with the sociology of health and medicine. Indeed, SNA is now often applied in Acquired Immunodeficiency Syndrome (AIDS) and drug abuse studies." The terms *social network* and *network* may be used interchangeably from this point on, unless otherwise stated.

Social networks are normally self-organising, growing, evolving and multifaceted. For instance, globally consistent patterns and properties result from the local relations and exchanges of the resources that represent the network (Wellman, 1996; Newman et al., 2006). These patterns become more obvious as network size increases. Nevertheless, a widespread SNA of, for instance, the entire social interactions in the universe is not feasible and would likely comprise a lot of useless data. Therefore, social networks are analysed by the quantity and kind of relations applicable to the scholar's theoretical investigation. For instance, the analysis may be restricted to a specific research question or may be targeted to analyse particular types of relationship. Although the levels of analysis are not essentially mutually exclusive, there are three general levels into which networks may fall: actor level, dyadic level and network level.

2.2.1. Actor-Level Social Network Theories

The minimum element of analysis in a social network is an actor in his or her social environment. Actor-level social network theories regularly centre on network features such as centrality, efficiency, constraint and roles such as bridges and liaisons. Such theories are most commonly used in the fields of psychology or other genealogical studies of relationships between individuals. The following sections explore the major actor-level social network theories.

2.2.1.1. Structural Holes Theory

A key limitation in extant research into social networks, such as the study by Coleman et al. (1957), is that it assumes that actors are capable of keeping connections within their individual or professional network steady over time. It likewise assumes that each connection is a supplier of an exceptional resource or information. These assumptions lead to illogical explanations of why a very dense social network might paralyse an actor's capacity to learn better.

In response to this limitation, Burt (1992) contributed to social network theory and the idea of structural influences on the actor's outcome by moving the attention from *network structure and relations* to *network position*. His theory on structural holes presents a new and a unique concept in clarifying why some actors learn and adapt well whereas others do not. In other words, Burt's (1992) theory of structural holes takes the research of Coleman et al. (1957) a step further by proposing a clarification of why social practices such as innovation dissemination can occur more quickly from a structural positional viewpoint rather than from a relational viewpoint.

Burt (1992) contends that the structural arrangement of an actor's network which offers an optimised *brokerage* position is what influences structural benefits such as information uniqueness. He argues that maximising the number of ties in an actor's network does not inevitably produce such benefits. On the contrary, opportunity costs appear and the preservation of connections become expensive in terms of resources and time. Additionally, as an actor's social network develops, the information passing from closely joined groups tends to be redundant. Logically, an actor cannot keep more than 40 or more close relations on a regular basis. This amount shows at best, an actor motivated to keep relations with his or her contacts. Maintaining relations with such a number of contacts is time consuming and socially expensive. Therefore, the foundation of Burt's (1992) argument capitalises on his theory of structural holes by focusing on the significance of structural *position* rather than structural relations (i.e., strength of ties) or structural *properties* (i.e., the density or centrality of the network).

The concept of structural holes is instinctive. 'Holes' in the network represent the lack of connections which could join separate groups together. Actors who bridge these holes obtain a valuable location that gains information benefits. For that reason, "structural holes theory" is established on the notion that individuals are in a superior location to benefit from exchanges with others if they are linked to others who are not well-connected themselves. The absence of relations among those others creates the holes in the structure (and therefore, structural holes). Actors who reach structural self-sufficiency are those who bridge all structural holes. Closer scrutiny of the root of structural holes theory reveals that it is based on the network measure of *betweenness centrality*: that authority and influence accumulate to those who broker connections between isolated groups of individuals. Burt (1992) capitalises on the theory of betweenness centrality and extends it to illuminate the role of *brokerage* as a method of gaining structural independence which leads to enhanced learning and attaining novel ideas. This theoretical contribution provides an additional insightful viewpoint on individual learning, given that Guetzkow and Simon (1955) note that centrality in itself is not always a main predictor of individual learning. As an alternative, the theory proposes insightful description beyond the theory of centrality and centralisation, in that an actor's benefit grows from the level that the actor's network is efficient, effective and constrained. The next section discusses network efficiency and constraint in greater detail.

2.2.1.1.1 Network Efficiency and Effectiveness

In Burt's (1992) study of structural holes, he states that increasing the number of direct links without considering the variety reached by the contacts makes the network inefficient in several ways. As a result, a quantity of non-redundant contacts is essential, to the degree that redundant contacts would lead to similar people and therefore deliver identical information. The term "effectiveness" is used to indicate "the *average* number of individuals reached *per* primary contact", and the term "efficiency" indicates "the *total* number of individuals reached with *all* primary contacts". Therefore, effectiveness is about the *yield per primary contact* whereas efficiency is about the *yield of the entire network.* To illustrate, the social network diagrams in Figure 2.2 compare an inefficient network (A) to an efficient network (B).

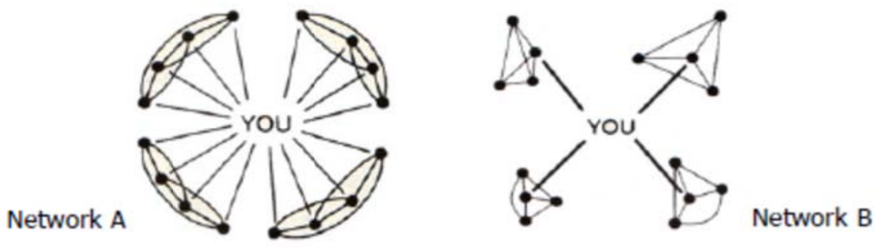


Figure 2.2: Inefficient (A) and efficient (B) networks (adapted from Burt (1992))

In network A, the actor (you) maintains sixteen connections with all contacts in the social network. This creates a substantial stress on the actor in terms of opportunity cost and time that could be devoted and capitalised on in other contacts. Network B is far more efficient than Network A. This is because the actor (you) merely needs to maintain ties with four primary contacts, thus achieving efficiency at a fourth of the cost compared to network A. Further, Network B is far more effective than Network A since primary contacts in this network are non-redundant, because they are linked to clusters that are not linked to each other. An effective network, for that reason, favours primary contacts as a channel of connection to various groups, thus achieving the optimum result of the complete social network.

To represent effectiveness in social networks, Burt (1992) uses the term "effective size". In network A, the size of the network is 16 whereas the *effective* size is 4. This is because the actor is able to acquire *novel information* and *resource benefits* from the four groups only, which are not linked to each other apart from through 'you'. The other three connections to each of the groups are redundant as they deliver similar information to that which is offered through the fourth. Hence, efficiency in network A (measured as effective size (4)/network size (16)) is 0.25. In network B, the size of the network is 4 and the effective size is 4. This will produce a perfect efficiency of 1 (measured as effective size (4)/network size (4)). The relationship between network size, effective size and efficiency is shown in the graph in Figure 2.3:

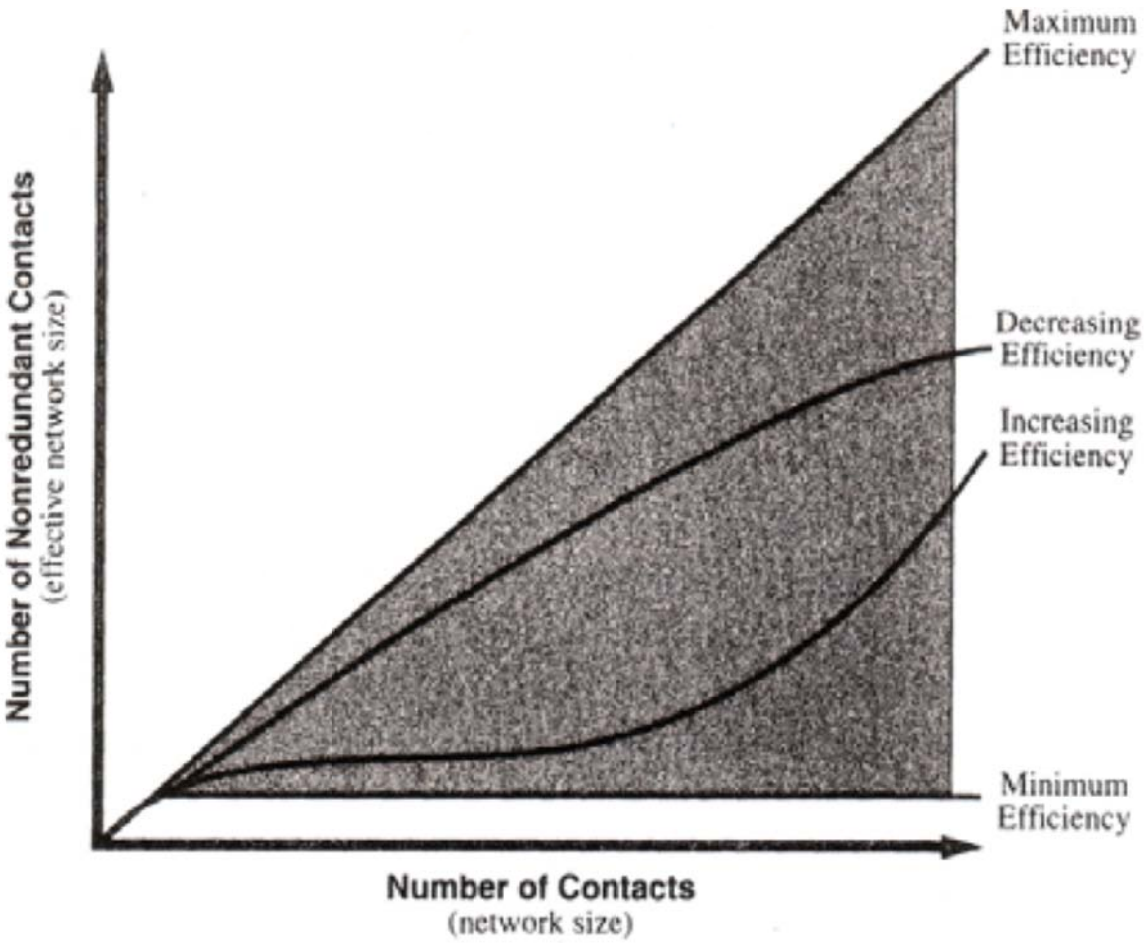


Figure 2.3: Relationship between network size and effective network size (Burt, (1992), p.71)

2.2.1.1.2 Network Constraint

Network constraint refers to the degree to which an actor's opportunities are restricted by spending the majority of an actor's network time and effort in relations that lead back to the single contact (Burt, 1992). Thus, if the actor has several contacts with other actors who in turn have many contacts to more others, the actor is relatively constrained. At organisational levels, an actor with a high constraint index is incapable of conceiving novel ideas and resource benefits because of the redundant nature of information that is obtained from a densely connected group of actors. Earlier studies have regularly revealed that low constraint and high efficiency indices are valuable signs of an actor's capacity to create novel ideas (Burt, 2004). In line with these arguments, it is probable that actors flourish on valuable knowledge and information from contacts. An actor with an efficient and low constrained network structure is therefore more likely to acquire useful and novel knowledge and information from diverse and non-redundant contacts, which has been linked to improved learning and performance.

2.2.1.2. Freeman's Concept of Actor-Level Centrality

The concept of centrality was first applied by Bavelas (1950) and Leavitt (1951). Freeman (1978) later made a major contribution to the concept of centrality which quickly became an essential notion in social network research studies. Freeman's effort formed a basis for researchers to use and extend the concept of centrality at both the actor and network level, theoretically and empirically. He revealed that the concept of centrality was not just useful in experimental studies. He explained that it was applicable in other study such as in understanding metropolitan development, the organisation of populated countries such as India, and in clarifying patterns of dissemination of technical novelty in the steel business. Therefore, Freeman studied several measures and overlapping notions of centrality by merging the measures and centrality concepts.

Specifically, Freeman (1978) explained centrality in terms of *degree*, *betweenness* and *closeness* centrality. Each of these centrality measures has significant consequences for social outcomes. Degree centrality can be measured according to the number of links to and from a node (i.e., degree). On the other hand, betweenness centrality refers to the level to which a node lies in the shortest path to all others in the network (Leydesdorff, 2007), whereas closeness centrality refers to the level to which a node is close to all others in the network. Every centrality notion has been associated with significant social events. For instance, degree centrality is observed as a key indicator of a node's communication activity; betweenness centrality is observed as an important indicator of the potential of a node's control of communication. On the other hand, closeness centrality is observed as an indicator of the minimum cost in time and efficiency for communicating with other nodes in the network.

Previous research has shown that both betweenness centrality (the extent of communication controlled), and degree centrality (the extent of communication activity) influence learning and performance from a network structure perspective, while closeness centrality (the extent of communication efficiency) does not. Therefore, this dissertation considers only betweenness centrality and degree centrality. In summary, the impact of Freeman's (1978) research is so significant that the concept of centrality is currently more or less always credited to him. By illuminating the instinctive concepts of centrality, Freeman delivered their particular conceptual and practical inferences, which are key contributions to network structure studies.

2.2.2. Dyadic-level Social Network Theories

Basically, a dyad is a social connection between two actors. Social network studies of dyads may focus on the structure of the relationship and tendencies toward reciprocity. Until now, research has focused on how actor-level social network factors (i.e., network constraint, network efficiency, etc.) have significant behavioural consequences for social outcomes (Knoke and Kuklinski, 1982). Nevertheless, at the dyadic level, the argument focuses not only on just how *actor-level social network factors* influence individual or system learning, but also on *relational components* of an actor's network. Evidence in the literature reveals that just as *actor-level social network factors* play an important role in the influence of individual and system learning, tie strength also has major effects (Borgatti et al., 1998; Mehra et al., 2001; Sparrowe et al., 2001; Reagans and McEvily, 2003; Hossain et al., 2006). The following sections explore the major dyadic-level social network theories.

2.2.2.1. Strength of Weak Ties Theory

Granovetter's (1973) concept of the strength of weak ties is the most influential work in social network research with respect to the relational element of an actor's social network. In his study, Granovetter debates that actors acquire new and unique information from *weak* ties (not from *strong* ties) within a social network. He argues that strong ties have a tendency to link similar individuals to each other, and that these similar individuals tend to group together so that they become entirely mutually linked. As such, information or ideas flowing through the network tend to be redundant in a short period of time. A group of individuals connected with each other by strong ties are hence not readily receptive to novel information. Those social networks are not favourable to innovation and are closed networks.

In his study, Granovetter (1973) proposes that the arrival of new and unique information must for that reason come from weak ties (hence the theory of the strength of weak ties). A weak tie functions as a *bridge* to a diverse group of individuals from which new and novel information originates. While the concept of strength of weak ties theory has widespread appeal, it suffers from the shortcoming of its implication that maximising the amount of weak ties in an individual's social network would produce new and novel information benefits which in turn, permit the individual to learn and perform better.

2.2.2.2. Strength of Strong Ties

Many scholars have studied the contradiction regarding the strength of ties, following the inspirational work on the strength of weak ties, and related it to individuals and group outcomes. For example, in a research study about a Silicon Valley company where "friendships networks" of 36 workers were compared, Krackhardt (1992) states that the "effect" level of strong ties is significant and cannot be overlooked. He concludes that strong ties were mainly significant particularly in the generation of trust within spreaders of major organisational change. In other research related to a pharmaceutical firm, a bank, and an oil and gas firm, Levin and Cross (2004) investigated the networks of 127 knowledge-intensive employees and demonstrated that strong ties led to the reception of useful and valuable knowledge for improving learning and performance. Nevertheless, when they controlled trust in their research model, the structural advantage of weak ties appeared, suggesting that weaker ties provided admission to non-redundant information. From this perspective, the outcomes are consistent with previous study by Hansen (1999) who examined 41 different subunits within an organisation and explored the relationship between tie strength, transfer of complex knowledge and performance in terms of project completion times. The theoretical model suggested by Hansen (1999) is represented in Figure 2.4:

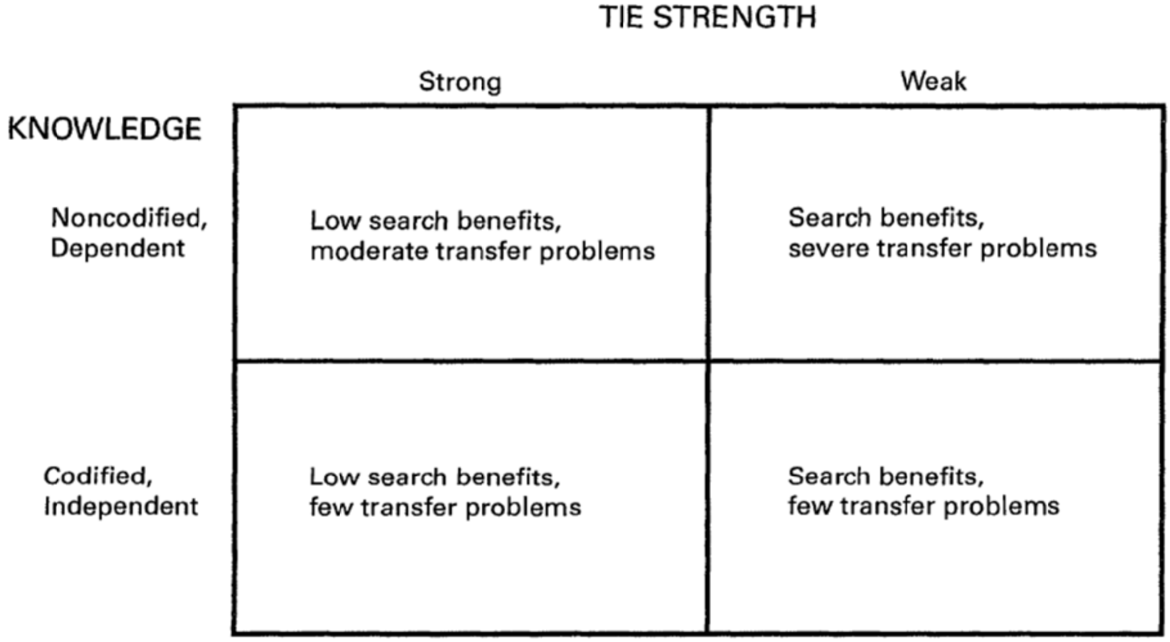


Figure 2.4: Search and transfer effects linked with four combinations of knowledge complexity and tie strength (Hansen, 1999)

According to Hansen (1999), weak ties enable quicker project completion times when the task is simple and allow quicker search for useful and valuable knowledge among other organisational subunits. Nevertheless, strong ties foster complex knowledge transfer more effectively than weak ties, which decelerate the transfer process when knowledge is extremely complex. The complexity of knowledge is determined by its tacitness and whether an actor is reliant on another for transfer and acquisition. Analogous outcomes are also reported in Reagans and McEvily's (2003) research study of a social network of 104 extremely skilful workers within a contract research and development company, where they found significant support for the positive association between tie strength and the ease of knowledge transfer in carrying out knowledge-intensive task activities. Consequently, strong ties enable complex knowledge transfer particularly to diverse individuals (Reagans and Zuckerman, 2001). For an actor to learn better, the significance of strong ties of an actor cannot be discounted.

2.2.3. Network-Level Social Network Theories

In network-level social network theories the emphasis is on explaining properties and characteristics of the network as a whole rather than those of individual or actors. Network-level social network theories use many of the structural measures and concepts developed by actor-level researchers. The main attention here is on outcomes at the network level. For example, network-level social network theories concentrate on structures and processes of the whole network, such as centralisation or density of the network as a whole. Recall that actor-level social network theories investigate how actor measures such as centrality might affect the performance or level of influence of individual actors. This viewpoint assumes that the success of one actor may or may not be critical to the success of the entire network. However, it shows that networks involve many actors working collaboratively toward a shared goal. The priority here is for optimisation of the whole social network, even if it comes at the cost of local optimisation for any actor or group of actors in the network. The following sections explore the major network-level social network theories.

2.2.3.1. Bavelas-Leavitt Experiment

One of the first research studies that linked network-level social network theories to group outcomes such as performance was the Bavelas-Leavitt Experiment (Bavelas, 1950; Leavitt, 1951). Drawing from the assumptions that (i) the success of any classes of tasks is determined by an effective flow of information (holding the nature and content of the information constant), and (ii) that fixed communication patterns influence task performance and the singular outcome, the interesting question in the research study is – "under what principles may a pattern of communication be determined that will in fact, be a fit one for effective and efficient effort?" The question to be answered is how the social network structure measured in terms of patterns of communication influences the work and life of actors within clusters, through a laboratory controlled experiment.

The investigation involved five individuals who communicated with each other using bounded compartments to solve a certain puzzle. Each individual was given five symbols from a set of six. All had unique symbols, but there was a shared symbol in all five. The problem was resolved when each cluster reached consensus as to what the common symbol was. The investigation was trialled fifteen times. None of the individuals knew each other, nor were they familiar with the outline of the communication structure, or the number of individuals in the research study. The experimenter controlled the channels of information. Depending on the structure of the communication networks, demonstrated in Figure 2.5, individuals could send as many messages as they desired through the compartment lines.

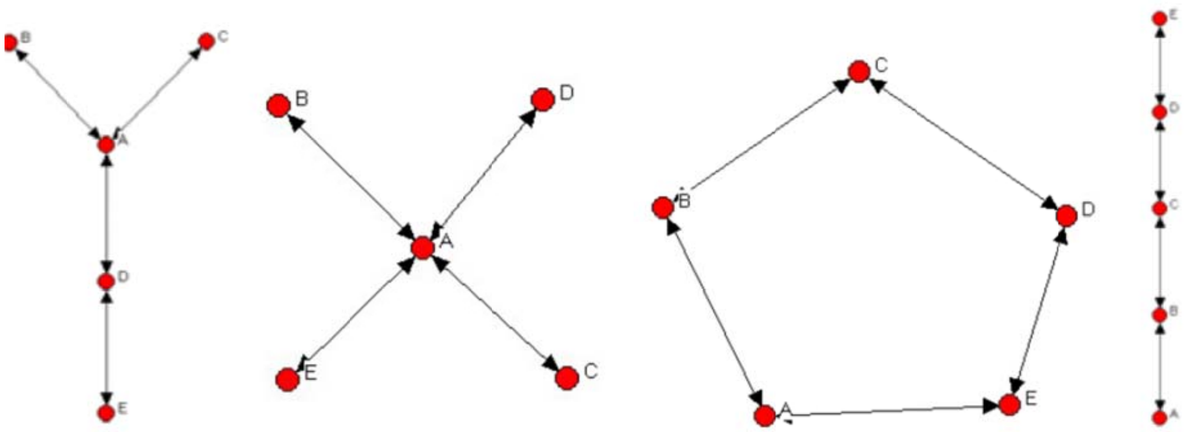


Figure 2.5: The Y, star, circle and line structures

The performance of network structures was assessed on the basis of pattern comparison and actor-level analysis. Performance of the task-oriented clusters was measured in terms of time required to complete the puzzle and number of errors made in the process of "guessing" the correct answer. When patterns of several structures were compared, the star and Y structures were on average moderately faster in completion time than the other structures (circle and line). The explanation presented by Leavitt (1951) was that centralisation was crucial to influencing performance. Using centralisation as an operational concept, it was established that patterns which revealed higher centralisation performed better. The information was better coordinated and shared when the individuals channelled all information through a central individual. Therefore, star (or hub-spokes or wheel) structures made the fewest errors and used the least number of messages compared to the other structures. It was shown that structures with higher centralisation likewise tended to have a leader arise through the task processes. The leaders evolved at locations of the highest centrality, as measured by degrees of communication activity. Thus, Y and star structures had actors with a very high degree of centrality compared to other actors within the structure, which led to better performance.

Unsurprisingly, an interesting outcome that developed as a result of this research was that centralised structures such as Y and star structures were more beneficial to performance, as measured by solving the puzzle faster, than decentralised networks such as the circle structure. The bottom line of that research is that information flow is ineffective in decentralised networks and hence less advantageous to performance. Nevertheless, a later study by Guetzkow and Simon (1955) demonstrated that decentralised structures in reality operated better when activities were more multifaceted. The complexity of tasks leads to complications and sub-tasks which cannot be done by an actor alone. The comparison is similar where central actors are overwhelmed with information. In that setting the circle network functioned far better than the star network. The all-channels structure in Figure 2.6 delivers an appropriate capability for task-relevant communication. For individuals, this permits a prospect to negotiate whether particular actors are to be brokers of information, details about what the task type is, and about ways of communication. The resulting communication patterns are hypothetically more effective.

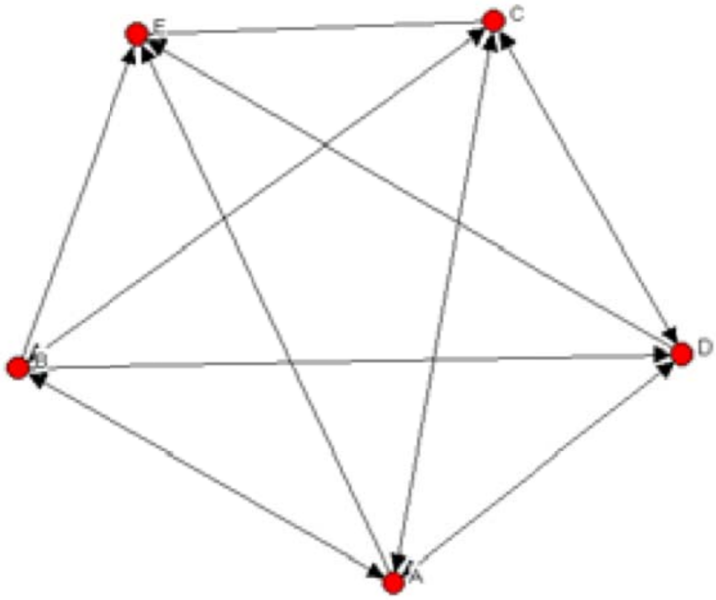


Figure 2.6: The “all channels” structure

As Guetzkow and Simon (1955) specify, individuals need to solve two problems. The first problem that needed to be solved was developing an organisation outline appropriate for finding the common symbol within the limitations of the specific network structures. The other problem was essentially finding the common symbol. Eventually, individuals will search for an organisational structure that operates to preserve interest and to pursue a 'better' form. Table 2.1 demonstrates the ideal match between task complexity and structure centralisation:

Table 2.1: Conditions under which centralisation/decentralisation structures are best (adapted from Borgatti (1997))

Variable	Simple Task	Complex Task
Least Messages	Centralised	Centralised
Least Time	Centralised	Decentralised
Least Errors	Centralised	Decentralised
Most Satisfactory	Decentralised	Decentralised

The study of Bavelas and Leavitt was a critical breakthrough as it introduced fresh vigour in the space of network structure-performance studies. Their main outcome was that centralisation leads to improved performance in simple tasks. Later research then found that decentralisation leads to effective performance in complex tasks. Conceptualisation of the influence of communication pattern on task performance opened up new research opportunities. Therefore, it required novel ideas and questions about understanding network-level outcomes such as performance or learning using a social network perspective.

2.2.3.2. Freeman's Concept of Network-Level Centrality

As described in an earlier section, Freeman (1978) proposed three measures for structural centrality: (i) degree centrality – indicating activity of actor and actor popularity, (ii) betweenness centrality – representing actor potential to control, and (iii) closeness centrality – stating the minimum cost to visit all other actors in the network. In a later study, Freeman et al. (1980) returned to the classic experiment of Bavelas (1950) to explore the effects of structural centrality on social communication. Freeman (1978) realised that, for research into social networks, scholars needed measures of network or centralisation based on differences in actor centralities. Therefore, he defined three network measures, each resembling one of the three actor-level measures used earlier to define the centrality of actors. These three measures as shown in the earlier section represent three distinct structural properties which were specified as bases for developing measures of actor centrality. Freeman et al. (1980) analysed the outcomes, using 100 university student volunteers as subjects for the experiment, and found that centralisation is a significant structural element influencing efficiency and leadership. Specifically, out of the three notions of structural centralisation, only two (degree centrality and betweenness centrality) showed notable outcomes and significance in their influence on performance.

Remarkably, an additional structural element, the overall density of information paths in the structural system, also appeared to be important in understanding network-level outcomes such as learning and performance. In research into the effects of network structure on diffusion of innovation, Coleman et al. (1957) studied 125 doctors' rates of adoption of a new drug and tried to understand the fundamental social processes involved. They found that doctors who were in general more combined with their colleagues (in denser networks) were quicker to accept the new drug. That research suggested, then, that the higher the number of connections an actor has, the greater the probability of adopting novelty more quickly. Such actors are faster to capitalise on the uniqueness of information and are therefore in a position to improve individual and group outcomes such as learning. These outcomes resonated strongly with analogous outcomes concerning the density notion proposed by Freeman et al. (1980). Since then, density and centralisation have been the main social network measures used for exploring effects on individual and group outcomes such as learning, improved performance, enhanced knowledge transfer and superior coordination (Pfeffer, 1980; Mullen et al., 1991; Faust, 1997; Sparrowe et al., 2001; Ahuja et al., 2003; Cross and Cummings, 2004; Hossain et al., 2006).

2.2.4. Summary of Network Theory Reviewed

To summarise, the preceding sections of this chapter have critically analysed key literature concerning social network theories. Regarding actor-level social network factors, Freeman (1978) demonstrated that individual and group outcomes were linked to the actor's property of centrality. Specifically, he acknowledged that degree centrality indicates the strength of communication flow, whereas betweenness centrality reveals communication power and influence. Furthermore, he showed that closeness centrality indicates the effectiveness of information flow. Burt's (1992) concept of structural holes was further based on the assumption of betweenness centrality. The concept showed that having a brokerage position provides information and control benefits. In fact, this change from the emphasis on network structure to network position was influential for additional research into the association of communication arrangements and individual outcomes.

At the relational or dyadic-level of network structure, the key concept reviewed was the strength of weak ties (Granovetter, 1973). This theory specifies that weak ties deliver valuable information. Nevertheless, later studies concerning the effects of strength of ties led to claims that strong ties are correspondingly and in turn significant for group outcomes such as learning. Regarding network-level social network factors, Bavelas (1950) and Leavitt (1951) revealed that centralised structures perform better when tasks are simple, but decentralised structures are more favourable for fewer errors, satisfaction, and the speed of task completion in complex tasks. This study consequently combines these theories to suggest that network structure, position and relations (actor, dyadic and network levels) individually and jointly impact on individual and team learning. Table shown 2.2 summarises the social network theories discussed so far. In the next section, an overview of learning and implications of networks on learning are introduced and incorporated.

Table 2.2: **Brief overview of theories in network structure**

Social Network Level of Analysis	Social Network Theories	Focus	Findings
Actor Level	**Burt (1992) (Structural hole)**	Node position in network structure (efficiency, constraint)	High efficiency Low constraint
	Freeman (1978) (Node centrality)	Node position in network structure	Degree centrality Betweenness centrality
Dyadic Level	**Granovetter (1973) Krackhardt (1992)**	Strength of ties	Weaker ties, for simple tasks Strong ties, for complex tasks
Network Level	**Bavelas (1950) (Network structure)**	Network structure (star, Y, line, circle)	Star, Y, for simple tasks Line, circle, for complex tasks
	Freeman (1978) (Network centralisation)	Network structure	Degree centralisation Betweenness centralisation

2.3. Overview of Learning

A substantial body of research (Zuboff, 1988; Watkins and Marsick, 1993; Weick and Roberts, 1993; Engeström and Middleton, 1998; Weick and Sutliffe, 2001) within environments demanding high reliability – which include emergency management work – suggests that under dynamic and uncertain conditions learning must become integral to the work itself (Owen, 2009): learning must become embedded in the everyday practice of work activity. This has led some experts working within environments requiring high reliability to examine closely the flow of information within organisations and to advocate for the creation of *generative* organisations where people can think and communicate effectively.

Many definitions of learning exist, as mentioned in Chapter 1. In summary, these definitions agree that the learning process involves the combination of two processes, an internal mental process of acquisition and elaboration and an external collaboration process between the learner and the environment (Illeris, 2003). From these processes, two broad families of learning theory are formed, (i) behaviourist and (ii) cognitive. Behaviourists assess the effectiveness of teaching methods through observable behaviour (Phillips, 1985). Behaviourists would not accept a student giving the correct answer as evidence of learning. However, their interpretations are based on impartial observation. It can be concluded from this that behaviourists do not try to understand or predict the hidden mechanisms of the mind, beyond what an impartial measure would be capable of recognising. The factors supporting the behaviourist orientation can surely be applied to organisations. The most significant system in place in many organisations would be the use of rewards programs for employees' high performance. A worker can obtain a bonus or a pay rise in the event of high productivity, or possibly because of long existing commitment to the company. This helps organisations to positively reinforce desired behaviours and improve productivity.

Unlike behaviourist theory, cognitive theory deals with the complexity of the mind (Greeno et al., 1996). Humans are observed as people who create careful thought with their own will. Cognitive theorists depend on complicated models of the human mind, with the understanding that humans use judgment and reflection to act and respond. Teaching using the cognitive concept can be done by helping learners to increase their mental capacity to accumulate and remember efficiently (Skinner, 1978). For instance, a teacher can use visualisation to improve students' memory and increase recall rates. Such methods can also have practical use in organisations. A common example would be the visual stimulus of signs posted around the organisation reminding employees of their tasks and duties, as well as of safety measures that are in place. It is clear that the organisational need for the coordination and appropriate management of resources favours the behaviourist approach, whereas teachers employ more cognitive approaches in educating others (Burns, 2002).

In the workplace, learning occurs in a myriad of ways (Eraut et al., 1998; Engestrom, 2001; Billett, 2002), and the concept of workplace learning has increasingly drawn the attention of psychological and social theorists as something that is formally organised and directed toward acquiring specific knowledge, attitudes and skills. Often referred to as either accredited learning or training, this type of learning is regarded as having a finite end point where the individual has gained some kind of competence and received accreditation. As well, learning may be characterised as an informal and sometimes incidental process embedded within work activity (Billett, 2002; Collin, 2006). These two characterisations are supported by two different theoretical positions within learning theory. In the first there is typically a focus on learning as an individual process, and the aspects of behaviour and cognition are emphasised. Within psychology, the "cognitive revolution" that followed the popularity of behaviourism emphasised that human beings are active, reflective creatures trying to make sense of their world. Attention within cognitive psychology has been given to what has been called symbolic or information-processing approaches to the learning process. These approaches have focused on how people use symbols in activity and problem solving and how they abstract mental models that can be generalised to other problems. Not surprisingly, the focus is on understanding processes of skill acquisition and the development of expertise (Chi et al., 1988).

In the second characterisation, learning is also seen to occur informally and sometimes incidentally. In this respect, workplace learning is embedded in the daily practices of acting, discussing and using the problem-solving skills that are part of the sharing process of working (Lave and Wenger, 2005). Such learning is entwined with the practical performance of work, its social networks being perceived as a collective social practice (Gherardi, 2001; Schulz, 2005; Collin, 2006). Theories of learning which support informal and incidental learning draw on socio-cultural perspectives. These theories highlight the effects on learning of both the nature of the environment and the significance of collective efforts (Engestrom, 2004; Collin, 2006).

For the purposes of this research, learning is regarded as a continuous process which becomes important particularly when work relies on interpersonal communication within and between work groups. In this research, *learning-related work activity* is defined as occurring when individuals and groups are engaged in deliberate and constant processes of reflection and conceptualisation about experience to generate alternative courses of action. Such activities include sharing ideas and observations, clarifying assumptions and courses of action, monitoring, and providing feedback on performance (Owen, 2009). Learning-related work activity, then, enables individuals and groups to work collectively to adapt and deal with the challenges posed by hazardous events. Learning-related work activity is particularly important in domains where there is high uncertainty and where conditions are dynamic and need personnel to act in ways that are coordinated and adaptive. If emergency management is about learning, then there must be at least three kinds of learning going on: *individual learning*, *team learning* and *network learning*.

While individual learning is about obtaining new, or modifying current knowledge, behaviour, abilities, standards, or preferences, and may include combining different kinds of information, Edmondson (1999) contended that team learning can be regarded as the process by which reasonably enduring changes arise in the behavioural repertoire of the group as a consequence of group collaborative actions through which individuals obtain, share, and combine knowledge. In this process, team knowledge is gained through correcting tactics in response to errors, discussing dissimilarities cooperatively, and creating new routines (Edmondson, 1999).Team learning also involves participants cooperatively reflecting about their team's courses and behaviours. These activities allow team members to improve their shared understanding of a specified circumstance and to determine the significance of preceding activities, thus assisting them to notice variations in their working atmosphere (Edmondson, 1999). Participating in these actions results in knowledge being created and embedded within the team, which eventually supports the development of performance (Olivera and Argote, 1999). Network learning is similar to team learning but pertains to network level rather than team level. It can be viewed as the process by which reasonably enduring changes arise in the behavioural repertoire of the network as a consequence of network collaboration activities through which members within the network obtain, share, and combine knowledge. Therefore, in the study of emergency management, it is pertinent to investigate the connections between enabling the practice of learning-related work activity at individual, team and network levels through engagement in social networks.

2.4. Network Effect on Learning

Previous research suggests that interactions between nodes in the network result in important opportunities for learning. This section explores the major studies which discuss the social network effect on learning based on actor-level, dyadic-level and network-level analyses.

2.4.1. Actor-Level Social Network Effect on Learning

Various studies have examined actor-level social network measures as significant predictors of individual learning. The first actor-level social network factors to be explored are efficiency and constraint, which were discussed earlier in this chapter. A famous study which addresses this is Burt's structural holes theory. As discussed earlier, Burt argues that the structural formation of an actor's social network which offers optimised "brokerage" location is what directs structural rewards such as information novelty and control. Burt invented and promoted the term *structural holes* to draw attention to several vital features of positional advantage/disadvantage of actors that result from how they are embedded in neighbourhoods. Burt's validation of these notions and his development of a number of measures such as efficiency and constraint have enabled an enormous amount of further thinking about how and why the methods of a person are linked affect the person's constraints and prospects, and therefore behaviour. Earlier studies have regularly revealed that high efficiency and low constraint measures are valuable signs of an actor's capability to generate novel ideas (Burt, 2004) and improve performance (Burt, 1992; Comet, 2007). From these arguments, it is predictable that actors prosper on the basis of valuable information from colleagues. An actor with an efficient and low constrained network structure is therefore more likely to acquire valuable information from diverse and non-redundant links, and that has been related to improve learning.

Another interesting actor-level social network factor to be explored is centrality. In a study of biotechnology firms, Powell, Koput et al. (1996) showed that centrality in a network facilitates the development of mutual understandings and collective principles of collaboration, thereby enhancing further exchange and improving learning. They argued that the locus of innovation and novelty will originate in networks of learning rather than in separate firms, as it offers timely access to knowledge and resources that are otherwise unobtainable. They developed a network approach to learning and assessed the contribution of cooperative ventures to the learning processes. They reviewed the literature on partnering and argued that collaboration enhances learning (Hamel, 1991; Dodgson, 1993).

Powell et al. (1996) proposed the learning model displayed in Figure 2.7, which they labelled cycles of learning. Firms can enter via research and development (R&D) ties or by some other type of tie. Early cooperative interactions activate the growth of experience in managing ties. R&D ties permit companies to have more diverse sources of cooperation and to gain more experience at managing relationships. The growth of experience allows a firm to become more central. Powell et al. argue that, as a result of this, centrally positioned firms are linked to the key element of the industry, providing access to novel knowledge. As well, a feedback process will be activated in which centrality leads to the start and extension of coalitions, thereby supporting the dynamics of learning. Powell et al. also take this growing connectivity as additional evidence that firms progressively use ties to improve the influx of particular knowledge and resources. Centrality in a network allows common understandings and shared principles of association. Therefore, centrality in a network can enhance further exchange and improve learning.

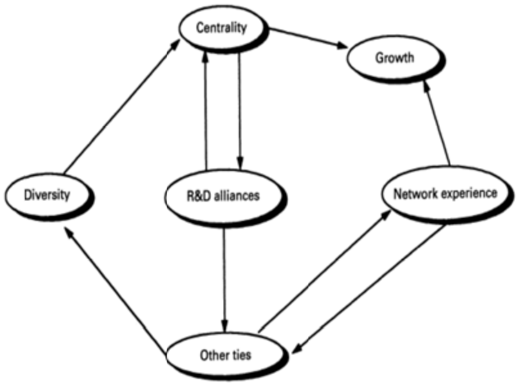


Figure 2.7: Cycles of learning in the biotechnology network (Powell et al., 1996).

Similar findings were reported in Tsai's (2001) study of 24 business units in a petrochemical company and 36 business units in a food-manufacturing company. Tsai found that organisational units can generate more innovations and enjoy improved performance if they occupy central network locations that offer access to novel knowledge developed by other units, as shown in Figure 2.8. This effect, however, depends on units' absorptive capacity, or ability to successfully replicate new knowledge. Knowledge transfer among organisational units offers opportunities for shared learning and collaboration that encourage the formation of novel knowledge (Kogut and Zander, 1992; Tsai and Ghoshal, 1998). Relations and networks are vital parts of a learning process in which organisational units discover new prospects and gain novel knowledge through networking with one another. Tsai (2001) argues that by connecting different units together, a network arrangement delivers a flexible learning structure.

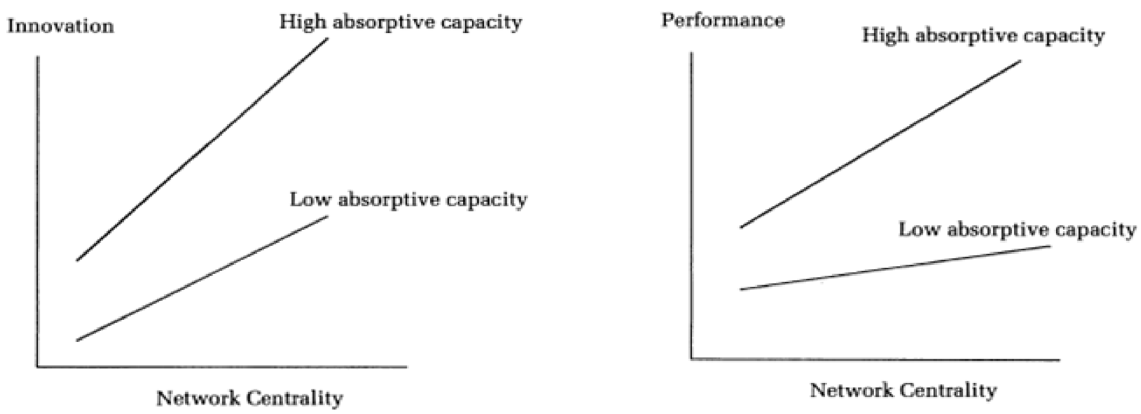


Figure 2.8: Tsai's (2001) findings about the effect of network centrality on innovation and performance

In another study of individual performance and learning, Cross and Cummings (2004) investigated 101 engineers and 125 consultants. They found significant support for the positive association between an actor's number of connections and learning. Secondly, they found that betweenness centrality in both information and awareness networks was linked to individuals' capability to acquire and apply appropriate information to resolve problems efficiently and effectively. Precisely, betweenness centrality in a network established by awareness of colleagues' expertise should increase an individual's access to appropriate knowledge in distant areas of a network and consequently assist that individual to act efficiently and effectively when new projects require different information or expertise. As a result, actors with a higher *reach* of information (degree centrality) and higher betweenness centrality are more likely to be exposed to unique and appropriate knowledge that is supportive in resolving complex problems and hence learning. These studies focused on the impact of actor-level social network factors within a stable and routine environment. However, few studies have been conducted in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles (problems), such as disasters. This study explores the effect of social networks on learning in the context of a dynamic environment.

2.4.2. Dyadic-Level Social Network Effect on Learning

Research suggests that interactions between nodes in the network result in important opportunities for learning. Seminal work in dyadic-level social networks and their effect on learning and innovation almost always begins with Granovetter's (1973) theory on the strength of weak ties which was described earlier. "The strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter, 1973, p. 1361). Granovetter argues that actors obtain new knowledge from weak ties within their network. That is, networks where strong ties tend to bond similar actors to each other are closed networks and, according to Granovetter, are not readily receptive to new information. The implication of Granovetter's theory is that the inflow of unique knowledge must come from weak ties which function as a bridge to a diverse group of actors.

However, Kraatz (1998) asserts that stronger ties between the nodes of the network will provide better opportunities to learn for those nodes. His study of 230 private colleges over 16 turbulent years further suggests that organisations in smaller networks, more homogeneous networks and older networks will be more likely to adapt their core features in response to environmental change. Kraatz argues that strong ties diminish ambiguity. As a result, these strong ties will encourage information sharing, thus stimulating an environment for learning and adaptation.

In another study that examined two separate research sites, Borgatti and Cross (2003) proposed a model of information seeking. They argue that as people update their understanding of others, they affect their probability of interacting with them in the future. As a result, a dynamic feedback system will be created (Figure 2.9). For instance, realising that an individual is not helpful decreases the likelihood of cooperating with that person. In contrast, having a constructive collaboration may diminish access obstacles and lead to upcoming connections. Over time, individuals may lock in to a restricted group of individuals with whom they often cooperate, which might be effective but might also produce suboptimal information if other individuals are better sources. The view of learning presented by previous studies is valid in stable environments, but this concept in studying and identifying social networks might not be adequate for research in non-routine situations, such as emergency incident management where a key feature of the work is dynamic change and uncertainty. Therefore, in the study of emergency management, the present research investigates learning through engagement in social networks in that dynamic environment. In light of these arguments, a significant association is expected between the strength of team members' ties and their learning in a dynamic environment.

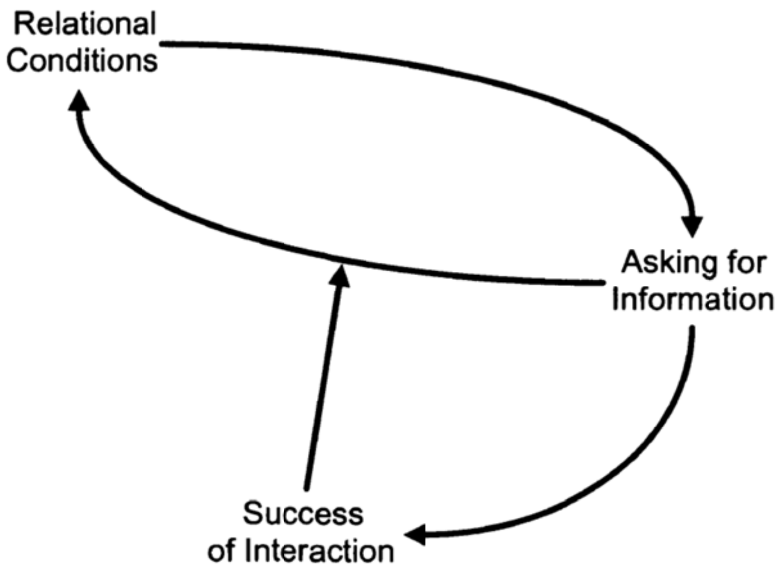


Figure 2.9: Dynamic model of learning in intentional search

2.4.3. Network-level Social Network Effect on Learning

Network effects on teams' ability to learn have been documented in studies in communications, social psychology and sociology (Guetzkow and Dill, 1957; Coleman, 1988). The first structural factor to be explored is the overall density of communication paths in the structural form, which has turned out to be relevant for understanding learning and performance. Previous studies have shown that dense networks are favourable for diffusion of

innovation (Coleman et al., 1966), intellectual performance (Coleman, 1988) and knowledge-sharing (Cross and Cummings, 2004). Highly dense networks usually indicate that an actor has many links which promote feelings of belonging, security and group identity and strengthen the links between the actors (Coleman, 1994). These strong relations are required to transfer tacit knowledge (which basically refers to the knowledge inside people's heads that is constructed through experience, individual learning and collaboration (Brannback, 2003; Gourlay, 2006)) and complex knowledge, which is crucial for learning (Reagans and McEvily, 2003).
Burt, however, takes on a structural perspective by suggesting that denser ties in an individual's social network are far less efficient than scattered networks because (1) they are costly to maintain, and (2) they provide redundant information. High-density networks may also have a negative effect on variety of knowledge because they promote uniformity of experience and attitudes among actors and limit the potential for innovation (Reagans and McEvily, 2003; Oh et al., 2004). This occurs, for example, through a high density of communication among actors that leads to a situation in which all actors tend to adopt an identical understanding of problems at hand, leading to a network that is not well receptive of new information. Networks with too many links to others may also lock an actor inside a political position (for instance) by peer-pressure, thereby limiting the ability to innovate and act (Frank and Yasumoto, 1998; Bodin et al., 2006).

As mentioned earlier in this chapter, in research into the effects of network structure on diffusion of innovation, Coleman et al. (1957) studied the rate of adoption of a new drug among 125 doctors, trying to understand the fundamental social processes that affected it. From their findings(Burt, 1992) the authors proposed that doctors who were in general more combined with their colleagues (in denser networks) were quicker in acceptance of the new drug. This research thus supports the contention that the more connections an actor has, the greater the probability of adopting novelty more quickly. Such actors are faster to capitalise on the uniqueness of the information and are therefore in a location to improve individual and group outcomes such as learning. These outcomes resonated strongly with analogous outcomes about the density notion reported by Freeman et al. (1980). Most of these studies about network density have investigated learning problems requiring stable working relationships with no environmental uncertainties, but the concepts in studying and identifying social networks may not be adequate for research in non-routine situations, such as emergency incident management.

Another interesting structural factor is centralisation, which is based on the actor-level centrality that was discussed earlier. All the experiments done by Bavelas and his research team established that centrality was linked to group efficiency in problem-solving, the perception of leadership and the individual satisfaction of participants (Bavelas, 1950). Their key finding was that centralisation leads to enhanced learning in the process of solving simple tasks because appropriate information can be transferred and synthesised to a few individuals who can make a decision and take action. For the same reason, high centralisation may also be valuable in times of change, when adequate coordination of individuals and resources might be needed (Bodin et al., 2006). However, a later research study on Bavelas's experiments by Guetzkow and Simon (1955) suggested that decentralised structures work better than centralised structures when tasks become more complex. A high degree of centralisation might initiate centralised management and therefore fewer experiments and less practical learning (Leavitt, 1951; Shaw, 1981).

In the late 1970s, Freeman (1978) wrote a seminal article about the instinctive background for measures of structural centrality, which directly became one of the core concepts in social network study. Specifically, Freeman (1978) explained the centrality concept in terms of degree centrality, betweenness centrality and closeness centrality. Each of these centrality measures has significant consequences on social outcomes. Degree centrality can be measured according to the number of links to and from a node. Betweenness centrality refers to the level to which a node lies in the shortest path to all others in the network. Closeness centrality refers to the level to which a node is close to all others in the network. Every centrality notion has been associated with significant social events. For instance, degree centrality has been observed as a key indicator of a node's communication activity, whereas betweenness centrality has been observed as an important indicator of the potential of a node's control of communication, and closeness centrality has been observed as an indicator of the minimum cost of time and efficiency for communicating with other nodes in the network.

In a later research study, Freeman et al. (1980) returned to the classic experiments by Bavelas (1950) to explore the effects of structural centrality on social communication. Freeman (1978) realised that for research into social networks, scholars need measures of network or centralisation based on differences in actor centralities. He therefore defined three network measures, each of which resembles one of the three actor-level measures used earlier to define the centrality of actors. As shown in the earlier section, these three measures represent three distinct structural properties which have been specified as bases for developing measures of actor centrality. Freeman et al. (1980) analysed the outcomes using 100 university student volunteers as subjects for the experiment, and revealed that centralisation was a significant structural element influencing efficiency and leadership. Specifically, of the three notions of structural centralisation, only two (i.e., degree centrality and betweenness centrality) revealed notable outcomes and significance in their influence on performance. Since then, density and centralisation have been the main social network measures used for exploring effects on individual and group outcomes such as learning, improved performance, enhanced knowledge transfer and superior coordination (Pfeffer, 1980; Mullen et al., 1991; Faust, 1997; Sparrowe et al., 2001; Ahuja et al., 2003; Cross and Cummings, 2004; Hossain et al., 2006).

Edmondson (1999) investigated 51 work teams in a manufacturing company, proposing a team learning model (Figure 2.10) which could be appropriate across multiple types of teams. This research supported an integrative viewpoint, in which both structural and social characteristics influence learning and performance in teams. Studies discussed earlier have investigated the effect of networking on learning and have suggested that the use of social networks by individuals and organisations provides sources of reliable information, which improves their learning (Powell et al., 1996; Beeby and Booth, 2000; Hartley and Allison, 2002; Knight, 2002). Those studies have focused on the impact of network structure within a stable and routine environment. However, few studies have been conducted in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles (problems), such as disasters. This study explores the effect of social networks on learning in a dynamic environment context.

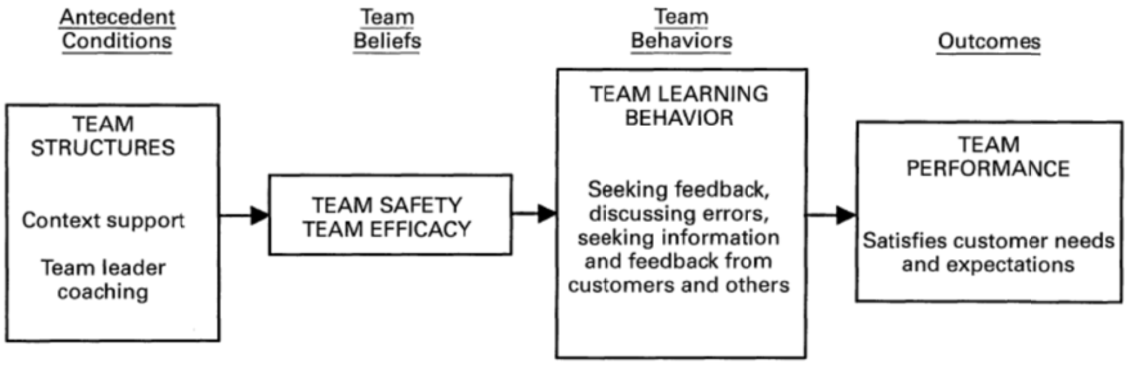


Figure 2.10: Team learning model proposed by Edmondson (1999)

2.5. Social Network and Learning in a Dynamic Context

A fundamental assumption of most of the social network research described earlier is that learning is influenced by social networks at actor level, dyadic level and network level. Most studies relating to social networks and learning have concentrated on the effect of networks on learning, at all level of analysis, within a stable and routine environment. However, few studies have been conducted in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles (problems), such as disasters. As mentioned earlier, catastrophic disasters are best characterised by surprising and remarkable interruptions to the communication and decision-making capabilities of the emergency response system itself, and an initial failure in coordination and communication (Kapucu and Van Wart, 2006). Although not all emergency events become disasters, the risk of an emergency management system becoming overwhelmed is a critical issue. It is therefore important to explore ways to improve emergency management systems to mitigate the vulnerability of local communities to extreme risk. This study focuses on the effect of social networks on learning in a dynamic environment context. In this section, studies of social networks in a dynamic environment are reviewed. As well, previous literature concerning learning in a dynamic environment is reviewed. At the end of the section, the few studies of network structure and learning in a dynamic environment are discussed.

2.5.1. Social Networks in Dynamic Context

Studies of social networks in a dynamic environment detail options for applying SNA to research in a dynamic environment such as disasters. Disasters present social network researchers the chance to explore social behaviour in periods in which social adaptation and instinct are often more obviously exposed. More essentially, though, social network research has potential importance for mitigating catastrophe loss, improving disaster responses, and assessing management performance. Numerous SNA studies of disasters mostly demonstrate that informal individual and group relations play a major part in disaster relief efforts, independent of government assistance and survivors' individual circumstances (such as income, education, the level of loss).

In a study of emergency services operations, Houghton et al. (2006) explored processes of command and control in emergency services from the perspective of social network theory. Their study was based on the eight basic command structures evaluated by Dekker (2002) within the Scud Hunt paradigm. These structures are summarised in Figure 2.11. Houghton et al. showed that observation of communication activity can help in developing network structures, which can be presented graphically. It is suggested that SNA is a valuable technique of investigation in the study of command and control.

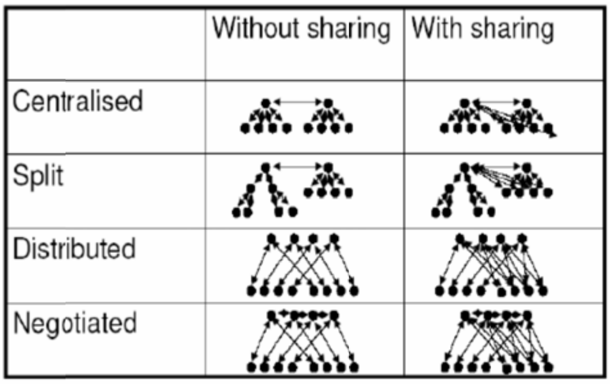


Figure 2.11: Dekker network architectures (Houghton et al. (2006))

In another study of social networks in a dynamic environment, Uddin and Hossain (2009) propose the framework of a model of coordination preparedness of soft-target organisations, as illustrated in Figure 2.12. The model is proposed for the assessment of coordination preparedness in order to optimise network performance. The model is built with a view to evaluate the existing state of coordination preparedness as a product of elements of network relations. Uddin and Hossain state that there is certainly a positive association between network relation and coordination readiness, such that by increasing a node's participation within the network, it is probable that the capacity of that node to coordinate in the emergency will also increase.

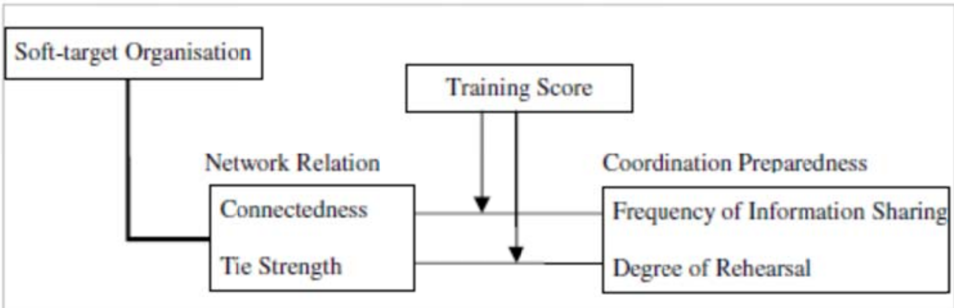


Figure 2.12: A model for assessing coordination preparedness (Uddin and Hossain, 2009)

In other study using social network methodology in the study of disasters, Varda et al. (2009) propose a descriptive model (Figure 2.13) summarising several roles and attributes of actors (i.e., individuals, groups, or communities) in pre- and post-disaster settings. The model is divided into four regions. In the first region (In/Seekers), actors are in the catastrophe zone, seeking something from others (e.g., victims seeking help). In the second region (In/Providers), actors are in the catastrophe zone, providing something to others (e.g., emergency staff members transporting victims outside the catastrophe zone). In the third region (Out/Seekers), actors are outside the catastrophe zone, seeking something from others (e.g., organisations seeking help to deliver resources to victims). In the fourth region, actors are outside the catastrophe zone, providing something to others (e.g., a hospital providing care for victims once they are out of the catastrophe zone).

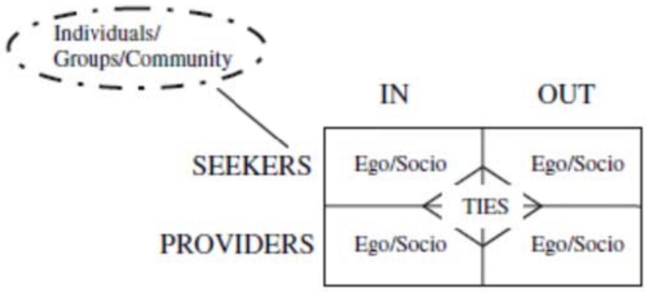


Figure 2.13: Social network actors in a post-disaster setting [specifically, their attributes]. In/ Out/Seekers/Providers (IOSP) framework (Varda et al., 2009)

In another study of disaster response preparedness coordination through social networks, Hossain and Kuti (2010) propose a research model (illustrated in Figure 2.14). The model portrays a framework for exploring coordination preparedness based on network connectedness (evaluated through SNA). Hossain and Kuti (2010) identified a positive relationship between social network connectedness and coordination within disasters.

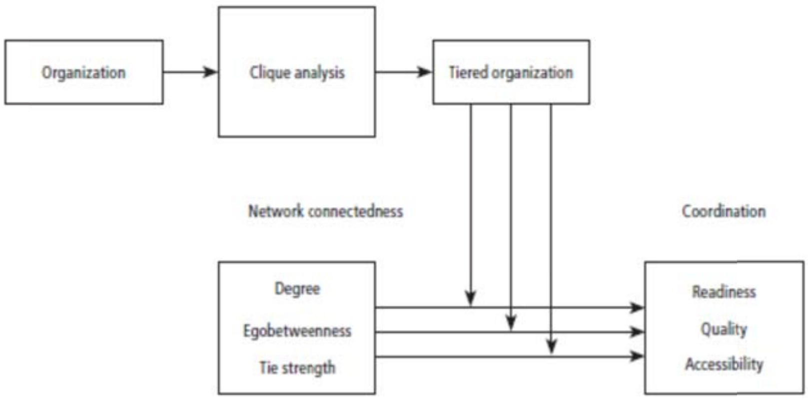


Figure 2.14: A model for assessing coordination preparedness in emergency response networks (Hossain and Kuti, 2010)

In a study of incident command systems (ICS), Moynihan (2009) illustrated the difference between a network governance and the hierarchical view of the ICS as Figure 2.15. The left-hand side of the figure characterises the main vision of the ICS. In this figure, a chain of command permits the incident commander to direct the emergency tasks of logistics, operations, planning, and finance/administration. The hierarchy is intended to ensure that all personnel have a recognised manager and each manager has a manageable span of control. Nevertheless, if the ICS is considered in terms of its members, it can be seen as a network as demonstrated by the right hand side of Figure 2.15. Moynihan uses a case study of the ICS in managing a bizarre animal disease outbreak which points to the significance of disaster features and management influences as possibilities affecting the job of the ICS.

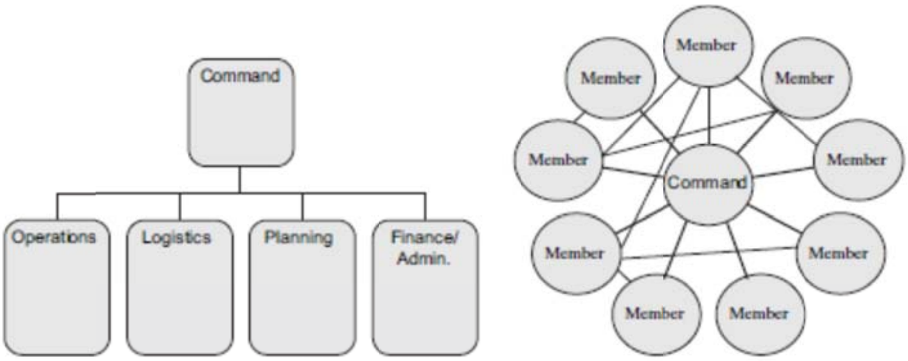


Figure 2.15: Hierarchy or network? Competing views of the ICS (Moynihan, 2009)

In summary, the SNA studies discussed earlier in this section propose that SNA is a useful method of enquiry in the study of dynamic complex environments such as disasters. SNA research studies may offer perceptions of the speed and effectiveness of catastrophe preparation, response and recovery efforts. Finally, SNA research might lead to some useful, policy-based recommendations. The studies discussed earlier have investigated the use of SNA in dynamic environments. However, no study has looked at the effect of social networks on learning in a dynamic environment. This study explores the effect of social networks on learning in a dynamic environment context.

2.5.2. Learning in Dynamic Context

In this section, studies of learning in a dynamic complex environment are reviewed. These studies detail the importance of learning in dynamic complex environments such as disasters. Disasters allow social network scholars to study social behaviour in periods in which social adaptation and instinct are more obviously exposed. The various examples of learning research on disasters generally show that learning theory is a vital tool with which to understand organisation coordination in response to an extreme event. The complexity of these events require a flexible learning methodology (Weick and Roberts, 1993; Weick and Sutliffe, 2001). This will requires the individuals and organisations dealing with these events to be flexible and adaptable to unpredictable conditions. However, the challenge of learning in the context of an emergency event as it unfolds is not easy (Comfort et al., 2009). Members of organisations engaged in the emergency must therefore improve their ability to learn during incidents in order to reduce the frequency and severity of errors (Blanco et al., 1996).

An example of the importance of learning in disasters is the events on September 11 and in the days and weeks that followed in New York City's massive destruction and social disruption. Helped by emergency personnel, residents of the World Trade Centre (WTC) and individuals in the nearby region helped one another to safety. Previous experience with the 1993 WTC bombing had led to substantial learning, and preparation and training contributed to the capacity to react in an adaptive style to extremely vague and intimidating circumstances (Kapucu, 2006). Comfort (1994) provides another example of learning in San Salvador and California. Comfort shows that earthquake responders benefited from the build-up of knowledge from preceding earthquakes. The actors involved had improved understanding of role expectations. Such valuable knowledge can be transformed into standard operating procedures (SOPs) that can be useful in other disasters and adapted as suitable.

In a study of learning in dynamic complex environments, Carley and Harrald (1997) explore the differences between organisational learning in theory and in practice, as revealed in the activities of the organisations responding to Hurricane Andrew in Miami. Their analysis proposes that organisational learning from unusual events occurs in steps. In Figure 2.16 they present a model of organisational learning as it takes place in response to exceptional events. The model is built on the basis that learning includes problem recognition, problem solving, and implementation of solutions. There are eight possible consequences given this classification, as shown in Table 2.3. Obviously, there are several methods by which an organisation can fail in the learning process.

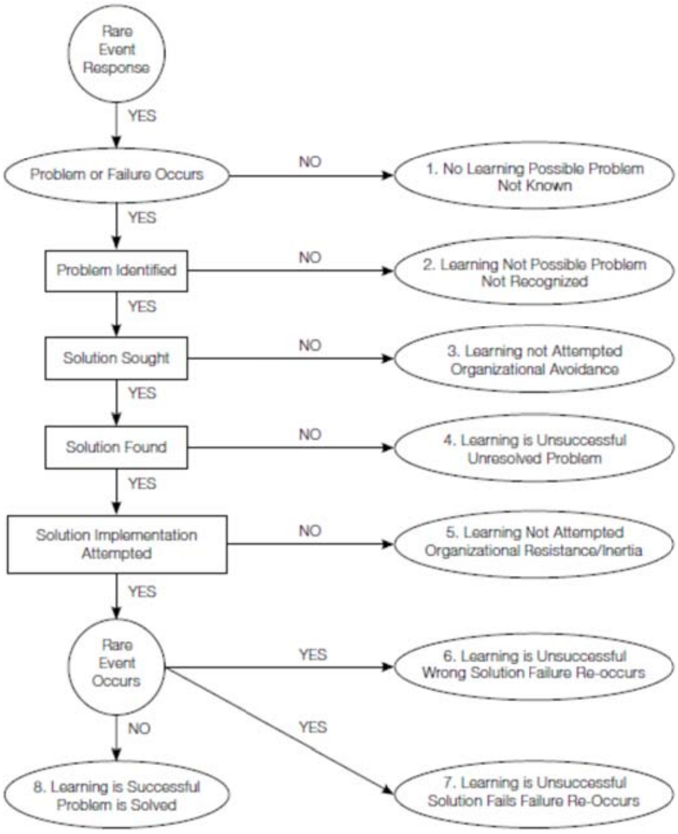


Figure 2.16: A taxonomy of organisational learning from rare events (Carley and Harrald, 1997)

Table 2.3: Organisational learning (Carley and Harrald, 1997)

1. Learning not possible	Potential problem did not occur
2. Learning not possible	Problem not recognized because of inadequate feedback, intelligence, or information processing
3. Learning not attempted	Solution not sought because of organizational avoidance
4. Learning not attempted	Solution sought but problem not solved
5. Learning not attempted	Solution found but not implemented because of organizational resistance or inertia
6. Learning is unsuccessful	Solution implemented but fails because of wrong solution
7. Learning is unsuccessful	Solution implementation is attempted but fails because of organizational resistance
8. Learning is successful	Problem does not recur

In Jia Wang's (2008) most recent study of the development of organisational learning capacity in crisis management, she conceptualises (Figure 2.17) the role of organisational learning in crisis management and its connection to change. She details how the critical learning constructs and processes—knowledge acquisition, knowledge diffusion, knowledge utilization, reflection, and organisational memory, which she draws from Huber's (1991) model—might play a major role in each stage of crisis management. She proposes that this unified framework of organisational learning for crisis management will possibly support organisational capability and flexibility in handling with crises and subsequent changes. The proposed model shows how organisations can prepare for and respond to the dangers through continual learning processes. This research contends that promoting organisational learning before, throughout, and after crises will most probably put organisations in a superior position for noticing crisis indicators, developing action strategies for the prevention and management of a crisis situation, learning efficiently from a crisis experience, and applying new learning to improve subsequent practices in crisis management.

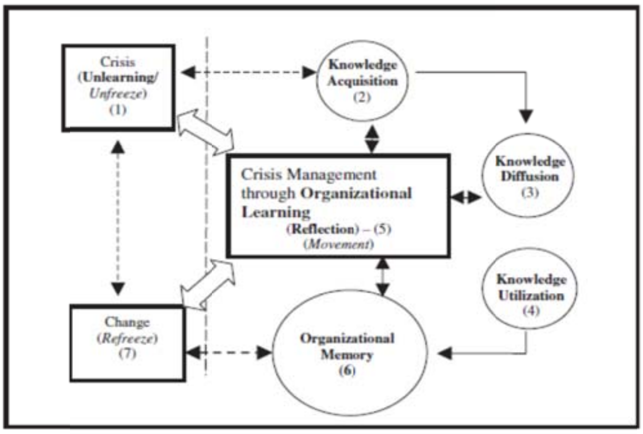


Figure 2.17: An integrated model of organisational learning for crisis management (Jia Wang, 2008)

Similar findings were reported in other studies (Roux-Dufort and Metais, 1999; Smith and Elliott, 2007). In their study of a French nuclear power producer, Roux-Dufort and Metais (1999) developed a theoretical model to demonstrate how organisational learning helps organisations to build a set of embedded knowledge assets (core competencies). They clarified the method of building core competencies in risk and crisis management, shown in Figure 2.18. The development of core competencies over time is determined by the capability of the company to sustain an extraordinary level of organisational learning. Roux-Dufort and Metais detailed how the most influential French electricity producer and supplier had learned from Three Mile Island in 1979 and Chernobyl in 1986 to develop and improve constantly its core competence in risk and crisis management.

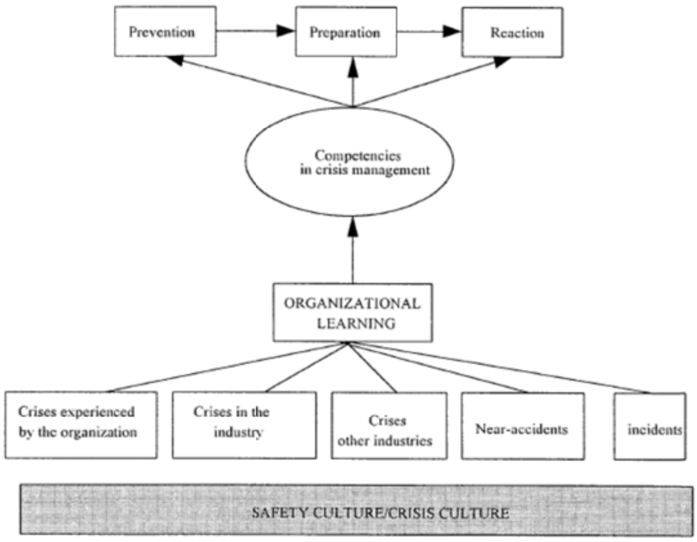


Figure 2.18: Crisis management as a core competence (Roux-Dufort and Metais, 1999)

In summary, the learning studies discussed in this section cite learning as important in the study of dynamic complex environments such as disasters. Learning is one of the important tools through which organisations come to stop and diminish the influence of catastrophes. The lessons of experience must permit the organisation to respond to imminent events in a more effective way, thus reducing the impact of failures (Carley and Harrald, 1997). By changing and adapting, organisations can respond better to upcoming catastrophes. That is, organisational responses must be well-timed and must lessen the impact of the catastrophe at all levels. Learning studies can finally lead to applied, policy-based recommendations. The studies discussed earlier have applied learning theories in dynamic complex environments. However, no study has looked at the effect of social networks on learning in a dynamic complex environment. This study explores the effect of social networks on learning in a dynamic complex environment context.

2.5.3. Social Networks and Learning in Dynamic Context

From the Venn diagram in Figure 2.19, it is clear that past studies have examined dynamic complex environment events using constructs of either network structure or learning, without examining in detail their interplay. There have been relatively few efforts designed to increase the current understanding of how network structures and patterns influence individual and team learning in a dynamic complex environment. Here, two such studies are discussed.

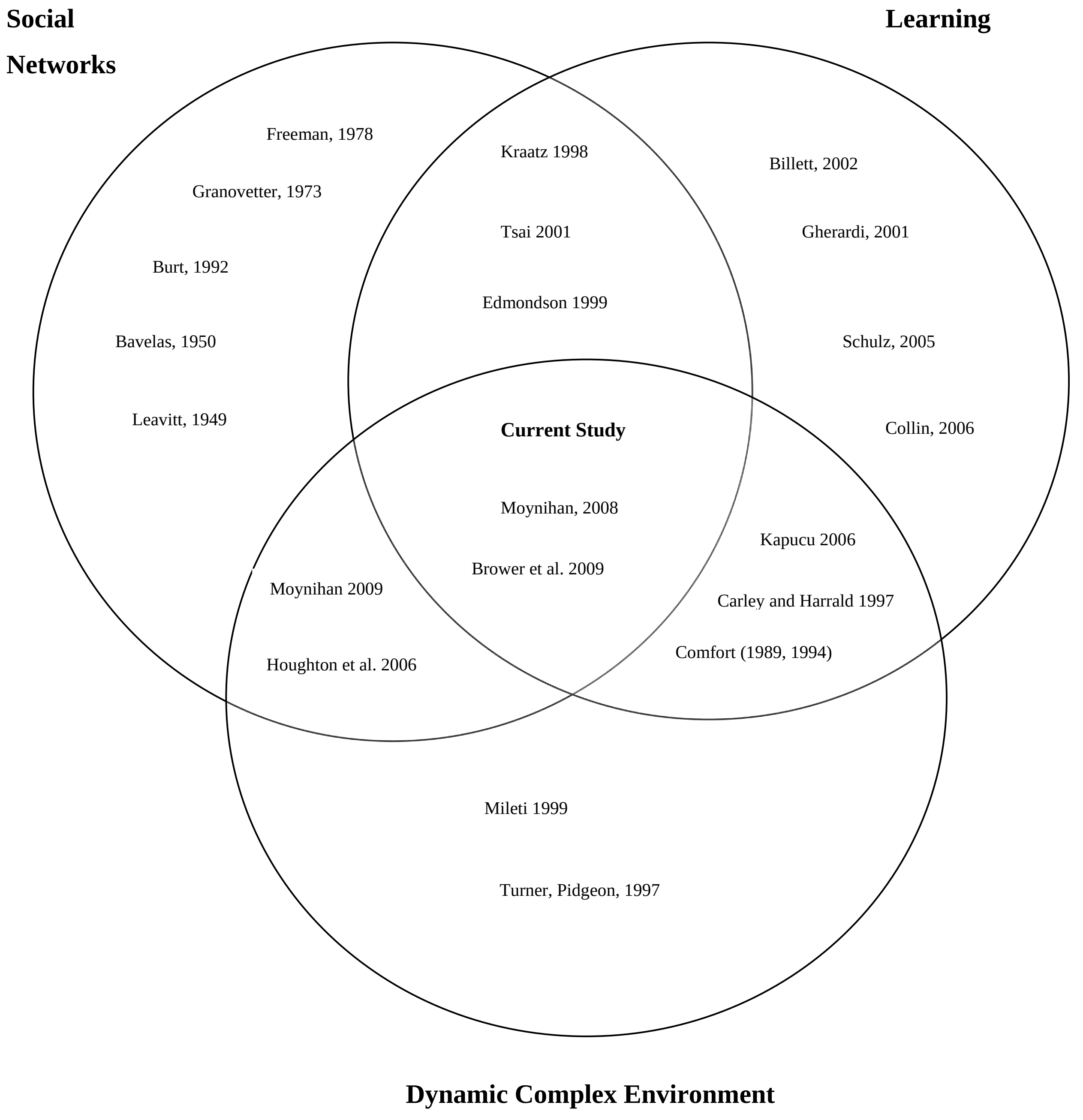


Figure 2.19: Venn diagram showing key literature relevant to this study

In a study of an exotic animal disease outbreak, Moynihan (2008) investigated learning in networks dealing with circumstances of high ambiguity. Moynihan defines learning, crisis and networks. Learning refers to the "identification and the embedding of practices and behaviours by the network to improve crisis response." Crises are characterised by "high consequentiality, limited time, high political salience, uncertainty, and ambiguity". Networks are "multiple organisations dependent on one another to achieve a common goal". The author identifies the basic difficulties of learning under crisis conditions, with barriers to effective learning during crises:

"● The high consequentiality of crises makes trial and error learning prohibitive.
● Crises require inter-organisational rather than organisational learning.
● There is a lack of relevant experience, heuristics, SOPs, or technologies to draw on.
● The scope of learning required is greater than for routine situations.
● The ambiguity of previous experience gives rise to faulty lesson drawing.
● Crises narrow focus and limit information processing.
● There is a rigidity of response: actors recycle old solutions to new problems.
● Political dynamics give rise to bargaining and suboptimal decisions.
● Crises provoke defensive postures and denial of the problem, responsibility, or error.
● Crises provoke opportunism as actors focus on their positive role."

Moynihan (2008) found that within a dynamic complex environment, networks had to learn most of the basics taken for granted in more established structural forms. The network achieved this learning with a variety of methods, including virtual learning, learning forums, learning from the past, using information systems and learning from other network members. *Virtual experience* provides the opportunity to understand emergency management challenges through preplanning, role-plays, on-the-job training, and simulations. Preplanning brings together relevant individuals who develop working relationships before emergency events occur (Boin, 2005). On-the-job-training delivers skills to network members who otherwise lack pertinent experience. *Learning from others* provides knowledge on how to deal with emergency events and transfer knowledge and information to others. By sharing knowledge, inter-organisational learning adopts partnership skills and diminishes ambiguity. *Learning from information systems* can decrease the necessity for monitoring and the potential for error.

Comfort et al. (1989) demonstrate that information systems are crucial in enabling emergency management network responses. Information systems that fail to provide timely information have little to no potential for learning (Lagadec, 1990).

Network memory through standard operating procedures guides organisational behaviour, institutionalising learning by recording, preserving, and retrieving experience through routine (Williamson, 1995; Crossan et al., 1999). This learning method simplifies decision-making in extremely ambiguous and complex settings. Finally, *learning from the past* might offer direction since earlier emergencies can be a clear source of lessons (Comfort et al., 1989). Learning from such emergency events would oblige existing network members to read reports from recent emergencies and to seek contributions from executives who had actual experience with these emergency events, to explore their perceptions.

In a more recent study of forms of inter-organisational learning in emergency management networks, Brower et al. (2009) present a conceptual model (see Figure 2.20) that demonstrates challenging connections between organisational and inter-organisational learning and the effectiveness of networks of voluntary and public organisations that deliver emergency management services. The authors believe that network effectiveness is quite different under the wild environmental circumstances of emergency management, and that the kinds of structures supposed to generate network effectiveness in more stable institutional circumstances might not work in emergency management.

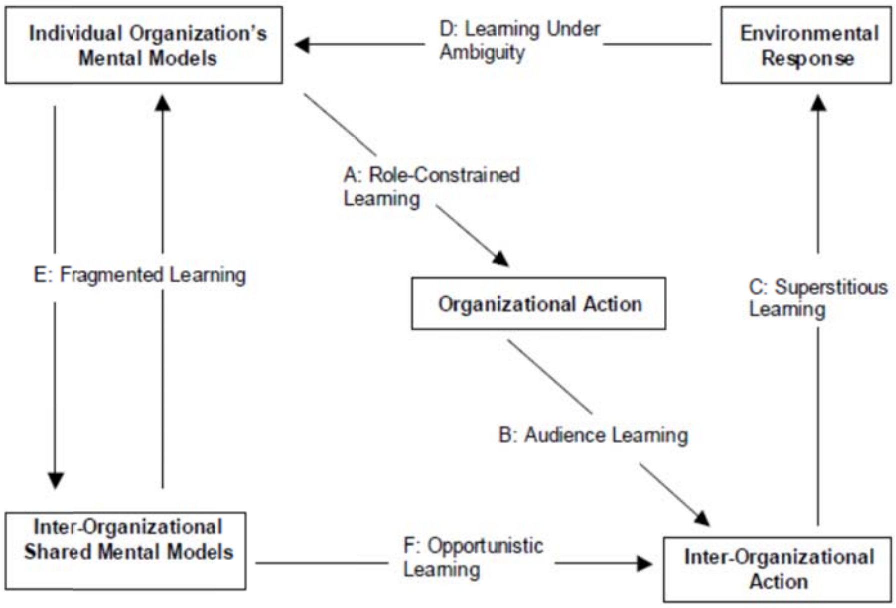


Figure 2.20: Conceptual model presented by Brower et al. (2009)

The conceptual model in Figure 2.20 indicates that organisational actions arise in large part from specific organisational mental models. These actions, in turn, guide inter-organisational action, which creates some environmental response. The cycle is complete when perceived alterations in the environment affect organisational mental models. This model similarly proposes the transmission of learning through the interchange of individuals and shared mental models. Schön and Argyris (1997) propose that organisational and inter-organisational learning occurs merely when new knowledge and information guide collective members to generate new, replicable, behaviour configurations. Therefore, Choi et al. (2009) believe that the mental models in individual organisations affect learning in inter-organisational networks by influencing mental models that are shared inter-organisationally. Current mental models include simultaneously the potential for facilitating and for restricting individual change in organisations (Giddens, 1979).

The conceptual model in Figure 2.20 includes six circumstances where the learning cycle is incomplete; each of these problematic circumstances can be considered a factor that exists to a higher or lower level in the learning cycle. Role-constrained learning (Point A, Figure 2.20) may take place when organisational learning has a reduced influence on organisational action because the cycle is damaged by the restrictions of the roles allocated or attributed to organisations in the network. This is expected to remain a recurrent occurrence in emergency management systems, since emergency policies naturally recommend precise, restricted, duties for organisations in several emergency response roles, e.g., shelter, food, aid, donations, volunteers, and so on.

Audience learning (Point B, Figure 2.20) may happen while the linkage between organisational action and inter-organisational action turn outs to be problematic. Regularly, this loss of learning takes place when distinct organisations' efforts are excessively large and too self-governing to be coordinated efficiently. Another problematic connection in the learning cycle is "superstitious experiential learning" (Point C, Figure 2.20). In these circumstances, one or more organisations within a network takes action. The action creates inter-organisational behaviour which seems to result in favourable environmental change and therefore network learning takes place. However, the links between inter-organisational action and environmental response are, in fact, spurious. Inter-organisational members have superstitiously linked their actions to environmental responses not produced by their actions.

With learning under ambiguity (Point D, Figure 2.20), organisations try to learn and influence inter-organisational action which affects the environment. However, it is often not obvious what actions were taken or what resulted. Furthermore, observers are often uncertain what they are observing and how to describe or relate it to their current mental models. Uncertainty is experienced not merely by organisational members but by all people affected by the catastrophe. Their reactions, frequently built upon a vague understanding of conditions, compound the environmental uncertainty for responding organisations. For executives, the struggle regularly arises as a difficulty of defining "the big picture." In fragmented learning (Point E, Figure 2.20), organisations learn, but the network as a whole does not. When the connection between individual organisations' mental models and the network's shared mental models are shattered, fragmented learning takes place. In emergency management, authorities in individual organisations can learn extensive lessons within the setting of a catastrophe or emergency event, but if the network does not record and relate the new-found knowledge to the network's actions, fragmented learning might occur. For instance, many private organisations take actions in the presence of a catastrophe without network administrators becoming aware of those actions.

Opportunistic learning (Point F, Figure 2.20) is the sixth problematic connection in the learning cycle. There are periods when the network or certain members deliberately attempt to bypass standard operating procedures because they perceive traditional methods of doing work as obstacles. Certain members need to cut the connection between shared mental models and inter-organisational action in order to seize an opportunity that cannot wait for the network to change. In these circumstances, members bypass the standard mental models and successfully generate new routines. Opportunistic learning occurs when inter-organisational actions are taken as a consequence of an individual's or individual organisation's activities rather than of the network's commonly shared mental models. In summary, Brower et al. (2009) suggest that effective networks diminish role-constrained, audience, superstitious, and fragmented learning and learning distorted from ambiguous environmental signals. However, effective networks exploit opportunistic learning.

The studies just discussed show how learning occurs in networks dealing with conditions of high uncertainty. These studies identify the basic difficulties of learning under crisis conditions. The two studies in this section investigated learning in networks in a dynamic complex environment based on qualitative analyses of the events. However, in the study of emergency management, it is also of interest to investigate the connection between enabling the practice of learning-related work activity through engagement in social networks using both quantitative and qualitative analysis. In the following section, the context of the present study is highlighted. Finally, the domain is defined within which the conceptual model for the study is applied.

2.6. Context of the Study – Australia's Emergency Incident Management System Response to Bushfires

The context of this study is Australia's emergency incident management system in the domain of bushfires in Australia. Bushfire can be considered as an emergency event in which the dynamics of the situation are particularly important. When a number of agencies respond to bushfire the coordination of activities is complex and develops over time. Crises and emergency events present an exceptional test for public organisations (Kapucu, 2009). Such events require coordination of actions among multiple agencies, as well as the integration of multiple organisations into an operative response system. Developing a means of increasing the capacity of coordinated response systems to adapt and respond under severe pressure is a major challenge for public organisations. The dynamic and complex context of emergency events requires rapid search, transfer, and reception of information across many organisations, rapid interpretation of threat, the capacity to predict the spread of risk and make decisions under extreme stress, and discovery of the logic of ambiguity among multiple organisations (Comfort, 1999; Weick and Sutliffe, 2001). There has been no systematic empirical study of the dynamics of emerging learning behaviour and knowledge transfer during bushfire. Therefore, this study of emergency management investigates the connection between learning and the engagement of social networks in the dynamic environment of emergency management.

Coordination of emergency events in Australia and New Zealand frequently involves responding to events such as bushfires, cyclones and earthquakes. Responding to emergency events falls within the area of a range of government organisations with emergency services responsibilities. These organisations need to successfully handle the threat in order to mitigate the effects of an emergency incident (Dwyer and Owen, 2009).

In Australia, the organising procedures used in emergency events caused by natural hazards are documented in the Australasian Inter-service Incident Management System (AIIMS). AIIMS was adapted from the National Incident Management System (NIMS) which is established in the United States of America. NIMS had developed from an emerging incident control system concept from coordinating responses to earlier key events. These involved the main forest fires that occurred within the US during the 1980s and 90s. The objective to enhance coordination originated from lessons learned throughout those catastrophes, mainly the forest fires in the 1990s where several problems related to the emergency response were recognised. These were loaded spans of control, lack of trustworthy information, poor and incompatible communications, lack of interagency coordination, vague lines of authority, lack of a shared language between responding organisations, and blurred or undetermined incident goals.

In Australia, even though AIIMS had been used by organisations for some time (as was NIMS in the U.S.) it was not until 2003 that the Australasian Fire and Emergency Service Authorities Council (AFAC) coordinated external collaboration with its participant organisations that then led to validation of AIIMS in Australia as a nationwide system in 2004 (AFAC, 2005). AIIMS has three main principles: management by objectives, functional management and span of control (AFAC, 2005). These three key principles indicate that the elements handling the incident have the responsibility to scale up or down appropriately (AFAC, 2005). The potential to scale up or down like this is perceived by advocates of the system as crucial in allowing effective incident management work practices and procedures (Dwyer and Owen, 2009). Crucial to doing so is the role of active teamwork to support such coordination. The purpose of this thesis is not to report the entire mechanisms of AIIMS as an organising structure (see AFAC, 2005, for more policy detail). However, a brief summary is valuable for those unfamiliar with the system.

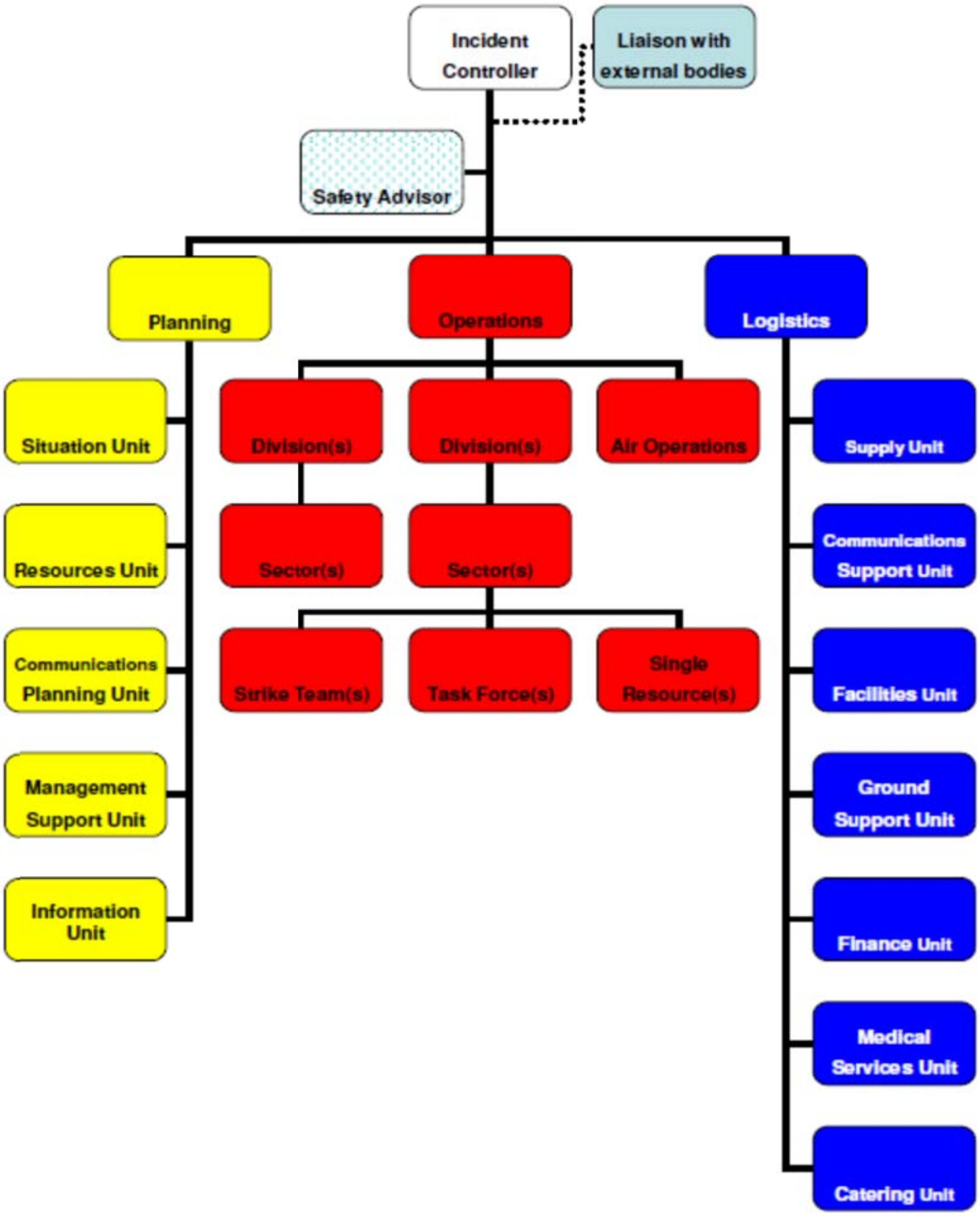


Figure 2.21: AIIMS Structure (Source: AFAC AIIMS Manual, 2005)

The AIIMS structure (Figure 2.21) is supported by team-based functioning members across different roles within the incident management system. According to AFAC (2005), the essential driver is the work undertaken within an Incident Management Team, which critically demands effectiveness and capability in minimising the effect of the incident on the public and the environment (AFAC, 2005). The Incident Management Team is formed to support the

Incident Controller in approving that the control of the emergency incident is correctly planned, has sufficient resources, and delivers for the safety and health of ground staffs. An Incident Management Team is created once all roles (i.e., Control, Operations, Planning and Logistics) turn out to be essential because of the scale of the event. At its simplest level, the Incident Management Team includes the Incident Controller, Planning Officer, Operations Officer and Logistics Officer.

When an incident grows in complexity, the Incident Management Team “scales up”, and additional staff are added to the essential functional components. Those staff then report to each of the officers of the basic team (e.g., a Planning Officer is the head of a planning function, and has a media unit, information unit, situation unit, etc.). It is similarly vital to recognise that the work planned in the Incident Management Team is carried out on the fire (the incident) ground by inter-connected teams. Teams which are in very large-scale events include Division and Sector Commanders. In addition, those teams include, within the sectors crew leaders, crews and strike teams. Within the emergency management organisation responsible for the emergency event, mainly if the emergency includes a number of incident management teams, there is similarly state level coordination and possibly a regional level of coordination. Obviously the diverse teams working at different layers in the incident control system have different job burdens. They likewise must work together successfully. The AIIMS structure is therefore designed to allow effective incident management regardless of the nature or scale of the incident (AFAC, 2005).

2.7. Towards a Social Networks-based Model for Learning

The studies by Moynihan (2008) and Brower et al. (2009) described earlier are coherent because both are focused on networks of learning in emergency events. In the present research the focus is on the same area, but it uses quantitative analysis to complement the qualitative literature in this area. Although most of the research evidence discussed above pertains to networks of learning in a routine and stable environment, this study focuses on networks of learning in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles (problems).

So far, the discussions mentioned earlier have drawn on theories from sociology and social network studies which relate to learning and adaptability in dynamic complex environments. Having established that learning is also influenced by social networks, the present research model is different from those of past studies that looked at learning through a social network perspective. Both Moynihan (2008) and Brower et al. (2009) utilised agents' (1) network within a dynamic complex environment and (2) extent of *learning* in a dynamic complex environment, the conceptual model in this thesis is described in the context of emergencies in Australia along with hypotheses developed from the literature.

The proposed model is based on the review of literature. Unlike previous models, which assumed stable environments, the framework of the proposed conceptual model, as illustrated in Figures 2.22, 2.23 and 2.24, is intended to assess the capacity of personnel to undertake learning-related work activity in the environment of dynamic emergency management. The models in Figures 2.22, 2.23 and 2.24 represent the same concept, but the details of each model are different. The models here are defined based on the level of detail: as the level increases the model becomes more detailed. The model in Figure 2.22 is a general model at level 0; the model in Figure 2.23 is a more detailed model at level 1; the model in Figure 2.24 is the most detailed, at level 2. There is a gap in literature addressing the relationship between networks and learning in a dynamic complex environment. The aim of the model is to fill this gap and to evaluate the connection between networks and learning in dynamic emergency management environments. In developing the measures of social networks and those of learning in a dynamic complex environment, two sources of data were used. These were: (1) observations of the field, experience and subject matter experts, and (2) analysis of the literature (Dekker and Hansen, 2004; Corbacioglu and Kapucu, 2006). The attributes measured are the degree to which the model enhances flexibility and satisfaction with the quality of information flow by personnel engaged in emergency management in order to optimise emergency management network performance in unstable environments. The model is constructed with a view to assess the current state of learning-related work activity which is argued to be a product of attributes of network relations.

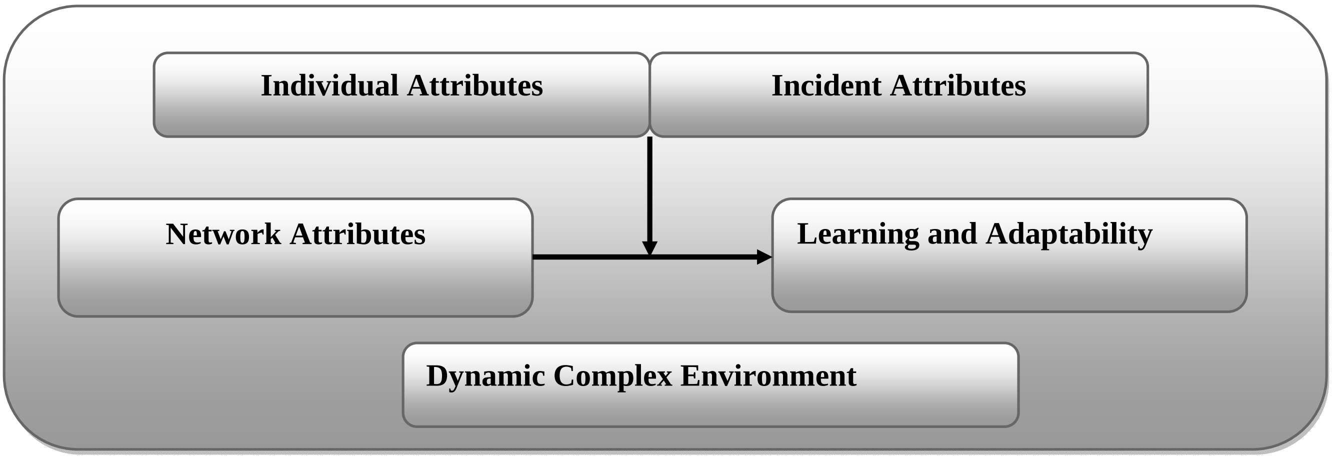


Figure 2.22: The Social Networks-based Model for Learning (Level-0)

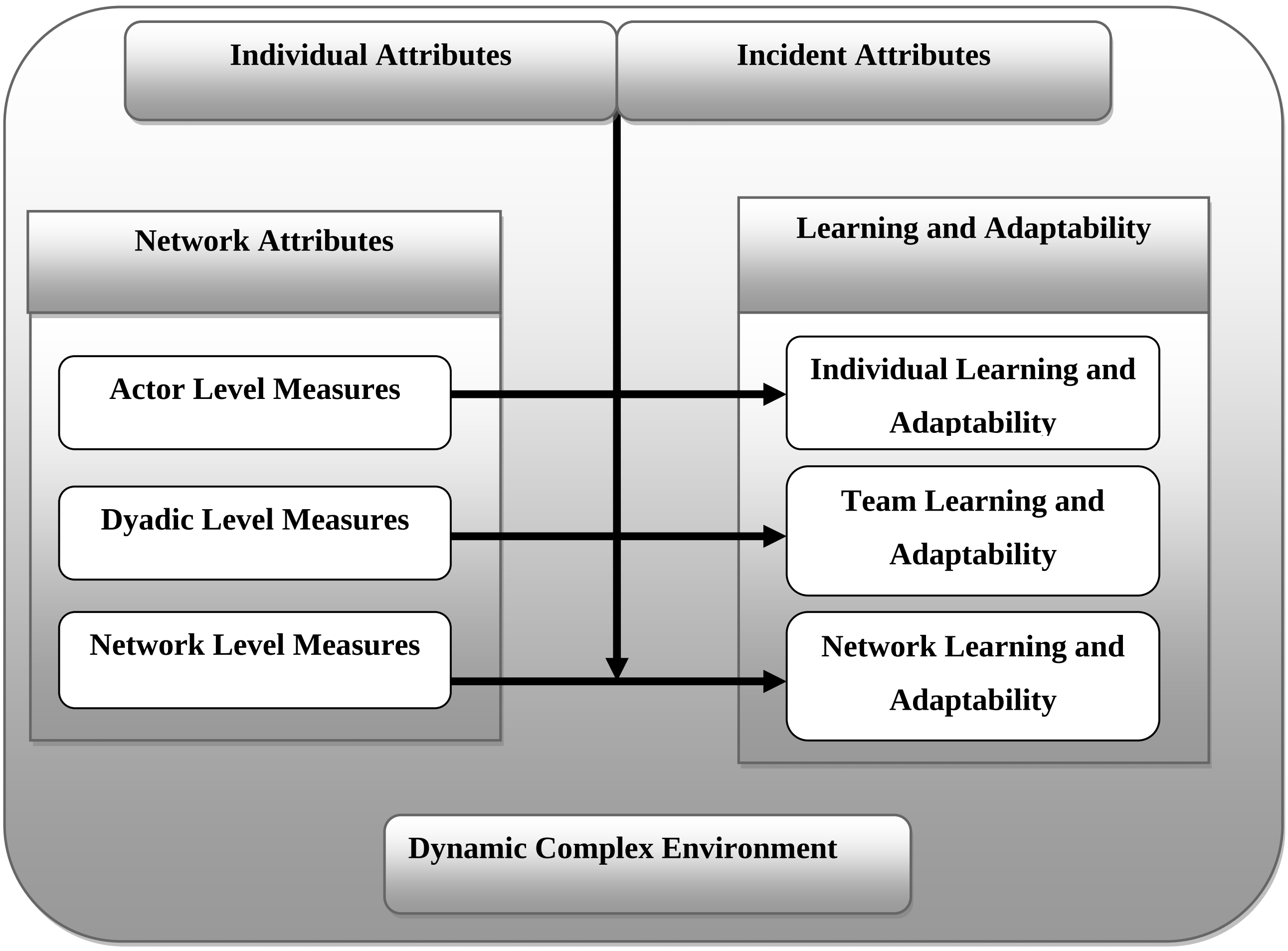


Figure 2.23: The Social Networks-based Model for Learning (Level-1)

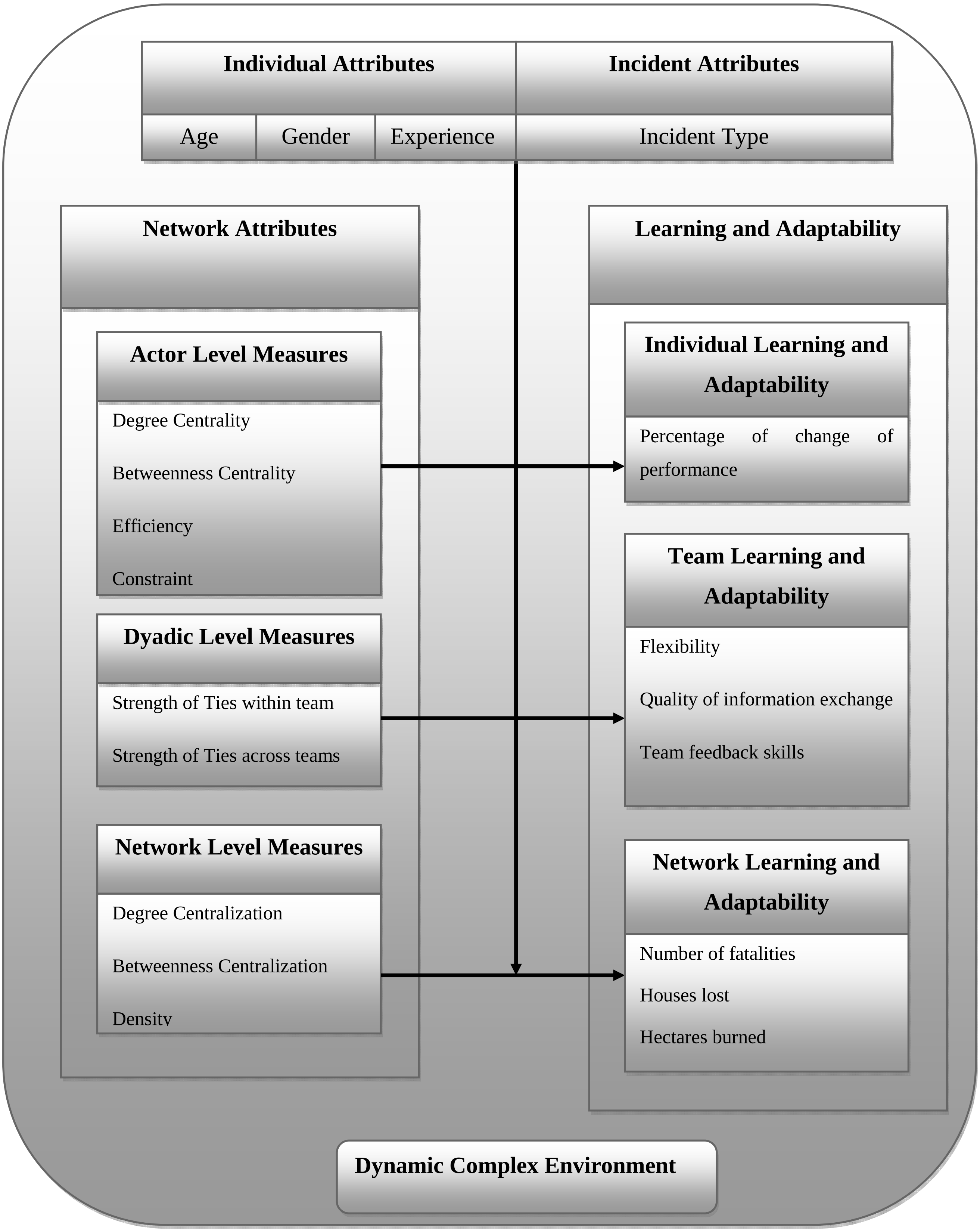


Figure 2.24: The Social Networks-based Model for Learning (Level-2)

As Figure 2.24 depicts, the framework consists of three sets of variables:

(1) Three groups of independent variables describe the characteristics of social networks: actor level, dyadic level and network level. These variables collectively describe the social networks at all levels of analysis (actor level, dyadic level and network level).
(2) Four moderating variables describe the characteristics of incidents and individuals that assist in the management of coordination: individual attributes (gender, age, experience) and incident attributes (type). These variables collectively describe the attributes of individuals and incidents that affect the direction and/or strength of the relation between social network measures (independent variables) and learning (dependent variables).
(3) One dependent variable captures the success in dealing with the challenges posed by hazardous events: learning. This study investigates learning at an individual, team and network level.

The framework depicted in Figure 2.24 identifies the relationships between independent variables, moderating variables and the dependent variable that are hypothesised to be significant. The framework proposes that dyadic-level network measures are moderated by both incident and individual attributes. The use of this model implies that the impact of social network characteristics in teams on learning is fundamentally dependent on individual and incident attributes. Alternately, the framework suggests that variations in the level of learning can be explained by the misfits between social network characteristics and individual and incident attributes. The framework also suggests that learning is driven by social network variables, and that incident and individual attributes have a role in moderating the effects of these factors.

2.7.1. Construct Definition

In this section, definitions of the constructs in the framework are presented. Descriptions of the final set of scale items that measure constructs and rationalisations for measures are deferred to Chapter 3. In terms of literature, there are a number of dimensions that are essential to address in any theoretical modelling and empirical measures.

2.7.1.1. Learning Indicators (Dependent Variables)

2.7.1.1.1 Individual Learning

As mentioned earlier in this chapter, individual learning is about obtaining new or modifying current knowledge, behaviour, abilities, standards, or preferences, and may include combining different kinds of information. Learning usually leads to improved performance over time and leads the individual to adapt and become better suited to the environment. Development and adaptation over time tend to follow learning curves. Adaptation denotes both the dynamic evolutionary process that guides the adaptation and the present state of being adapted. To measure individual learning, researchers need to monitor the individual under study over time and see whether that individual is adapting over time. In this study, learning is measured by quantifying how an individual adapts to another type of situation or behaviour. In other words, learning is characterised by a type of behaviour that permits an individual to change a disruptive behaviour to something more constructive. For example, a continuous repetitive action might be re-focused on something that generates or builds something. In other words, the behaviour can be adapted to something else.

2.7.1.1.2 Team learning

As stated earlier, team learning can be viewed as the process by which reasonably enduring changes arise in the behavioural repertoire of a group as a consequence of group collaboration actions through which individuals obtain, share, and combine knowledge. There are some indicators of team learning, which are:

Flexibility. Flexibility refers to the ability and readiness to adapt performance strategies rapidly and appropriately to changing task demands (Corbacioglu and Kapucu, 2006). In this study flexibility is demonstrated in teamwork when team members are open to changes in strategies based on feedback from others. Teams need to maintain flexibility in order to respond to surprising incidents (Mendonca et al., 2001). When such situations arise, flexibility will help emergency managers to be better prepared and to improvise to meet the requirements of the current situation. The capacity to adjust to a rapidly changing emergency condition is important for reducing the vulnerability of local communities. Therefore, an analysis of perceived flexibility is used to indicate openness of an actor to learn from other team members.

Quality of information exchange. Previous research has shown that the major influence on work-related learning activity is the quality of information exchange, which comprises passing significant information to team members who need it, in a timely manner, including transmitting and receiving (Dekker and Hansen, 2004). Researchers suggest that dissemination of knowledge is an important behavioural aspect of learning (Dekker and Hansen, 2004). Sharing lessons within an organisation or a larger inter-organisational field obviously leads to more broad-based learning (Huber, 1991). Researchers also highlight that adequate organisational structures for information sharing can help members of organisations to learn and adapt rapidly to shifting conditions in their environments (Corbacioglu and Kapucu, 2006). Therefore, analysis of the perceived quality of information exchange is used to indicate the resources available for learning.

Team feedback skills. Studies have characterised learning as dependent on attention to feedback (Schon, 1983). Feedback skill is defined as the ability to assist team members to communicate their observations, concerns, proposals and demands in a clear and direct way without becoming aggressive and defensive. Team feedback skills are essential drivers for learning. Learning has been conceptualised at the group level of analysis as a process of seeking feedback by which reasonably enduring changes arise in the behavioural repertoire of the group as a consequence of group collaboration actions through which individuals obtain, share, and combine knowledge (Edmondson, 1999). Differential effects of feedback on learning and team performance have also been found in crisis situations (Rouse et al., 1992). Therefore, indicators of perceived team feedback skills are included to determine interpersonal conditions to support learning.

2.7.1.1.3 Network Learning

Network learning can be viewed as the process by which reasonably enduring changes arise in the behavioural repertoire of the network as a consequence of network collaboration activities through which members of the network obtain, share, and combine knowledge. A ‘learning’ or adaptive network is a set of interacting or interdependent agents creating a cohesive whole that together is capable of responding to environmental changes.

2.7.1.2. Social Network Indicators (Independent Variables)

2.7.1.2.1 Actor-level Indicators

Efficiency. Efficiency, as discussed already, is about maximising the number of non-redundant associates in the network to maximise the yield in structural holes per contact. Given two networks of equal size, the one with more non-redundant associates delivers more benefits. Time and energy are better spent promoting a new interaction to unreached individuals.

Constraint. Constraint dictates the degree to which an actor's opportunities are restricted by spending the majority of his or her network time and effort in relations that lead back to a single contact (Burt, 1992). According to Hanneman and Riddle (2005), constraint similarly measures the degree to which an actor is linked to others who are linked to one another.

Degree Centrality. The construct of degree centrality is defined as the number of ties connected to a node. In the case of a directed network, two measures of degree centrality are usually defined, 'indegree' and 'outdegree'. Indegree is the total number of contacts linked to the actor and outdegree is the total number of contacts that the actor links to others. Indegree is often understood as a form of popularity, and outdegree as gregariousness.

Betweenness Centrality. Betweenness is a centrality measure of a node within a social network. Freeman (1978) presented betweenness as a measure for determining the control by an actor of the communication between other actors in a social network. High betweenness nodes are those that have a high possibility of occurring on a randomly selected shortest path between two randomly selected nodes.

2.7.1.2.2 Dyadic Level Indicators

Strength of ties. The construct of strength of ties was defined in literature review as "The strength of a tie is a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter, 1973). The notion of strength of ties is considered one of the key network measures used for studying network effects on individual and group outcomes such as learning and performance (Granovetter, 1973; Kraatz, 1998). In this thesis, the strength of ties between members within a team is used to determine whether this team is at an operational level or at the Incident Management Team (IMT) level.

Strength of Ties between IMT and Incident/fire Ground. In emergency management responses, information flows between first responders (e.g., those on the fire or incident ground) and those charged with the responsibility of managing the emergency (the IMT), and this part of the overall network is crucial (Hamra et al., 2012b). In previous research, information flow between these two components in an incident management structure has been found to be the first to break down (Dwyer and Owen, 2009). Given the importance of the relationships between those on fire or incident ground and those on the IMT, this is the focus of this study.

2.7.1.2.3 Network-level Indicators

Degree Centralisation. Degree centralisation is the variation in degrees of nodes divided by the maximum possible variation in a network of the same size. The star network is the most centralised network. Freeman's (1978) network centralisation measures express the level of inequality in an observed network as a percentage of that of a star network of the same size.

Betweenness Centralisation. Betweenness centralisation is defined as the average difference between the relative centrality of the most central node in terms of betweenness, and that of all other nodes. The star network is the most centralised network. Freeman's (1978) network centralisation measures express the level of inequality in an observed network as a percentage of that of a star network of the same size.

Density. Network-level density is the proportion of ties in the network relative to the total possible ties (sparse versus dense networks). In comparing two populations, if it is noted that there are many nodes in one that are not connected to any other ("isolates"), and in the other population most nodes are embedded in at least one dyad, it could be concluded that social life is very different in the two populations. Measuring the density of a network provides a ready guide to the degree of dyadic connection in a population.

2.7.1.3. Individual and Incident Indicators (Moderating Variables)

Moderating variables generally originate from the socio-demographic characteristics of individuals such as age, gender and area of domicile. The answer to the question, *"Is there any factor that moderates the relation between networks and learning variables?"* might help to identify factors that moderate the relation between independent and dependent variable. The age of emergency personnel, for example, might moderate the hypothetical relation between the independent variable of strength of ties between team members and dependent variable of team learning. Four moderating variables are used in this research to test the relationships between independent variables and dependent variables at cluster level: gender, age, and experience of emergency personnel, and type of incident. These four variables are found in different studies as important predictors for learning.

Age. Age is defined as a period of individual life, which is typically marked by a definite stage or degree of mental or physical development and includes legal accountability and capability. Research on memory and aging has found deterioration in many kinds of memory with ageing, but not in general knowledge such as vocabulary, which typically increases or remains stable until late adulthood (Schaie, 2005). In this study, age of respondents is used as a moderating variable to see if it moderates the relation between network variables (more specifically strength of ties) and the learning variable.

Gender. Gender is a variety of attributes used to differentiate between males and females, mainly in the case of men and women and masculine or feminine characteristics allocated to them. Research in many fields examines whether biological differences between males and females affects the growth of gender in human beings; both enlighten discussion about how far biological differences affect learning (Udry, 1994). In this study, gender of respondents is used as moderating variable to see if it moderates the relation between network variables (more specifically strength of ties) and the learning variable.

Experience. Experience is a common notion that includes knowledge of or ability with some thing or some occasion gained through participation in or contact with that thing or occasion. In this study, the level of experience of respondents is used as moderating variable to see if it moderates the relation between network variables (more specifically strength of ties) and the learning variable.

Types of emergency incidents. The type of emergency incident managed may play a major role in moderating the relation between network variables (more specifically strength of ties) and the learning variable. The incident might be forest, scrub, or grass fire, rural/urban interface fire, structure fire, as well as emergency incidents including cyclones, floods and storms.

2.7.2. Research Hypotheses

2.7.2.1. The Actor Level Social Network Hypotheses

The actor-level social network research hypotheses and their development are discussed in this section.

2.7.2.1.1 Relationship between Efficiency and Learning

As discussed earlier, efficiency is about maximising the number of non-redundant associates in the network to maximise the yield in structural holes per contact. As efficiency increases, the number of non-redundant contacts increases. High levels of non-redundant contacts lead to new people, and hence provide novel information benefits and consequently improve learning for the actor. Most studies examining the effect of actor efficiency on learning have been based in a stable environment; few studies have been conducted in a dynamic environment context. In the light of these arguments, a positive association between the efficiency of an actor and his/her learning is expected in a dynamic complex environment. This discussion leads to the hypothesis:

HYPOTHESIS la. *Efficiency is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*

2.7.2.1.2 Relationship between Constraint and Learning

Constraint refers to the degree to which an actor's opportunities are restricted by spending the majority of an actor's network time and effort in relations that lead back to the single contact (Burt, 1992). If an actor has several contacts with other actors who in turn have many contacts to more others, the actor is relatively constrained. At organisational levels, an actor with a high constraint index is incapable of conceive novel ideas and resource benefits because of the redundant nature of information that is obtained from a densely connected group of actors. Earlier studies have regularly revealed that low constraint indices are valuable signs of an actor's capacity to create novel ideas (Burt, 2004). In line with these arguments, it is expected that actors in knowledge-intensive work prosper on valuable knowledge and information from peers. An individual in a dynamic complex environment with a low-constraint network structure is thus more likely to obtain valuable knowledge from diverse and non-redundant contacts, which has been linked to improved learning. This discussion leads to the hypothesis:

HYPOTHESIS lb. *The constraint of an actor's network position is negatively associated with the learning-related work activity of an actor in a dynamic complex environment.*

2.7.2.1.3 Relationship between Degree Centrality and Learning

As discussed earlier, numerous researchers have examined the number of ties as a significant predictor of actor learning (Powell et al., 1996; Tsai, 2001; Cummings and Kiesler, 2007). Most of those studies have found significant support for a positive association between an actor's number of ties and actor learning. Therefore, actors with higher *reach* of information are more likely to be exposed to unique and significant knowledge, which is useful in solving complex problems, and hence learning in a dynamic complex environment. This discussion leads to the hypothesis:

HYPOTHESIS lc. *Degree centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*

2.7.2.1.4 Relationship between Betweenness Centrality and Learning

Betweenness centrality promotes the idea of the brokerage position of an actor as providing information and control benefits for that actor. The idea of betweenness centrality as a concept of brokerage control provided the basis for Burt (1992) to argue that actors who bridge structural holes, the absence of ties among unconnected groups of people, are able to benefit in terms of job promotion, novel ideas and better learning. Betweenness centrality in a network established by awareness of associates' capabilities should increase an actor's access to appropriate knowledge in distant areas of a network and so help the person to act efficiently and successfully when new emergency events demand different information or expertise. This discussion leads to the hypothesis:

HYPOTHESIS ld. *Betweenness centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*

2.7.2.2. Dyadic Level Social Network Hypotheses

Dyadic-level social network hypotheses and their development are discussed in this section.

2.7.2.2.1 Relationship between Strength of Ties within a Team and Learning

As discussed earlier, Granovetter (1973) argues that actors acquire new and novel information from weak ties rather than strong ties within their group structure. However, other research by Kraatz (1998) shows that stronger ties between the nodes of the network will provide better opportunities to learn for those nodes as trust is developed. The views of learning presented by Granovetter (1973) and Kraatz (1998) are valid in stable environments, but this concept in studying and identifying social networks may not be adequate for research in non-routine situations such as emergency incident management, where a key feature of the work is dynamic change and uncertainty. In light of these arguments, a significant association between team members' ties strength and their learning is expected in a dynamic complex environment. This preceding discussion leads to the hypothesis:

HYPOTHESIS 2a. *Strength of ties within a team is positively associated with the learning-related work activity of a team in a dynamic environment.*

2.7.2.2.2 Relationship between Strength of Ties across Teams and Learning

The construct of strength of ties across teams is similar to that of strength of ties within a team, but the focus here is on the ties between teams rather than between individuals. The concept of strength of ties is considered one of the vital network measures for studying network effects on individual and group outcomes such as learning and performance (Granovetter, 1973; Kraatz, 1998). In light of these arguments, a significant association between teams' ties strength and their learning is expected in a dynamic complex environment. This discussion leads to the hypothesis:

HYPOTHESIS 2b. *Strength of ties across teams is positively associated with the learning-related work activity of a team in a dynamic environment.*

2.7.2.2.3 Relationship between Interaction of "Age and Strength of Ties" and Learning

Several research studies have sought to discover the effect of age of actors on their learning. Research on aging has revealed that learning ability does not deteriorate with age. If older individuals remain fit, their intellectual skills and abilities do not deteriorate (Ostwald and Williams, 1985). In this study, age of respondents is used as moderating variable to see if it moderates the relation between network measures (more specifically strength of ties) and the learning variable.

2.7.2.2.4 Relationship between Interaction of "Gender and Strength of Ties" and Learning

Various studies have sought to explore the effect of gender on learning. Studies of students' learning found no significant difference in learning style preferences between males and females (Uzuntiryaki et al., 2004). In another study of male and female undergraduates in different baccalaureate-granting institutions, the findings showed that males participated less often in active and collective learning activities. In this study, gender of respondents is used as moderating variable to see if it moderates the relation between network measures (more specifically strength of ties) and the learning variable.

2.7.2.2.5 Relationship between Interaction of "Experience and Strength of Ties" and Learning

Many studies have sought to explore the effect of people's level of experience on their learning. Experience indicates that, the more times a task has been performed, the less time is required on each succeeding task. In a study of aircraft manufacture, Arrow (1962) found that each time entire aircraft manufacture doubled, the necessary labour time reduced by approximately 15 percent. In this study, respondents' level of experience is used as moderating variable to see if it moderates the relation between network measures (more specifically strength of ties) and the learning variable.

2.7.2.2.6 Relationship between Interaction of "Type of Incident and Strength of Ties" and Learning

Many studies have sought to explore the effect of the environment on learning. Research has shown that the learning environment has a significant effect on learning outcomes (Trigwell and Prosser, 1991; Rayneri et al., 2006). However, a working environment designed to ease learning does not guarantee worker uptake of the learning opportunities presented. Conversely, a working environment where there seems to be only a slight chance to participate in learning does not guarantee that no learning will occur (Billett, 2002). In this study, type of incident is used as moderating variable to see if it moderates the relation between network variables (more specifically strength of ties) and the learning variable. The incident may be forest, scrub, or grass fire, rural/urban interface fires, structural fires, as well as emergency incidents including cyclones, floods and storms. This discussion leads to the hypothesis:

HYPOTHESIS 2c. *The relations H2a and H2b are mediated by moderating variables of age, gender and experience of respondents and type of incident. This means that these demographic characteristics and incident type can be used to predict the relation between strength of ties of team members and the bushfire-team's perceived level of learning for that team.*

2.7.2.3. Network Level Social Network Hypotheses

The network-level social network research hypotheses and their development are discussed in this section.

2.7.2.3.1 Relationship between Density and Learning

The first structural factor to be explored is the overall density of communication paths in the structural form which turned out to be relevant for understanding learning and performance. As discussed earlier, previous studies have shown that dense networks are favourable for diffusion of innovation (Coleman et al., 1966), intellectual performance (Coleman, 1988) and knowledge-sharing (Cross and Cummings, 2004). Burt (1992), however, takes on a structural perspective by suggesting that denser ties in an individual's social network are far more inefficient than scattered networks because (1) they are costly to maintain, and (2) they provide redundant information. Most of these studies have looked at learning problems requiring stable working relationships with no environmental uncertainties, but their concepts in studying and identifying social networks may not be adequate for research in non-routine situations, such as emergency incident management. In light of these arguments, a positive association between the density of the network and its learning is expected in a dynamic complex environment. This discussion leads to the hypothesis:

HYPOTHESIS 3a. *The density of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*

2.7.2.3.2 Relationship between Degree Centralisation and Learning

Another interesting structural factor to be explored is centralisation, which is based on the actor-level centrality discussed earlier. All the experiments done by Bavelas and his research team established that centrality was linked to group efficiency in problem-solving, the perception of leadership and the individual satisfaction of participants (Bavelas, 1950). Their key finding was that centralisation leads to enhanced learning in the process of solving simple tasks because appropriate information can be transferred and synthesised to a few individuals who can make a decision and take action. However, follow-up research by Guetzkow and Simon (1955) suggested that decentralised structures work better than centralised structures when tasks are more complex. A high degree of centrality might initiate centralised management, resulting in fewer experiments and less practical learning (Leavitt, 1951; Shaw, 1981). Freeman (1978) developed measures to show how centralised a network is. One of these measures is degree centralisation, which derives from the variation in degrees of actors divided by the maximum possible variation in a network of the same size. As the degree centralisation index increases, the network will be more centralised. Most of the studies mentioned earlier examined network structures based on small groups in a stable environment. Few studies have been conducted in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable problems such as emergencies. This study adopts the view of networks of learning in a dynamic environment context. In light of these arguments, a positive association is expected between degree centralisation of the network and its learning in a dynamic complex environment. This discussion leads to the hypothesis:

HYPOTHESIS 3b. *The degree centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*

2.7.2.3.3 Relationship between Betweenness Centralisation and Learning

As discussed earlier, Freeman (1978) developed measures that show how centralised a network is. One of these measures is betweenness centralisation, which was defined as the average difference between the relative centrality of the most central actor in terms of betweenness, and that of all other actors. As the degree betweenness index increases, the network will be more centralised. Most of the studies mentioned earlier examined network structures based on small groups in a stable environment. Few studies have been conducted in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable problems such as emergencies. This study adopts the view of networks of learning in a dynamic environment context. In light of these arguments, a positive association is expected between betweenness centralisation of the network and its learning in a dynamic complex environment. This preceding discussion leads to the hypothesis:

HYPOTHESIS 3c. *The betweenness centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*

To summarise, the preceding sections of this chapter have critically analysed key literature concerning social network and learning theories. Hypotheses relating to network factors (actor level, dyadic level and network level), demographic attributes and learning in a dynamic complex environment have been suggested. The chapter concludes with a conceptual model for the research study. Table 2.4 provides a summary of the social network and learning theories together with the hypotheses presented earlier. That is followed by the conclusion of this chapter.

Table 2.4: Brief overview of the hypotheses and related key theories

Level of Analysis	Hypotheses	Hypotheses Statement	Key Theories
Actor Level	**HYPOTHESIS la**	*Efficiency is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	**Burt (1992) (Structural Hole)**
	HYPOTHESIS lb	*The constraint of an actor's network position is negatively associated with the learning-related work activity of an actor in a dynamic complex environment.*	**Burt (1992) (Structural Hole)**
	HYPOTHESIS lc	*Degree centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	**Freeman (1978), Powell, Koput et al. (1996), Tsai (2001) (Node Centrality)**
	HYPOTHESIS ld	*Betweenness centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	**Freeman (1978), Cross and Cummings (2004) (Node Centrality)**
Dyadic Level	**HYPOTHESIS 2a**	*Strength of ties within a team is positively associated with the learning-related work activity of a team in a dynamic environment.*	**Granovetter (1973), Krackhardt (1992)**
	HYPOTHESIS 2b	*Strength of ties across teams is positively associated with the learning-related work activity of a team in a dynamic environment.*	**Granovetter (1973), Krackhardt (1992)**
	HYPOTHESIS 2c	*The relations H2a and H2b are mediated by moderating variables of age, gender and experience of respondents and type of incident. This means that these demographic characteristics and incident type can be used to predict the relation between strength of ties of team members and the bushfire-team's perceived level of learning for that team.*	**Trigwell et al. (1991), Billett (2002)**
Network Level	**HYPOTHESIS 3a**	*The density of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	**Burt (1992), Coleman et al. (1966), Cross et al. (2004)**
	HYPOTHESIS 3b	*The degree centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	**Freeman (1978) (Network Centralisation)**
	HYPOTHESIS3 c	*The betweenness centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	**Freeman (1978) (Network Centralisation)**

2.8. Conclusion

This chapter began with a summary of social networks and the relationships between analysis of social networks and individual and group outcomes were presented. The chapter was organised by the levels of analysis (actor level, dyadic level and network level). At the actor level, the argument hinges on how the *structural position* of an individual in a network affects outcomes, such as performance or learning capabilities, of that person (Borgatti et al., 1998; Mehra et al., 2001; Sparrowe et al., 2001; Reagans and McEvily, 2003; Hossain et al., 2006). At the dyadic level, traditional theories of social networks, such as the strength of weak ties, along with their underlying assumptions are investigated in order to support the development of a conceptual model for understanding the relationship between social networks and learning in a dynamic complex environment. At the network level, the chapter reviewed the theoretical foundations of network structure and its implications on performance starting with the experiments of Bavelas (1950) and Leavitt (1951). It then reviewed Freeman's (1978) notion of centralisation as a social network concept, which has been widely applied at both the social structural and relational level.

The chapter then discussed the implications and important secondary effects of learning. Learning is important to the degree that it affects individual and group production efficiency. The chapter also reviewed the social influence model and implemented features of structuration theory, as theoretical inspiration, to explore the social influences of learning. Hypotheses relating to network factors (actor level, dyadic level and network level), demographic attributes and learning in a dynamic complex environment were suggested. The chapter concluded with a conceptual model for the research study, providing discussion of the notion of learning – how it is defined and applied. In the next chapter, the research framework, the domain of the study, and the design of the study, including the collection of data, validation and administration, are discussed.

Chapter 3

3. Research Methodology: Social Network Analysis – Data Collection, Processing and Analysis

The primary objective of this study is to understand the influence of social networks on learning in a dynamic complex environment in the context of emergency events. In the preceding chapter, a thorough review of the literature on social network theories and the effect of social networks on learning in a dynamic complex environment was provided. That chapter finished with the conceptual model for investigating in detail the relationship between social networks and learning in a dynamic complex environment within the context of bushfires. As stated in Chapter 2, the following research questions motivated this study: (1) How can learning in a dynamic complex environment be explored through the emergent patterns of social processes? How can it be evaluated? (2) What is the role of social networks in understanding learning in a dynamic complex environment? Why is the understanding of social network structure and position important for understanding learning in a dynamic complex environment? (3) Is there a relationship between the configuration of social network structures and learning in a dynamic complex environment? (4) How can the properties of social networks within various levels of relations among actors help in modelling the dynamics of learning?

In attempting to answer the above questions, this chapter discusses the scheme and outline for the research study. The research scheme begins with a methodological outline of SNA, including a discussion of network data collection methods, and how data were collected from the domain of Australia's emergency incident management system using both survey data and transcripts of the 2009 Victorian Bushfires Royal Commission reports. The measures and items for demographics, social networks and learning components are outlined and discussed. In order to determine whether the item sets measure what they intend to measure and whether they are internally consistent, validity and reliability tests are carried out correspondingly. Sampling strategies, data collection and ordering, and the processes used in preparing the bushfire network dataset for examining the proposed model are also discussed. The chapter concludes with a justification for the methods used for data analysis. Figure 3.1 provides an overview of this chapter.

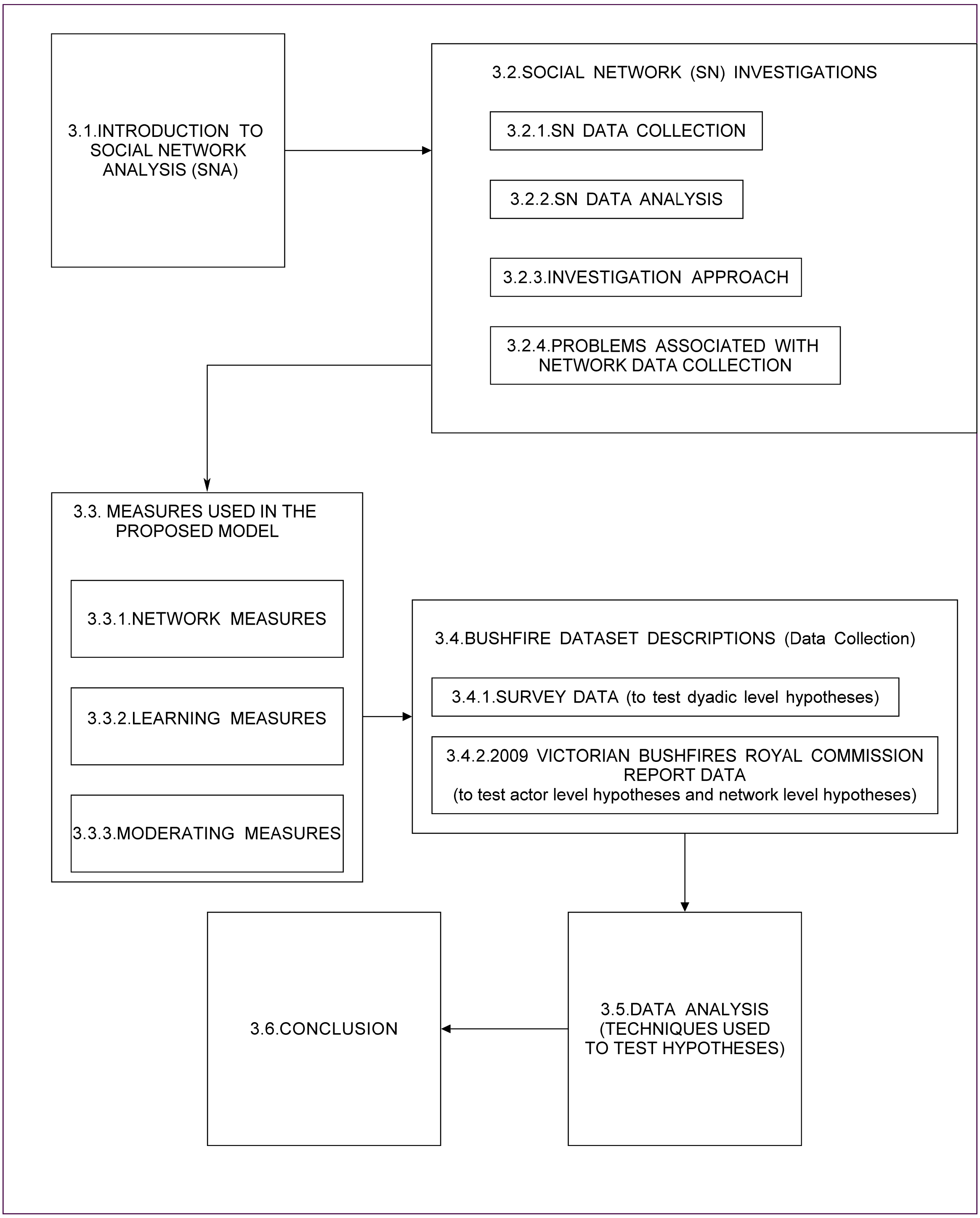


Figure 3.1: Overview of Chapter 3

3.1. Introduction to Social Network Analysis (SNA)

Social network analysis is the mapping and quantifying of relationships among nodes to create both a graphical and a mathematical analysis of social network relations (Carrington et al., 2005). It has been successfully used to assess the position of actors within networks. SNA can also help to identify people with vital knowledge and connections and address the problem of random failure of nodes in the network. It can increase innovation, responsiveness and productivity through plugging "know-who" gaps. As well, SNA can also help to make smarter and improved decisions about organisational changes and establishment of key knowledge roles. Moreover, SNA provides insight into challenges of knowledge transfer and helps us to understand how information flows within an organisation and to achieve a fuller understanding of the organisation as a holistic entity (Schoeneborn, 2011). The advantage of using SNA to analyse networks is acknowledged across many disciplines because of its capacity to evaluate network behaviour and structural patterns (Brandes and Fleischer, 2005). By exploring a network in terms of nodes and relationships, an evaluation of prediction can be made, which allows forecasting of events as diverse as the dissemination of information or the outbreak of disease (Borgatti, 2005). Moreover, SNA allows us to examine a network to reveal insights into how and why information within a network flows, which may in turn have consequences for learning. The ability to undertake this type of analysis and to graphically visualise the network might be particularly valuable to develop and design patterns for learning.

3.2. Social Network Investigations

Like other empirical investigations, the study of social networks follows steps such as data collection, data analysis, and the choice of investigation approach. In this section, network data collection procedure is discussed and an overview of the context for this study is provided.

3.2.1. Social Network Data Collection

There are many ways in which social network data can be collected. Examples of techniques include surveys, interviews, observations, reports. In all these techniques, data can be collected about network actors and the ties among them. Many standards procedure are exercised in network science research to collect data using these techniques. One such procedure is the cognitive science structure. In contrast to the typical sociometric practice of questioning respondents about their ties, in this process respondents are requested to provide information on their insights about other individuals' network connections (Krackhardt, 1987). Another type of data collection procedure is experimental design. The basic method for conducting such experimentation is to select a set of individuals and witness their connections in an experimentally controlled condition. The interactions or communications between pairs of actors are then recorded for the research purpose. Connections might be detected between all pairs of individuals. In a variation of this experimental method, an individual may not only select individuals but may similarly identify which pairs of individuals are allowed to interconnect with each other during the progress of the experiment. Group problem-solving experiments (Bavelas, 1950; Leavitt, 1951), in which actors have specific positions within the network and are allowed to communicate only with other specific actors, are examples of this type of experimental setup. A third type of data collection procedure begins with a focal individual or set of individuals. Each of these individuals is requested to name some or all of their connections to other individuals. Then all second level individuals (i.e., those who were not the part of the original list) are questioned for some or all of their connections. This process continues until no new actors are identified or the experimenters decide to stop for other reasons such as time and resource constraints (Goodman, 1961). The potential drawback of this procedure is that actors who are not connected (i.e., isolate actors) cannot be located. Another limitation of this procedure is the absence of standard guidelines as to how to choose the initial focal actor(s). An incorrect assumption as a starting point may result in missing whole sub-sets of actors who are connected.

Data collection is rapidly changing as technology advances. There is another way of looking into the approaches of data collection, by active data collection approaches and passive data collection approaches. Active data collection requires effort and engagement by surveyor, respondent, or both (e.g. surveys). In that approach, there are interactions between surveyors and respondents and opportunities to ask questions. The limitation of this approach is that it is labour intensive and has limited scoping. There is also the problem of burdening respondents and can lead to refusal of some respondents to interact. In contrast, passive data collection uses technology to collect information (e.g. GPS, Bluetooth, video capture, loop detectors). It allows for real-time, continuous monitoring. But that approach has problems of privacy and bias. Other limitations of the approach are that significant post-processing is required and there is limited information about users, qualities, or motives.

3.2.2. Social Network Data Analysis

The selection of measures and methods for analysis of network data is extensively guided by consideration of the levels of relations among actors. These levels of relations may be classified as: (i) actor level, (ii) dyadic level, (iii) triadic level, (iv) subset level, and (v) network level. Distinct measures are appropriate for specific levels of actor network relations. *Centrality*, for example, is an actor level network measure which further has three sub-classifications, closeness centrality, betweenness centrality, and degree centrality. Measures that are relevant for one level of relation cannot be applied to another level. Table 3.1 provides definitions for different levels of network relations, along with examples of appropriate network measures.

Table 3.1: Examples of Different Levels of Analysis

Level of Analysis	**Example**
Actor level	Centrality, efficiency, constraint, prestige and roles such as isolates, liaisons, bridges, etc.
Dyadic level	Tie strength, distance and reach ability, structural and other notions of equivalence, and tendencies toward reciprocity
Triadic level	Balance and transitivity
Subset level	Cliques, cohesive subgroups, components
Network level	Connectedness, diameter, centralisation, density, prestige, etc.

3.2.3. Investigation Approach

This section highlights and defines two key methods of social network data collection – whole network and egocentric network approach.

3.2.3.1. Whole or Sociocentric Network Approach

The sociocentric approach of SNA assumes the availability of complete network information, such as who is in the network, ego-alter characteristics of all potential actors, and boundary of the whole network under consideration. In a whole network research study, the individuals of the network are generally known or easily identified. Therefore, a sociometric social network research study regularly emphasises *"closed"* networks, suggesting that the borders of the whole network are a priori defined. In many circumstances, this method remains the gold standard by reason of its consideration of the entire current network relations for analysis purposes. In studying large networks, as in inter-organisational investigations, the sociometric approach of SNA is considered very valuable, as explained by (Marsden, 1990). Nevertheless, access to complete social network data for large networks is sometimes impossible, which could skew any analysis based on measures of the network structure.

Collection of data using whole network methods typically includes listing the names of the nodes. Dependent on the name generator question asked, respondents typically check off the names of persons they know. For instance, in a fire that consists of 130 emergency personnel including the fire-fighters and personnel within the incident management team, a whole network study might be conducted in order to understand the communication network of the fire. A roster of the names of all the emergency personnel in the fire would be presented to each of the emergency personnel. A simple name generation question, such as “In the past fire, who did you communicate with more than twice in an hour within the fire in order to carry out your task?” Clearly, an explanation of what constitutes a task needs to be given to the respondent.

There are challenges for collecting social network data using a whole network approach in the context of bushfire. To conduct a whole network study of the bushfire would mean that all the names of the emergency personnel responding to a bushfire need to be known. This can result in a huge list of names. Earlier research proposes that scrutinising through extensive lists of names and identifying the numerous kinds of links with each individual on the list leads to exhaustion and recall difficulties (Bernard et al., 1982). Given these problems, an alternative approach for social network data collection that trades off respondent numbers with information richness and practicality is the egocentric network approach.

3.2.3.2. Egocentric Network Approach

The egocentric approach to network analysis focuses on individual actors, known as *ego*, and their surrounding associates, known as *alter*. Termed by Carrasco et al. (2008) a “*network of me”*, such studies are naturally directed when the identities of *egos* are known, but not their ‘*alters’*, and emphasis is on the social settings surrounding individual actors (Borgatti and Foster, 2003; Chung et al., 2005). Research built on the egocentric method depends largely on the *egos* to offer information about the identities of *alters*. Thus the research creates a contained network assessment, and may deliver comprehensive information about precise features of the network under investigation, such as sub-network grouping or cliques

(Marsden, 1990). The application of the egocentric method is derived, according to Carrasco et al. (2008), from situations where network data is incomplete or network boundaries are difficult to define, as in the case of large scale inter-organisational networks.

3.2.4. Problems Associated with Network Data Collection

As social network studies are concerned with studying patterns of social structure, the significant problem related to network data is whether the collected network data represent the correct structure. Collecting data only from participants who are willing to contribute will not represent a true network in most circumstances, and may not include individuals with vital roles in the network. Klovdahl (2005) urges that gathering responses from all network contributions is very doubtful in any social network research study, as information about members may be incomplete or inaccurate. Different social network researchers (Kimball Romney and Weller, 1984; Hammer, 1985; Freeman et al., 1987) further argue that specific interactions are not the main concern in network research, but reasonably stable patterns of interaction are of most interest. In searching for a stable pattern of interaction, scholars must deal with the problem of sample size: *"What should the sample size be for any research project under consideration that will show a stable communication pattern?"*

3.3. Measures Used in the Proposed Model

This section presents the description of the final set of measures that quantify social network effect, learning and the moderating variables in the model shown in Figure 2.24.

3.3.1. Network Measures

The theory and measures of social networks are applied to quantify social network effects in modelling the network-based learning. To model learning during a bushfire event, the following SNA measures are used to quantify the social network measures.

3.3.1.1. Actor Level Measures

3.3.1.1.1 Measures of Network Position – Efficiency and Constraint

In order to quantity efficiency, it is first essential to calculate the effectiveness or the effective size of the ego network. Effective size is the amount of non-redundant contacts within an ego network. It is measured as the amount of 'alters' minus the average degree of 'alters' within the ego network, not including links to the ego. The effective size of an actor's network is defined as:

$\sum_j \left[1 - \sum_q p_{iq} m_{jq}\right], q \neq i, j$

where i is the ego, actor j is a primary contact, and actor q is also a primary contact who has strong ties with the ego i (represented by p_{iq}) and actor j (represented by m_{jq}).

Efficiency is measured by dividing the effectiveness by the number of 'alters' in the ego's network.

Ego c*onstraint,* on the other hand, measures the opportunities held back by the degree to which the ego has invested time and energy in relationships with alters that lead back to a single contact (Burt, 1992). In other words, it measures the degree to which the ego's links are to others who are associated with one another. Constraint on an actor's network is defined as:

$$\left(p_{ij} + \sum_q p_{iq} p_{qj}\right)^2, q \neq i, j$$

where i is the ego, actor j is a primary contact, and actor q is also a primary contact who has strong ties with the ego i (represented by p_{iq}) and actor j (represented by p_{qj}).

3.3.1.1.2 Measures of Network Centrality – Degree and Betweenness

There are two main measures of network centrality: (a) degree centrality and (b) betweenness centrality. Each of these measures addresses different attributes related to actors to assess their level of centrality within the network:

(i) Degree centrality indicates the activity of actor and actor popularity. The normalized degree centrality is defined as the number of links of an actor divided by the maximum possible number (Abbasi and Altmann, 2011). The normalized degree centrality d_i of node i is given as:

$$d_i = \frac{\sum_j a_{ij}}{(n-1)},$$

where a_{ij} indicates the existence or non-existence of a link between node i and node j, and n represents the number of nodes. If there is any link between node i and node j, a_{ij} = 1. If there is no link, a_{ij} = 0.

(ii) Betweenness centrality represents the actor's potential to control. It is defined as the ratio of the number of shortest paths (between all pairs of nodes) that pass through a given node divided by the total number of shortest paths (Abbasi and Altmann, 2011). The normalized betweenness centrality b_i of node i is given as:

$$b_i = \sum_{j,k^\wedge i \neq j \neq k} \frac{g_{jik}}{g_{jk}} \Big/ \frac{(n-1)(n-2)}{2}$$

where n is the number of nodes, g_{jk} is the number of shortest paths from node j to node k, and g_{jik} is the number of shortest paths from node j to node k that pass through node i.

3.3.1.2. Dyadic-level measures

The only dyadic-level measure used here is *tie strength.* Tie strength expresses the excellence of connection between two nodes in a network. According to Granovetter (1973), the strength of the relationship between two nodes can be expressed as a mixture of the amount of time and the mutual services which distinguish the link between them. Extending Granovetter's theoretical concept of tie strength, Marsden and Campbell (1984) established that 'emotional closeness' was the best effective indicator of tie strength in preference to the other indicators of 'frequency of contact', 'reciprocity of services' and 'intimacy' (mutual confiding). Besides emotional closeness, frequency of contact is extensively used as a measure of tie strength (Lin et al., 1978; Granovetter, 1995). The other indicators are extremely subjective and have not been broadly accepted by researchers to date. In the context of bushfire, strength of ties between team members and strength of ties between the IMT and incident/fire ground are considered independent variables in the model to measure network ties.

3.3.1.2.1 Strength of Ties between Team Members

Strength of ties between team members are measured using a six-item scale. Scale items to measure strength of ties between team members are drawn from the literature (Lin et al., 1978; Granovetter, 1995). Here, the general definition is modified for the context of measuring strength of ties between team members in the context of bushfire. Six items are included in the survey to assess perceptions with regard to the strength of ties between team members, namely:

- Team members effectively monitored each other's performance
- Team members exhibited a strong 'we are in this together' attitude
- Team members anticipated the needs of others
- Team members trusted each other
- New team members were quickly integrated into the team
- Comfort approaching members of the team for help when needed

3.3.1.2.1 Strength of Ties across Team Members

Strength of ties between IMT and incident/fire ground are measured using a five-item scale. Scale items to measure the strength of ties between team members are drawn from the literature (Lin et al., 1978; Granovetter, 1995). Here, the general definition is adapted for the context of measuring strength of ties between team members in the context of bushfire. Five items are included in the survey to assess perceptions with regard to the strength of ties across teams (between IMT and incident/fire ground personnel), namely:

- IMT and Incident/Fire Ground personnel effectively monitored each other's performance.

- IMT and Incident/Fire Ground personnel exhibited a strong ‘we are in this together’ attitude.
- IMT and Incident/Fire Ground personnel were able to state and maintain opinions openly with each other.
- IMT and Incident/Fire Ground personnel anticipated the needs of others.
- IMT and Incident/Fire Ground personnel trusted each other.

3.3.1.3. Network Level Measures

3.3.1.3.1 Density

Generally, the first measure of network structure is mostly the cohesiveness of the network. For example, when identifying the network position of an individual within a network, the results can be understood in light of the cohesiveness of the network. Density is a measure of network cohesiveness and is the ratio of the existing number of ties to the maximum possible ties (Porac et al., 1995; Chung, 2009). For an undirected graph with n nodes, density D is defined as:

$$D = \frac{\sum_{i,j=1}^{n} x_{ij}}{n(n-1)/2}$$

where x_{ij} is the value of the connection from i to j.

3.3.1.3.2 Degree Centralisation

As mentioned earlier, degree centralisation is the variation in degrees of nodes divided by the maximum possible variation in a network of the same size. The centrality of the whole network must measure the tendency of a node to be more central than all other nodes in the network. Such measures of the network centrality are based on differences between the centrality of the most central node and that of all others. Freeman (1978) defined degree centralisation as:

$$C_D = \frac{\sum_{i=1}^{n} [C_D(p*) - C_D(p_i)]}{n^2 - 3n + 2}$$

Where:

n = number of nodes

C_D (pi) = centrality of one of the nodes defined above

C_D (p) = largest value of CD(pi) for any node in the network*

C_D is a general formula for determining the centrality of a network in terms of degree.

3.3.1.3.3 Betweenness Centralisation

Betweenness centralisation is the average difference between the relative centrality of the most central node in terms of betweenness, and that of all other nodes. The centrality of the whole network measures the tendency of a node to be more central than all other nodes in the network. Such measures of the network centrality are based on differences between the centrality of the most central node and that of all others. Freeman (1978) defined betweenness centralisation as:

$$C_B = \frac{\sum_{i=1}^{n}[C_B(p*) - C_B(p_i)]}{n^3 - 4n^2 + 5n - 2}$$

Where :

n = number of nodes

CB(pi) = centrality of one of the nodes defined above

CB(p) = largest value of CD(pi) for any node in the network*

CB is a general formula for determining the centrality of a network in terms of betweenness

Freeman (1978) demonstrated that this measure takes its maximum value for the star or wheel network. Thus, C_B offers an overall measure of graph or network centrality based on betweenness. All these measures (degree and betweenness centralisation) agree in allocating the highest centrality measure to the star or wheel network. Moreover, they all have an understanding that the lowest measure is allocated to the complete network (where all connections are available), since all nodes in that network are same. However, outside those extreme circumstances, agreement breaks down.

3.3.2. Learning Measures

To assess the network relationship against learning behaviour, some dependent variables are defined which form the basis of the learning behaviour measure. Affective learning is difficult to measure, but researchers have proposed a variety of methods to measure learning for both individuals and group. Most of these measures focus on measuring the learning of students in school. For example, Richmond et al. (1987) introduced the Learning Loss Scale in 1987 to measure cognitive learning for students in school. Other studies have shown that students' performance on learning indicators is positively related to their feelings of empowerment, state motivation, affective learning, and relevance (Frymier and Houser, 1999). However, some theories of measuring learning in other environments have been developed recently and are used in this research. The following sections explore the measures of learning based on the level of analysis (actor-learning, team learning and network learning).

3.3.2.1. Actor Level Learning

A new way has been developed to measure actor-level learning. It is based on definitions of learning discussed in Chapter 2. To recap, actor-level or individual learning is defined as obtaining new or modifying current knowledge, behaviour, abilities, standards, or preferences, and may include combining different kinds of information. From this perspective, learning will usually lead to improved performance over time and will lead the individual to adapt and become better suited to its environment. Development and adapting over time tends to follow learning curves. 'Adaptation' refers both to the dynamic evolutionary process that guides to the adaptation and to the present state of being adapted.

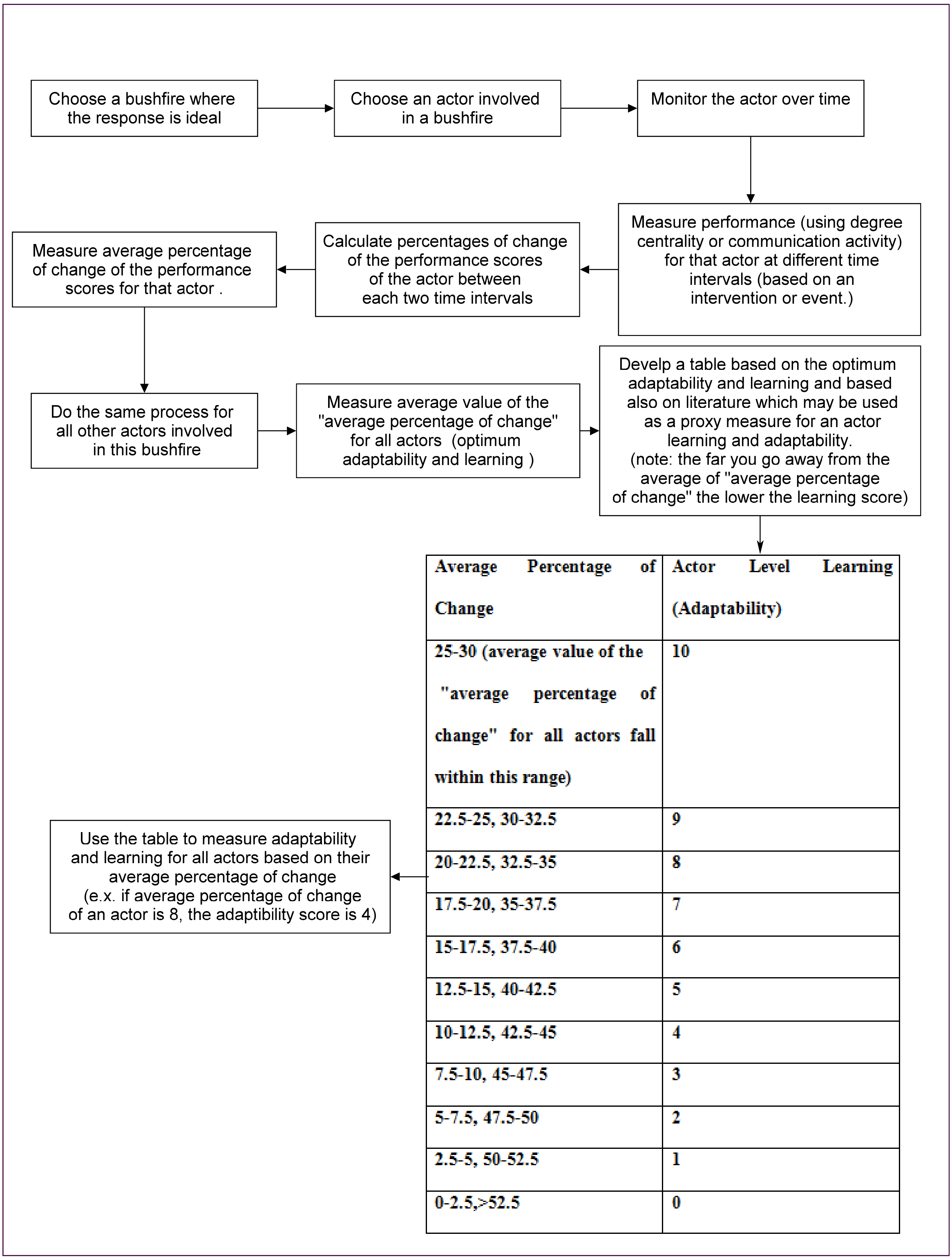
To measure individual learning, researchers need to monitor the individual under study over time and see whether the individual is adapting over time. In this study, learning is measured by quantifying how the individual is adapted to another type of situation or behaviour. In other words, learning is characterised by a type of behaviour that permits an individual to change a disruptive behaviour to something more constructive. For example, a continuous repetitive action might be re-focused on something that generates or builds something. In other words, the behaviour can be adapted to something else. Every individual must learn a set of skills and abilities that is useful for the surroundings and society. Adaptive skills are crucial for accessing and developing from local or distant communities. For example, to go to the cinema, a teenager will have to learn to navigate through the city or take a train, to read the film timetable and to pay for the film. Adaptive skills permit harmless exploration since they provide learners with an improved awareness of their surrounds and of alterations in an environment that need novel adaptive responses to encounter its difficulties and risks.

Measuring individual learning based on adaptability requires exploration of the networks under investigation continuously over time. While individuals in a traditional SNA model are static, individuals in a dynamic network analysis model have the ability to learn. Properties change over time; individuals can adapt. For example, a firm's staff can learn new skills and abilities and increase their worth to the network. Change spreads from one individual to the next and so on. Dynamic network analysis enhances the critical component of a network's development and reflects the conditions under which alteration is expected to happen.

In the context of bushfires, the process of measuring the learning of individuals is shown in Figure 3.2. Learning of individuals in this study is measured by monitoring the individual over time to see whether the individual is adapting over time to the environment. This is done by measuring performance for each actor at different time intervals of the incident. The performance measure for each actor is measured using degree centrality (activity of communication). Studies have shown that degree centrality has high correlation with performance (Powell et al., 1996; Sparrowe et al., 2001; Tsai, 2001; Cross and Cummings, 2004). As degree centrality increases (better communication activity) performance improves. The time intervals are usually decided based on an intervention or event. Then to measure adaptability, the percentages of change of centrality scores of the actors are calculated between each pair of intervals. The percentage of change is the difference between two numbers, expressed as a comparison to the size of one or both of them. Such measures are unit-less quantities. Such quantities are frequently used as a numerical indicator of quality control for repetitive measurements where the outcomes are estimated to be similar.

Based on those measures, the average percentage of change of centrality scores for each actor can be measured. Table 3.3 can be used to measure adaptability or learning score for each actor based on the actor's average percentage of change of centrality scores. Research has shown that when an actor's behaviour changes smoothly, the actor involved in the response system is more prepared and has acted according to a plan and has adapted well to the environment (Comfort et al., 2009). However, when a much more chaotic pattern is seen for the actor's behaviour, it means that the behaviour does not evolve, but changes dramatically. Also, if an actor's behaviour does not change at all with time, this actor is not adapting to the changes in the environment. While a degree of change is essential for better performance, a degree of stability is also essential to ensure an effective response. Therefore, the "average percentage of change" of all actors is used as a proxy measure for the actor's learning and adaptability. This measure is validated in the literature. Carley (2002) uses "percentage of change of performance" to calculate adaptability. She defines adaptability as "the percentage difference in performance, as measured at the beginning and end of the mission".

The ideal "percentage of change" for optimum learning and adaptability is calculated based on the data. This is shown in Table 3.2, which shows the method used for measuring average percentage change of individual performance. The data in Table 3.2 are extracted from the Bunyip bushfire which is shown later in this chapter. The average "percentage of change" for each actor was calculated and then the average value of the "average percentage of change" for all actors was measured. The value of this average was 28.83%. It is assumed, then, that this value is the ideal percentage of change which indicates optimum adaptability and learning for an actor. This is because the response for the Bunyip bushfire was ideal and this average represents adaptability scores for all actors. Therefore, Table 3.3 was developed based on optimum adaptability and learning. That table can be used as a proxy measure for actors' learning and adaptability.



Average Percentage of Change	Actor Level Learning (Adaptability)
25-30 (average value of the "average percentage of change" for all actors fall within this range)	10
22.5-25, 30-32.5	9
20-22.5, 32.5-35	8
17.5-20, 35-37.5	7
15-17.5, 37.5-40	6
12.5-15, 40-42.5	5
10-12.5, 42.5-45	4
7.5-10, 45-47.5	3
5-7.5, 47.5-50	2
2.5-5, 50-52.5	1
0-2.5,>52.5	0

Figure 3.2: Process of measuring the learning of individuals

Table 3.2: The method used for measuring average percentage change of individual performance

Actor	% of change at t1	% of change at t2	% of change at t3	% of change at t4	% of change at t5	Average % of change
Division Commander_DSE_Day_Shift	17.44	21.67	25.34	1.42	30.12	19.20
IC_DSE_Day_Shift	27.21	31.35	7.92	20.42	50.06	27.39
Deputy_IC_CFA_Day_Shift	22.14	16.66	78.39	5.60	10.29	26.62
Division Commander_DSE_Night_Shift	23.69	100.00	0.00	0.00	0.00	24.74
IC_DSE_Night_Shift	22.12	100.00	0.00	0.00	0.00	24.42
sector commander, west sector, Day shift	23.02	53.50	12.04	54.70	13.15	31.28
sector commander, east sector, Day shift	31.20	7.56	18.38	29.41	63.62	30.03
Operations Officer_DSE_Night_Shift	217.84	0.00	0.00	0.00	0.00	43.57
Behaviour analyst, fban unit team leader	0.20	2.18	0.19	1.75	0.00	0.87
Operations Officer_DSE_Day_Shift	16.91	12.10	3.23	2.11	6.53	8.17
rce Leader for a Gippsland Taskforce, DSE	100.00	0.00	0.00	0.00	0.00	20.00
Air Attack Supervisor	100.00	0.00	0.00	0.00	0.00	20.00
VicPol	14.75	107.94	1.55	7.66	2.10	26.80
SP AusNet	26.59	75.47	12.04	22.07	24.63	32.16
RDO_DSE_Night_Shift	100.00	0.00	0.00	0.00	0.00	20.00
SES	3.81	33.33	30.25	61.61	70.00	39.80
Strategic Operations Officer_CFA_Day_Shift	60.47	41.40	17.20	28.57	24.18	34.36
RDO_DSE_Day_Shift	100.00	0.00	0.00	0.00	0.00	20.00
VicRoads	100.00	0.00	0.00	0.00	0.00	20.00
Division Commander 1, CFA	7.56	53.88	11.98	16.79	8.57	19.75
Longwarry Brigade Captain	8.30	100.00	0.00	0.00	0.00	21.66
VLine	100.00	0.00	0.00	0.00	0.00	20.00
SDO1_DSE_Day_Shift	100.00	0.00	0.00	0.00	0.00	20.00
Ground observers	8.80	64.85	12.04	34.74	65.00	37.09
Division Commander Assistant	65.74	100.00	0.00	0.00	0.00	33.15
BOM	22.69	100.00	0.00	0.00	0.00	24.54
Longwarry Fire Brigade Lieutenant	84.03	100.00	0.00	0.00	0.00	36.81
Region 8 Operations Officer	38.72	46.57	32.80	55.85	65.51	47.89
Operations Manager Region 9	100.00	0.00	0.00	0.00	0.00	20.00
DSE Land and Fire Manager, Central Area	122.22	45.31	12.04	54.70	5.71	48.00
Planning Officer_DSE_Day_shift	0.00	0.00	0.00	0.00	0.00	0.00
c forest, Plant Operations Manager in IMT	100.00	0.00	0.00	0.00	0.00	20.00
Operations Manager Region 8	13.62	24.68	25.30	33.78	65.51	32.58
Aircraft Officer	8.61	25.66	69.07	43.16	77.79	44.86
Division Commander Assistant 1	6.72	0.00	0.00	0.00	0.00	1.34
Chief Fire Officer of DSE	8.09	86.00	0.00	0.00	0.00	18.82

Division Commander 2, CFA	2.12	12.10	46.72	11.10	3.30	15.07
Resources Officer	100.00	0.00	0.00	0.00	0.00	20.00
Region 8 Operations Officer_DSE_Day_Shift	2.85	41.44	100.00	0.00	0.00	28.86
Cardinia Group Officer	2.12	53.88	100.00	0.00	0.00	31.20
MERO	54.07	0.00	0.00	0.00	0.00	10.81
DHS	100.00	0.00	0.00	0.00	0.00	20.00
Information Unit Officer 1	2.12	53.88	50.37	1.16	20.77	25.66
SDO1_DSE_Night_Shift	2.85	100.00	0.00	0.00	0.00	20.57
MERC	0.00	0.00	0.00	0.00	0.00	0.00
Major Incident Operation Officer	6.06	11.34	22.97	19.34	28.42	17.63
Sector Z Commander	5.59	75.85	58.00	48.43	84.74	54.52
Tactical Operations Officer	16.25	281.03	13.87	54.86	84.49	90.10
Sector A Commander	3.95	28.75	11.98	10.59	18.20	14.69
IC_CFA_Night_Shift	12.55	5.48	2.51	0.92	143.04	32.90
Strategic Planning Officer	22.21	65.78	18.81	5.76	10.49	24.61
Logistics	51.14	19.66	18.82	0.79	1.96	18.48
Sector B Commander	20.42	250.94	43.98	54.70	70.47	88.10
Egg Rock fire tower	6.00	183.02	30.67	17.76	3.35	48.16
Deputy Operations Officer	0.38	250.94	43.98	21.31	70.98	77.52
RECC	0.38	75.47	124.09	14.40	19.39	46.74
Information Unit Officer 4	1.12	15.85	0.00	0.00	46.64	12.72
SDO2_DSE_Day_Shift	40.21	162.26	25.04	1.92	0.78	46.04
Logistic_Officer_DSE_Day_Shift	0.75	0.75	0.00	0.75	0.76	0.60
Information Unit Officer 2	0.00	0.00	87.20	0.00	0.00	17.44
Information Unit Officer 3	0.00	0.00	73.33	0.00	92.56	33.18
Air Operations Manager	0.00	0.00	73.33	0.00	92.56	33.18
Situation Officer	0.00	0.00	7.20	50.86	88.28	29.27
RDO_CFA_Night_Shift	0.00	0.00	0.00	50.48	7.75	11.65
Communications Planning unit	43.15	28.70	17.34	42.42	13.33	28.99
Deputy Planning Officer	235.46	75.41	45.44	37.11	46.14	87.91
Average % of change for all actors						**28.83**

Table 3.3: The method used for measuring individual learning and adaptability

Average Percentage of Change	**Actor-Level Learning (Adaptability)**
25-30	**10**
22.5-25, 30-32.5	**9**
20-22.5, 32.5-35	**8**
17.5-20, 35-37.5	**7**
15-17.5, 37.5-40	**6**
12.5-15, 40-42.5	**5**
10-12.5, 42.5-45	**4**
7.5-10, 45-47.5	**3**
5-7.5, 47.5-50	**2**
2.5-5, 50-52.5	**1**
0-2.5,>52.5	**0**

By way of illustration, here are three examples to show how actor-level learning (Adaptability) is measured based on the percentage of change as shown in Table 3.4 and Figure 3.3. The behaviour of actor 1 changes dramatically with time. It does not evolve and adapt to the environment. The average percentage of change for actor 1 is 176.7 %, which is above 52.5 % based on Table 3.3, which means that actor-level learning (Adaptability) for actor 1 is 0 (the behaviour is not evolving and adapting to the environment). On the other hand, the behaviour of actor 2 does not change. Therefore, the actor's behaviour is not evolving and adapting to the environment. The average percentage of change for actor 2 is 0 %, which is between 0 and 1, which means the actor-level learning (Adaptability) for actor 2 is 0 based on Table 3.3. For actor 3, the average percentage of change is 12.7 % which is between 12.5 and 15. This means that actor level learning (Adaptability) for actor 3 is 8, based on Table 3.3. Actor 3 has a high adapting score, which makes sense. A similar technique is used to measure actor-level learning (Adaptability) for all actors involved in the 2009 Victorian bushfires investigated. On that basis, the thesis explores whether actor-level network measures have any effect on the learning and adaptability of those actors.

Table 3.4: Examples showing how actor-level learning (Adaptability) is measured based on percentage of change.

	T1	T2	T3	T4	Average Percentage of Change	Actor-Level Learning (Adaptability)
A1	5	10	2	9		
Percentage of change A1	100%	80%	350%		176.7	0
2	5	5	5	5		
Percentage of change A2	0%	0%	0%		0	0
A3	5	6	6	7		
Percentage of change A3	20%	0%	16.8%		12.67	8

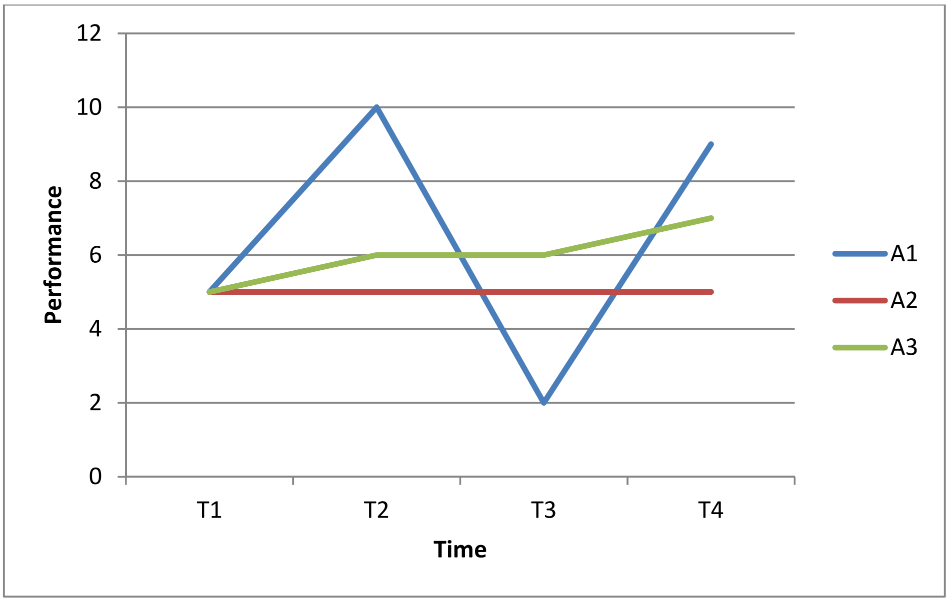


Figure 3.3: Individual performance changes over time

3.3.2.2. Team learning

To assess the network relationship against learning behaviour, some dependent variables are defined which form the basis of the learning behaviour measure.

3.3.2.2.1 Flexibility

As discussed earlier, the variable *flexibility* refers to the ability and readiness to adapt performance strategies rapidly and appropriately to changing task demands. Three items are included in the survey to assess levels of satisfaction with team flexibility. The items are:

· Strategies were adjusted in a timely manner as the incident unfolded.

· Roles were effectively re-allocated as the situation changed.

· When problems occurred, the team was able to recover quickly and get on with the job.

These scale items to measure flexibility are drawn from the literature (Serfaty et al., 1998; Ekornas et al., 2001).

3.3.2.2.2 Quality of information exchange

An analysis of quality of information exchange is undertaken to determine aspects of an actor's current state of learning. *Information exchange* comprises passing significant information to team members who need it, in a timely manner, including transmitting and receiving. Five items are included in the survey to assess perceptions with regard to the quality of information exchange:

· Team members exchanged information clearly.

· Team members exchanged information accurately.

· Team members kept one another well informed about work-related issues.

· There were genuine attempts to share information.

· Team members interacted effectively with stakeholders outside their own team.

These scale items to measure the quality of information exchange are drawn from the literature (Orasanu and Salas, 1993; Serfaty et al., 1998; Smith-Jentsch et al., 1999; Salas and Cannon-Bowers, 2001; Schaafstal et al., 2001).

3.3.2.2.3 Team feedback skills

Analysis of *team feedback skills* (a dependent variable) was further performed to determine aspects of an actor's current state of learning. In this framework, team feedback skills is defined as the ability to assist team members to communicate their observations, concerns, proposals and demands in a clear and direct way without becoming aggressive and defensive.

The survey includes four items aimed at assessing levels of satisfaction with team feedback indicators. These were:

· Team members provided helpful advice to each other.

· Team members were able to state and maintain opinions openly.

· Team members provided constructive feedback to each other.

· Team members shared individual knowledge with each other to better understand the situation.

These scale items to measure the quality of information exchange are drawn from the literature (Orasanu, 1990; Smith-Jentsch et al., 1999; Schaafstal et al., 2001).

3.3.2.3. Network Learning

To investigate the effect of the structure of the whole network on learning, a network learning measure is developed. A learning or adaptive network is a set of interacting or interdependent actors forming a combined whole that together are capable of responding to environmental changes or changes in the interacting actors. Feedback loops represent an important feature of adaptive networks, allowing responses to changes. In this study, five bushfires are investigated. Therefore, network learning and adaptability can be measuring by evaluating the losses from each bushfire. The fire with the lowest loss will indicate that the network responding to that fire has learned from and adapted well to the environment and the response was effective. Measures of number of fatalities, houses lost, hectares burned and economic loss are essential in determining how adaptive a network is and in determining the impact of the fire on a community. Community loss data was collected from the 2009 Victorian Bushfire Royal Commission report as shown in Table 3.5.

Table 3.5: Summary of damage by locality (Source: 2009 Victorian Bushfires Royal Commission)

Area	Area (ha)	Fatalities	Buildings destroyed	Ignition source	Fire name/origin
Kinglake Area	180,000+	120	1,244 houses, many commercial buildings	Power lines	Kilmore East fire
Marysville Area	150,000+	39	590 houses, many commercial buildings	Unknown	Murrindindi Mill fire
Central Gippsland	32,860+	11	247 houses	Arson	Churchill-Jeeralang fire
Bunyip State Park	24,500	0	24 houses, several other buildings	Arson/lightning suspected	Bunyip State Park fire
Totals	**450,000+**	**173**	**3,500+ (2,029+ houses)**		

3.3.3. Moderating Measures

As mentioned earlier, moderating measures are used to see whether they moderate the relation between network variables (more specifically strength of ties) and the learning variable. Moderating variables mostly originate from the socio-demographic characteristics of individuals such as age, gender and area of domicile of individuals. Demographic details were solicited from emergency personnel who responded to the survey. Four moderating variables are used to test the relationships between independent variables and dependent variables at cluster level. Gender, age and the experience attribute of emergency personnel, and type of incidents were used as moderating variables. Gender and age are straightforward measures to indicate the age and gender of respondents. The experience measure is based on the number of years of experience of emergency personnel fire and emergency management. Another factor that may play a major role in moderating the relation between network variables (more specifically strength of ties) and the learning variable is the type of emergency incidents managed. The incident might be a forest, scrub, or grass fire, rural/urban interface fire, structural fire, as well as emergency incidents including cyclones, floods and storms.

3.4. Bushfire Dataset Descriptions

In Chapter 1, it was noted that this research is theoretically and methodologically motivated. As noted in Chapter 2, section 2.6, the context for exploring the interplay between social network and learning in this study is the domain of Australia's emergency incident management system in the context of bushfires in Australia. To recap, the choice of the domain of bushfires in Australia is important for two reasons:

1. Current studies have linked age, physical fitness and experience of fire-fighters as a contributing factor to the decline in learning but have not highlighted the role of social structure and relations that influence learning (Hytten and Hasle, 1989; Quińones et al., 1995; Rana, 2004).
2. Most studies have measured learning in routine situations. However, a few studies have measured learning in non-routine situation such as emergencies.

The data required to compile the proposed model could be collected either by conducting survey-like studies, with primary data collection about details of the response to bushfire, or from a third party such as transcripts of the Royal Commission Report where the key emergency personnel provide statements about their response to bushfire. Both sources of data are used here to test the model. The survey data used in this analysis comes from primary research collected from a research team supported by the Bushfire CRC and led by my co-supervisor Dr Christine Owen. The analysis reported here is thus a secondary analysis conducted as part of a subsequent collaboration. As well, data from the transcripts of the 2009 Victorian Bushfires Royal Commission Report are used to test the effect of actor-level social network measures and network-level social network measures on learning. The data from the survey will only be used to test the effect of the dyadic-level measures on learning. In conclusion, to understand social network effects on learning, both relational and attribute data need to be collected and linked to assist the analysis. Attribute data include learning and personal attributes such as age and gender. Relational data include elicitation of 'alters' with whom the emergency personnel contact during the bushfire.

3.4.1. Survey Data

The collection of data from a social network survey includes gathering relational data along with attribute data. The relational data is essential for understanding important features of an actor's relational and social surroundings. Analysis of both attribute and relational data yields richer awareness to clarify social outcomes. The use of both relational and attribute data thus provides a very valuable method of exploring actor outcomes in a particular social environment. Nevertheless, the gathering of relational data is fairly different from traditional surveys and is burdened with working problems and disputes which require substantial care. This section explores the details of the survey instrument design and development process and the quantitative data collection process for understanding the relationship between social networks and learning in a dynamic complex environment.

The collection of data from a social network using a survey is most commonly used (especially when the actors are people) (Wasserman and Faust, 1994). The survey usually contains questions about the respondent's ties to the other actors. Surveys are most useful when the actors are people, and the relation(s) that are being studied are ones that the respondent can report on. Collecting data using surveys has many advantages. Firstly, surveys can be undertaken in less time than other approaches. Secondly, surveys can be cost-effective. Thirdly, surveys are useful for describing the characteristics of a large population, assuming that the sampling is valid and that the survey can be administered remotely via websites, mail, e-mail, mobile devices, phone, etc. Fourthly, surveys are also effective in gathering data from a huge number of individuals and statistical methods can be applied to the survey data. Finally, an extensive variety of data can be gathered (e.g., attitudes, beliefs, relationships and behaviour) using surveys and, because surveys are homogeneous, they are moderately free of numerous kinds of errors. The data from the survey used in this study are used to test the effect of the dyadic-level social network measures on team learning, as mentioned earlier in this chapter.

The data used in this analysis comes from primary research collected from a research team supported by Bushfire CRC.[1] The analysis reported here is thus a secondary analysis conducted as part of a subsequent collaboration. To collect the primary data, a survey was distributed to 25 agencies (579 respondents) in Australia aiming to assess how information flowed between emergency incident management personnel within different layers of the Australian and the New Zealand incident control system, and what permitted and inhibited coordination between those emergency staff members. Emergency management in Australia is created on the AIIMS, which in turn was based on the American model of the NIMS (AFAC, 2005).

Bushfire work is organised in distributed work teams, with emergency staff members working on the fire- or incident ground, within a locally-based IMT and supported through coordination practices at regional and state levels. Decisions about managing the incident are made at IMT level and communication between the IMT and the fire-or-incident ground is critical to the success of the operation. Survey respondents were asked to give their insights on a variety of indicators of information flow and teamwork within the AIIMS system. They were requested to consider one incident and to identify the characteristics of that incident (e.g., whether they received a briefing or incident action plan, whether specific risk management and valuation tools were in use and whether specific teamwork indicators were in use.).

3.4.1.1. Survey Instrument Design and Development

Development of the 2008 survey went through a number of phases. The 2003 survey conducted by AFAC had earlier been revised and descriptive data summarised for the AFAC AIIMS Steering Committee. The 2003 survey directed by AFAC as part of its consultation process worked as a template to initiate work for the 2008 data collection process. In doing so a number of questions that were asked in 2003 were asked again in 2008 in order to yield relative information. Moreover, a number of questions asked in 2003 were revised to improve clarification. Similarly a number of new sections were added.

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1 The Bushfire Co-operative Research Centre is a nationally funded research centre [For more information, see - http://www.bushfirecrc.com/]

3.4.1.2. Evaluation of the Survey

The draft survey went through a number of stages of assessment by both stakeholders and users. Subject matter experts and participants of the AFAC AIIMS steering committee delivered comprehensive feedback on some questions and likewise made adjustment recommendations on others. The draft survey endured an experimental period where it was completed by three distinct focus groups (comprising between 20 and 25 subject matter experts) to deliver pilot survey responses and panel feedback. Participants in the focus groups were knowledgeable in emergency incident management and came from organisations in Victoria and Tasmania. In each of these, focus group members were required to complete the survey. The time taken was documented. Following completion, to evaluate and enhance validity, participants were at that time asked for their views about what they believed specific questions were trying to evaluate, and their views on whether the questions worked or required amendment. Participants were likewise asked to classify any possible problems that should be addressed but were absent from the experimental form of the survey. This contribution was then used to review the survey, which was then distributed back to the participants of the AFAC AIIMS steering committee for their input. The survey was then authorised by the National AFAC AIIMS steering committee for dissemination at its May 2008 meeting.

3.4.1.3. Structure of the survey

Throughout the survey, participants were asked to either tick a box or provide a score on a 7-point Likert Scale (Field, 2009). The last form of the 2009 survey was separated into six sections as described below (see also Appendix A). Note that each participant answered the survey based on one incident; hence in the data, one participant equals one incident.

Section 1 of the survey sought to gain a summary of the latest main incident in which participants had been involved (for instance, questions were asked about the kind of incident, where it occurred, how complex it was, what was endangered, the organisations involved, the length of the event, the numbers of individuals involved, role distributions, and reporting pathways).

Section 2 of the survey asked questions about participants' region of accountability throughout one particular shift at the emergency event detailed in the Section 1 (for example, questions were asked about the stage of the emergency event, briefing and incident action plan problems, incident management problems in regard to what helped/hindered individuals in doing their jobs, reporting structures, communications strategies, resourcing capability, safety matters, convenience of risk management tools, staff expertise, group self-confidence, information administration, and use of technology).

Sections 3 and 4 of the survey sought data about teamwork and relations between the IMT and others involved in addressing the emergency event (for instance, crew leaders and divisional commanders on the Incident/Fire ground). Section 3 comprised indicators of effective teamwork drawn from the research literature.

Section 4 of the survey used related indicators and asked participants to reflect on the collaboration between the IMT and the fire/incident ground. This was considered significant since communication and information flow between these layers in the incident management system are crucial for effective emergency incident management.

Section 5 of the survey focused on determining levels of satisfaction with incident management system actions and methods, specifically how these methods affected the efficiency of organisation inter-operability. The final section, Section 6, sought a demographic profile of participants, including their experience with numerous methods of training and learning initiatives.

3.4.1.4. Distribution of the survey

The survey received ethics approval (HREC 8810) for circulation. Instructions were delivered to the contacts on how to distribute the survey within their own organisation. Organisation contacts were given a variety of choices with regard to completing the survey. Participants were advised that they could use either an online survey or paper copy. Contacts were asked to formulate a distribution list, to complete a distribution plan and to return it to researchers. The distribution plans were established in order to attempt to reach a stratified sample of between 15 to 30 individuals in each of the role groups recognised for targeting in the survey. The sample was therefore stratified to contain staff working on the fire/incident ground, staff working in incident management teams and staff working in a regional or state level of coordination. Contacts were similarly asked to circulate an ethics information sheet accompanying the survey. For this survey, third parties were used to disseminate the questionnaire. It was not possible to know exactly how many people received the questionnaire and thus what the response rate is for every agency. Where known however, the response rate varied between 10% and 100%. This is one of the limitations of this study.

3.4.1.5. *Data Preparation (Reliability and Validity Analysis)*

Data preparation for this study was divided into two phases to test the dyadic-level social network hypotheses. Table 3.6 shows a summary of the method used and the purpose of each method. The first phase involved importing data records into Microsoft Excel. This was done by placing the data into columns of Microsoft Excel, representing survey responses. Once this stage was complete, variables were prepared and invalid responses were removed. In the second phase, all the variables were placed into the SPSS program to implement certain statistical tests for validity and reliability and to execute statistical analyses for hypothesis testing, as defined in the proposed model.

Table 3.6: Overview of software and phases of data preparation

Data Preparation Methods		Purpose of Software
Microsoft Excel	Phase 1	Clean raw data file, measure variables
SPSS	Phase 2	Perform statistical tests and analyses

Churchill Jr's (1979) eight-step process that is used to establish complete and reliable measures is iterative. Scale items must be purified by testing for reliability and validity before they can be used in estimating relationships or testing hypotheses. In this section, a brief summary of the purification process is presented. For the purpose of this research, the analysis is narrowed to focus only on complex emergency events, for the reasons discussed earlier. The only incidents which are considered are incidents on ICS (Incident Control System) level 3. A level 3 incident is defined as one that is sufficiently complex to involve the full deployment of an ICS. The incidents examined are those where the perceived complexity level is high; the number of people involved at the peak of the incident is more than 100; the number of agencies involved at the peak of the incident is more than 7; and the number of threats is more than 6, and the threats affected the infrastructure. Thus, for analysing this data, the number of cases is reduced to 69.

Analysis of the dataset for the purposes of this research first involved thorough exploration of the survey instrument to identify possible questions that would provide relational data to assess the respondents' social network, or questions relevant to learning measures as proposed in the model. As can be seen from Table 3.7 and as discussed earlier, there were six items assessing the strength of ties between team members and five items assessing the strength of ties between IMT and the fire/incident ground for social network measures. For learning measures, three survey items were included to assess perceptions of team flexibility, five items for information exchange and four items for team feedback skills. For any key indicator, scores of the items were combined to form the respondent's degree of that indicator.

Table 3.7: Survey items relevant to network and learning measures

Variable	Survey Items
Strength of ties between team members	3.2.5 Team members effectively monitored each other's performance 3.2.6 Team members exhibited a strong 'we are in this together' attitude 3.2.14 Team members anticipated the needs of others 3.2.18 Team members trusted each other 3.2.19 New team members were quickly integrated into the team 3.2.23 Comfortable approaching members of the team for help when needed
Strength of ties between IMT and incident/fire ground	4.1.4 IMT and Incident/Fire Ground personnel effectively monitored each other's performance. 4.1.5 IMT and Incident/Fire Ground personnel exhibited a strong 'we are in this together' attitude. 4.1.11 IMT and Incident/Fire Ground personnel were able to state and maintain opinions openly with each other. 4.1.14 IMT and Incident/Fire Ground personnel anticipated the needs of others. 4.1.18 IMT and Incident/Fire Ground personnel trusted each other.
Flexibility	3.2.13 Strategies were adjusted in a timely manner as the incident unfolded. 3.2.15 Roles were effectively re-allocated as the situation changed. 3.2.22 When problems occurred the team was able to recover quickly and get on with the job.
Information exchange	3.2.1 Team members exchanged information clearly. 3.2.2 Team members exchanged information accurately. 3.2.8 Team members kept one another well informed about work-related issues. 3.2.9 There were genuine attempts to share information. 3.2.16 Team members interacted effectively with stakeholders outside their own team.
Team feedback skills	3.2.3 Team members provided helpful advice to each other. 3.2.4 Team members provided constructive feedback to each other. 3.2.10 Team members shared their individual knowledge to gain a better understanding of the situation at hand. 3.2.21 Team members received clear direction in relation to the tasks at hand (from the supervisor or officer in charge).

3.4.1.5.1 Reliability Analysis

The first step in the analysis process was to conduct an analysis of the reliability of the scale items in the instrument. Tests using Cronbach's alpha coefficient were conducted to assess the internal reliability of the items. One scale item was dropped from the set of items measuring strength of ties between team members because it substantially lowered the reliability of the scale. Following Kohli (1989), after the item was dropped, reliability estimates were re-computed. The details of the statistics are shown in Table 3.8. Table 3.9 describes the correlation between the constructs. The reliability coefficients of independent variables range from 0.92 to 0.97. The reliability coefficient of dependent variable ranges from 0.81 to 0.91. The Cronbach's alpha coefficients surpass the 0.7 threshold recommended by Cronbach (1951) and Nunnally (1978) to be satisfactory. Thus all the measures are considered reliable.

Table 3.8: Reliability statistics

Variable	N of Items	Mean	Standard Deviation	Cronbach's Alpha
Strength of ties between team members	6	5.64	.92	0.971
Strength of ties between IMT and incident/fire ground	5	5.34	1.06	0.923
Flexibility	3	5.57	.99	0.812
Information exchange	5	5.62	.93	0.906
Team feedback skills	4	5.66	1.00	0.875

Table 3.9: Correlation matrix for all variables

	Variable	1	2	3	4	5
1	**Strength of ties team**	1.00				
2	**Strength of Ties IMT ground**	.78**	1.00			
3	**Flexibility**	.81**	.72**	1.00		
4	**Information exchange**	.87**	.75**	.76**	1.00	
5	**Team feedback skills**	.88**	.74**	.76**	.89**	1.00

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

3.4.1.5.2 Validity Analysis

The learning measures were derived and validated from the human factors literature as discussed earlier. For each learning indicator item, the exact wording of the item and a reference to the literature discussing the construct/item can be found in Owen and Dwyer (2009). For social network indicators, scale items are drawn from the social network literature as mentioned earlier in this section (Granovetter, 1973; Kraatz, 1998).

Convergent and discriminant validities were established using factor analysis. Exploratory factor analysis was conducted on the 23 scale items that measure both dependent and independent variables. A five-factor solution emerged. The number of factors that emerged was identical in number and nature to those expected a priori. The factor analyses (the factor loadings are presented in absolute form in Table 3.10) suggested that for strength of ties between team members, strength of ties between IMT and ground and the quality of information exchange, the priori hypothesised relationship between scale items and the constructs they were intended to measure holds. This relationship is weaker for the other two constructs. One item from each of the set of items measuring the flexibility scale and team feedback skills had loadings less than 0.5 (the respective loadings were 0.46 and 0.34). These items were retained for three reasons: (1) among the constructs of interest, they loaded highest on the construct they were intended to measure; (2) dropping them would have significantly lowered the reliability of the scale; and (3) several prior studies (Kohli, 1989) have retained scale items with similar factor loadings.

3.4.1.6. Data Limitation

The first data limitation in this study, as in most quantitative studies, is that the sample might not be generalisable to the complete population of staff involved in emergency management. Second, it should be appreciated that participants were asked to remember incidents that in some cases might have occurred a year or more earlier. It is consequently conceivable that there are inaccuracies in the data basically because individuals' memory of what occurred was incomplete. The responses might be prejudiced through recollection and the motivations of individuals who took the time to complete it. Again, this likelihood was diminished by implementing the same data collecting techniques as those used in 2003 by AFAC. Third, the survey on which the analysis is based was not set up to undertake research into social networks. For this purpose, it was demonstrated that the processes undertaken did extract what are believed to be useful proxies of network relations. From this perspective, it is vital to review the results carefully and to reflect on directions they might show for additional research validation.

Table 3.10: Summary of the factor analysis

Construct	Scale Item	Strength Of Ties Team	Strength Of Ties IMT Ground	Flexibility	Information Exchange	Team Feedback Skills
Strength of ties Team	3.2.5 Team members effectively monitored each other's performance	0.89				
	3.2.6 Team members exhibited a strong 'we are in this together' attitude	0.82	0.84	0.74		0.58
	3.2.14 Team members anticipated the needs of others	0.79			0.25	0.54
	3.2.18 Team members trusted each other	0.73	0.26	0.25		0.75
	3.2.19 New team members were quickly integrated into the team	0.71				
	3.2.23 Comfortable approaching members of the team for help when Needed	0.65			0.75	
Strength of ties IMT Ground	4.1.4 IMT and Incident/Fire Ground personnel effectively monitored each other's performance.		0.87	0.45		0.54
	4.1.5 IMT and Incident/Fire Ground personnel exhibited a strong 'we are in this together' attitude.	0.45	0.84		0.45	
	4.1.11 IMT and Incident/Fire Ground personnel were able to state and maintain opinions openly with each other.	0.52	0.75	0.35		0.45
	4.1.14 IMT and Incident/Fire Ground personnel anticipated the needs of others.	0.85	0.69		0.45	
	4.1.18 IMT and Incident/Fire Ground personnel trusted each other.		0.84			
Flexibility	3.2.13 Strategies were adjusted in a timely manner as the incident unfolded			0.85	0.69	0.85
	3.2.15 Roles were effectively re-allocated as the situation changed	0.21		0.81		
	3.2.22 When problems occurred the team was able to recover quickly and get on with the job			0.46		0.41
Informa-tion exchange	3.2.1 Team members exchanged information clearly		0.25		0.93	
	3.2.2 Team members exchanged information accurately				0.87	
	3.2.8 Team members kept one another well informed about work-related issues	0.25		0.47	0.84	0.57
	3.2.9 There were genuine attempts to share information				0.82	
	3.2.16 Team members interacted effectively with stakeholders outside their own team			0.58	0.80	
Team feedback skills	3.2.3 Team members provided helpful advice to each other (from the supervisor or officer in charge)	0.32	0.29			0.79
	3.2.4 Team members provided constructive feedback to each other					0.77
	3.2.10 Team members shared their individual knowledge to gain a better understanding of the situation at hand		0.24	0.38	0.40	0.58
	3.2.21 Team members received clear direction in relation to the tasks at hand					0.34

3.4.2. 2009 Victorian Bushfires Royal Commission Report Data

To test the effect of actor-level social network measures and network-level social network measures on learning, the data from transcripts of the 2009 Victorian Bushfires Royal Commission Report was used. Some social network scholars measure ties by exploring measurements taken from the archives of communications. Such archives can take numerous forms, such as measurements of past political interactions among nations, formerly published citations of one scholar by another, and so on. Burt and Lin (1977) argue that social networks may be acquired from archival data, such as journal articles, newspapers, court records, minutes of meetings, and so on. Regularly, as noted by Burt and Lin, such data give rise to longitudinal relationships and may be used to rebuild links that existed in the past. For example, (Burt, 1975; Burt, 1983) obtained information on interaction among corporate actors from the front pages of formerly published issues of *The New York Times*. There are many advantages of using such data sources for research purposes. First, data analysis is inexpensive as the data are already collected. Second, data are free from certain biases that might put the validity of the primary data collection in question. Finally, the use of archival data allows scholars to confirm the outcomes based on primary data.

3.4.2.1. The 2009 Victorian Royal Commission Report

A Royal Commission into the 2009 Victorian bushfires was initiated, in a procedure that attempted to define the exact nature of the reasons, readiness of responsible organisations, conditions during the event and the sequence of events (Teague et al., 2009). One of the major problems in the Black Saturday bushfires is attributed to poor communications between fire operations on the ground and the various Incident Control Centres (ICCs) some distance away. The communication problems restricted coordination of the fire-fighting effort. The data were analysed from four bushfires that struck Victoria in 2009. The analysis articulates first, the response network as it functioned in Victoria after the overwhelming effect of the Kilmore Bushfire on February 7, 2009. Second, the same method was used to describe the response network that developed following the Murrindindi Bushfire, Churchill Bushfire and Bunyip Bushfire that stuck broadly a different area in Victoria, but at the same time.

Kilmore East Fire

Although the four bushfires struck broadly in the same state in Australia, there were significant differences in both the physical infrastructure and populations affected that influenced the evolution of the respective response systems. The Kilmore East fire formed just before midday on 7 February, when high winds pulled down a 2 km section of power lines owned by "Victoria's electricity transmission network operator" in Kilmore East, triggering a fire in open grasslands. The fire was blown by extreme north-westerly winds, and moved 50 km (31 mi) southeast in a narrow fire front. A cool change passed through the area later in the day, bringing strong south-westerly winds. The wind alteration turned the primary lengthy and narrow fire band into a wide fire-front that travelled in a northeast direction. The area became the worst impacted in the state, with a total of 120 deaths and more than 1,200 homes destroyed (Teague et al., 2009). Figures 3.4 and 3.5 show the map and the timeline summarising the events associated with the Kilmore East bushfire.

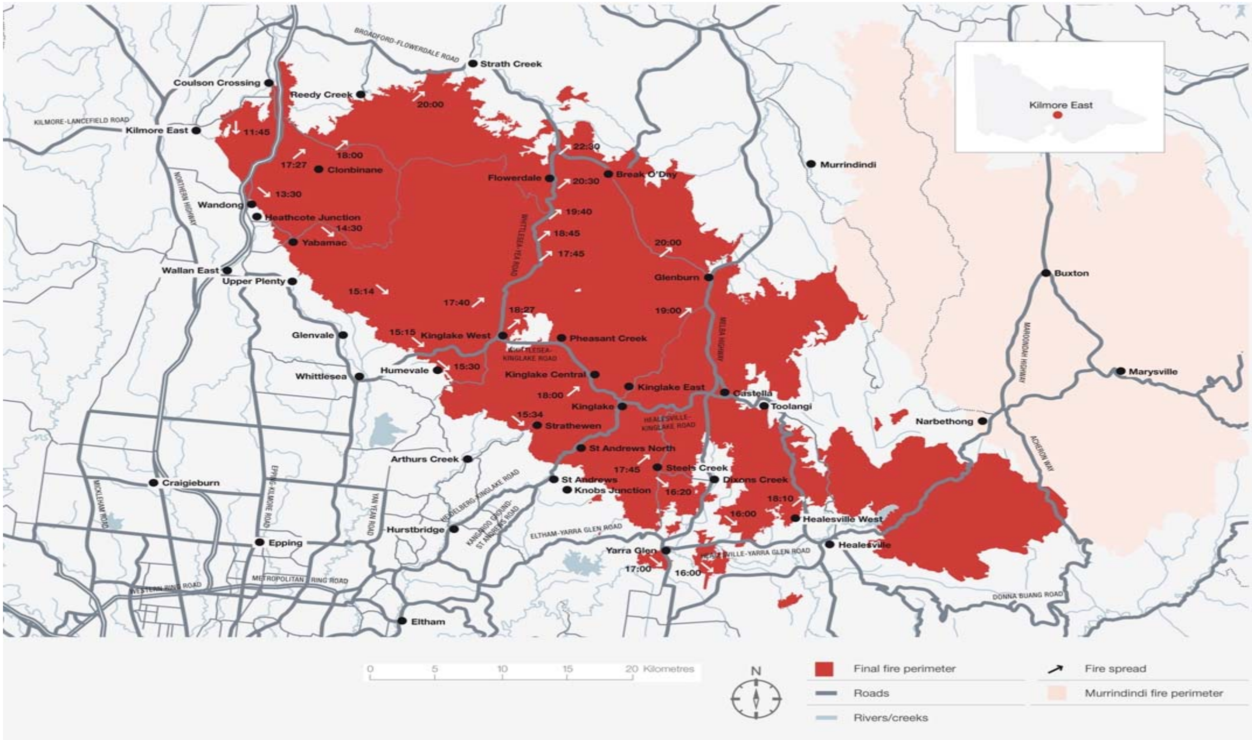


Figure 3.4: Kilmore East fire map (Teague et al., 2009)

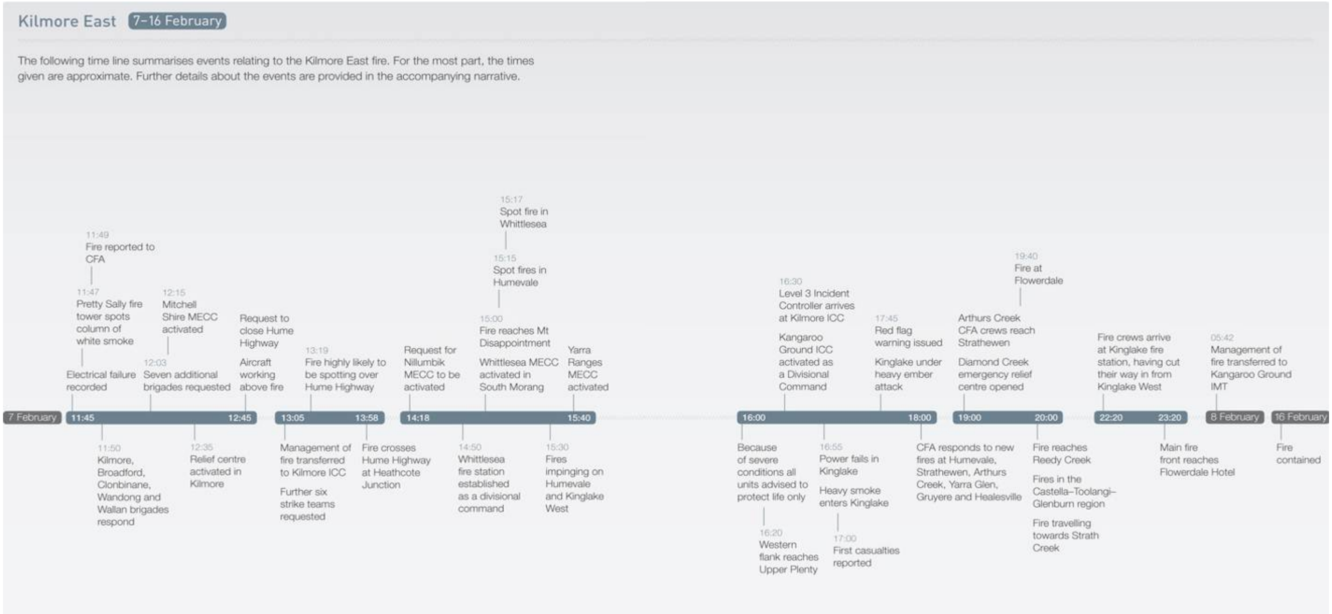


Figure 3.5: Timeline for Kilmore East fire (Teague et al., 2009)

Murrindindi Fire

Murrindindi is around 100 kilometres north-east of Melbourne, in the Shire of Murrindindi. The Murrindindi fire started at about 14:55 on 7 February 2009, to the north of a sawmill in Murrindindi. It travelled rapidly and by 16:30 was affecting the town of Narbethong. Following a wind change that arrived at about 18:15, the fire swept through the communities of Marysville, Buxton and Taggerty. It continued to burn for weeks in heavily forested public land and was not formally declared contained until 5 March. By this time the Kilmore East and Murrindindi fires, which had merged, had burnt 168,542 hectares and, among other things, threatened Melbourne's water catchments. The fire resulted in the deaths of 40 people, and more than 500 houses were destroyed or damaged, mainly in and around Marysville, Narbethong and Buxton. The commercial centre of Marysville was destroyed, as was the core of the town's economic activity in tourism and hospitality. Much of the town's public infrastructure—including the police station, primary school, kindergarten and health clinic—was also destroyed (Teague et al., 2009). Figures 3.6 and 3.7 show the map and the timeline summarising the events associated with the Murrindindi bushfire.

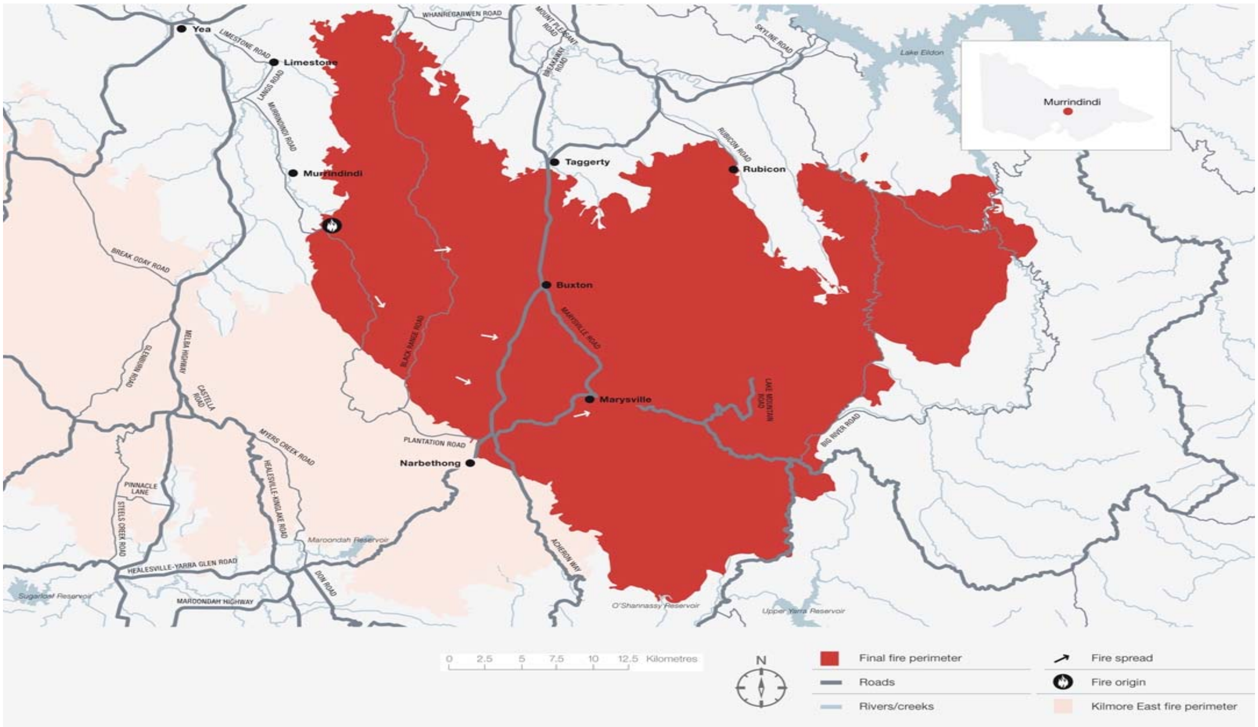


Figure 3.6: Murrindindi fire map (Teague et al., 2009)

Figure 3.7: Timeline for Murrindindi fire (Teague et al., 2009)

Churchill Fire

Churchill is a small settlement in Latrobe City and Wellington Shires, about 160 kilometres south-east of Melbourne. The Churchill fire started at about 13:32 on 7 February 2009, 3 kilometres south-east of the Churchill fire station. During the afternoon and early evening the fire travelled rapidly, affecting Jeeralang North, Balook, Le Roy, Koornalla, Callignee, Callignee North, Callignee South, Hazelwood South, Hazelwood North, Traralgon South, Devon, Yarram and Carrajung South. The Loy Yang power station, part of Victoria's critical infrastructure, is about 25 kilometres from Churchill and came under threat. Although the fire was at its most destructive on 7 February, it was not reported as controlled until 19 February. Eleven people died as a result of the fire, 145 houses were destroyed, and more than 25,861 hectares were burnt (Teague et al., 2009). Figures 3.8 and 3.9 show the map and the timeline summarising the events associated with the Churchill bushfire.

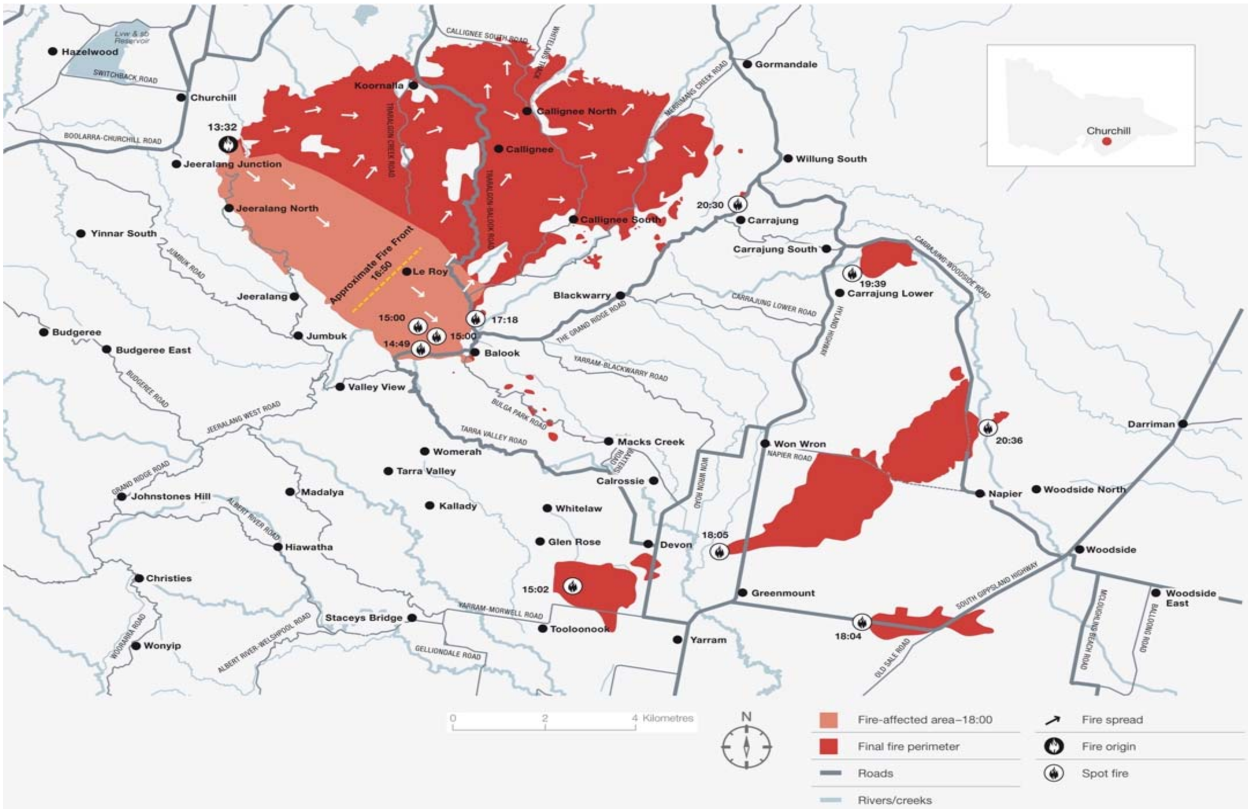


Figure 3.8: Churchill fire map (Teague et al., 2009)

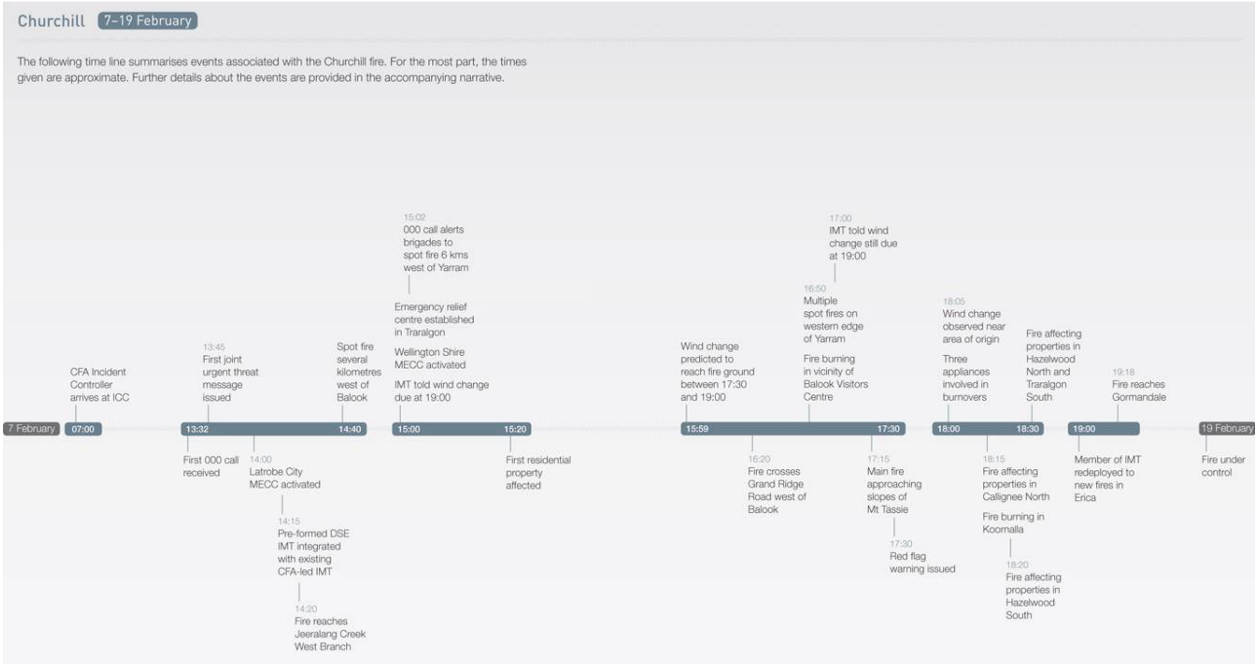


Figure 3.9: Timeline for Churchill fire (Teague et al., 2009)

Bunyip Fire

Bunyip State Park is in West Gippsland, in the Shires of Cardinia and Baw Baw and about 95 kilometres south-east of Melbourne. Among the nearby towns are Labertouche, Jindivick, Jindivick West, Jindivick North, Drouin West, Longwarry North and Robin Hood. Another fire started at Bunyip Ridge in the Bunyip State Park on 4 February, initiating near walking pathways; it was thought to have been intentionally ignited (Teague et al., 2009). The fire broke out of the park on 7 February, and burnt out 2,400 hectares (5,900 acres) of forest and farmland; threatening surrounding towns. The fire destroyed approximately a dozen houses. The fire burned through 24,500 hectares (61,000 acres). The losses from this bushfire were significantly less.

Given the substantial losses in lives, property, and disturbance of financial, social, and cultural activities from the Kilmore East bushfire, the question is whether the different social network structures of the response systems had any effect on the improved performance and learning (adaptability) in response to threat for the Bunyip bushfire. Figures 3.10 and 3.11 show the map and the timeline summarising the events associated with the Bunyip bushfire.

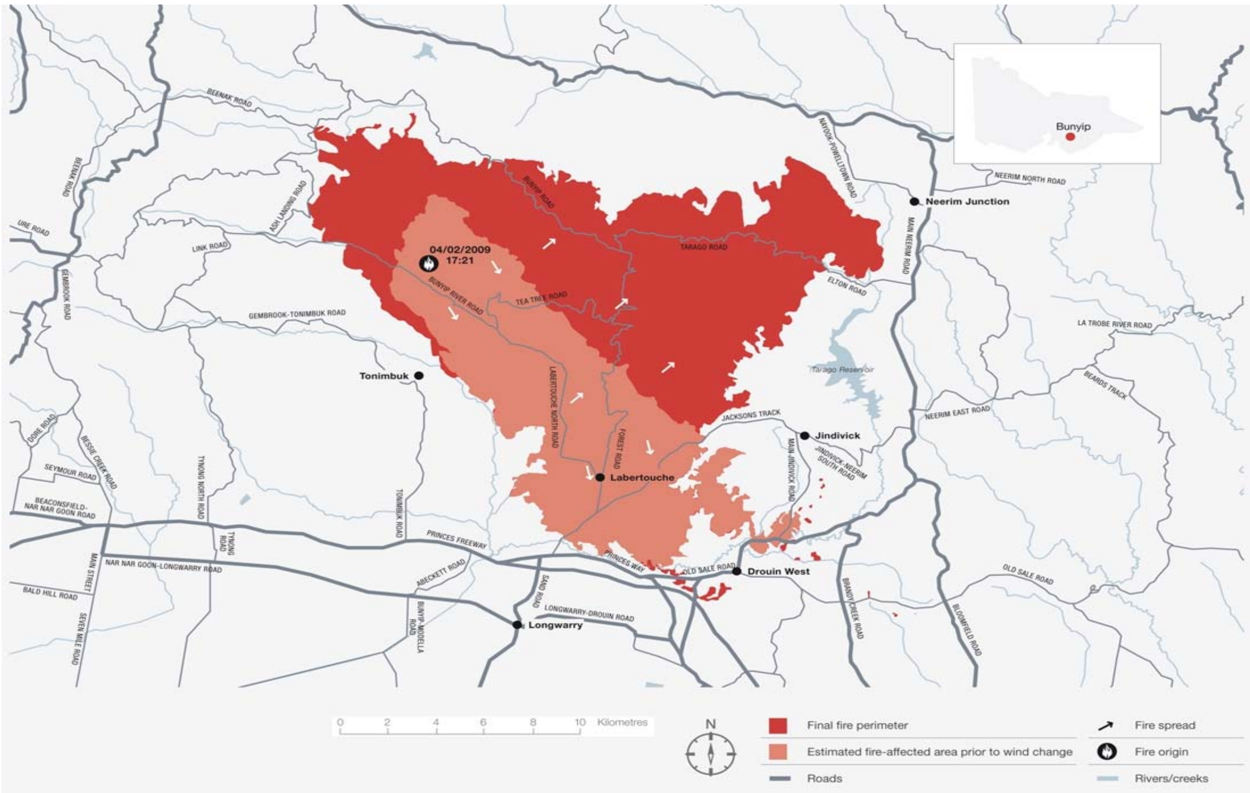


Figure 3.10: Bunyip fire map (Teague et al., 2009)

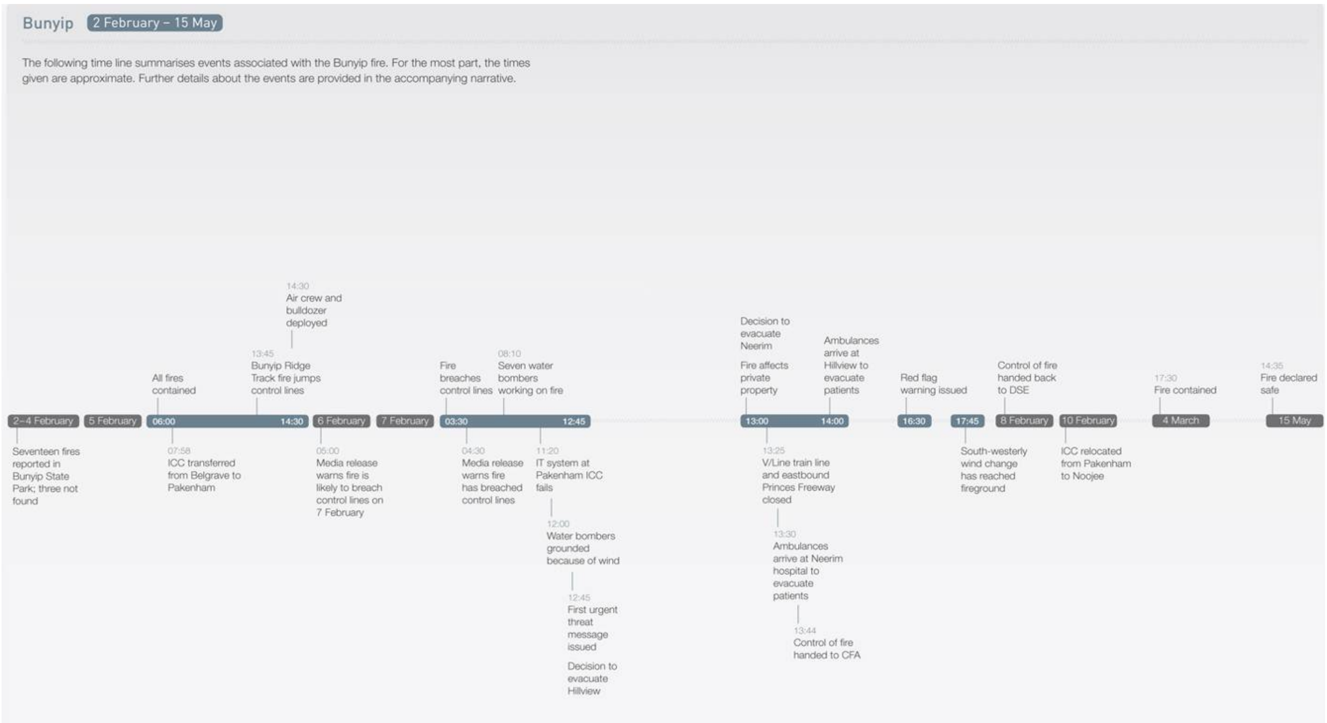


Figure 3.11: Timeline for Bunyip fire (Teague et al., 2009)

3.4.2.2. Data Extraction and Preparation

The approach to this comparative analysis was to characterise the response systems for the four bushfires over the period of operations during each bushfire. Figure 3.12 shows the 2009 Victorian Bushfires data extraction and preparation framework. To identify the entry of nodes into the response system, content analysis was conducted on the transcripts of the 2009 Victorian Bushfires Royal Commission Report. More specifically, statements of personnel within emergency management organisations (see Appendix D) were used. In all the investigated fires, the exhibits provided with their statements were used to ensure accuracy. An exhibit is a document or other item presented as evidence through the Commission's hearings. The most helpful exhibit found was the Incident Management Log, which contains the notes and a running log which was used to prepare their statements (see Appendix E). Then, all the content analyses were combined into one master document to undertake the final network analysis presented in the dissertation.

The nodes were identified by name and by role. Then the number of interactions reported by the node at the time of the interactions, the mode of communication (i.e., email, mobile phone, fax, teleconference, verbal, etc.) and the content of this communication were also identified. These data were then used to identify the networks of interaction of personnel involved in bushfire response and carrying out the various activities of the emergency event response. A similar approach was used for all bushfires, to develop an understanding of how the emergency personnel coordinate and adapted their responses to emergency incidents.

During the analysis, interactions among the participating personnel with emergency management organisations for each response system were recorded, using the Excel software program. A network matrix was then developed as the basis for network analysis. The UCINET software (Borgatti et al., 2002) was employed for the visual demonstration of bushfire response coordination (UCINET is a comprehensive program for analysing social networks). The program contains network analysis routines (e.g., centrality measures, dynamic cohesion measures, positional analysis algorithms, etc.). The UCINET software was used then to measure actor-level and network-level social network measures. The UCINET software provides the following measures:

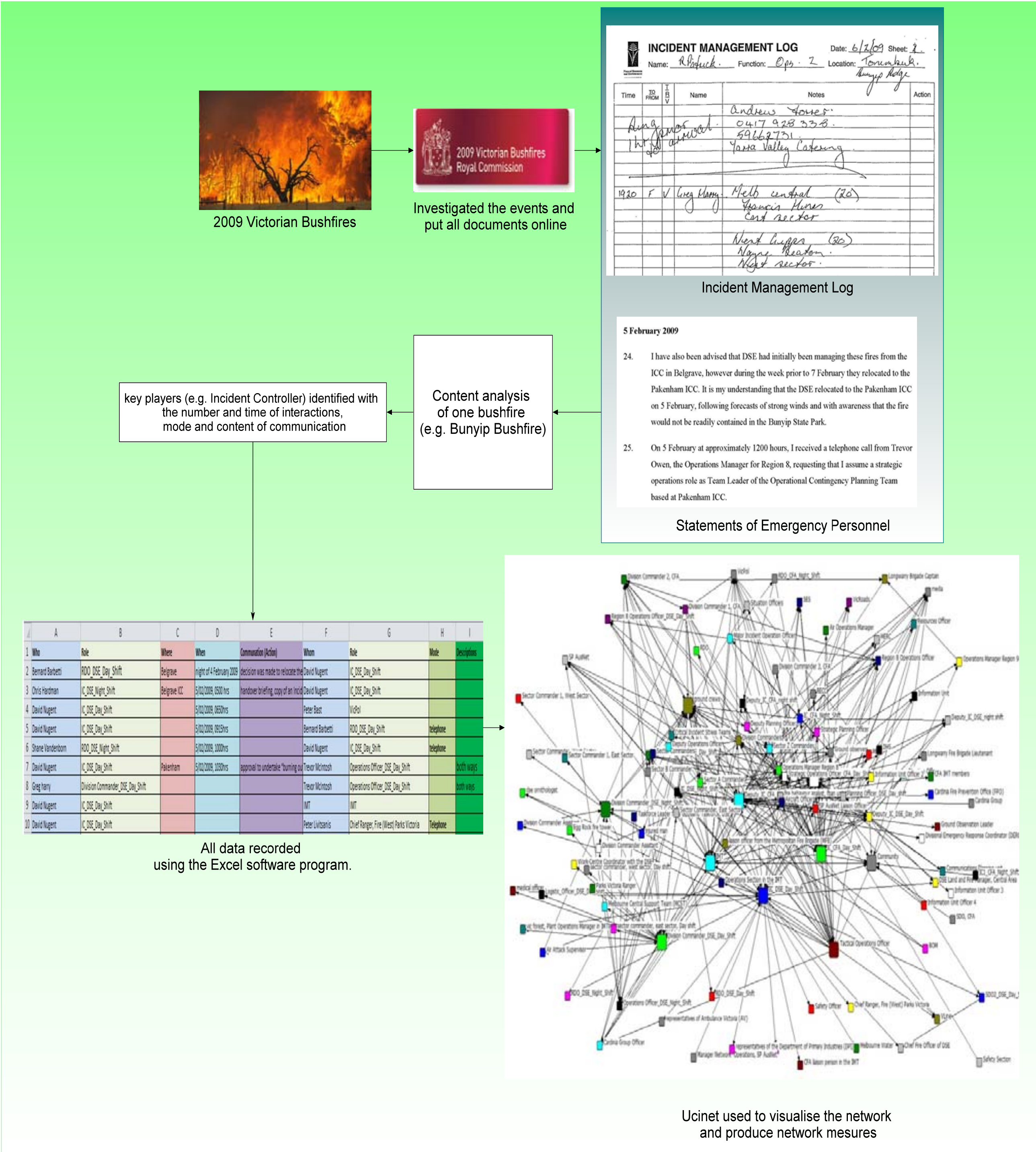


Figure 3.12: 2009 Victorian bushfires data extraction and preparation framework

Actor-level measures:

1- Efficiency

2- Constraint

3- Degree centrality

4- Betweenness centrality

Network-level measures:

1- Density

2- Degree centralisation

3- Betweenness centralisation

For the learning measures, actor-level learning measures were extracted as discussed earlier from the time analysis of the performance of individuals during the bushfire. Network learning measures were extracted from the performance measures of the whole network at a certain bushfire (e.g., number of hectares burned, lives lost). Both learning measures were discussed earlier and were validated using literature and expert judgment. Now, with both network and learning measures extracted and validated, statistical analysis could be used to test the hypotheses developed in Chapter 2.

3.4.2.3. Data limitation

As with any secondary data source, the most important data limitation for this study is that the available data may not meet specific research needs. Its answers may not exactly fit the researcher's questions. The data from the 2009 Victorian Bushfires Royal Commission Report could not be used by itself to test all hypotheses developed in Chapter 2 and to answer all the research questions. There was no control over how the data were collected. The dyadic-level social network hypotheses were not tested using these data because there was lack of strength of ties data. It was still possible, however, to collect other social network data from this source. Secondly, the available data might not be as accurate as desired. Transcripts from the 2009 Victorian Bushfire Royal Commission Report do not include the statements from all the actors involved in the bushfire. Therefore, the social network developed may not represent the actual network. As well, there may be biases in the data that are unknown. Moreover, the existing data on responses to emergencies and fires in Australia do not characterize 100 percent reportage of emergencies happening inside Australia.

3.5. Data Analysis (Techniques Used to Test Hypotheses)

Three hypotheses (*H1*-*H3*) based on the proposed network-based learning model are tested in this study. Hypothesis H1 has four sub-hypotheses, and hypotheses H2 and H3 have three sub-hypotheses each. These ten sub-hypotheses examine the relationships between independent and dependent variables of the proposed learning models, except for Hypothesis H2c which tests the effect of four moderating variables (*"age"*, *"gender", "experience"* and *"incident type")* for the network-based learning model**.**

The selection of data analysis method depends on a number of factors ranging from the research questions to data dissemination to sample size. Assuming that the distribution (at least the dependent variables) is fairly normal and that the sample size is sufficient given the number of independent variables, a multiple regression model would be most suitable for the purpose of exploring the relationship between variables of social networks and learning. (Tabachnick et al., 2001) propose the following formula to compute sample size *(N)* requirements, taking into account the number of independent variables: $N > 50 + 8m$ (where m = number of independent variables) and learning and its potential interaction effects (Venter and Maxwell, 2000). In this circumstance, numerous assumptions of linearity, multicollinearity, normality and homoscedasticity need to be accounted for as multiple regression models are fairly sensitive to violation of these assumptions. In any case, initial analysis of the data relating to its distribution and possible relations amongst variables needs to be accounted for. This can be done using descriptive statistics, histograms, tests of normality and scatterplots. If the data are normally distributed, statistical tests that examine relations among variables, such as Pearson's correlations and multiple regression, can be used. If the distribution is not normal, then non-parametric tests such as Spearman's rank order correlation and Mann-Whitney U tests need to be considered. Details of the justification and selection of data analysis methods are found in Chapter 4.

Correlation: Partial Correlation and Zero-order Correlation. Correlation is a statistical measurement of the association between two variables (Field, 2009). It has the value range from +1 to –1 for the relationship between two variables, where a zero value indicates that there is no relation between those two variables. A -1 value implies a perfect negative relation between them, which means that when one variable goes up, the other variable goes down. On the other side, a +1 value reflects a perfect positive relation between the variables, indicating that both variables move in the same direction together.

Partial correlation is defined as the measure of the association between two variables after removing the common effects of one or more control variables (Hinton, 2004; Levin, 2006). When there is no control variable in the measurement of the correlation between two variables, it is called zero-order correlation. If there is one control variable then it is called first-order correlation. For example, in Figure 3.13a the third variable (i.e., *third*) is correlated with both the *first* and *second* variables. In this case, *partial correlation must be chosen* in order to find out the correlation between the *first* and *second* variables. However, in Figure 3.13b, partial correlation does not need to be used in measuring the correlation between *first* and *second* – a *zero-order correlation* can indicate the correlation between *first* and *second* appropriately.

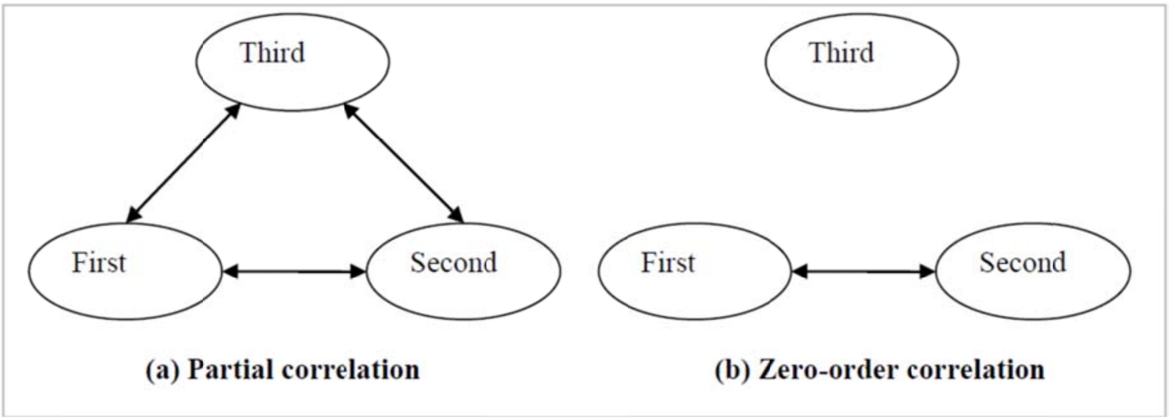


Figure 3.13: Illustration of (a) partial and (b) zero-order correlation

To measure the zero-order correlation between any pair of independent and dependent variables of the proposed model, both parametric and non-parametric tests can be applied. For the proposed model, Pearson tests were used to quantify the zero-order correlation between any combination of independent and dependent variables of actor- and dyadic-level hypotheses of the model. The histogram of the model follows a normal distribution (Motulsky, 1999).

To examine *H1, H2* and *H3*, the correlations for all combinations of independent and dependent variables of the proposed learning model must be checked. As illustrated in Table 3.9, correlations exist among the independent variables which influence the choice of a partial correlation method to check the relation between independent and dependent variables of this model. To test the moderating effects H2c of all moderating variables, independent and dependent variables of the proposed model must first be clustered based on the values of moderating variables. Then the zero-order correlation between independent and dependent variables must be measured and compared for each of those clusters in order to calculate the moderating capability of all moderating variables.

Regression

Regression is a way of predicting the outcome variable from one or more predictive variable(s) (Healey, 2011). In simple regression, a predicting variable is used to quantify the outcome variable, whereas more than one predicting variable are used to predict the outcome variable in multiple regression. In regression analysis, the following mathematical equation is used to predict the value of the dependent variable (denoted by Y) on the basis of the independent variable (denoted by X). $Y = a + bX + e$, where a denotes a baseline amount given to all dependent variables, b denotes an additional amount given for each independent variable and e is called error terms or disturbance terms. Regression technique is applied in order to develop relational models which can predict dependent variables by using the independent variables from the proposed learning model.

To summarise, the preceding sections of this chapter have first provided an appraisal of social network approaches to collecting social network data, outlining the pros and cons of each approach. The measures that constitute each theoretical construct of social network and learning were then discussed. Demographic items that were included in the survey were also discussed. Furthermore, there was discussion of the triangulation of both the survey and content analysis methods used in the study. Table 3.11 presents the key methods used in this thesis in regards to research methodology. It shows both existing methods and methods used in this thesis for data collection, processing and analysis.

Table 3.11: Brief overview of the hypotheses and related key theories

Research Methodology	Existing methods	Methods used in this thesis
Data Collection	Surveys, interviews, observations, reports, and so forth	Triangulation of both the survey and content analysis methods
	Primary and secondary data sources	Secondary data sources
	Active and passive data collection	Passive data collection
	Whole or sociocentric network approach and egocentric network approach	Egocentric network approach
Data Processes	Network measures (i.e. constraint, efficiency, degree centrality, betweenness centrality, strength of ties, density, degree centralisation, betweenness centralisation)	Same network measures as in existing methods
	Learning measures (e.g. Learning Loss Scale, Richmond et al., (1987), etc.)	- Individual learning (New way to measure it based on adaptation (percentage of change of performance), see Figure 3.2 for more detail) - Team learning (measured based on survey items of flexibility, quality of information exchange and team feedback skills) - Network learning (measured based on number of fatalities, houses lost and hectares burnt)
Data Analysis	Level of analysis may be actor level, dyadic level, triadic level, subset level, and/or network level.	- Actor level - Dyadic level - Network level
	Techniques used to test hypotheses: correlation, regression, etc.	- Social network analysis - Partial correlation - Zero-order correlation - Regression - T-test

3.6. Conclusion

This chapter discussed the design and framework of the study. The chapter detailed how the theoretical model could be made operational in the context of Australia's emergency Incident Management System. The chapter first provided an appraisal of social network approaches for collecting social network data, outlining the pros and cons of each. It then discussed the measures that constituted each theoretical construct of social network and learning. Demographic items that were included in the survey were also discussed. Furthermore, the chapter discussed the triangulation of both the survey and content analysis methods used in the study. It also described the limitations of each method. In the next chapter, the analysis and results from the data collected are reported.

Chapter 4

4. Results and Findings

This chapter reports the results from the analysis of data for exploring the inherent relationship between social networks and learning and tests the hypotheses developed from the model in Chapter 2. The data are based on transcripts of the 2009 Victorian Bushfires Royal Commission Report and on 579 responses to a survey from fire and emergency services personnel, who worked within 25 agencies representing all Australian states and territories. First, descriptive statistics of the research data are presented, including tests of normality and a brief discussion on the distribution of each data variable. Preliminary results of the relations between the variables are also provided. Subsequently the results of hypothesis testing using parametric techniques such as t-tests and multivariate techniques such as multiple regression models are reported and discussed. Figure 4.1 provides an overview this chapter.

4.1. Descriptive Statistics

The next section provides descriptive statistics of the data gathered from the participants in the survey. The first section presents demographics of the sample. The second section presents descriptive statistics of the variables of interest in the research model, namely learning and social network variables.

4.1.1. Participants' Demographic Data

This section presents the demographics of the sample. This analysis is taken from the review of incident management teamwork and multi-agency collaboration (Owen and Dwyer, 2009).

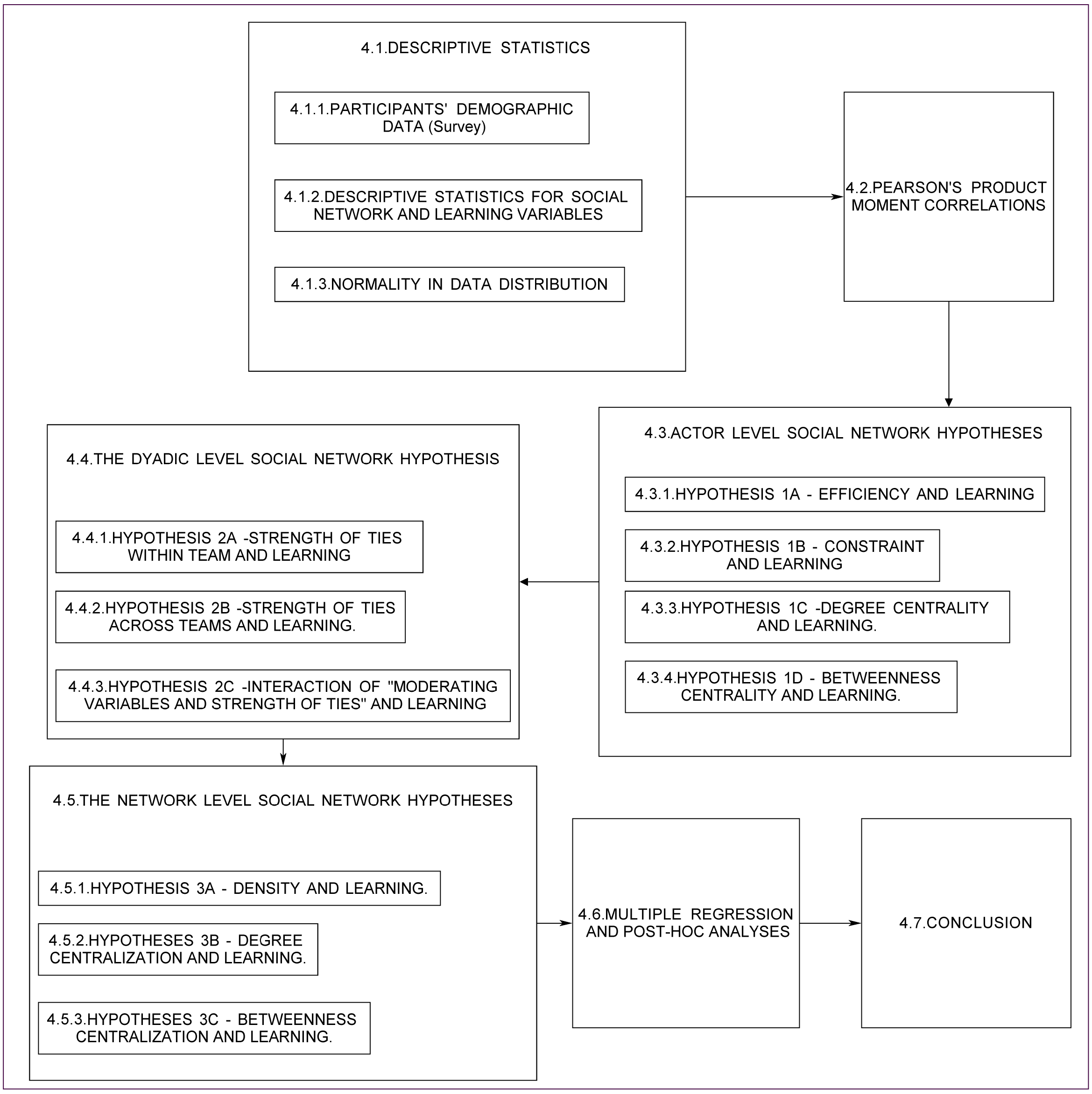


Figure 4.1: Overview of Chapter 4

4.1.1.1. Functional Areas of Participants

This report is based on the first download of 579 participants (July 2009). Figure 4.2 shows the total distribution of participants relative to their particular roles within the incident management system. It can be seen there is a reasonable range of responses from individuals involved in the Incident/Fire ground (n = 109). Roles of staff completing the survey with involvement in the fire or incident ground included Division Commander, Section Commander, Crew Leader, Officer in Charge of an Appliance and Fire Fighter.

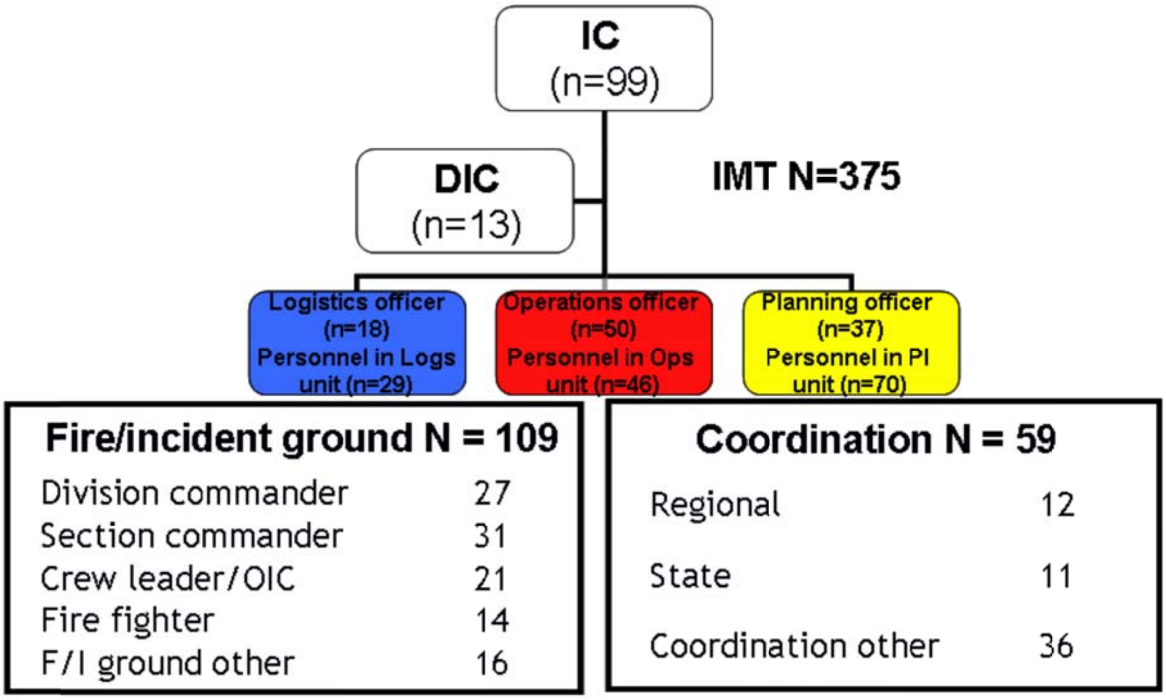


Figure 4.2: Participants' functional areas

4.1.1.2. Gender and Incident Management

Table 4.1 presents responses for males and females who completed the AFAC survey in 2008. The involvement rate for females in 2008 was 12.5% and for males was 73.0%.

Table 4.1: Gender and participation in incident management

	%
Male	73
Female	12.5
Unidentified	14.5
Total	100

Figure 4.3 displays age distributions of participants. The majority of the participants were over 40 years of age.

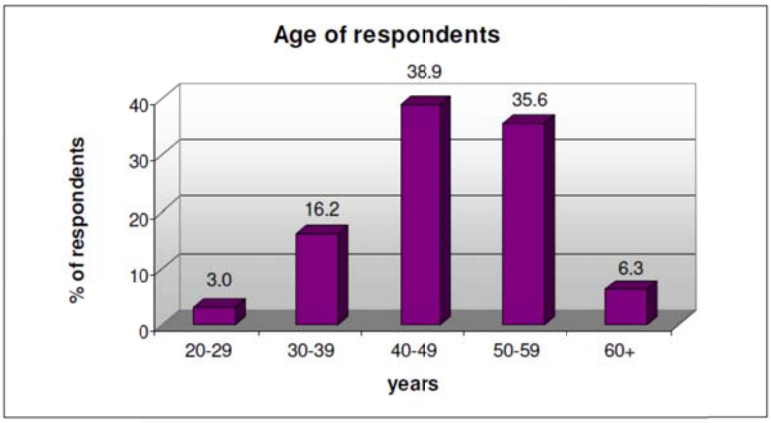


Figure 4.3: Age of participants

Figure 4.4 displays a breakdown of the age distribution by gender. Women involved in the incident management system were much younger than their male colleagues.

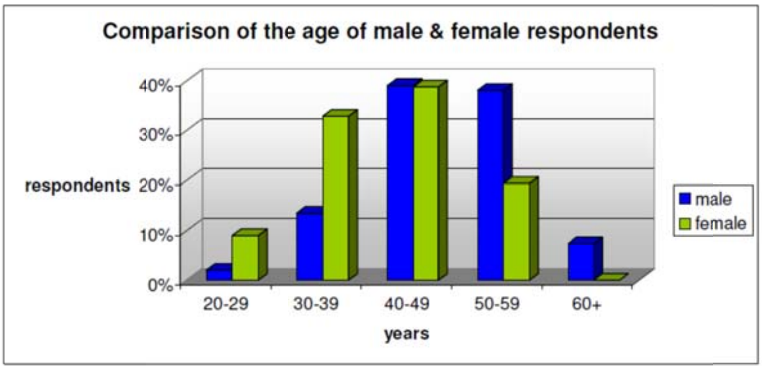


Figure 4.4: Age comparison of the age of male and female participants

Table 4.2 presents the total ages of the participants by their roles within the incident management team. It can be seen here that the age of Incident Controllers was the highest (probably because they had the most experience). These results suggest (a) the likely need for succession planning and (b) the need for mentoring of women within the incident management system.

Table 4.2: Comparison of ages within IMT roles

Comparison of age within IMT roles										
Age	IC		DIC		PO		LO		OO	
	N	%	N	%	N	%	N	%	N	%
20-29	0	0.0	0	0.0	1	3.0	1	5.9	1	2.1
30-39	4	4.4	3	23.1	8	24.2	0	0.0	6	12.8
40-49	37	41.1	3	23.1	15	45.5	9	52.9	21	44.7
50-59	45	50.0	5	38.5	8	24.2	6	35.3	15	31.9
60+	4	4.4	2	15.4	1	3.0	1	5.9	4	8.5
Total	90	100.0	13	100.0	33	100.0	17	100.0	47	100.0

Where IC: Incident Controller
DIC: Deputy Incident Controller
PO: Planning Officer
LO: Logistics Officer
OO: Operations Officer

Table 4.3 presents the average number of years participants had been in their current roles. The participants at the coordination level had fewer than 5 years' experience in their role. This was mainly because this role at a regional level had been only recently established. Table 4.3 similarly demonstrates that ICs/DICs had the most experience (13 incidents).

Table 4.3: Comparison of experience levels

		N	%	Mean years exp in role	% <5 years exp in role	Ave N of incidents attended in role
Incident Ground	Fire ground	109	18.8	11	26.3	13
Incident Management Team	IC/DIC	112	19.3	13	24.3	15
	Operations	96	16.6	13	29.6	12
	Planning	107	18.5	8	38.4	11
	Logistics	60	10.4	9	44	8
Coordination	Coordination	59	10.2	N/A	42.9	5
	TOTAL	543	93.8			

Figure 4.5 displays several stages of the emergency event reported in the survey. It can be seen that there is a good cross-section of participants reporting on an emergency event at the beginning phase (29.2% of responses), the escalation phase (38.5% of responses) and the middle phase (29.7% of responses) of the operation. There were few responses from individuals involved in the mop up (2.2%) or recovery phases (0.4%).

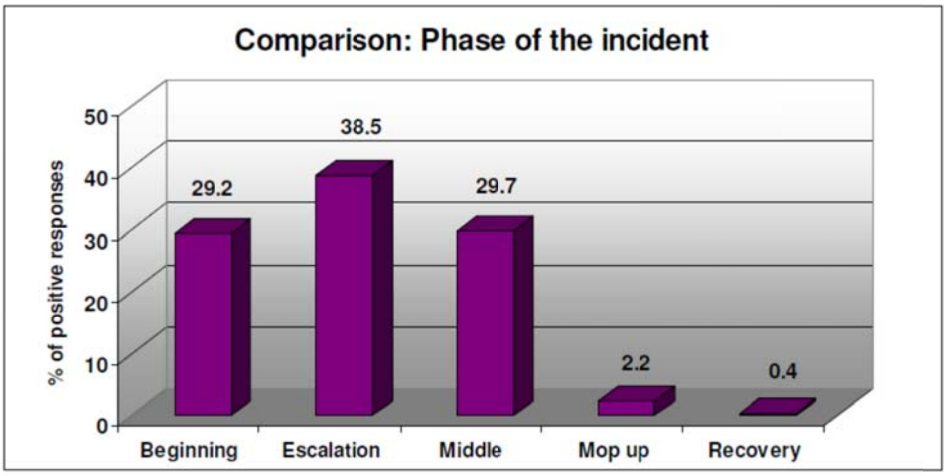


Figure 4.5: Comparison: The phase in the emergency event of the reported shift

Figure 4.6 displays the elapsed time the emergency event had been on-going prior to the presence of the participant. It can be seen from the Figure 4.6 that half of survey responses related to emergency events that had been on-going for fewer than 12 hours. In part, this would account for urban fire organisations where it is anecdotally reported that 90% of fires attended are extinguished within 3 hours.

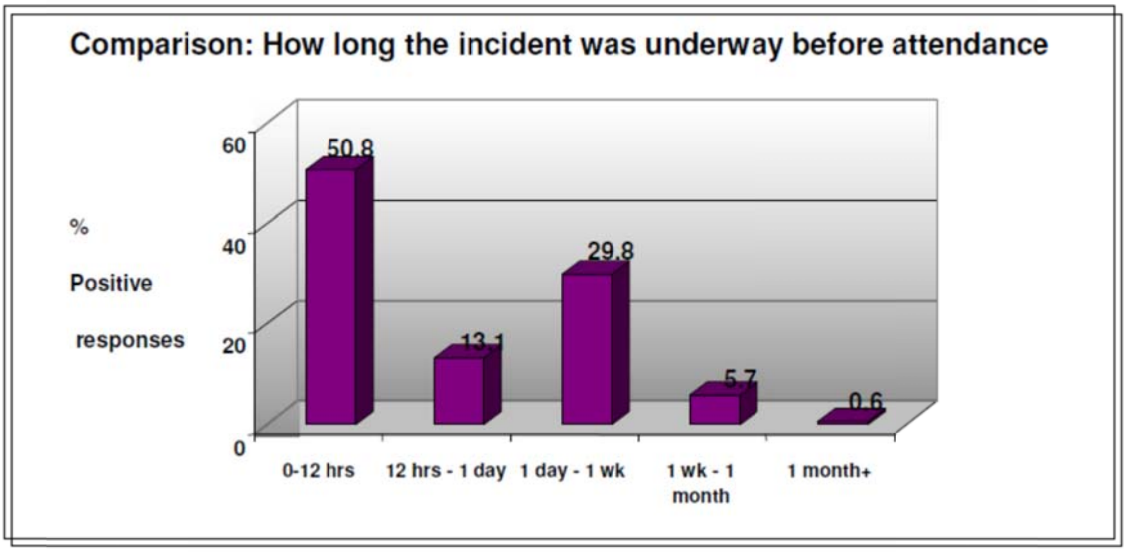


Figure 4.6: Comparison of duration of the emergency event before attendance

4.1.1.3. The Agency Sample

Responses were gained from individuals operating within 25 organisations across all states and territories of Australia as well as New Zealand (see Figure 4.7).

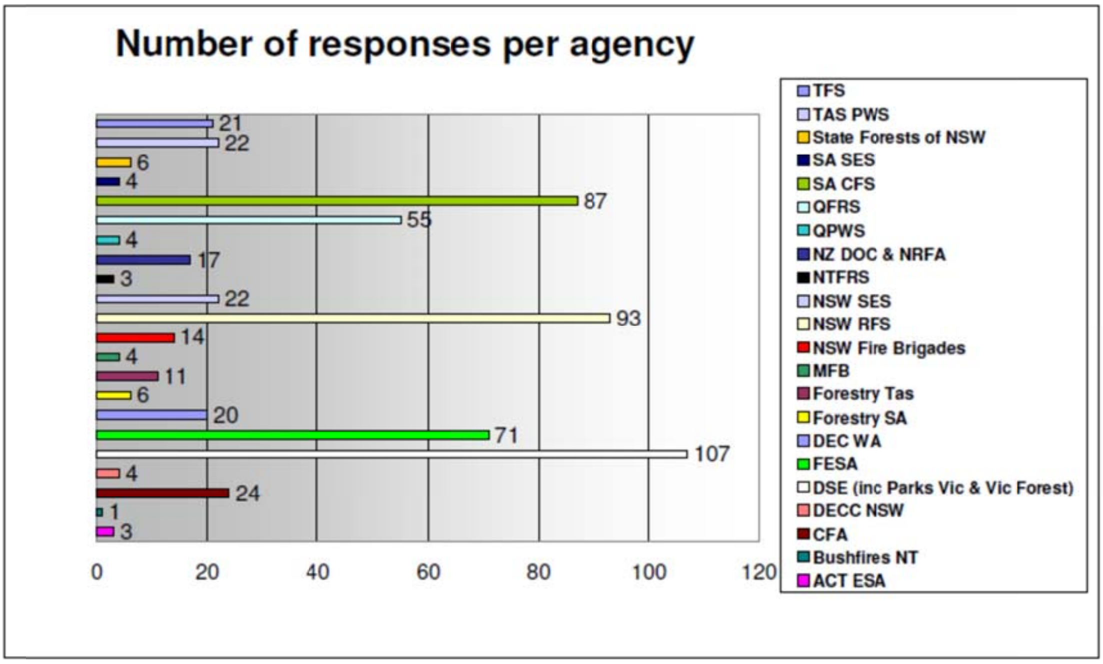


Figure 4.7: Number of responses from each agency

4.1.1.4. Agency Functions

Figure 4.8 displays the functions of the organisations responding to the survey.

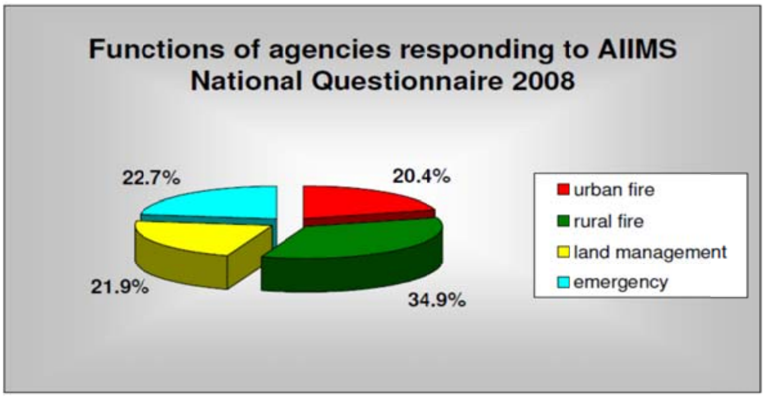


Figure 4.8: **Functions of agencies responding to AIIMS National Survey 2008**

Figure 4.9 displays the location of the emergency events reported by survey participants. There was a general representation of emergency events around the country, though the main events reported were from New South Wales and Victoria.

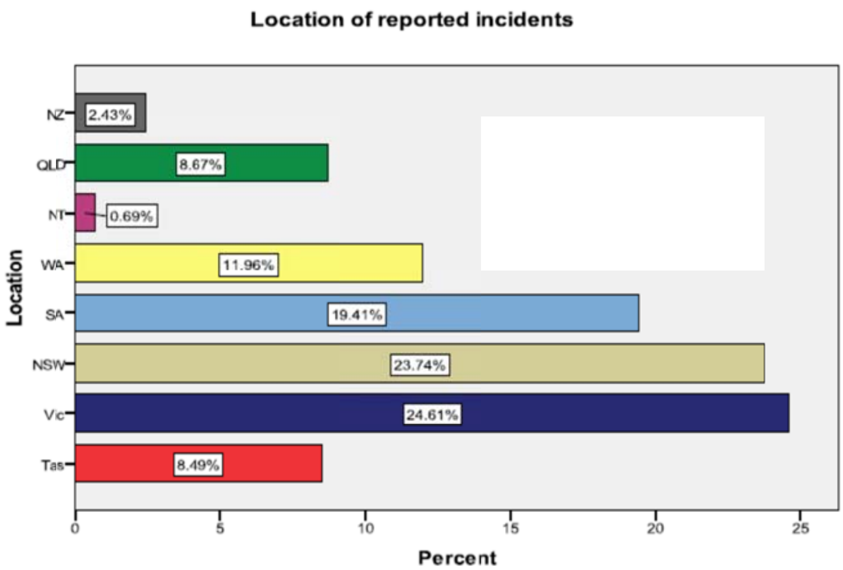


Figure 4.9: Number of responses by location

Figure 4.10 displays when the emergency event occurred. The figure shows that 93.2% of the emergency events reported occurred in the previous three years.

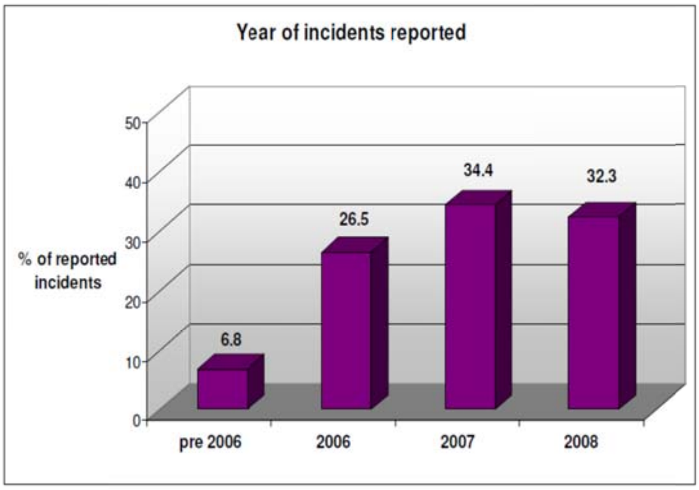


Figure 4.10: Year of emergency event reported

4.1.1.5. Types of Emergency Events Managed

As Figure 4.11 displays, unsurprisingly, given the arrangement of the responding organisations, the major emergency event type to which participants responded was forest or scrub fires. Nevertheless, it is also important to note that there was general reporting of rural/urban interface fires as well as emergency incidents including cyclones, floods and storms

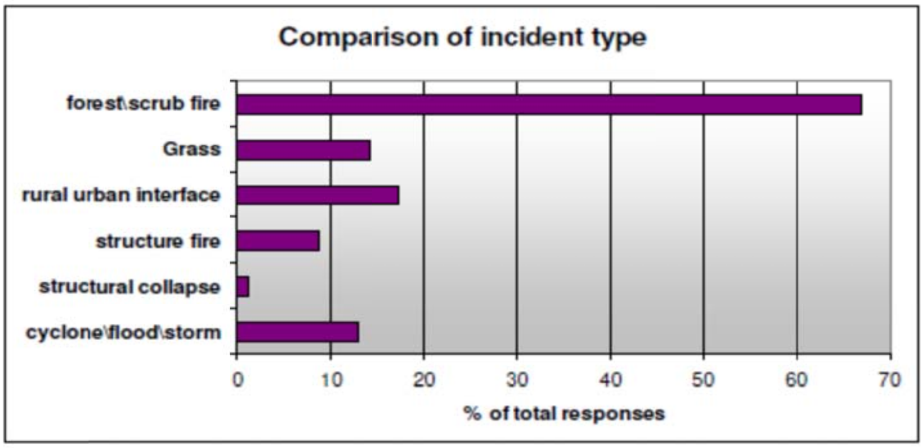


Figure 4.11: Comparison of emergency event types

4.1.1.5.1 Emergency Threats

Table 4.4 reports the number of emergency events where threats were involved. It is interesting to note that in 42% of the emergency events there were six or more threats, with 11.5% of emergency events involving more than 9 threats. In 56% of all emergency events, life was threatened and in 55% of emergency events some form of critical infrastructure (water, gas or electricity) was threatened.

Table 4.4: Number of incidents where threats were involved

Incidents where threats were involved		
Threats	Incidents	
	N	%
1-2 threats	106	19.6
3-5 threats	206	38.1
6-8 threats	167	30.9
9+ threats	62	11.5
Total	541	100

4.1.1.5.2 Complexity of Emergency Events Managed

Figure 4.12 displays the emergency events reported by participants in terms of ICS levels, according to the AFAC AIIMS Manual. It can be seen that 70.7% of the emergency events reported were at ICS level 3. A level 3 emergency event is defined as one that is adequately complex to require the full deployment of an ICS (AFAC, 2005). This does not imply that most emergency events managed are ICS level incidents, but rather that these are expected to be the most unforgettable.

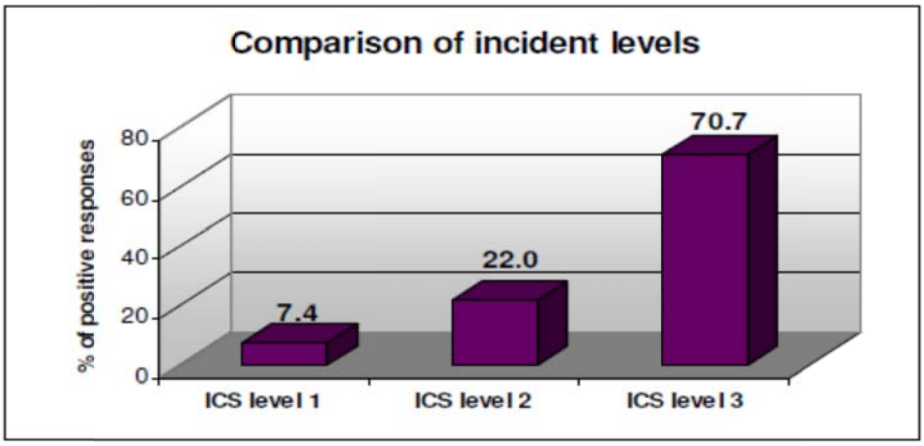


Figure 4.12: Comparison of incident levels

Participants were also asked to rate the complexity of the emergency event on a scale of 1-7. A cross-tabulation of ICS level 3 incidents by perceived levels of complexity (see Figure 4.13) shows that there was a range of level 3 incidents that had varying levels of complexity according to the participants. Given the new ratings of fire danger indices, it may be suitable to evaluate what establishes ICS level 3 incidents. It may also be suitable to evaluate whether there is adequate difference in the emergency incident management system with the current three levels in operation.

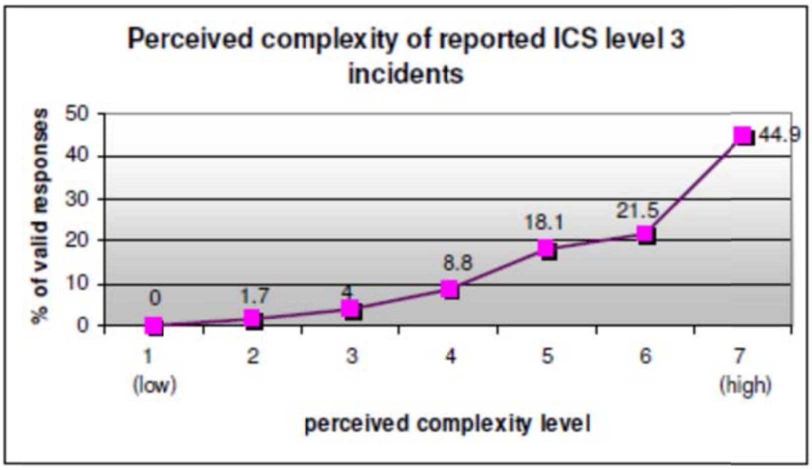


Figure 4.13: Participants' perceived levels of complexity of ICS level 3 incidents

4.1.1.5.3 Personnel Engaged in the Emergency

The survey asked participants to estimate how many individuals were available at the peak of the emergency event (see Figure 4.14). It is remarkable that nearly one third of the emergency events (27.4%) included more than 250 individuals at the peak of the event.

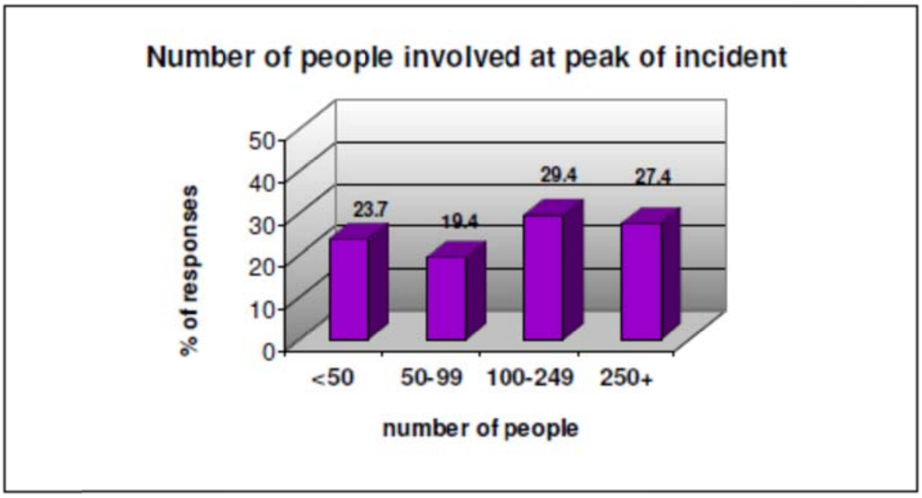


Figure 4.14: Number of people involved at peak of emergency event

4.1.1.5.4 Supporting Agencies Involved

The survey sought information on the number of supporting organisations involved in the emergency event. It can be seen from Table 4.5 that 47.7% of emergency events involved seven or more support organisations.

Table 4.5: Number of agencies involved at peak of emergency event

Agencies involved at incident peak		
Number of agencies	%	N
Less than 4	23.4	112
4 - 6 agencies	28.9	138
7 - 9 agencies	23.0	110
More than 9 agencies	24.7	118
Total	100.0	478

Table 4.6 presents the number of organisations cross-tabulated by ICS level. The table indicates that as the complexity increases, the number of supporting organisations involved increases too. In the ICS level 3 incidents reported, for example, 34% had more than 9 organisations involved. It is worth noting that with more support organisations requiring

coordination there is an extra degree of difficulty in managing emergency incidents. "The exchange of timely and accurate information and the capacity of disparate agencies to find, absorb and adapt to that information is fundamental to the ability of those same agencies to integrate their activities" (Comfort and Kapucu, 2006).

Table 4.6: **Number of supporting agencies cross-tabulated with emergency event levels**

Number of supporting agencies crossed with incident ICS level						
	ICS Level 1		ICS Level 2		ICS Level 3	
	N	%	N	%	N	%
Less than 4 agencies	9	34.6	41	45.1	49	15.6
4 - 6 agencies	9	34.6	35	38.5	73	23.2
7 - 9 agencies	5	19.3	12	13.1	85	27.1
More than 9 agencies	3	11.5	3	3.3	107	34.1
Total	26	100.0	91	100.0	314	100.0

In summary, this section has illustrated the approaches used and the demographic details of the sample of the survey, together with a brief summary of some of the features of emergency events reported. The nature of the emergency events described is mainly forest/scrub fires. Fires on the urban/rural interface, structure fires as well as cyclones, floods and storms are also included. The majority of emergency events reported (71%) are ICS level 3 incidents. These emergency events were complex in nature, involving an enormous number of individuals in handling the emergency event. There is an extensive variety of perceived complexity reported in ICS level 3 incidents.

4.1.2. Descriptive Statistics for Social Network and Learning Variables

Table 4.7 lists the descriptive statistics for the social network and learning variables. These variables are measured on a continuous scale. Histograms showing distribution of the variables are provided in Appendix B.

Table 4.7: Descriptive statistics for social network and learning variables

	Mean	Standard Error	Median	Mode	Standard Deviation	Sample Variance	Kurtosis	Skewness	Minimum	Maximum	Count
Actor-Level Social Network Measures											
Efficiency	0.819	0.022	0.845	1.000	0.176	0.031	-0.661	-0.598	0.418	1.083	62.000
Constraint	0.764	0.049	0.732	1.000	0.389	0.152	-0.440	0.379	0.108	1.837	62.000
Degree	0.343	0.059	0.124	0.062	0.467	0.218	6.909	2.503	0.021	2.380	62.000
Betweenness	1.107	0.321	0.123	0.000	2.526	6.379	11.437	3.261	0.000	13.251	62.000
Individual Learning and Adaptability	6.129	0.401	7.000	7.000	3.160	9.983	-0.479	-0.815	0.000	10.000	62.000
Dyadic-Level Social Network Measures											
Strength of ties between team members	5.624	0.046	5.830	6.000	1.029	1.059	0.785	-0.928	1.670	7.000	498.000
Strength of ties between IMT and incident/fire ground	5.297	0.056	5.600	6.000	1.194	1.426	0.306	-0.741	1.000	7.000	461.000
Team Learning Measures											
Flexibility	5.704	0.044	6.000	6.000	1.018	1.036	1.703	-1.141	1.330	7.000	525.000
Information exchange	5.708	0.041	6.000	6.000	0.968	0.937	0.799	-0.911	2.000	7.000	559.000
Team feedback skills	5.714	0.043	6.000	6.000	1.015	1.030	1.363	-1.068	1.000	7.000	560.000

4.1.3. Normality in Data Distribution

Before any statistical analyses it is essential to investigate the distribution of data by visualising graphs (e.g., histograms) and conducting statistical tests. It is vital to determine whether the data distribution of the variables of interest is normal or not. In order to test more precisely for normality of data, apart from visual histogram inspection, the Kolmogorov-Smirnov test of normality was also conducted (Tables 4.8 and 4.9).

Table 4.8: Kolmogorov-Smirnov Test of Normality for actor-level hypotheses

	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
Degree	.261	62	.000
Betweenness	.331	62	.000
Efficiency	.110	62	.058
Constraint	.088	62	.200*
Adaptability	.254	62	.000

Table 4.9: Kolmogorov-Smirnov Test of Normality for dyadic-level hypotheses

	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
flexibility	.156	376	.000
informationExchange	.119	376	.000
teamfeedbackskills	.140	376	.000
Strength_of_ties_between_team_members	.128	376	.000
Strength_of_ties_between_IMT_and_incidentfire_ground	.101	376	.000

The test of normality shows that only two variables, "Efficiency" *(sig=.058)* and "Constraint" *(sig=.200)* have a normal distribution because the Kolmogorov-Smirnov statistic shows a non-significant result (i.e., significance value of more than 0.05). All the other variables have violated assumptions of normality (because the significance value is less than 0.05). It seems, therefore, that for most tests where the distribution of the variable of interest is not normal, non-parametric tests should be applied. However, such results from the Kolmogorov-Smirnov tests are quite common (where n > 60), and the histograms for the dependent variables "Adaptability" *(mean=6.129, std. dev=3.160)*, "Flexibility" *(mean=5.704, std. dev=1.108)*, "Information Exchange" *(mean=5.708, std. dev=0.968)* and "Team feedback skills" *(mean=5.714, std. dev=1.015)*, are fairly normally distributed. Given these results, parametric tests such as t-tests, Pearson's product-moment correlations and regression analysis may still be run as there are no obvious outliers or extreme irregularities in the data distribution of these variables. Moreover, these parametric tests are robust enough to handle the variations in normality observed in the histograms in Appendix B (Tabachnick et al., 2001).

4.2. Pearson's Product Moment Correlations

Pearson's Product moment correlation indices of actor-level social network measures and individual learning variables are shown in Table 4.10, and those of the dyadic-level social network measures and the team learning variable are shown in Table 4.11. These correlation coefficients are vital because they permit preliminary examination of which variables are associated with each other. The coefficients complement outcomes from the hypothesis test results in the following sections and similarly in Chapter 5, where the outcomes are discussed in light of theory and existing literature. To visualise the association between variables in the correlation matrix in Table 4.10, scatterplot diagrams are available in Appendix C.

Table 4.10: Pearson's Product Moment Correlation of actor-level network and learning variables

		Degree	Betweenness	Efficiency	Constraint	Adaptability
Degree	Pearson Correlation	1	.781**	.282*	-.453**	.137
	Sig. (1-tailed)		.000	.013	.000	.145
	N	62	62	62	62	62
Betweenness	Pearson Correlation	.781**	1	.246*	-.558**	.323**
	Sig. (1-tailed)	.000		.027	.000	.005
	N	62	62	62	62	62
Efficiency	Pearson Correlation	.282*	.246*	1	-.552**	.057
	Sig. (1-tailed)	.013	.027		.000	.329
	N	62	62	62	62	62
Constraint	Pearson Correlation	-.453**	-.558**	-.552**	1	-.358**
	Sig. (1-tailed)	.000	.000	.000		.002
	N	62	62	62	62	62
Adaptability	Pearson Correlation	.137	.323**	.057	-.358**	1
	Sig. (1-tailed)	.145	.005	.329	.002	
	N	62	62	62	62	62

**. Correlation is significant at the 0.01 level (1-tailed).

*. Correlation is significant at the 0.05 level (1-tailed).

Table 4.11: Pearson's Product Moment Correlation of dyadic-level network and learning variables

Correlations

		Flexibility	InformationEx-change	Teamfeedback-skills	Strength_of_ties_between_team_members	Strength_of_ties_between_IMT_and_incidentfire_ground
Flexibility	Pearson Correlation	1	.747**	.766**	.791**	.656**
	Sig. (1-tailed)		.000	.000	.000	.000
	N	525	503	503	462	424
InformationExchange	Pearson Correlation	.747**	1	.896**	.869**	.657**
	Sig. (1-tailed)	.000		.000	.000	.000
	N	503	559	536	486	448
Teamfeedbackskills	Pearson Correlation	.766**	.896**	1	.887**	.670**
	Sig. (1-tailed)	.000	.000		.000	.000
	N	503	536	560	484	443
Strength_of_ties_between_team_members	Pearson Correlation	.791**	.869**	.887**	1	.670**
	Sig. (1-tailed)	.000	.000	.000		.000
	N	462	486	484	498	411
Strength_of_ties_between_IMT_and_incidentfire_ground	Pearson Correlation	.656**	.657**	.670**	.670**	1
	Sig. (1-tailed)	.000	.000	.000	.000	
	N	424	448	443	411	461

**. Correlation is significant at the 0.01 level (1-tailed).

4.3. Actor-level Social Network Hypotheses

The following section reports the results relating to the hypotheses about actor-level social network factors and individual learning factors.

4.3.1. Hypothesis 1a – Efficiency and Learning

H1a: Efficiency is positively associated with the learning-related work activity of an actor in a dynamic complex environment.

To test the first hypothesis (H1a), a partial correlation test was applied. The test explores the relationship between efficiency and learning. Then in order to complement the finding from the partial correlation test, the independent samples t-test was applied to test for the significant difference between high and low efficiency actors based on their learning scores. If the difference between high and low efficiency actors is statistically significant then it is an indication that efficiency is related to learning in a dynamic complex environment.

The cut-point of the high and low efficiency clusters was chosen by first arranging the data based on the efficiency index in ascending order. The median of the index was selected as the cut-point. The median for the efficiency score was 0.845 in this study (see Table 4.7). Therefore, emergency personnel with an efficiency score greater than the median are termed the "high efficiency group" and emergency personnel with efficiency scores lower than the median are termed the "low efficiency group".

In Table 4.13, the independence samples test shows that the significance value for the Levene's test for equality of variances is larger than .05 (i.e., 0.754). This indicates that the assumption of equal variances for the two groups has not been violated, therefore, the t-value and its significance level of the row "Equal variances assumed" should be used.

Table 4.12: Partial correlation between *Efficiency* and *Individual Adaptability (Learning)*

Control Variables			Adaptability	Efficiency
Degree & Betweenness & Constraint	Adaptability	Correlation	1.000	-.141
		Significance (1-tailed)	.	.143
		df	0	57
	Efficiency	Correlation	-.141	1.000
		Significance (1-tailed)	.143	.
		df	57	0

Table 4.13: t-test statistics for Efficiency and Learning Attitudes

A: Group Statistics

	Low_high	N	Mean	Std. Deviation	Std. Error Mean
Individual_learning_and_adaptability	Low efficiency	31	6.2903	3.35851	.60321
	High efficiency	31	5.9677	2.99426	.53778

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Individual_learning_and_adaptability	Equal variances assumed	.099	.754	.399	60	.691	.32258	.80813	-1.29391	1.93908
	Equal variances not assumed			.399	59.226	.691	.32258	.80813	-1.29435	1.93951

The partial correlation testing (Table 4.12) for this sub-hypothesis provides no correlation (rho= -0.141, p>0.05, 1-tailed) between efficiency of emergency personnel and their learning in a dynamic complex environment. The t-test in Table 4.13 also confirms this result and shows that high efficiency and low efficiency groups have no statistically significant difference in learning scores for the high *(M=5.97, SD=2.99, n=31)* and low *(M=6.29, SD=3.36, n=31)* efficiency groups, *t(60)*=-0.399, *p*=0.691 (two-tailed). Therefore, the null hypothesis that the e*fficiency of an actor's network position is not associated with the learning of emergency personnel in a dynamic complex environment* cannot be rejected. Consequently, there is no association between efficiency and individual learning in a dynamic complex environment.

4.3.2. Hypothesis 1b – Constraint and Learning

H1b: The constraint of an actor's network position is negatively associated with the learning-related work activity of an actor in a dynamic complex environment.

For this hypothesis, a partial correlation test was also adopted to test the relationship between constraint and learning. Then in order to complement the finding from the partial correlation test, the t-test was also adopted in order to test the difference between the high constraint group and the low constraint group on learning. If a statistically significant difference exists in the mean learning attitude scores of high and low constraint groups, then an association exists between constraint and learning attitudes. Again, the direction of the association depends on the direction of the difference between the two groups.

The technique involving segregation of the high and low constraint groups is the same as that performed for the efficiency groups. The cases of data of the emergency personnel were ranked in ascending order based on constraint scores, thus ranking constraint scores. The median constraint score or index was then chosen as the cut-point to divide the dataset into higher or lower constraint groups. In this study, the median constraint score was 0.732. Emergency staff members with constraint scores greater to 0.732 were grouped as the "high constraint group" and those with constraint scores less than the median were grouped as the "low constraint group".

Table 4.14: Partial correlation between *Constraint* and *Individual Adaptability (Learning)*

Control Variables			Adaptability	Constraint
Degree & Betweenness & Efficiency	Adaptability	Correlation	1.000	-.274
		Significance (1-tailed)	.	.018
		df	0	57
	Constraint	Correlation	-.274	1.000
		Significance (1-tailed)	.018	.
		df	57	0

Table 4.15: t-test statistics for Constraint and Learning Attitudes

A: Group Statistics

	const1	N	Mean	Std. Deviation	Std. Error Mean
adapt1	>= .7320	31	4.645161	3.6290346	.6517939
	< .7320	31	7.612903	1.6057692	.2884047

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
adap	Equal variances assumed	40.785	.080	-4.164	60	.000	2.9677419	.7127499	4.3934541	1.5420298
	Equal variances not assumed			-4.164	41.314	.000	2.9677419	.7127499	4.4068380	1.5286459

Results from the partial correlation test in Table 4.14 indicate a negative correlation (rho= -0.274, $p<0.05$, 1-tailed) between constraint scores of emergency personnel and their learning. A higher value for the *constraint* score of emergency personnel indicates lower learning level.

The t-test (Table 4.15) confirms this result and reveals a significant difference in the learning attitude scores of the high constraint group (*M=4.65, SD=3.63, n=31)* and the low constraint group (*M=7.61, SD=1.61, n=31*); t (60) = -4.164, p=.000 (one-tailed). Further investigation from the correlation results in Table 4.10 shows a significant negative correlation *(r=-0.358; p<0.05)* between constraint scores and learning scores. Therefore, there is sufficient evidence to support the hypothesis that the constraint of an actor's network position is negatively associated with learning.

4.3.3. Hypothesis 1c – Degree Centrality and Learning

H1c: Degree centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.

This hypothesis tests the association between degree centrality and attitudes to learning. Again, a partial correlation test was adopted to test the relationship between degree centrality and learning. Then in order to complement the finding from the partial correlation test, the t-test was used to evaluate whether there was a statistically significant difference between the means of learning scores of emergency staff members with high degree centralities and those with low degree centralities. The technique involving segregation of the high and low degree centrality groups was performed in the same way as for the efficiency groups. The cases of data of the emergency personnel were ranked in ascending order based on degree centrality scores. The median centrality score was selected as the cut-point. In this case, the median centrality was 0.124. Consequently, emergency staff members with degree centrality lower than the median were categorised in the "low centrality group", and those with degree centrality greater than the median were categorised in the "high centrality group"

Table 4.16: Partial correlation between *Degree Centrality* and *Individual Adaptability (Learning)*

Control Variables			Adaptability	Degree
Betweenness & Efficiency & Constraint	Adaptability	Correlation	1.000	-.188
		Significance (1-tailed)	.	.077
		df	0	57
	Degree	Correlation	-.188	1.000
		Significance (1-tailed)	.077	.
		df	57	0

Table 4.17: t-test statistics for Degree Centrality and Learning Attitudes

A: Group Statistics

	Degree1	N	Mean	Std. Deviation	Std. Error Mean
Adaptability2	>= .124	36	6.13889	3.243920	.540653
	< .124	26	6.11538	3.102604	.608471

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Adapta-bility2	Equal variances assumed	.537	.467	.029	60	.977	.023504	.819929	-1.616599	1.663607
	Equal variances not assumed			.029	55.395	.977	.023504	.813967	-1.607461	1.654470

The partial correlation testing (Table 4.16) for this sub-hypothesis provides no correlation (rho= -0.188, p>0.05, 1-tailed) between degree centrality scores of emergency personnel and their learning within a dynamic complex environment. The t-test (Table 4.17) shows that there is no significant difference in learning scores of emergency personnel with high degree centrality *(M=6.14, SD=3.24, n=36)* and emergency personnel with low degree centrality *(M=6.12, SD=3.10, n=26)*; *t* (60) = 0.029, *p=.977* (one-tailed). Therefore, the null hypothesis that there is no association between degree centrality of an actor and actor learning cannot be rejected. Therefore, there is not sufficient evidence to support hypothesis *H1c.*

4.3.4. Hypothesis 1d – Betweenness Centrality and Learning

H1d: Betweenness Centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.

This hypothesis tests the association between Betweenness centrality and attitudes to learning. Again, a partial correlation test was adopted to test the relationship between Betweenness centrality and learning. Then in order to complement the finding from the partial correlation test, the t-test was used to evaluate whether there was a statistically significant difference between the means of learning scores of emergency staff members with a high Betweenness centrality and those with a low Betweenness centrality. The technique involving segregation of the high and low Betweenness centrality groups in the same way as was performed for the efficiency groups. The cases of data of the emergency personnel were ranked in ascending order based on Betweenness centrality scores, thus ranking degree centrality scores. The median degree was chosen as the cut-point. In this study, the median Betweenness centrality was 0.123. Consequently, emergency personnel with a Betweenness centrality greater than the median were categorised in the “high centrality group”, and those with a Betweenness centrality lower than the median were categorised in the “low centrality group”.

Table 4.18: Partial correlation between *Betweenness Centrality* and *Individual Adaptability (Learning)*

Control Variables			Adaptability	Betweenness
Efficiency & Constraint & Degree	Adaptability	Correlation	1.000	.236
		Significance (1-tailed)	.	.036
		df	0	57
	Betweenness	Correlation	.236	1.000
		Significance (1-tailed)	.036	.
		df	57	0

Table 4.19: t-test statistics for Betweenness Centrality and Learning Attitudes

A: Group Statistics

	Betweenness	N	Mean	Std. Deviation	Std. Error Mean
adapt2	>= .1230	31	6.806452	2.8684416	.5151873
	< .1230	31	5.451613	3.3350533	.5989933

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
adap	Equal variances assumed	2.032	.159	1.715	60	.042	1.3548387	.7900702	-.2255370	2.9352144
	Equal variances not assumed			1.715	58.687	.042	1.3548387	.7900702	-.2262646	2.9359421

Results from the partial correlation test (Table 4.18) indicate a positive correlation (rho= 0.236, $p<0.05$, 1-tailed) between Betweenness centrality scores of emergency personnel and their learning. A higher value for the Betweenness centrality score of emergency personnel indicates a higher learning level.

The t-test (Table 4.19) confirms this result and reveals a significant difference in the learning attitude scores of the high Betweenness centrality group (*M=6.81, SD=2.87, n=31)* and the low Betweenness centrality group (*M=5.45, SD=3.34, n=31*); t (60) = 0.159, p=.042 (one-tailed). Consequently, there is no indication to support the null hypothesis that Betweenness centrality is not associated with learning. Therefore, there is sufficient evidence to support the hypothesis stated (H1d).

4.4. The Dyadic-Level Social Network Hypotheses

The following section provides a discussion of the results of hypothesis testing of associations between dyadic-level social network measures and attitudes to learning.

4.4.1. Hypothesis 2a – Strength of ties within Team and Learning

H2a: Strength of ties within a team is positively associated with the learning-related work activity of a team in a dynamic environment.

Hypothesis 2a tests the positive association of strong ties with attitudes to learning. In terms of hypothesis testing, a partial correlation test was adopted to test the relationship between strength of ties within a team and learning. Then, to complement the finding from the partial correlation test, the t-test was used to test the difference between the strong tie group and the weak tie group on learning. For the t-test, scores of three items (flexibility, the quality of information exchange and team feedback skills) were combined to form the team learning measure. To distinguish a strong tie from a weak tie, the median tie strength was chosen as the cut-point. Consequently, emergency personnel teams with an average tie strength score greater than or equal to 5.830 were grouped as "Strong Ties" and those with less than 5.830 were termed "Weak Ties".

Table 4.20: Partial correlation *between Strength of Ties between Team Members* and *Team Learning*

Control Variables			flexibility	informationExchange	teamfeedbackskills	Strength_of_ties_between_team_members
Strength_of_ties_between_IMT_and_incidentfire_ground	flexibility	Correlation	1.000	.540	.560	.608
		Significance (1-tailed)	.	.000	.000	.000
		df	0	373	373	373
	informationExchange	Correlation	.540	1.000	.802	.778
		Significance (1-tailed)	.000	.	.000	.000
		df	373	0	373	373
	teamfeedbackskills	Correlation	.560	.802	1.000	.801
		Significance (1-tailed)	.000	.000	.	.000
		df	373	373	0	373
	Strength_of_ties_between_team_members	Correlation	.608	.778	.801	1.000
		Significance (1-tailed)	.000	.000	.000	.
		df	373	373	373	0

Table 4.21: t-test statistics for *Strength of Ties between Team Members* and *Team Learning*

A: Group Statistics

	Strength_of_ties_between_ team_members	N	Mean	Std. Deviation	Std. Error Mean
Team_Learning	>= 5.8300	266	6.318076	.4769148	.0292415
	< 5.8300	232	4.972924	.8010425	.0525910

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Differ-ence	Std. Error Differ-ence	95% Confidence Interval of the Difference	
									Lower	Upper
Team_Lear ning	Equal variances assumed	43.804	.060	23.09 6	496	.000	1.345152 6	.0582427	1.230719 8	1.459585 3
	Equal variances not assumed			22.35 4	365.4 60	.000	1.345152 6	.0601738	1.226822 3	1.463482 9

The results from the partial correlation test (Table 4.20) indicate that there is a positive correlation between tie strength between team members and all the learning dependent variables. This indicates that an increase in tie strength between team members is associated with an increase in flexibility (rho= 0.608, p<0.05, 1-tailed), the quality of information exchange (rho= 0.778, p<0.05, 1-tailed) and team feedback skills (rho= 0.801, p<0.05, 1-tailed). Therefore, this indicates an increase in team learning.

The t-test (table 4.21) also confirms this result and reveals a significant difference in the team learning attitude scores of the strong ties group (*M=6.32, SD=0.48, n=266)* and the weak tie group (*M=4.97, SD=0.80, n=232*); *t* (496)= 23.096, *p*=.000 (two-tailed). Consequently, there is no evidence to support the null hypothesis that strong ties within a team are not associated with team learning attitudes. Therefore, there is sufficient evidence to support the hypothesis stated (H2a) in terms of attitudes to learning.

4.4.2. Hypothesis 2b – Strength of Ties across Teams and Learning

H2b: Strength of ties across teams is positively associated with the learning-related work activity of a team in a dynamic environment.

Hypothesis 2b tests the positive association of strong ties across teams with attitudes to learning. In terms of hypothesis testing, a partial correlation test was adopted to test the relationship between strength of ties across teams and learning. Then, to complement the finding from the partial correlation test, the t-test was used to test the difference between the strong tie group and the weak tie group on learning. For the t-test, scores of three items (flexibility, the quality of information exchange and team feedback skills) were combined to form the team learning measure. To distinguish a strong tie from a weak tie, the median tie strength was chosen as the cut-point. Consequently, if the average tie strength score across teams was greater than or equal to 5.600 the teams were grouped as “Strong Ties” and those with less than 5.600 were termed “Weak Ties”.

The results from the partial correlation test (Table 4.22) indicate that there was a positive correlation between tie strength across emergency management teams and all the learning dependent variables. This indicates that an increase in tie strength across emergency management teams is associated with an increase in the flexibility (rho= 0.237, $p<0.05$, 1-tailed), quality of information exchange (rho= 0.214, $p<0.05$, 1-tailed) and team feedback skills (rho= 0.263, $p<0.05$, 1-tailed) of those teams, and therefore an increase in team learning.

The t-test (Table 4.23) also confirms this result and reveals a significant difference in the team learning scores of strong tie groups (*M=6.23, SD=0.56, n=232)* and weak tie groups (*M=5.14, SD=0.97, n=229*); t (459) = 14.848, p=.000 (two-tailed). Consequently, there is no evidence to support the null hypothesis that strong ties across teams are not associated with team learning attitudes. Therefore, there is sufficient evidence to support the hypothesis stated (H2b) in terms of attitudes to learning.

Table 4.22: Partial correlation between *Strength of Ties between IMT and Incident Fire Ground* and *Team Learning*

Control Variables			flexibility	informationExchange	teamfeedbackskills	Strength_of_ties_between_IMT_and_incidentfire_ground
Strength_of_ties_between_team_members	flexibility	Correlation	1.000	.177	.206	.237
		Significance (1-tailed)	.	.000	.000	.000
		df	0	373	373	373
	informationExchange	Correlation	.177	1.000	.505	.214
		Significance (1-tailed)	.000	.	.000	.000
		df	373	0	373	373
	teamfeedbackskills	Correlation	.206	.505	1.000	.263
		Significance (1-tailed)	.000	.000	.	.000
		df	373	373	0	373
	Strength_of_ties_between_IMT_and_incidentfire_ground	Correlation	.237	.214	.263	1.000
		Significance (1-tailed)	.000	.000	.000	.
		df	373	373	373	0

Table 4.23: t-test statistics for *Strength of Ties between IMT and Incident Fire Ground* and *Team Learning*

A: Group Statistics

	Strength_of_ties_between_IMT_and_incidentfire_ground1	N	Mean	Std. Deviation	Std. Error Mean
Team_Learning	>= 5.6000	232	6.232845	.5588196	.0366883
	< 5.6000	229	5.139098	.9665049	.0638684

B: Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Team_Learning	Equal variances assumed	47.422	.071	14.898	459	.000	1.0937473	.0734167	.9494727	1.2380219
	Equal variances not assumed			14.849	364.159	.000	1.0937473	.0736560	.9489028	1.2385919

4.4.3. Hypothesis 2c – Interaction of "Moderating Variables and Strength of Ties" and Learning

H2c: The relations H2a and H2b are mediated by moderating variables of age, gender and experience of respondents and type of incident. This means that these demographic characteristics and incident type can be used to predict the relation between strength of ties of team members and the perceived level of learning of bushfire teams.

A moderator is a variable that affects the strength and/or direction of the relationship between an independent and a dependent variable (Hinshaw, 2007). In a correlational analysis model, a moderator is a third variable that affects the zero-order correlation between two other variables. In the *Social Network Based Learning Model* there are four moderating variables – *age*, *gender, level of experience* and *the type of incident*. To check the moderating ability of these variables, the research dataset is first grouped based on the values of those moderating variables. Then the zero-order correlation is measured for all mixtures of independent and dependent variables of those clusters. The correlation coefficient values between each of the independent variables and dependent variable of the proposed model for each cluster are reported in Table 4.24.

4.4.3.1. Interaction of "Age and Strength of Ties" and Learning

On the basis of age of emergency staff members, the dataset is divided into two groups: age group 1 (AG1) and age group 2 (AG2). The age 50 is considered as a cut point for these two clusters. All emergency personnel who are younger than 50 years belong to AG1 and the rest belong to AG2. Though correlation coefficients indicate strong positive relations between independent and dependent variables of the proposed model, AG1 shows stronger correlation coefficients for any pair of independent and dependent variables than AG2 (see Table 4.24). This implies that the age of emergency staff members moderates the relation between independent and dependent variables of the proposed model.

4.4.3.2. Interaction of "Gender and Strength of Ties" and Learning

The research dataset is first grouped in two clusters based on the gender of emergency staff members: a male cluster and a female cluster. All independent variables show strong positive relations with *team learning* for both clusters. Further investigation of the correlation coefficient matrix (see Table 4.24) reveals that female cluster shows a stronger positive relation between all combination of independent variables and *team learning* than male. This indicates that the gender of emergency staff members acts as a moderating variable in the proposed model.

4.4.3.3. Interaction of "Experience and Strength of Ties" and Learning

On the basis of the experience of emergency staff members, the dataset is divided into two groups: experience group 1 (EG1) and experience group 2 (EG2). The number of major incidents previously attended by the emergency personnel is considered for a cut point for these two clusters. All emergency personnel who had attended fewer than 10 incidents belong to EG1 and the rest belong to EG2. Though correlation coefficients indicate strong positive relations between independent and dependent variables of the proposed model, EG1 shows stronger correlation coefficients for any pair of independent and dependent variables than EG2 (see Table 4.24). This implies the experience of emergency personnel moderates the relation between independent and dependent variables of the proposed model.

Table 4.24: Zero-order correlation coefficients between each independent and dependent variable (for different clusters) of learning network model

	Team Learning					
	Age		Gender		Experience	
	AG1	AG2	Male	Female	EG1	EG2
Number of cases	**286**	**191**	**401**	**66**	**252**	**224**
Strength of ties within team	**0.901****	**0.810****	**0.810****	**0.879****	**0.904****	**0.898****
Strength of ties across teams	**0.731****	**0.635****	**0.699****	**0.764****	**0.731****	**0.683****
Note: **. Correlation is significant at the 0.01 level (1-tailed).						

4.4.3.4. Interaction of "Type of Incident and Strength of Ties" and Learning

The research dataset is first grouped into five clusters based on the incident type: forest or scrub fires; grass fires; rural/urban interface fires; structure fires; and other emergency incidents including cyclones, floods and storms. All independent variables show strong positive relations with learning for all clusters. Further investigation of the correlation coefficient matrix (see Table 4.25) reveals that the grass fires cluster shows the strongest positive relation between strength of ties within a team and team learning of all incidents. However, the structure fires cluster shows the strongest positive relation between strength of ties across teams and team learning. This illustrates that the incident type acts as a moderating variable in the proposed model.

Table 4.25: Zero-order correlation coefficients between each independent and dependent variable (for different types of incident) of learning network model

	Team Learning				
	Type of Incident				
	Forest/ Scrub fires	Grass fires	Rural/urban interface fires	Structure fires	Other Incidents
Number of cases	**306**	**76**	**93**	**51**	**69**
Strength of ties within team	**0.908****	**0.924****	**0.880****	**0.894****	**0.879****
Strength of ties across teams	**0.671****	**0.605****	**0.672****	**0.785****	**0.664****
Note: **. Correlation is significant at the 0.01 level (1-tailed).					

4.5. The Network-Level Social Network Hypotheses

In order to test the network-level social network hypotheses, it is useful first to look at the different bushfire response networks. The basic statistics of these four networks and the main features of these networks are given on Table 4.26. The network graphs that reveal the patterns of interactions among personnel within emergency organisations for the four response systems show clearly different patterns in coherence, density and centralisation. The graphs for each fire are shown in Figures 4.15, 4.16, 4.17 and 4.18. Graphs are very useful ways of presenting information about social networks. However, when there are many nodes and relationships, graphs can become so complex that they are hard to comprehend (Hanneman and Riddle, 2005). Therefore, to analyse the collected social network data, the matrix format was used as a basis for analysing the data. Representing the information in this way also allows the application of mathematical and computer tools such as UCINET to summarise and find patterns. Using this, social network analysis is applied and the density for each network is measured and different network-level centrality measures (i.e., degree centralisation and betweenness centralisation) are extracted. For this section, the network-level measures of centrality (not actor-level measures) are used to explore how learning is affected by the network structure.

Table 4.26: Summary statistics of four bushfire response networks

Social Network Measures	Kilmore East Bushfire	Murrindindi Bushfire	Churchill Bushfire	Bunyip Bushfire
Number of actors	282	261	132	151
Number of links	697	662	286	442
Density	0.0117	0.010	0.017	0.019
Degree centralisation	5.851%	5.32 %	2.84%	2.19%
Betweenness centralisation	33.77%	14.6%	13.36%	12.55%

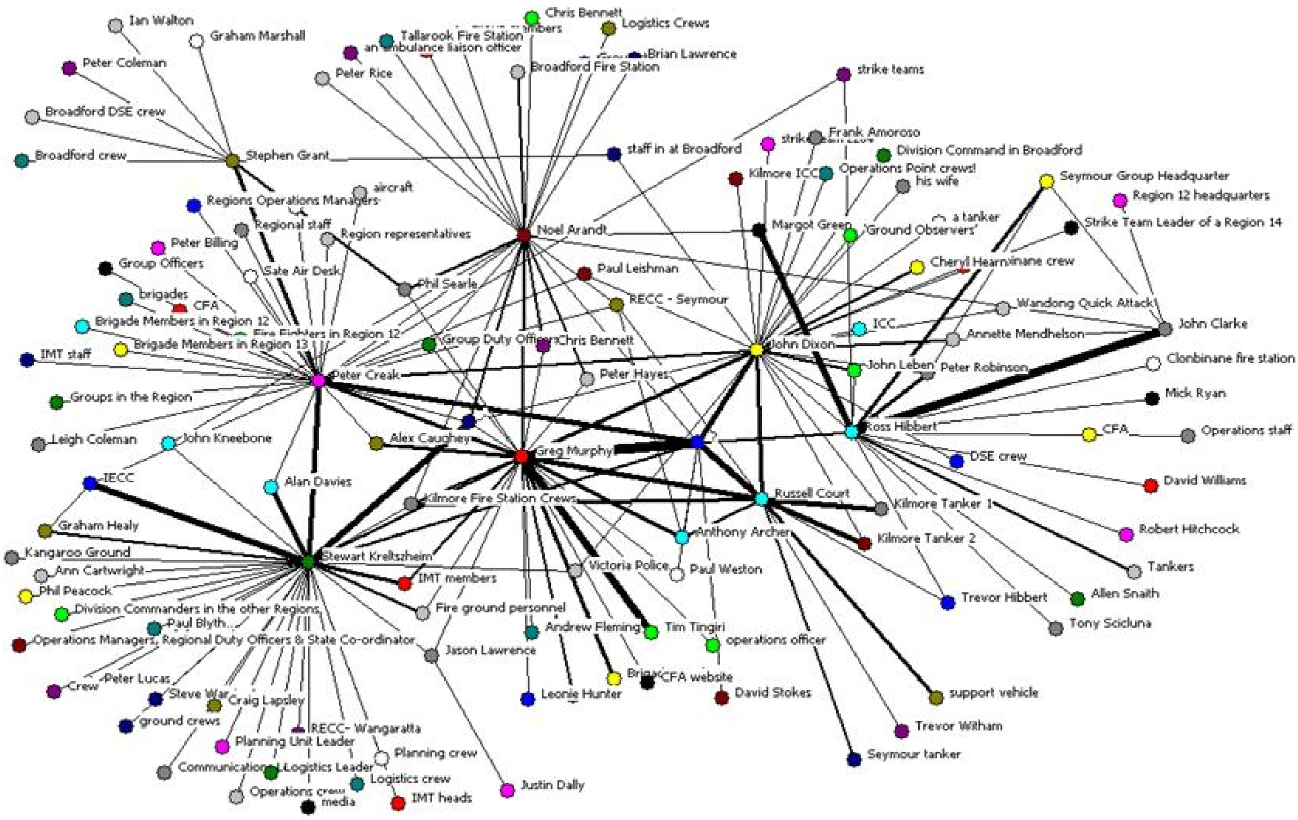


Figure 4.15: Social network diagram for Kilmore East bushfire

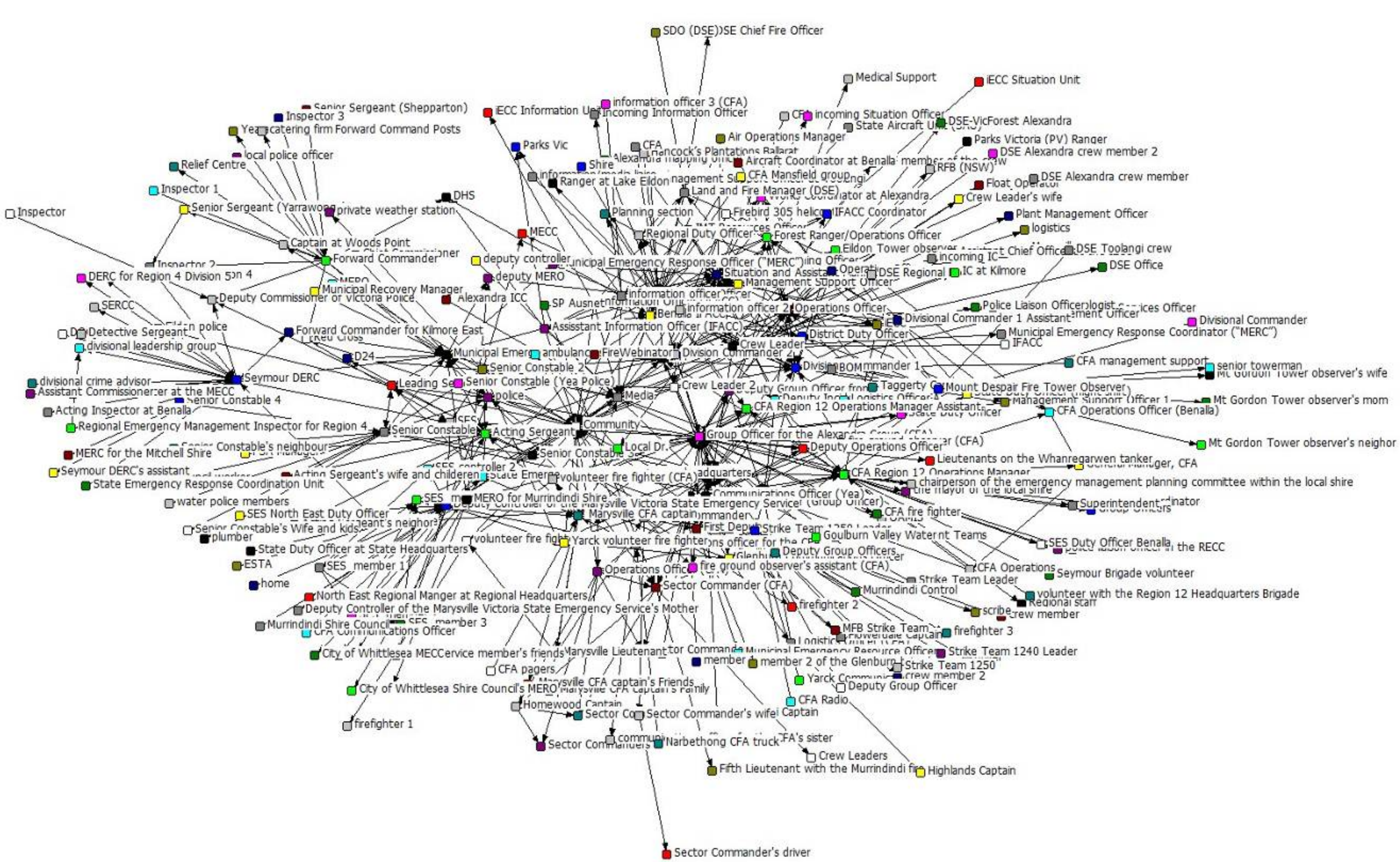


Figure 4.16: Social network diagram for Murrindindi bushfire

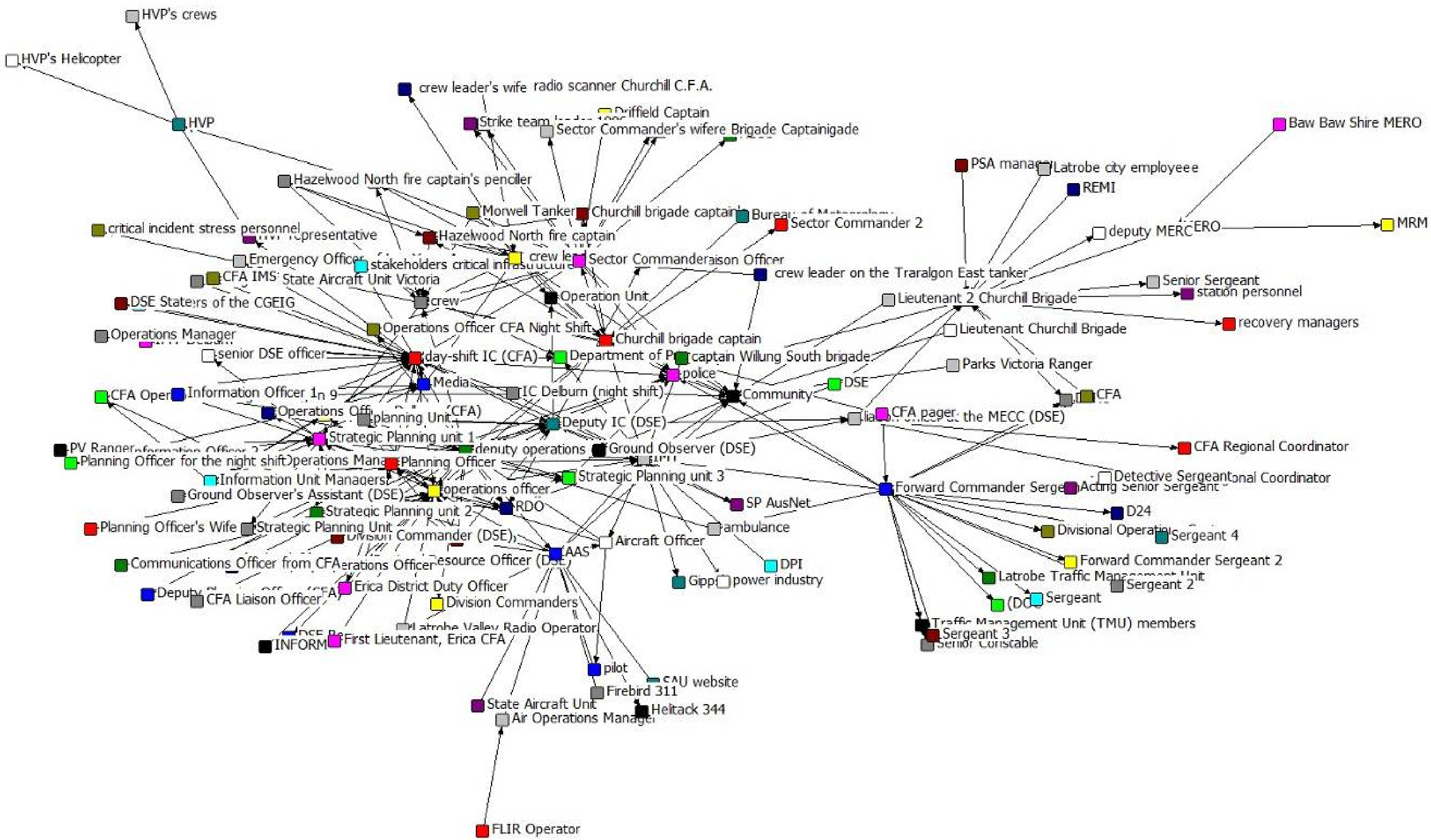


Figure 4.17: Social network diagram for Churchill bushfir

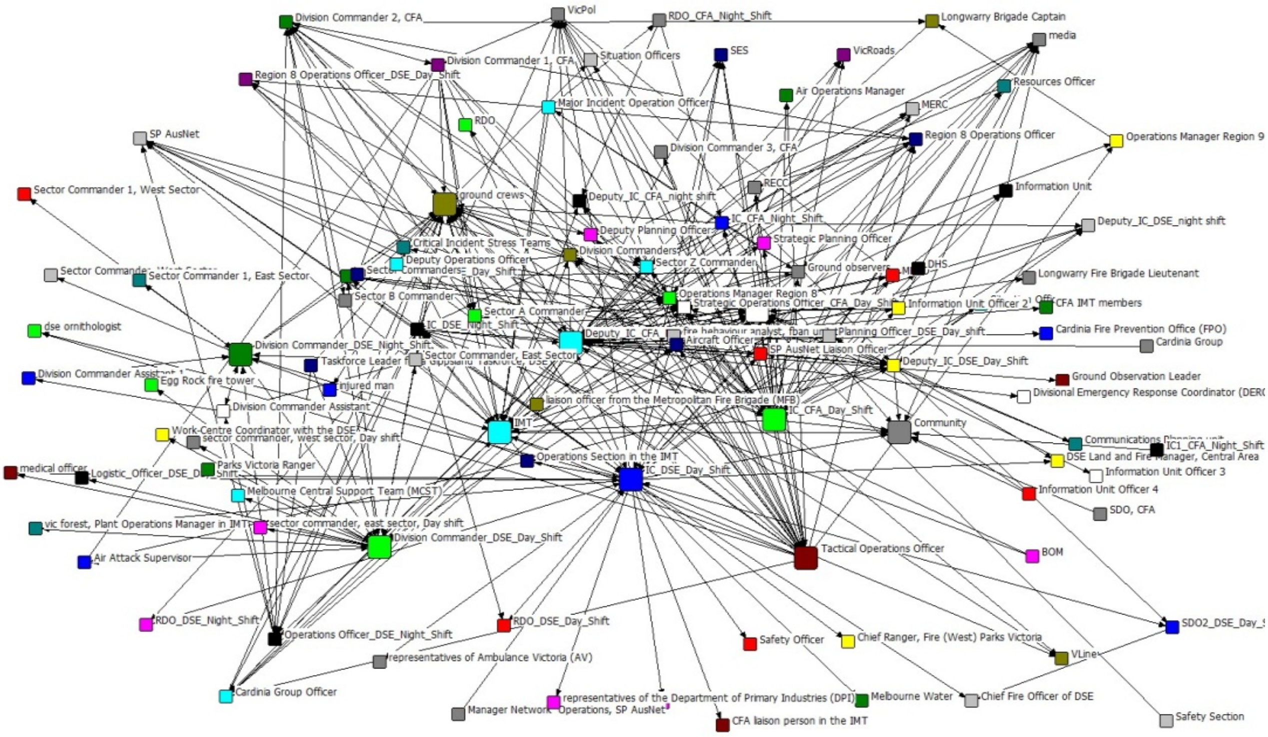


Figure 4.18: Social network diagram for Bunyip bushfire

4.5.1. Hypothesis 3a – Density and Learning

H3a: The density of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.

Table 4.27 shows the measures for the bushfire response networks. Empirical results suggest that the network structure of emergency personnel plays a crucial role in learning and performance. The results reveal that the network for the Bunyip Bushfire is denser than all the other networks. The dense network structure for the emergency staff responding to the Bunyip Bushfire contributed to their ability to respond in an adaptive fashion to highly ambiguous and threatening conditions, compared with the other response networks. It is evident from these results that the density of the network is positively correlated with the learning-related work activity of a network in a dynamic complex environment. Thus, the analysis shows that H3a holds true.

Table 4.27: Density measures for bushfire response networks

Social Network Measures	Kilmore East Bushfire	Murrindindi Bushfire	Churchill Bushfire	Bunyip Bushfire
Density	0.0117	0.010	0.017	0.019

4.5.2. Hypothesis 3b – Degree Centralisation and Learning

H3b: The degree centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.

Table 4.28 shows the measures for all bushfire response networks. Empirical results suggest that the network structure of emergency personnel plays a crucial role in learning and performance. The results reveal that the network for the Kilmore Bushfire is more centralised in terms of degree centralisation than the other networks. The network structure (more decentralised) for emergency staff responding to the Bunyip Bushfire contributed to their ability to respond in an adaptive fashion to highly ambiguous and threatening conditions. It is evident from these results that the degree centralisation of a network is negatively correlated with the learning-related work activity of the network in a dynamic complex environment. Thus, the analysis shows that H3b holds true.

Table 4.28: Degree centralisation measures for bushfire response networks

Social Network Measures	Kilmore East Bushfire	Murrindindi Bushfire	Churchill Bushfire	Bunyip Bushfire
Degree Centralisation	5.851%	5.32 %	2.84%	2.19%

4.5.3. Hypotheses 3c – Betweenness Centralisation and Learning

H3c: The betweenness centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.

Table 4.29 shows the measures for all bushfire response networks. Empirical results suggest that the network structure of emergency personnel plays a crucial role in learning and performance. The results reveal that the network for the Kilmore Bushfire is more centralised in terms of betweenness centralisation than all the other networks. The network structure (more decentralised) for emergency staff responding to the Bunyip Bushfire contributed to their ability to respond in an adaptive fashion to highly ambiguous and threatening conditions. It is evident from these results that the betweenness centralization of a network is negatively correlated with the learning-related work activity of the network in a dynamic complex environment. Thus, the analysis shows that H3c holds true.

Table 4.29: Betweenness centralisation measures for bushfire response networks

Social Network Measures	**Kilmore East Bushfire**	**Murrindindi Bushfire**	**Churchill Bushfire**	**Bunyip Bushfire**
Betweenness centralisation	33.77%	14.6%	13.36%	12.55%

4.6. Multiple Regression and Post-hoc Analyses

In this section, results from post-hoc analyses which were conducted after testing the hypotheses above are discussed. The findings from all the sub-hypotheses of *H1 and H2* can only enable us to develop suggestions for controlling individual learning and team learning. Therefore, post-hoc analyses were conducted, with the prime objective of delineating the following questions:

- Of actor-level social network variables, which best explains the variance in the relationship with individual learning, controlling for any effects that other independent variables might bear on the relationship?
- Of dyadic-level social network variables, which best explains the variance in the relationship with team learning, controlling for any effects that other independent variables might bear on the relationship?

4.6.1. Explaining Predictors of Individual Learning

In this section, the procedure takes a step further to predict the outcome variable (i.e., individual learning) from four independent variables of the proposed model, using regression analysis. Four regression models are proposed, which are reported in Table 4.30. The first model regresses the *"efficiency"* attribute on individual learning. In the second regression model, the second independent variable (i.e., *constraint*) enters into the model. In the third regression model, the third independent variable (i.e., *degree*) enters into the model. Finally, in the fourth regression model, the fourth independent variable (i.e., *betweenness*) enters into the model. This means that four independent variables are regressed to predict the outcome variable (i.e. individual learning) in the fourth model. Using these regression models, emergency managers or administrators can compare actual individual learning with that predicted, which in turn makes it possible for them to investigate the success of implementation of the findings from H1.

To validate the application of regression analyses, it is important to address the assumptions of the regression analysis prior to discussing the results.

4.6.1.1. Checking Regression Assumptions

Several assumptions need to be true in order to draw conclusions based on regression analysis conducted on a sample (Venter and Maxwell, 2000; Field, 2009). These regression assumptions guide the choice of regression analysis in terms of (i) variable types, (ii) homoscedasticity, (iii) linearity, (iv) independent errors, (v) normally distributed errors, and (vi) multicollinearity.

Variable Types

This assumption states that all independent variables must be quantitative or categorical (two categories only), and the dependent variable must be quantitative, continuous and unbounded. Unbounded means there must be no restriction on the variability of the outcome (Field, 2009). For instance, if the outcome is a measure ranging from 1 to 10 and the data gathered differ between 3 and 7, then these data are bounded or constrained. The processes described in Chapter 3 that were followed to measure all the variables of the Actor-level Social Network Model confirm that the criteria of required variable types for a regression model were met.

Homoscedasticity and Linearity

According to this regression assumption, the residuals at each level of the independent variables must have the same variance. When the variances are very close, then it is said to be homoscedastic. On the other hand, the chance of heteroscedasticity in the data is evidenced when variances are very unequal. Although minor heteroscedasticity has little effect on significance tests (Tabachnick et al., 2001), extremely obvious heteroscedasticity can lead to severe misrepresentation of outcomes and can seriously degrade the analysis. The linearity assumption assumes that the relationships between predictor and outcome variables are linear in nature. If the relationship between predictor and outcome variables is not linear or if a non-linear relationship is modelled using a linear model then the results of the regression model will under-estimate the correct relationship (Field, 2009).

To test linearity and homoscedasticity, a plot of *ZRESID (standardised residual) against *ZPRED (standardised predicted value) is drawn using SPSS. The points of the plot (see Figure 4.19) are randomly and nearly evenly dispersed throughout the plot area. This pattern for the research dataset is indicative that the assumptions of linearity and homoscedasticity have been met (Field, 2009).

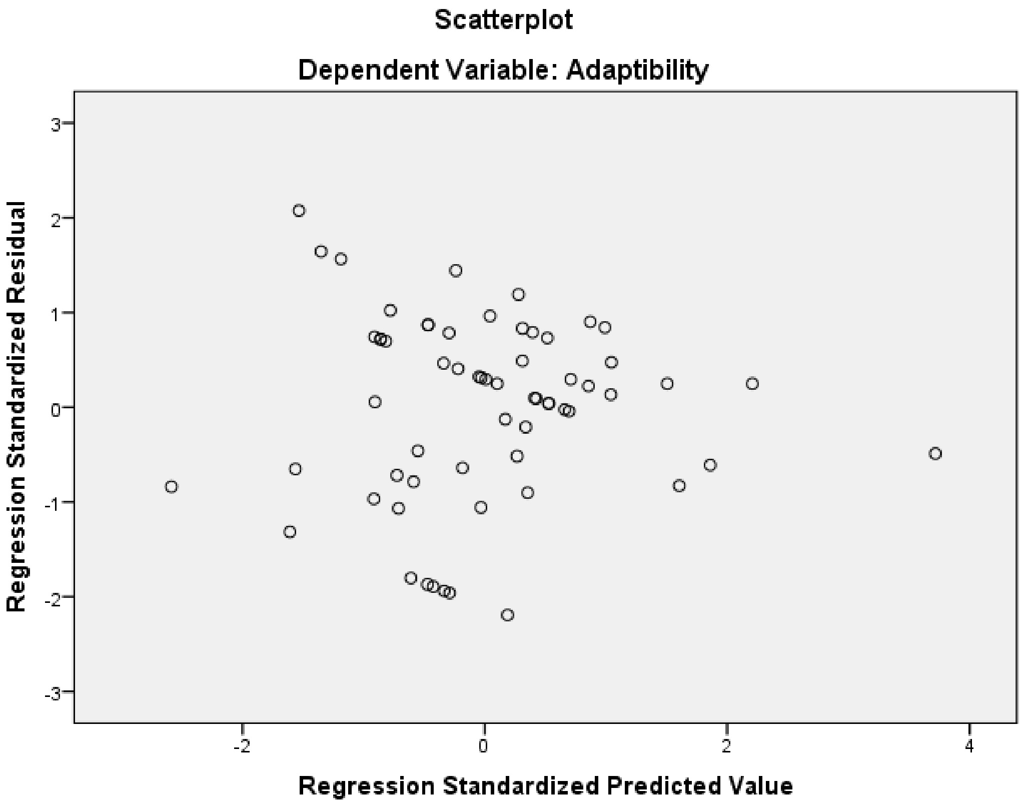


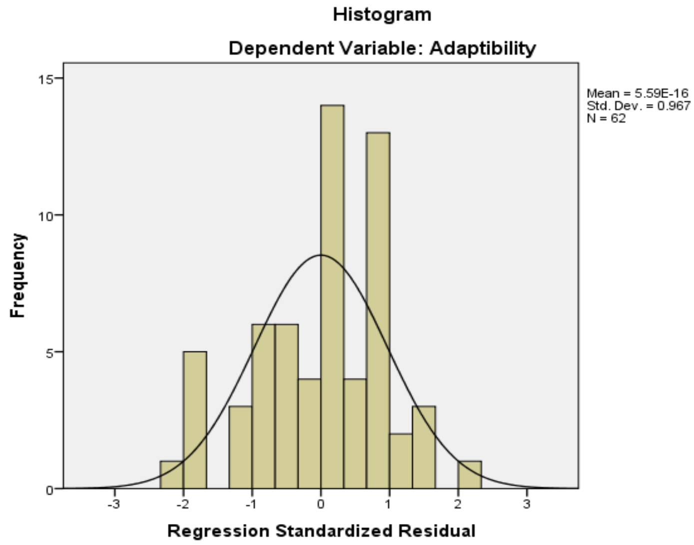
Figure 4.19: Plots of *ZRESID against *ZPRED for *Actor-level Social Network Model*

Independent Errors

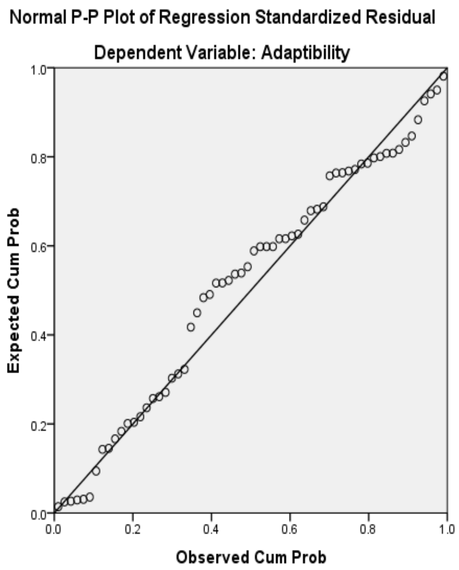
This assumption states that the residual terms should be uncorrelated or independent for any two observations. This is eventually something defined as a lack of autocorrelation among residuals. This assumption can be verified using the Durbin-Watson test (Durbin and Watson, 1951), which inspects for serial correlation between errors. The test statistic for the Durbin-Watson test is almost equal to *2(1-r)*, where *r* is the sample autocorrelation of the residuals. As *r* indicates a correlation coefficient, its value can vary from -1 to +1, which eventually sets up the range for Durbin-Watson test statistic between 0 and 4. A value of 2 indicates that the residuals are uncorrelated. As reported in the *model summary* section of Table 4.30, the Durbin-Watson test statistic is 1.949, which is very close to the standard value of 2. Thus, the residuals are independent or there is no correlation among them.

Normally Distributed Errors

The residuals in the model are assumed to be random and normally distributed with a mean of zero. To validate this assumption, the histogram and then P-P plots for residuals are first examined using the original dataset. The histogram and the corresponding P-P plot are illustrated in Figure 4.20. The histogram (Figure 4.20a) is very close to a bell-shaped curve. Similarly, the P-P plot (Figure 4.20b) resembles the P-P plot of a normally distributed dataset.



(a)



(b)

Figure 4.20: (a) Histogram and (b) Normal P-P plot for *Actor-Level Network Model*

Multicollinearity

Multicollinearity exists in a regression model when a strong correlation exists between two or more independent or predictor variables. For multiple regressions, multicollinearity poses difficulties because simple regression needs only one independent variable. Perfect collinearity exists when one independent variable can be measured perfectly by using one or more other variable(s) such as the relation: $x2 = x1+3$ between the independent variables x1 and x2. The presence of multicollinearity among independent variables makes a regression model unreliable and raises doubts as to the generalisability of the model. The *"ball-park"* method of identifying multicollinearity is to scan the correlation matrix of independent variables. A very high correlation coefficient (i.e., a value of 0.80 or 0.90) in the correlation matrix shows the presence of multicollinearity among independent variables. SPSS also produces numerous multicollinearity diagnostics, one of which is the *variance inflation factor (VIF)*. The VIF indicates whether a predictor has significant correlation with one or more other independent variable(s). For an individual independent variable, a VIF value of 10 is too high and there is a reason for concern (Field, 2009). Considering all independent variables, if the average VIF is significantly greater than 1 then multicollinearity may bias the regression model (Field, 2009). SPSS also measures the tolerance statistic, which is the reciprocal of VIF, to test for the presence or absence of multicollinearity. Values below 0.10 for the tolerance statistic show serious problems for regression due to the presence of multicollinearity among independent variables.

From Table 4.10, it is clear that no strong correlation exists between any two independent variables. Also, as showed in the *coefficients'* section of Table 4.30, the average value of VIF for the final model (i.e., *model 4*) is 2.2845 ($1.484+1.982+2.625+3.047 = 9.138$; $9.138 \div 4 = 2.2845$), which is close to 1. Further, the *tolerance* statistics for the same model from Table 4.30 indicate that no multicollinearity exists among the independent variables of the proposed model, as the average value for the *tolerance* score is 0.472 ($0.674+0.505+0.381+0.328 = 1.888$; $1.888 \div 4 = 0.472$), which is higher than its standard value (i.e., 0.1). It is now clearly evident that the research dataset meets the basic assumptions of *variable types*, *homoscedasticity* and *linearity*, *independent errors*, *normal distribution of errors*, and *multicollinearity* for regression analysis.

4.6.1.2. Summary of Regression Model

The regression method is applied to assess the ability of the independent variables of the proposed model to predict individual learning. The details of the regression analysis findings are reported in Table 4.30. From the *Model Summary* section of Table 4.30, it is noted that there is a positive change in the R^2 (i.e., the proportion of variance explained by the model) value, which indicates improvements in the regression model with the inclusion of the new independent variables. The explained proportion of variance ranges from 0.3% for the first model to 20.4% for the fourth model. The results reveal that the variables *efficiency* and *degree* explain almost nothing of the variance (0.3% and 0.0%). However, the independent variable *constraint* as a whole explains 15.3% (R square change = .153 in Model 2) of the variance in learning attitude. In addition, the independent variable *Betweenness* as a whole explains 4.7% (R square change = .047 in Model 4) of the variance in learning attitude. It is also revealed from this section of Table 4.30 that the changes in R^2 value are significant for Model 2, as the values of the column labelled by *Sig F Change* are less than 0.05. Further, the *F Change* statistics shows that regression Model 2 is statistically significant. From *ANOVA* (i.e., Table 4.30b), it is clear that Models 2, 3 and 4 fit the research data significantly. The column labelled *Sig.* in *ANOVA* has a value less than 0.05 for those models, which also indicates a significant fit of the data with regression models. Moreover, the *F* value indicates that regression Models 2, 3 and 4 are statistically significant. The standardised positive beta values in the *Coefficients* section of Table 4.30 indicate that the independent variable *constraint* has a contribution in the predicted value of individual learning. The values under the columns labelled *t* and *Sig.* further show that the contribution is statistically significant. Therefore, one may conclude that among the variables – *efficiency, constraint, degree* and *betweenness* – *constraint* makes the largest unique contribution to explaining the variance in individual learning. By using one of those models as presented in Table 4.30, emergency managers or administrators can predict or evaluate the current practice structure in their respective emergency organisations.

Table 4.30: Regression model for *Actor-Level Network Model*

a: Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.057[a]	.003	-.013	3.180573	.003	.198	1	60	.658	
2	.395[b]	.156	.128	2.951298	.153	10.684	1	59	.002	
3	.396[c]	.157	.113	2.975821	.000	.032	1	58	.860	
4	.451[d]	.204	.148	2.917078	.047	3.359	1	57	.072	1.949

a. Predictors: (Constant), Efficiency
b. Predictors: (Constant), Efficiency, Constraint
c. Predictors: (Constant), Efficiency, Constraint, Degree
d. Predictors: (Constant), Efficiency, Constraint, Degree, Betweenness
e. Dependent Variable: Adaptability

b: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.005	1	2.005	.198	.658[b]
	Residual	606.963	60	10.116		
	Total	608.968	61			
2	Regression	95.068	2	47.534	5.457	.007[c]
	Residual	513.899	59	8.710		
	Total	608.968	61			
3	Regression	95.348	3	31.783	3.589	.019[d]
	Residual	513.619	58	8.856		
	Total	608.968	61			
4	Regression	123.935	4	30.984	3.641	.010[e]
	Residual	485.032	57	8.509		
	Total	608.968	61			

a. Dependent Variable: Adaptability
b. Predictors: (Constant), Efficiency
c. Predictors: (Constant), Efficiency, Constraint
d. Predictors: (Constant), Efficiency, Constraint, Degree
e. Predictors: (Constant), Efficiency, Constraint, Degree, Betweenness

c: Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.284	1.940		2.724	.008					
	Efficiency	1.032	2.317	.057	.445	.658	.057	.057	.057	1.000	1.000
2	(Constant)	11.999	2.732		4.393	.000					
	Efficiency	-3.620	2.579	-.201	-1.404	.166	.057	-.180	-.168	.695	1.438
	Constraint	-3.805	1.164	-.469	-3.269	.002	-.358	-.392	-.391	.695	1.438
3	(Constant)	12.102	2.815		4.299	.000					
	Efficiency	-3.600	2.603	-.200	-1.383	.172	.057	-.179	-.167	.694	1.441
	Constraint	-3.889	1.264	-.479	-3.076	.003	-.358	-.374	-.371	.599	1.669
	Degree	-.163	.916	-.024	-.178	.860	.137	-.023	-.021	.793	1.261
4	(Constant)	10.750	2.856		3.764	.000					
	Efficiency	-2.789	2.589	-.155	-1.077	.286	.057	-.141	-.127	.674	1.484
	Constraint	-2.905	1.351	-.358	-2.150	.036	-.358	-.274	-.254	.505	1.982
	Degree	-1.875	1.296	-.277	-1.447	.153	.137	-.188	-.171	.381	2.625
	Between-ness	.473	.258	.378	1.833	.072	.323	.236	.217	.328	3.047

a. Dependent Variable: Adaptability

d: Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	Collinearity Statistics VIF	Collinearity Statistics Minimum Tolerance
1	Constraint	-.469[b]	-3.269	.002	-.392	.695	1.438	.695
	Degree	.131[b]	.973	.335	.126	.920	1.086	.920
	Betweenness	.329[b]	2.590	.012	.319	.939	1.065	.939
2	Degree	-.024[c]	-.178	.860	-.023	.793	1.261	.599
	Betweenness	.163[c]	1.129	.264	.147	.683	1.464	.506
3	Betweenness	.378[d]	1.833	.072	.236	.328	3.047	.328

a. Dependent Variable: Adaptability
b. Predictors in the Model: (Constant), Efficiency
c. Predictors in the Model: (Constant), Efficiency, Constraint
d. Predictors in the Model: (Constant), Efficiency, Constraint, Degree

4.6.2. Explaining Predictors of Team Learning

To explain the interrelationship among the set of variables that affects team learning, a stepwise multiple regression was conducted in order to model the interrelationship among the variables. The stepwise multiple regression technique determines an independent variable that is statistically significant. This variable is then entered into the multiple regression equation. This process is iterated until all statistically significant independent variables have been entered into the multiple regression equation such that the insignificant ones are excluded, leaving behind the statistically significant independent variables only. This technique thus allows us to infer the most potent predictor(s) of the dependent variable from a set of significant ones.

Four models were postulated as reported in Table 4.31. The first model simply regressed the strength of ties between team members on the dependent variable, team learning, because of its positive correlation. In the second model, the strength of ties across teams (IMT and Ground) was entered while controlling, as a whole, for the effect of strength of ties between team members on team learning. In the third model, the age of emergency personnel (respondents) was added. In the fourth model, the dummy variable "type of incident" (whether an incident is a fire or not) was added. The sections following discuss the assumptions and results of the regression analyses to explaining the predictors of team learning.

4.6.2.1. Checking Regression Assumptions

As mentioned earlier, several assumptions need to be true in order to draw conclusions based on regression analysis done on a sample (Venter and Maxwell, 2000; Field, 2009). These regression assumptions guide the choice of regression analysis in terms of (i) variable types, (ii) homoscedasticity, (iii) linearity, (iv) independent errors, (v) normally distributed errors, and (vi) multicollinearity.

Variable Types

As mentioned earlier for the previous regression model, this assumption states that all independent variables must be quantitative or categorical (two categories only), and the dependent variable must be quantitative, continuous and unbounded. The problem with the dyadic-level data is how to deal with a categorical predictor variable (the type of incident) with more than two levels (forest or scrub fires; grass fires; rural/urban interface fires; structure fires; emergency incidents including cyclones, floods and storms). Since categorical predictor variables cannot be entered straight into a regression model and be meaningfully interpreted, some additional method of dealing with data of this type must be established. This method, which is called dummy coding, produces dummy variables based on the categorical variables. For instance, if a categorical variable has five categories, then four binary (dummy) variables can be built that cover the same information as the single categorical variable. Dummy variables can be entered directly into the regression model. This process was done here for the variable "type of incident". After performing this process, all the variables of the Dyadic-level Social Network Model confirm that the criteria of required variable types for regression model have been met.

Homoscedasticity and Linearity

As mentioned for the previous regression model, the residuals at each level of independent variables must have the same variance. To test the linearity and homoscedasticity, a plot of *ZRESID (standardised residual) against *ZPRED (standardised predicted value) is drawn by using SPSS. The points of the plot (see Figure 4.21) are randomly and nearly evenly dispersed throughout the plot area. This pattern for the research dataset is indicative that the assumptions of linearity and homoscedasticity have been met (Field, 2009).

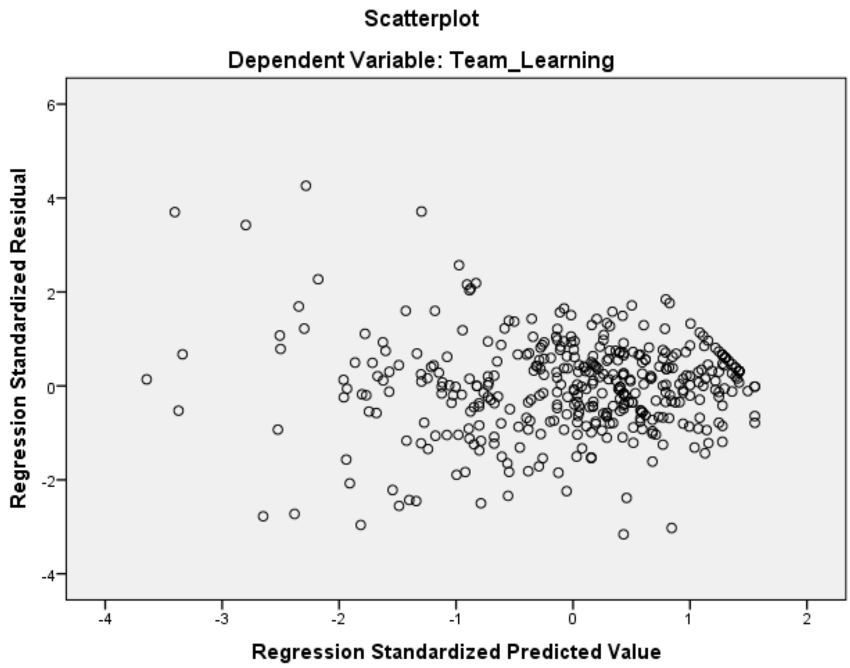


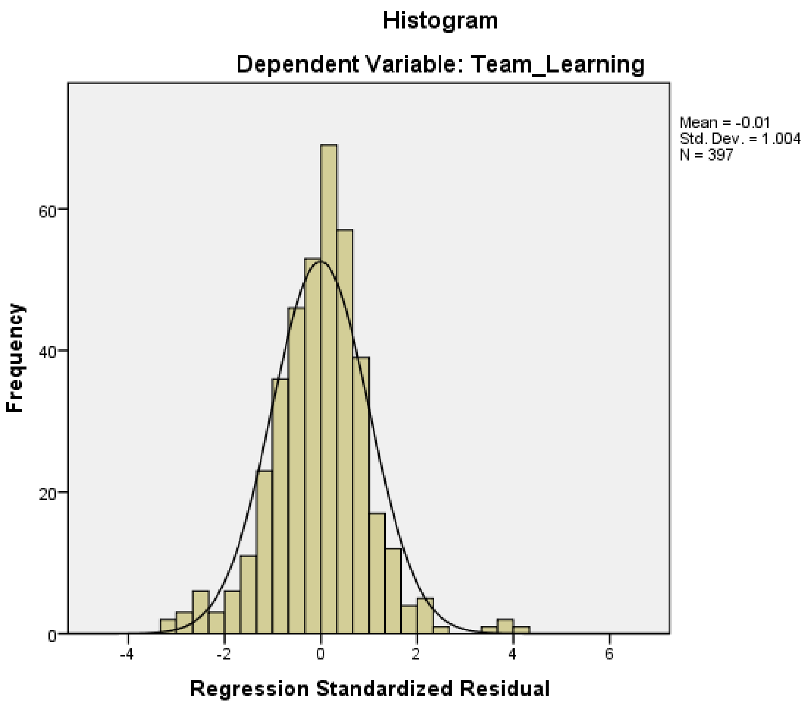
Figure 4.21: Plots of *ZRESID against *ZPRED for *Dyadic-Level Social Network Model*

Independent Errors

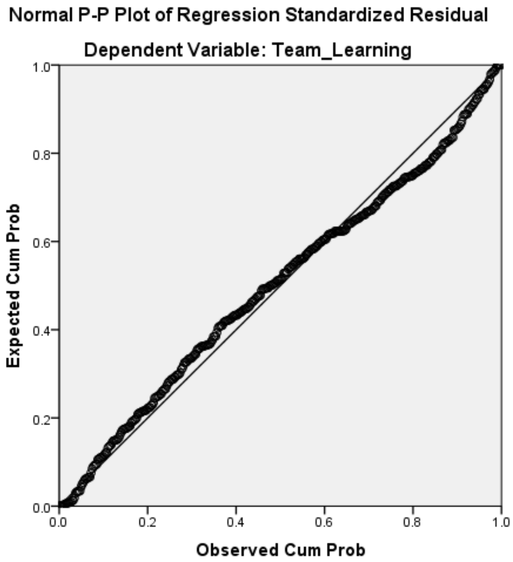
As mentioned for the previous regression model, this assumption states that for any two observations the residual terms should be uncorrelated or independent. As reported in the *model summary* section of Table 4.31a, the Durbin-Watson test statistic is 2.079, which is very close to the standard value of 2. Thus, the residuals are independent or there is no correlation among them.

Normally Distributed Errors

As mentioned for the previous regression model, it is assumed that the residuals in the model are random and are normally distributed variables with a mean of zero. To validate this assumption, the histogram and the P-P plots for residuals are first examined using the original dataset. The histogram and the corresponding P-P plot are illustrated in Figure 4.22. The histogram (Figure 4.22a) is very close to a bell-shaped curve. Similarly, the P-P plot (Figure 4.22b) resembles to the P-P plot of a normally distributed dataset.



(a)



(b)

Figure 4.22: (a) Histogram and (b) Normal P-P plot for *Dyadic-level Network Model*

Multicollinearity

As mentioned for the previous regression model, multicollinearity exists in regression models when there is a strong correlation between two or more independent or predictor variables. From the Table 4.11, it is clear that no strong correlation exists between any two independent variables. Also, as showed in the *coefficients'* section of Table 4.31c, the average value of VIF for the final model (i.e., *Model 4*) is 1.4175 (1.811+1.833+1.001+1.025 =5.67; 5.67÷ 4= 1.4175), which is very close to 1. Further, the *tolerance* statistics for the same model, from Table 4.31c, support the conclusion that there is no multicollinearity among the independent variables of the proposed model, as the average value for the *tolerance* score is 0.472 (0.552+0.546+0.999+0.976= 3.073; 3.073÷ 4 = 0.768), which is higher than its standard value (i.e., 0.1). It is now clearly evident that the research dataset has met the basic assumptions of *vari1able types*, *homoscedasticity* and *linearity*, *independent errors*, *normal distribution of errors*, and *multicollinearity* for regression analysis.

4.6.2.2. Summary of Regression Model

The regression method is applied to assess the ability of the independent variables and moderating variables of the proposed model to predict team learning. The details of regression analysis findings are reported in Table 4.31. From the *Model Summary* section of Table 4.31, it is noted that there is a positive change in the R^2 (i.e., the proportion of variance explained by the model) value, which indicates improvements in the regression model with the inclusion of new independent variable. The explained proportion of variance ranges from 83.7 % for the first model to 85.6% for the fourth model. The results reveal the moderating variables *gender* and *type of incident* (all dummy variables except for the 'other incidents' dummy variable) explain nothing of the variance (excluded from all models). In addition, the results reveal that the moderating variables *age* and *type of incident* (the 'other incidents' dummy variable) explain almost nothing of the variance (0.2% and 0.2%). However, the independent variable *strength of ties between team members as a whole* explains 83.7% (R Square Change = .837 in Model 1) of the variance in learning attitude. In addition, the independent variable *strength of ties between IMT and incident fire ground as a whole* explains 1.6% (R Square Change = .016 in Model 2) of the variance in learning attitude. It is also revealed from this section of Table 4.31a that the changes in R^2 value are significant for all models, as the values of the column labelled *Sig F Change* are below 0.05. Further, the *F Change* statistics show that all regression models are statistically significant. From the *ANOVA* (i.e., Table 4.31b), it is clear that all models fit the research data significantly. The column labelled *Sig.* in *ANOVA* has a value less than 0.05 for those models, which also indicates a significant fit of the data with the regression models. Moreover, the *F* value indicates that all regression models are statistically significant. Therefore, one may conclude that among all independent and moderating variables, *strength of ties between team members* makes the largest unique contribution to explaining the variance in team learning. By using one of the models presented in Table 4.31, emergency managers or administrators can predict or evaluate the current practice structure in their respective emergency organisations.

Table 4.31: Regression model for *Dyadic-level Network Model*

a: Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.915[a]	.838	.837	.367	.838	2027.965	1	393	.000	
2	.924[b]	.854	.853	.349	.016	44.106	1	392	.000	
3	.925[c]	.856	.855	.347	.002	4.851	1	391	.028	
4	.926[d]	.858	.856	.345	.002	4.816	1	390	.029	2.079

a. Predictors: (Constant), Strength_of_ties_between_team_members
b. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground
c. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40
d. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40, Other_Incidents
e. Dependent Variable: Team_Learning

b: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	273.848	1	273.848	2027.965	.000[b]
	Residual	53.069	393	.135		
	Total	326.918	394			
2	Regression	279.216	2	139.608	1147.253	.000[c]
	Residual	47.702	392	.122		
	Total	326.918	394			
3	Regression	279.800	3	93.267	773.967	.000[d]
	Residual	47.117	391	.121		
	Total	326.918	394			
4	Regression	280.375	4	70.094	587.345	.000[e]
	Residual	46.543	390	.119		
	Total	326.918	394			

a. Dependent Variable: Team_Learning
b. Predictors: (Constant), Strength_of_ties_between_team_members
c. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground
d. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40
e. Predictors: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40, Other_Incidents

c: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.150	.103		11.215	.000	.949	1.352					
	Strength_of_ties_between_team_members	.809	.018	.915	45.033	.000	.774	.845	.915	.915	.915	1.000	1.000
2	(Constant)	1.024	.099		10.325	.000	.829	1.219					
	Strength_of_ties_between_team_members	.707	.023	.800	30.817	.000	.662	.753	.915	.841	.595	.552	1.810
	Strength_of_ties_between_IMT_and_incidentfire_ground	.132	.020	.172	6.641	.000	.093	.171	.708	.318	.128	.552	1.810
3	(Constant)	.851	.126		6.743	.000	.603	1.099					
	Strength_of_ties_between_team_members	.708	.023	.801	30.991	.000	.663	.753	.915	.843	.595	.552	1.810
	Strength_of_ties_between_IMT_and_incidentfire_ground	.130	.020	.171	6.597	.000	.091	.169	.708	.316	.127	.552	1.812
	Q6.3AgeGrpd.under.40	.098	.045	.042	2.203	.028	.011	.186	.060	.111	.042	.999	1.001
4	(Constant)	.863	.126		6.868	.000	.616	1.111					
	Strength_of_ties_between_team_members	.707	.023	.800	31.109	.000	.663	.752	.915	.844	.594	.552	1.811
	Strength_of_ties_between_IMT_and_incidentfire_ground	.126	.020	.164	6.358	.000	.087	.165	.708	.306	.121	.546	1.833
	Q6.3AgeGrpd.under.40	.099	.044	.042	2.222	.027	.011	.186	.060	.112	.042	.999	1.001
	Other_Incidents	.113	.052	.042	2.195	.029	.012	.215	.158	.110	.042	.976	1.025

a. Dependent Variable: Team_Learning

d: Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Strength_of_ties_between_IMT _and_incidentfire_ground	.172[b]	6.641	.000	.318	.552
	Gender	-.005[b]	-.234	.815	-.012	.999
	Q6.3AgeGrpd.under.40	.047[b]	2.300	.022	.115	1.000
	Q1.5Grass	-.002[b]	-.114	.909	-.006	1.000
	Q1.5RuralUrbanInterface	.003[b]	.157	.875	.008	1.000
	Q1.5ForestScrub	-.017[b]	-.854	.394	-.043	.987
	Q1.5StructureFire	.039[b]	1.918	.056	.096	.995
	Other_Incidents	.055[b]	2.735	.007	.137	.987
2	Gender	-.005[c]	-.243	.808	-.012	.999
	Q6.3AgeGrpd.under.40	.042[c]	2.203	.028	.111	.999
	Q1.5Grass	.002[c]	.110	.912	.006	.998
	Q1.5RuralUrbanInterface	.008[c]	.435	.664	.022	.998
	Q1.5ForestScrub	-.006[c]	-.308	.758	-.016	.979
	Q1.5StructureFire	.024[c]	1.258	.209	.064	.982
	Other_Incidents	.042[c]	2.175	.030	.109	.976
3	Gender	.004[d]	.196	.845	.010	.959
	Q1.5Grass	.004[d]	.205	.838	.010	.997
	Q1.5RuralUrbanInterface	.010[d]	.505	.614	.026	.997
	Q1.5ForestScrub	.000[d]	-.025	.980	-.001	.963
	Q1.5StructureFire	.019[d]	.998	.319	.050	.967
	Other_Incidents	.042[d]	2.195	.029	.110	.976
4	Gender	.006[e]	.303	.762	.015	.957
	Q1.5Grass	.009[e]	.490	.624	.025	.980
	Q1.5RuralUrbanInterface	.016[e]	.816	.415	.041	.978
	Q1.5ForestScrub	.027[e]	1.224	.222	.062	.726
	Q1.5StructureFire	.019[e]	.981	.327	.050	.966

a. Dependent Variable: Team_Learning
b. Predictors in the Model: (Constant), Strength_of_ties_between_team_members
c. Predictors in the Model: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground
d. Predictors in the Model: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40
e. Predictors in the Model: (Constant), Strength_of_ties_between_team_members, Strength_of_ties_between_IMT_and_incidentfire_ground, Q6.3AgeGrpd.under.40, Other_Incidents

To summarise, the preceding sections of this chapter have tested the hypotheses relating to network factors (actor level, dyadic level and network level), demographic attributes and learning in a dynamic complex environment. The results of these tests have been presented. The chapter then details the regression models. Table 4.32 provides a summary of the social network and learning theories together with the hypotheses and key findings presented earlier.

Table 4.32: Brief overview of the hypotheses and related key theories and the key findings from thesis

Level of Analysis	Hypotheses	Hypotheses Statement	Key Theories	Key findings from thesis	Was the hypothesis supported or not supported?
Actor Level	**HYPOTHESIS la**	*Efficiency is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	Burt(1992) (Structural Hole)	There is no association between efficiency and individual learning in a dynamic complex environment.	not supported
	HYPOTHESIS lb	*The constraint of an actor's network position is negatively associated with the learning-related work activity of the actor in a dynamic complex environment.*	Burt(1992) (Structural Hole)	The constraint in an actor's network position is negatively associated with learning.	supported
	HYPOTHESIS lc	*Degree centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	Freeman (1978) (Node Centrality)	There is no association between the degree centrality of an actor and the actor's learning.	not supported
	HYPOTHESIS ld	*Betweenness centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.*	Freeman (1978) (Node Centrality)	Betweenness centrality is positively associated with the learning-related work activity of an actor in a dynamic complex environment.	supported
Dyadic Level	**HYPOTHESIS 2a**	*Strength of ties within a team is positively associated with the learning-related work activity of a team in a dynamic environment.*	Granovetter (1973) & Krackhardt (1992)	Strength of ties within a team is positively associated with the learning-related work activity of a team in a dynamic environment.	supported
	HYPOTHESIS 2b	*Strength of ties across teams is positively associated with the learning-related work activity of a team in a dynamic environment.*	Granovetter (1973) & Krackhardt (1992)	Strength of ties across teams is positively associated with the learning-related work activity of a team in a dynamic environment.	supported
	HYPOTHESIS 2c	*The relations H2a and H2b are mediated by moderating variables of age, gender and experience of respondents and type of incident. This means that these demographic characteristics and incident type can be used to predict the relation between strength of ties of team members and the bushfire-team's perceived level of learning for that team.*	Trigwell et. al.(1991) & Billett (2002)	The results reveal that the moderating variables 'gender' and 'type of incident' explain nothing of the variance (excluded from all models). In addition, the moderating variables 'age' and 'type of incident' (the 'other incidents' dummy variable) explain almost nothing of the variance (0.2% and 0.2%).	not supported
Network Level	**HYPOTHESIS 3a**	*The density of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	Burt (1992), Coleman et. al.(1966) & Cross et. al.(2004)	The density of a network is positively correlated with the learning-related work activity of the network in a dynamic complex environment.	supported
	HYPOTHESIS 3b	*The degree centralization of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	Freeman (1978) (Network Centralisation)	The degree centralisation of a network is negatively correlated with the learning-related work activity of the network in a dynamic complex environment.	supported
	HYPOTHESIS3 c	*The betweenness centralisation of a network is correlated with the learning-related work activity of the network in a dynamic complex environment.*	Freeman (1978) (Network Centralisation)	The betweenness centralisation of a network is negatively correlated with the learning-related work activity of the network in a dynamic complex environment.	supported

4.7. Conclusion

This chapter has presented results from the data analysis comprising descriptive statistics, tests of normality, inferential statistics consisting of Pearson's Product Moment correlations, partial correlations and independent sample t-tests for hypothesis testing, and multiple regression models to explain the best predictors for learning. In the next chapter, a discussion is provided to illuminate these outcomes in light of current theory and the social networks–learning literature.

CHAPTER 5

5. Synthesis: Social Networks and Learning in a Dynamic Complex Environment

The primary objective of this study is to understand the influence of social networks on learning in a dynamic complex environment in the context of emergency events. As stated in Chapter 2, the following research questions motivated this study: (1) How can learning in a dynamic complex environment be explored through the emergent patterns of social processes? How can it be evaluated? (2) What is the role of social networks in understanding learning in a dynamic complex environment? Why is the understanding of social network structure and position important for understanding learning in a dynamic complex environment? (3) Is there a relationship between the configuration of social network structures and learning in a dynamic complex environment? (4) How can the properties of social networks within various levels of relations among actors help in modelling the dynamics of learning?

In attempting to answer the above questions, this chapter is devoted to discussing and interpreting the results and outcomes in light of existing theory and within the context of disasters. In particular, the discussion is structured and driven by: (1) the actor-level social network hypotheses, which consider the influence of efficiency, constraint, degree centrality and betweenness centrality on individual learning, (2) the dyadic-level social network hypotheses, which consider the influence of strength of ties within and across teams on team learning, and (3) the network-level social network hypotheses, which consider the influence of density, degree centralisation and betweenness centralisation on network learning. Finally, the validity of the theoretical model is discussed as a whole, along with the major findings. Figure 5.1 displays an overview of this chapter.

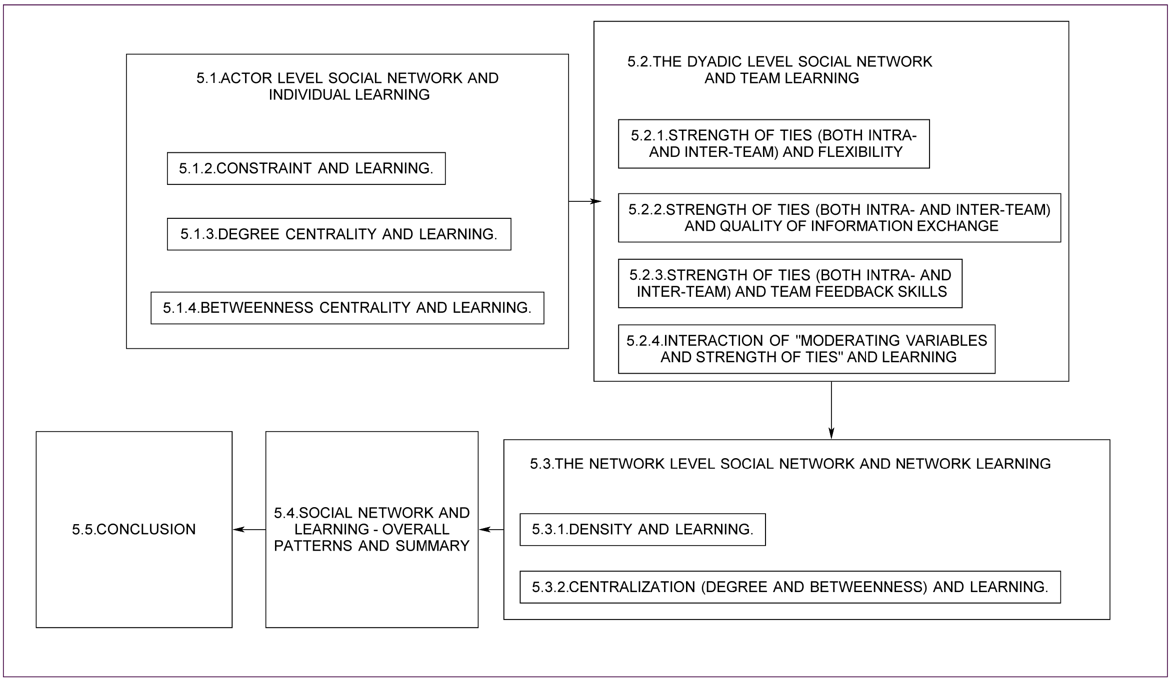


Figure 5.1: Overview of Chapter 5

5.1. Actor-level Social Network and Individual Learning

This section is devoted to discussing and interpreting the results and findings from the tests used to explore the relationship between actor-level social network and individual learning (as detailed in Chapter 4) in light of existing theories (as discussed in Chapter 2) and within the context of bushfires.

5.1.1. Efficiency and Learning

Previous research has claimed that ego-network measures of an actor's network position are powerful predictors of learning (Burt, 1992; Rosenthal, 1997; Aral et al., 2007). In particular, ego-network efficiency, the degree to which an individual acquires information and control benefits from non-redundant ties, is theorised as positively affecting learning.

Even though network efficiency appeared to be a significant predictor of learning (Aral et al., 2007), the findings from this research study show no support for this specific factor in the model. The correlation coefficients in Table 4.10, for example, are suggestive of the fact that there is no significant relationship between network efficiency and learning. This could be related to the fact that actors, such as emergency personnel, involved in a dynamic complex environment, are satisfied with their sources of information. It does not appear vital for such actors to be *efficient* in regard to obtaining information for the provision of a superior response. Unlike marketing employees, or real estate agents where the rivalry for information is expected to offer reasonable benefit so as to improve bonuses and income raises (Burt et al., 2000; Crowston et al., 2001; Burt, 2007), emergency personnel in dynamic complex environments such as bushfires have no such motivations and the nature of their occupation is non-competitive.

5.1.2. Constraint and Learning

On the other hand, constraint, the extent to which an actor lacks the opportunity to benefit from information and control benefits, is suggested to negatively impact learning. At the individual level, the outcomes from this investigation are fairly interesting, in that they question the concepts and assumptions from past studies and contribute to the few research studies of ego-network position and individual learning.

That said, attention now shifts to the significance of network *constraint*. An actor's network is extremely constrained to the degree that the actor seeks information from co-workers which lead back to the same individual. In the context of emergency personnel responding to bushfires, results show that constraint has a marginally detrimental effect on individual learning and adaptability. That is, higher the constraint for an individual emergency staff member, the lower the score for individual learning and adaptability *($r=-.274$, $p<.05$)*. A highly constrained professional network for an emergency staff member means that the emergency staff member seeks information from the network which leads back to the same individual. As a result, this may constrain the emergency staff member from learning novel ideas and interacting with diverse range of emergency staff members. A low constraint score of an emergency staff member indicates the ability to seek advice and information from non-redundant contacts.

With respect to individual learning and adaptability in a dynamic complex environment such as a bushfire, the finding of ego-network constraint being negatively associated with learning follows the literature (Rosenthal, 1997; Aral et al., 2007). Nevertheless, it was unexpected and thought-provoking to discover that network efficiency did not show the hypothesised correlation with learning and adaptability in a dynamic complex environment. It can therefore be claimed that while measures of ego-network position such as efficiency were established on the basis of theories of social competition, its effects on learning and adaptability might not be obviously revealed or valid in dynamic complex environments such as bushfires where individuals are working in a highly unstable environment. This obviously translates into an opportunity for further research with respect to the effects of ego-network efficiency and learning in dynamic complex domains.

5.1.3. Degree Centrality and Learning

The two factors which conceptualised ego-network structure in this research are ego-network degree and betweenness centrality. These theories are crucial and relevant to this research because traditional social network studies dating back to the work of Bavelas (1950) and Freeman (1978) related the significance of degree and betweenness centrality to better learning. The research question based on these ideas motivates the question of which centrality scores for actors are favourable to learning at the individual level. In terms of degree centrality, there was literally no association (negative or positive) with the learning-related work activity of an actor in a dynamic complex environment. These findings do not agree with the work of Cross and Cummings (2004), who found significant support for a connection between degree centrality and individual learning.

The present results reveal that, in a dynamic complex environment such as a bushfire, actors who are more central in the term of degree centrality (actors who have more connections) are not necessary able to learn and adapt to the extremely ambiguous environment. During such events, having more connections with other people can cause more pressure and stress to the actor under investigation and may harm the ability of that actor to respond effectively to the disaster. Moreover, during such extreme events, information seeking is intensified. Emergency personnel are required to process all the information received from all their connections and to send accurate and timely information to their links. Individuals with high degree centrality would find it difficult and nearly impossible to process such a high information load. It is recommended, therefore, that emergency personnel have a moderate number of connections in order to learn and adapt effectively to disasters. The results agree with the span of control concept underpinning AIIMS, where direct reporting complement of five personnel only is recommended.

Span of control is a notion that relates to the number of groups or persons that can be successfully managed by one individual. During emergency events, the environment in which supervision is required can quickly change and become hazardous if not managed efficiently. Up to five reporting groups or persons are considered to be necessary, as this maintains a supervisor's ability to efficiently monitor and assess performance. When that span of control is exceeded (high degree centrality), the supervising officer should consider delegating responsibility to others. On the other hand, when the span of control is lower or the responsibilities are less (for instance, in a de-escalating emergency event), the supervisor may reassume responsibility or reorganise the delegation to fit the tasks required.

The way in which AIIMS is "scalable" is that it does not necessitate a full-scale response to every emergency event; it permits the build-up of resources and response activity. For instance, a single floor house does not require an Incident Control Centre (i.e., control room) with seven individuals managing the incident. Nevertheless, the 2009 Victorian bushfires clearly required entire functional areas to be occupied by a separate person as other individuals filled the other roles which came under each functional area (e.g., Operations, Planning…). In these circumstances, a single individual would not be capable of managing the logistics/planning etc. alone, as would be expected in the single story fire (at least in the first instance).

5.1.4. Betweenness Centrality and Learning

Betweenness centrality revealed a significant positive association with respect to the learning-related work activity of an actor in a dynamic complex environment, the correlation coefficient for the association being $r=.236, p<.01$. Moreover, the t-tests also revealed a significant difference in the scores of learning-related work activity between the two independent centrality groups (high and low centrality groups) of emergency personnel. In particular, emergency personnel with higher betweenness centrality scored higher than those with lower betweenness centrality in terms of learning-related work activity. These findings resonate with those of Burt (1992), who argues that actors with high betweenness centrality and who bridge structural holes (the absence of ties among unconnected groups of people) are able to benefit in terms of job promotions, novel ideas and better learning. Specifically, betweenness centrality in a network established by awareness of one's fellows' capabilities should increase access to appropriate knowledge in distant areas of a network and so help emergency personnel to act efficiently and successfully when complex emergency events demand different information or expertise. Consensus can therefore be reached regarding betweenness centrality, in that it represents the extent of information control, which in turn is influential for learning-related work activity of an actor in a dynamic complex environment (Freeman, 1978).

5.2. Dyadic-level Social Network and Team Learning

This section is devoted to discussion and interpretation of the results and findings from the tests used to explore the relationship between dyadic-level social networks and team learning (as described in Chapter 4) in light of existing theories (as discussed in Chapter 2) and within the context of bushfires.

Firstly, this research hypothesised that strong ties within teams of emergency management would be positively associated with the learning-related work activity of a team in a dynamic complex environment. Starting with the theory on the strength of weak ties (Granovetter, 1973), arguments to express the hypothesis were formulated as to how strong ties link people who work frequently with each other (Granovetter, 1983). Additionally, it was argued that strong ties produce trust, which allows the reception of valuable knowledge (Reagans and McEvily, 2003; Levin and Cross, 2004) and that the effect level is conducive to learning (Krackhardt, 1992). In the following sections, discussion of the results is structured and driven by the measures of team learning (flexibility, the quality of information exchange, and team feedback skills)

5.2.1. Strength of Ties (both Intra- and Inter-team) and Flexibility

Using the framework of the research study, the results show support for Hypotheses 2a and 2b that stronger ties (both intra- and inter-team) are significantly associated with learning measured by team flexibility. On that basis, it can be argued that more investment in existing social relationships (both intra- and inter-team) will enable individuals and teams to know each other's roles and to broaden their knowledge of the work. This will enhance the ability of individuals and teams to adopt changing strategies which in time could improve their flexibility. Effective flexibility allows a team to deal successfully with the unexpected and to maintain regularly safe and effective service. As a result of this, individuals and teams will be more able to recover quickly and get on with the job when problems occur during emergency events, because of better networked relationships. As the situation changes during emergency events, improved working relationships may also cause roles to be effectively re-allocated and strategies to be adjusted in a timely manner, generating better learning and responses.

5.2.2. Strength of Ties (Both Intra- and Inter-team) and Quality of Information Exchange

As mentioned earlier, the results show that stronger ties (both intra- and inter-team) provide an ideal atmosphere for team members to exchange information effectively. This exchange implies improved access to information of better quality, which enables emergency staff members to perform their role better because of the information sharing that occurs. The better networked relationships (both intra- and inter-team) also lead to improved access to resources that would permit individuals and teams to exchange information accurately, clearly and in a timely manner. Effective information exchange helps team members to build and maintain their own situation awareness as well as to contribute to the team's understanding of the big picture. It can be said, on the basis of the results, that better networked relationships will motivate individuals and teams to share information and keep others informed about work-related issues. This will induce more attempts to share information and thus facilitate further learning.

5.2.3. Strength of Ties (Both Intra- and Inter-team) and Team Feedback Skills

Findings from this study also show that stronger ties (both intra- and inter-team) provide an ideal atmosphere for team members to provide helpful advice and constructive feedback to each other. Investing in existing social relationships can build trust and common shared knowledge (Bolton et al., 2008). This will encourage emergency staff members to provide constructive feedback to each other and to receive clearer direction in relation to the task at hand from the supervisor or officer in charge, which can facilitate team support learning-related work activities. With effective team feedback skills, the team can correct and prevent errors, resolve conflict and continuously improve performance. Moreover, better networked relationships allow members to foresee the information needs of others, support one another during extreme stress periods and avoid frustration and conflict. Thus it can be argued that when members and teams in an emergency network invest in existing relationships to strengthen their bond, inter-organisational dependency is supported through the development practices that support learning-related work activity. Therefore, the results support the main hypotheses that improved working relationships would have a positive effect on sharing, which may facilitate further learning and enhance the perceived state of readiness to interact with other personnel involved in emergency management.

5.2.4. Interaction of "Moderating Variables and Strength of Ties" and Learning

In relation to demographic and incident attributes and their effect on network ties, and learning-related work activity of a team in a dynamic complex environment, the hypotheses were categorised according to the demographic attributes of age, gender and level of experience, and according to types of incident. Although the results early in Chapter 4 showed that these variables have some effect on the perceived value of team learning, the findings from the regression model reveal the moderating variables "gender" and "types of incident" (all dummy variables, excluding the "other incidents" dummy variable) explain nothing of the variance (excluded from all models). As well, the results reveal that the moderating variables "age" and "types of incident" (the "other incidents" dummy variable) are significant but explain almost nothing of the variance (0.2% and 0.2%). Therefore, based on these results, the findings from this study reveal that the moderating variables have no effect on the perceived value of team learning.

5.3. Network-level Social Network and Network Learning

This section is devoted to discussing and interpreting results and findings from the tests used to explore the relationship between network-level social network factors and network learning (as described in Chapter 4) in light of existing theories (as discussed in Chapter 2), and within the context of bushfires.

5.3.1. Density and learning

The results suggests that emergency management personnel who are generally more integrated with their peers, that is, with denser networks, are more able to adapt appropriately to threats than those who were more isolated. In highly dense networks, individuals within the network have many links to others in the network and have access to many individuals from whom knowledge and information can be collected or to whom it can be distributed, both of which can be crucial in time of crisis. Having many links also makes the loss of single actors less disruptive. In conclusion, it can be argued that highly dense networks indicate that a high number of individuals know one another, which makes network members feel greater confidence in one another, and thus be more likely to provide enhanced access to information and the necessary support, benefiting the spread of information in times of crisis. Therefore better relationships are developed within the network, enhancing preparedness to respond to emergency events.

Networks with high density may also contribute to reinforcing the trust between individuals and groups and thereby also increase the potential for social control (Granovetter, 1985; Coleman, 1994). This control is important during emergency events as it decreases the risk and cost of collaborating with others, which is a fundamental requirement for collective action and coordination during such events (Burt, 2002). Moreover, it promotes the development of and compliance with shared norms with respect to what is recognised as satisfactory in relation to resource usage and extraction (Coleman, 1994).

It can be suggested from this finding that emergency managers should invest in existing relationships across teams to strengthen their bonds. This can be implemented by encouraging teamwork through formal and informal team-building activities. For example, an emergency manager can arrange an outing, such as bowling or mini-golf, or involve the office in a team-based charitable activity. These better networked relationships enhance flexibility and satisfaction with the quality of information flow by personnel engaged in emergency management, optimising emergency management network performance in unstable environments. Investing in existing social relationships can build trust and common shared knowledge, and can open the personnel to a potentially large number of feedback possibilities from the network. Such relationships can support learning-related work activity and the perceived state of readiness to interact with other personnel involved in emergency management.

5.3.2. Centralisation (Degree and Betweenness) and Learning

Another key finding from this study is that decentralised structures (in terms of both degree and betweenness) are far more conducive to enhanced performance and learning than centralised structures. A decentralised network structure can minimise the problems associated with a centralised structure of having a single point of vulnerability by modularising a centralised network into smaller stars connected with additional links. A decentralised structure provides a better opportunity for organisations to maintain self-reliance because emergency management personnel are adapted to working independently. This is essential in situations where an emergency manager is away from a site because of illness or another type of emergency. A decentralised network can also make decisions more quickly than one with a centralised structure which allows the organisation to react quickly to emergencies. An emergency manager usually can make a decision without having to wait for it to go up a chain of command, a feature that allows emergency agencies to react quickly to situations where fast action can mean saving lives. As well, networks in which a few actors have a high degree of centrality may induce increasingly centralised decision making, which in turn may have a negative influence on learning. This is because it reduces the access of emergency personnel to multiple sources of information, which are needed in time of crisis. Moreover, a decentralised network relieves some of the load of emergency managers when others are allowed to perform some tasks. Emergency managers can then spend more time on big-picture items and concentrate on the most important decisions.

A high degree of betweenness centrality of emergency personnel exposes a network to fragmentation should these individuals disappear. Social networks should usually have a certain degree of separation of groups in the network, which is essential to maintain variety. However, a high degree of separation among groups can weaken the development of trust, which is needed during emergency events for enhanced adaptation and response. As well, a very high degree of betweenness centralisation can promote grouping of people into "us" and "them", which accordingly leads to locking individuals in fixed political positions and restricting their capacity to act and seek agreement (Borgatti and Foster, 2003).

This finding contradicts the findings of Bavelas findings in the controlled laboratory experiment but conforms to the findings of Guetzkow and Simon (1955) that decentralised structures work better than centralised structures when tasks become more complex. Unlike the laboratory setup of those experiments, this study explores complex dynamic networks that evolve within a bushfire response. In such extreme and dynamic events, standard operating procedures cannot always be followed. These events require a dynamic coordinated system that can adapt to unanticipated and rapidly changing conditions. The complexity of tasks during a bushfire response imposes more constraints, such as information exchange, which brings further obstacles to the working environment during the task completion period. In such situations, tasks that are complex in nature cannot be handled effectively by an individual alone. The same is true when the central actors of any network structure are overwhelmed with many communications from the other actors in that structure.

5.4. Social Network and Learning – Overall Patterns and Summary

The emergent pattern of relationships among network and learning variables in this study is quite clear. Examining the actor-level variables closely, firstly, there is no significant association between the independent variables of network efficiency and degree centrality with the learning-related work activity of individuals in a dynamic complex environment (dependent variable). However, there is a significant association between the independent variables of network constraint and betweenness centrality and the learning-related work activity of individuals in a dynamic complex environment (dependent variable). In the post-hoc analyses that were undertaken after all hypotheses were tested, the following question was asked: “Among the independent actor-level variables, which variable best predicts learning-related work activity of individuals in dynamic complex environment?” The multiple regression model revealed two important predictors of individual learning: network constraint and betweenness centrality. Network constraint, however, explained 15.3% of the variance in individual learning as a whole, whereas betweenness centrality explained 4.7% of the variance in individual learning as a whole. Therefore, network constraint emerged as the most potent predictor of learning-related work activity of individuals in a dynamic complex environment.

For the dyadic-level analysis, learning-related work activity of teams is mainly attributed to stronger ties within and across teams of emergency management. Findings from this study show that stronger ties (both intra- and inter-team) provide an ideal atmosphere for team members to give each other helpful advice and constructive feedback. Investing in existing social relationships can build trust and common shared knowledge. This encourages emergency staff members to provide constructive feedback to each other and to receive clearer direction in relation to the task at hand from the supervisor or officer in charge. Therefore, investing in existing social relationships can facilitate team support learning-related work activities. Learning-related work activity of teams is also influenced by the age, gender and level of experience of respondents to the survey. As well, learning-related work activity of teams is similarly influenced by the type of incident. In the post-hoc analyses undertaken after all hypotheses were tested, the following question was postulated: “Among the independent dyadic-level variables, which variable best predicts learning-related work activity of teams in dynamic complex environment?” The stepwise multiple regression model revealed two important predictors for team learning: “strength of ties between team members” and “strength of ties between IMT and incident fire ground”. “Strength of ties between team members”, however, explained 83.7% of the variance in team learning as a whole, whereas “strength of ties between IMT and incident fire ground” explained 1.6% of the variance in team learning as a whole. Therefore, “strength of ties between team members” emerged as the most potent predictor for learning-related work activity of individuals in a dynamic complex environment.

For network-level analysis, learning-related work activity of the network is mainly attributed to network-level factors of density, degree centralisation and betweenness centralisation.

Results suggest that emergency management personnel who were generally more integrated with their peers, that is, with denser networks, were more able to adapt appropriately to threats than those who were more isolated. Another key finding from this study is that decentralised structures (in terms of both degree and betweenness) are far more conducive to performance and learning than centralised structures. Thus, the study advocates the importance of social networks at all level of analysis, as they can be useful and important indicators of learning-related work activity of individuals and teams in a dynamic complex environment.

5.5. Conclusion

This chapter has delivered a complete synthesis of existing theory and current outcomes from the study. It concludes that social network factors at all level of analysis (actor level, dyadic level and network level) are critical components of individual and group learning outcomes. The findings demonstrate that ego-network constraint is the single strongest predictor of individual learning. As well, this research demonstrated that strong ties within and across teams of emergency management are positively associated with the learning-related work activity of a team in a dynamic complex environment. These results are interpreted within the context of Australia's emergency incident management system. While most of this study's results confirm findings from past literature, the research also asks new questions and examines assumptions from earlier theory. The next chapter concludes the thesis by providing a complete summary of important outcomes, including implications for research and practice, future directions for research, and limitations of this research.

CHAPTER 6

6. Conclusion: Implications and Future Directions

In this concluding chapter, final notes are made about the main outcomes of this research in terms of theory, method and domain. In conclusion, the limitations of the research, along with implications for future research and practice, are presented. Figure 6.1 shows an overview of this chapter.

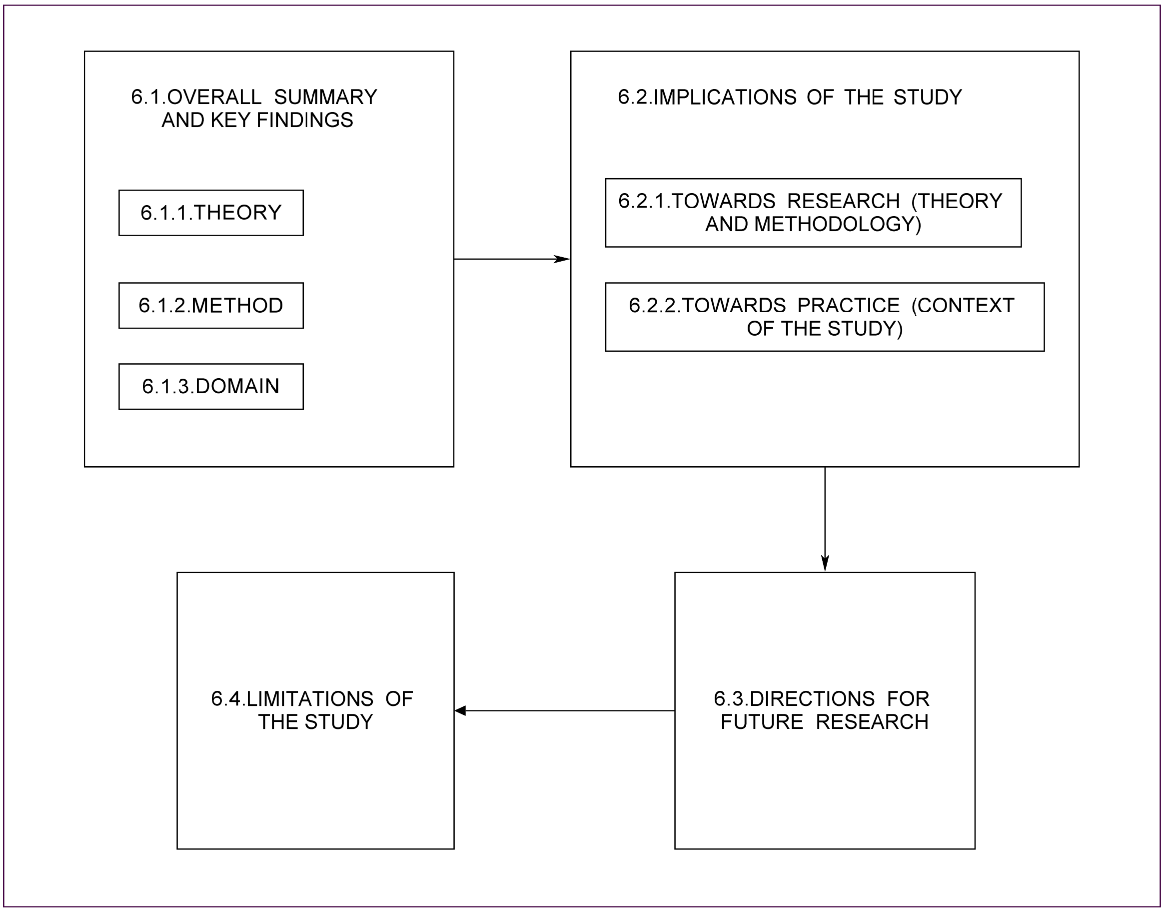


Figure 6.1: Overview of Chapter 6

6.1. Overall Summary and Key Findings

This thesis contributes to the growing literature on the relationship between social networks and learning. In summary, the key findings confirm evidence from network theory that social network factors play a vital role in learning at the three different levels of analysis (actor level, dyadic level and network level). The second key contribution of this thesis is addressing a major gap in the literature about understanding the social processes that influence learning in a dynamic complex environment.

Methodologically, this research presents a novel method that utilises both quantitative and qualitative approaches for conducting the study. The quantitative process comprises a non-traditional "networks" way of data collection and analysis as a suitable supplement to established research approaches in behavioural research studies. The study also utilises two different sources of data (survey and reports) which make the approach in this study unique. Overall, a crucial strength of the study is its methodology, which is reliable and validated with theoretical vigour.

Below is a short summary of key findings from the research, followed by a summarised overview in terms of theory, methods and domain:

- The constraint of an individual's network position is negatively associated with learning in a dynamic complex environment.

- Betweenness centrality is positively associated with individual learning in a dynamic complex environment.

- Strong ties within a team are positively associated with the learning of the team in a dynamic complex environment.

- Strong ties across teams are positively associated with the learning of teams in a dynamic complex environment.

- Relations between the strength of ties (within a team and across teams) and team learning are mediated by moderating variables of age, gender and experience of respondents and type of incident. This means that these demographic characteristics and the incident type can be used to predict the relation between strength of ties of team members and a bushfire team's perceived level of learning.

- The density of a network is positively associated with the learning-related work activity of a network in a dynamic environment.

- The degree centralisation of a network is positively associated with the learning-related work activity of the network in a dynamic environment.

- The betweenness centralisation of a network is positively associated with the learning-related work activity of the network in a dynamic environment.

6.1.1. Theory

The questions that currently challenge philosophical concepts of social networks at all level of analysis, and the impact of those networks on individual, team and network learning in a dynamic environment were addressed in Chapter 2. In particular, the key motivating question asked whether the learning process could be understood through the emergent patterns of social processes that constitute the learning process; that is, whether a relationship exists between the configuration of social network properties at all level of analysis (actor, dyadic and network levels), and learning at all levels of analysis (actor, dyadic and network levels). If such relationships exist, what is the role of social networks and to what extent do social networks that create social influence affect learning in a dynamic complex environment?

This research extends the classic work of Bavelas (1950) and Leavitt (1951), who began their laboratory controlled experiment with the following research question, "under what principles may a pattern of communication be determined that will in fact, be a fit one for effective and efficiency human effort?" There are two important differences between this study and that of the Bavelas-Leavitt experiment. Firstly, Bavelas and Leavitt explored relations between network structure and performance, with much emphasis on node centrality and network centralisation. This research, however, offers supplementary evidence of network position and ties and looks into their effect on learning and adaptability rather than on performance. Specifically, it empirically demonstrates that network constraint and betweenness centralities are the most potent predictors of individual learning. Further, the study indicates that strength of ties (within a team and across teams) is the most potent predictor of team learning. Moreover, the study shows that learning-related work activity of a network is mainly attributed to the network-level factors of density, degree centralisation and betweenness centralisation. While these findings have been separately examined in earlier studies at the group or organisational level, this study has tied network structural and positional concepts together to explain learning at the individual and team level. Secondly, observations of social processes that constituted the interactions were obtained from real-life settings of emergency personnel working in dynamic complex environments in the context of bushfires, rather than individuals working together in a controlled laboratory setting. The fact that data were gathered from these emergency personnel who worked in environments characterised by high uncertainty and ambiguity also serves as an important contribution to current literature, as most work to date has been carried out in traditional organisational settings such as corporate environments (Burt et al., 2000; Gabbay and Leenders, 2001; Burt, 2007). In this sense, the main outcome here is that the theories of social networks that were originally established to study the social structure of competition in traditional organisational environments are also valid and applicable to a large extent in the context of dynamic, complex, non-competitive environments such as emergency personnel responding to bushfires.

6.1.2. Method

In implementing and testing the conceptual model for this study, this research provides an analytical framework that moves beyond the traditional emphasis on the individual to a relational analysis. In many ways, it is a fundamental shift because it moves away from the typical "behavioural research" method, which links individual attributes to individual outcomes, to a "network perspective" method that uses individual relations to explain individual and group outcomes. That said, network analysis is still a basic field in terms of methodology, given the absence of training in the majority of disciplines and the absence of large experimental projects that span more than a year. Within network analysis methods there is a range of methods to collect relational data, with most being sociocentric, a few egocentric. Even then, there are very few conducted within a triangulation method.

In this research, a triangulation approach that involves both qualitative and quantitative techniques is implemented. The study also utilises two different sources of data (survey and reports), making the approach in this study unique. Chapter 3 describe the process of collecting network and attribute data for exploring the relationship between social network factors and learning in a dynamic complex environment. Firstly, a theoretical model was established in combination with field experts and based on the review of literature. Using current surveys, appropriate item sets were then developed for measuring different independent (network structure) and dependent variables (learning). Moreover, this study developed a new way to measure actor-level learning. To measure individual learning, researchers need to monitor the individual under study over time and see whether he or she is adapting over time. It should be noted that the approach itself is replicable, in that it provides a broader and more useful way of thinking about and conducting studies of individual behaviour and its consequences on learning. These features therefore form the greatest strength of the methodology.

6.1.3. Domain

At the domain level, the main incentive for considering emergency personnel involved in responding to bushfires as the context for the study derives the systematic review of studies and reports which showed that failure in emergency incident management coordination and learning in major events has long been recognised at both national and international levels. In extreme events, breakdowns of information flow and, in particular, breakdowns of coordination are common and always problematic. The findings from this study show the need not just to focus on producing different standard operating procedures. This study shows that, in devastating events, communication and coordination break down and fracture. Emergency personnel and emergency management organisations that do not learn from previous mistakes and lack sufficient capacity for self-adaptation make similar mistakes that increase their vulnerability to emergency events. This study seeks to better understand how multi-agency emergency management learning and coordination can be improved in order to reduce the consequences of the emergency event for communities.

6.2. Implications of the Study

This section discusses the implications of the study for research and practice.

6.2.1. Towards Research (Theory and Methodology)

This research has made numerous contributions in terms of theory. It has:

1. Utilised a social network perspective to understand individual, team and network learning in a dynamic complex environment.

2. Developed a conceptual model to explore the associations between social network factors at three levels of analysis (actor, dyadic and network levels) and learning within a dynamic complex environment.

3. Extended traditional theory of social networks and learning within the micro and individual level:

a. to include emergency incident organisations and individuals involved in disasters.

b. to explain the relationship between social network structure and learning by examining patterns of learning

4. Extended the social influence model of learning by showing how social network factors at all level of analysis (actor, dyadic and network levels) can be used empirically to measure and validate major constructs of the sociological component of the social influence model.

5. Demonstrated how the research model could be operationalised in the context of Australia's emergency incident management system. It is also the first study in Australia to measure learning for social network communication.

Studies of the associations between social networks and learning at group and individual levels have been largely based on organisations within a routine and stable environment. Few studies have been devoted to studying organisations in a dynamic environment context where agents must adapt to new situations and overcome possibly unpredictable obstacles (problems). This study contributes to the theory of social networks as applied at the micro level within the context of Australia's emergency incident management system. As emergency events entail a particular form of environment, empirical literature informing the social network's research community and its effects on learning in such environments are still rare.

Most social network studies have neglected the importance of learning that extends traditional network ties. This study includes learning as an important variable because of its primary and secondary effects on people and organisations. Much learning literature has proved this empirically. The secondary effect of learning is its sociological component, in that it allows people to overcome various boundaries of time, space, and organisation hierarchy.

6.2.2. Towards Practice (Context of the Study)

In terms of practice, this research informs emergency staff members involved in dynamic complex environments such as bushfires about the importance of peer-to-peer support, which is crucial to learning. From the survey data and the data from the transcripts of the 2009 Victorian Bushfires Royal Commission Report, the implication is clear that although personal characteristics such as professional experience, age, education and professional accreditations are important, one cannot discount the importance of social networks when it comes to learning.

From a social network perspective, it should be important to highlight the fact that emergency personnel who always seek advice from similar contacts (who also interact with their same contacts, and so on) within their own network are most likely to suffer from high information redundancy, and consequently a highly constrained network. As Burt (2004) demonstrates, high constraint is negatively geared towards learning, and in this study, constraint is also negatively linked to individual learning. As a result, a fine balance needs to be struck between large network size and the redundancy of ties. Preferably, connections with many valuable but non-redundant sources of information from different groups would contribute to better learning.

At this point, caution is needed in interpreting the implications of the outcomes for general practice. The implications stated are not necessarily reflective of the entire population of emergency personnel in Australia or around the world, but they are at least worthy of consideration within the context of the survey and the bushfire cases in this study. The level to which these implications may be generalised is considered in the discussion of limitations at the end of this chapter.

6.3. Directions for Future Research

This research builds upon the work of Moynihan (2008) and Brower et al. (2009), who seek to understand the interplay between social networks and learning in a dynamic complex environment. This understanding is useful in informing inter-disciplinary studies and practitioners and suggesting enhanced learning or optimal learning from a social network perspective.

As indicated earlier, in further research it would be valuable to conduct a new survey to investigate the emergency management organisational network from a social network perspective. Additional network analysis, such as exponential random graph modelling and clique analyses, could then be performed, offering a richer picture for the understanding of network and learning patterns.

The social network part of this study considers a snapshot in time about connections of a specific node at a specific time. The communication and movement of information through these connections suggests a unique idea. As time passes, connections progress and social networks evolve. Longitudinal research studies, gathering information on how these nodes initiate their network and how social network factors at all level of analysis (actor, dyadic and network levels) change over time, would definitely serve as a valuable complement to this research. Learning attitudes and, more importantly, the relationship between the learning variables and the network variables can be compared to establish changes in relationship patterns over time.

As an area for future research, it would be valuable to examine how technology and social media are used surrounding these events, and use them to collect social network data. It would be interesting to compare and contrast how the behaviour evidenced in the use of electronic communication media differs from that found with more traditional data collection methods. Social media like Facebook and Twitter can be used to engage, understand and profile the community and understand community expectations. The use of social media has proved crucial in times of disasters (Hiltz and Gonzalez, 2012), and traditional public media releases are becoming outdated. The world is changing in terms of expectations, climate change, high frequency and intensity of emergency events and high flow of information. Future research needs to address this new world with a new way of thinking and seize this opportunity by addressing social media.

Another valuable task for further research would be to apply the existing theoretical model in the context of another domain, preferably within a domain of unstable environment. For example, the model could be applied to disease outbreaks, to explore the elements of social networks that might affect learning. It would be exciting to test the model and see whether it is vigorous enough to produce analogous or different outcomes in other fields.

As an area of further research, it would be also valuable to analyze the emergency management network using the *Exponential Random Graph Model (ERGM)* technique. Exponential random graph (p*) models are probabilistic models that can effectively identify structural properties in social networks (Wasserman and Pattison, 1996; Lugano et al., 2006). This technique simplifies a complex structure down to a combination of basic parameters, and has many advantages. It is very general and scalable, because the architecture of the graph is represented by locally determined explanatory variables. As well, the choice of explanatory variables is quite flexible and can be easily revised. This theory-driven modelling approach also permits testing of the significance of structural parameters. The disadvantages of the approach include difficulty in estimating the execution time, complex interpretations when multiple parameters are considered, and sometimes difficulty in achieving convergence. Although most of the studies about ERG focus on building the theory of ERG models, recently researchers have applied ERG models in practice, such as, for understanding whether external connections beyond the department are important to the understanding of the departmental structure of an Australian Government Organization (Robins et al., 2004), to explore the dynamics of biological networks (Saul and Filkov, 2007), to examine what type of micro-level structures among physicians affect hospitalization cost and hospital readmission rate (Uddin et al., 2013), and to examine the communication dynamics of networks under stress (Hamra et al., 2011; Uddin et al., 2011).

The general form of the class of (homogeneous) exponential random graph models is as follows (Robins et al., 2007b):

$\Pr(X = x) = (1/\kappa) \exp\{\Sigma A \eta A g A(x)\}$tuo

where:

(i) the summation is over configuration types A; different sets of configuration types represent different models (e.g. dyadic independence or Markov random graph);

(ii) ηA is the parameter corresponding to the configuration of type A;

(iii) $gA(x)$ is the network statistic corresponding to configuration A (for homogeneous Markov graph models this is the number of configurations of type A observed in the network: for example, the number of triangles);

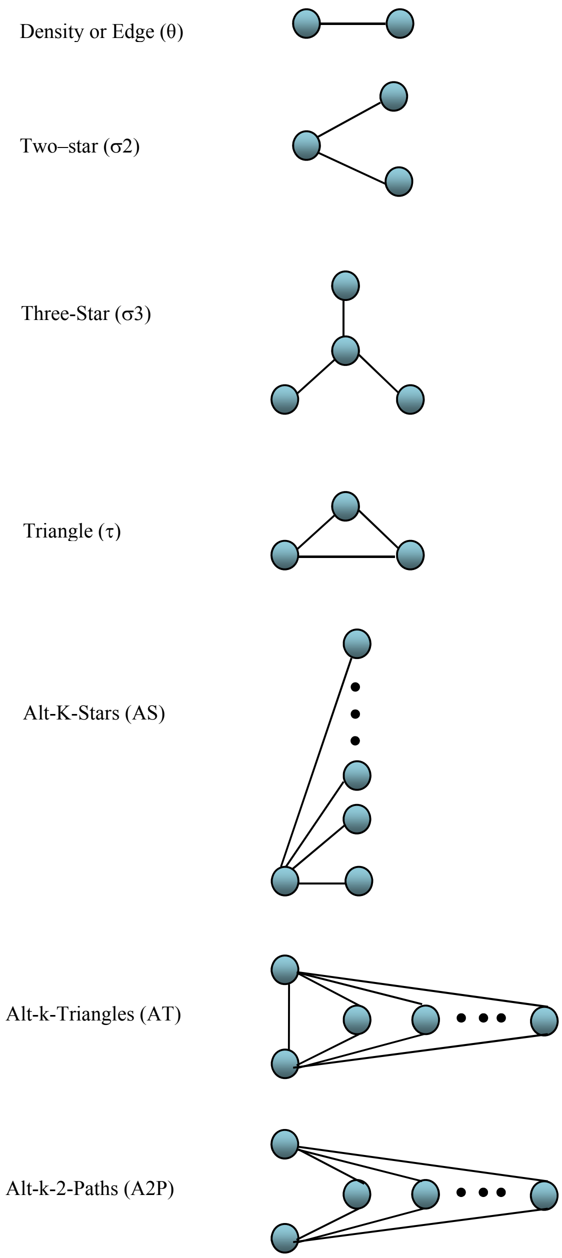
(iv) κ is a normalising quantity to ensure that (1) is a proper probability distribution.

The model presents a probability distribution of graphs on a fixed node set, where the probability of observing a graph is dependent on the presence of the various parameters expressed by the model. The structure of a typical graph in this distribution can be explained as the result of a combination of these particular local configurations. With suitable constraints on the number of configurations, it is possible to estimate parameters for a given observed network. The parameters then provide information about the presence of structural effects observed in the network data (Robins et al., 2007b).

For example, an ERGM for a non-directed network with edge, two-star, three-star and triangle effect is:

$\Pr(X=x) = (1/\kappa) \exp \{\theta L(x) + \sigma 2 S2(x) + \sigma 3 S3(x) + \tau T (x)\}$

where θ is the density or edge parameter and $L(x)$ refers to the number of edges inside the graph x; σk and $Sk(x)$ refer to the parameter associated with k-star effects and the number of k-stars in x; while τ and $T(x)$ refer to the parameter for triangles and the number of triangles, respectively (Robins et al., 2007a).



and other higher order configurations

Figure 6.2: Configurations and parameters for Exponentials Random Graph Models. From Robins Pattison, Kalish and Lusher 2007, p. 28.

In modelling emergency management networks against their perceived level of learning and adaptability, the ERGM technique may be applied in order to find out which micro-structures of Figure 6.2 are favourable to effective learning outcomes. For example, after applying ERGM technique to an emergency management network showing better learning, it could be revealed that edge and three-star micro structures would best represent that network. If similar outcomes are found for other effective emergency management networks, then it is suggested that emergency managers or administrators develop an emergency management culture that produces such effective and efficient networks having more edges and three-star micro structures.

Finally, another path for further research could be to obtain direct measures of learning at the domain level if possible and to subject the existing theoretical model to further empirical testing. It would be interesting to compare the differences obtained from the current study and the one proposed.

6.4. Limitations of the Study

As with most research studies, there are several limitations to this research which need to be recognised. The first limitation concerns the degree of generalisability of the results. As it is a triangulation study, one can argue that the quantitative component of the research study has collected 579 responses from individuals working within emergency organisations across Australia and New Zealand. The primary concern in this study is that the sample is not generalisable to the whole population of staff involved in emergency management. For this reason, various difficulties arose in terms of conducting additional advanced multivariate statistical analyses. Although the current sample size just about meets the requirements for the stepwise multiple regression, a normal rule of thumb as identified by Tabachnick and Fidell (2001) is to use the following formula to calculate sample size (N) requirements, taking into account the number of independent variables: $N > 50 + 8m$ (where m = number of independent variables). So for two independent variables, 66 cases are needed. This is a likely limitation for nearly all quantitative research studies (Burns, 2000). Steps were taken to try and attempt to diminish this likelihood with the 2008 survey but the findings should still be considered with this potential limitation in mind.

The second issue relating to generalisability is that the domain of this study is quite special and unique, in that emergency management personnel are working in a highly unstable, ambiguous, dynamic complex environment. This environment is thus quite different from other environments as found in organisations such as large corporations, small enterprises and so on. As such, answering the question of generalisability of the results to other areas becomes reasonably difficult. As indicated earlier in the implications of the research section, the outcomes are interpreted with caution and within the context of emergency management personnel working in bushfire, as this is the domain within which the theoretical model was tested. In the further research section above it is suggested that the model be verified in other areas, preferably those that share characteristics of uncertainty and unstable environments, while retaining the theoretical motivations and approaches for data collection and analysis.

It must be appreciated that survey respondents were asked to remember occasions that in some cases might have happened much earlier. Moreover, as in most self-completion surveys, the responses might be prejudiced through the memory and the motivations of individuals who took the time to complete it. From this perspective, it is significant to evaluate the outcomes carefully and to reflect on the directions they might indicate for extra research validation. Finally, given the scope of this research study, it was a bonus to be able to obtain access to emergency personnel practices across several areas, especially noting the fact that emergency personnel in Australia are extremely hard-pressed for time, dealing with much more complex problems than other individuals working in a stable environment, and are much more pressured at work. It is hoped that the qualitative and quantitative outcomes stir up new discussions and debates and produce new questions that would lead to better understanding of the relationship between social networks and individual and group outcomes. It is important to restate at this point that the suggested model of this research was predictive in nature, not causal, and that it does have some explanatory influence through the tests of association and correlations. In other words, the aim was not to explain all of the variance that accounted for learning, but to explore theoretical propositions that social network factors at all level of analysis (actor, dyadic and network levels) are significant sociological constructs which contribute to improved learning. In effect, the relationships were explored, although the study greatly emphasised the social network perspective. It is surely reasonable that other perspectives might be used to understand learning in a dynamic complex environment; an example of which could be to focus on specific models of organisation that individuals use in dynamic complex environments, given the uniqueness of their work context.

7. References

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Appendix A (AIIMS National Survey-2008)

AIIMS National Questionnaire

AIIMS National Questionnaire-2008

The Bushfire Co-operative Research Centre (BCRC) is working in partnership with the University of Tasmania, to conduct a four year study examining teamwork and co-ordination issues in incident management.

The research study is endorsed by the Australasian Fire Authorities Council (AFAC) / Australian Inter-service Incident Management System (AIIMS) Steering Committee. The research study has the AFAC AIIMS Steering committee as its Critical Reference Group. The results of this questionnaire will be reported to that group with, if necessary, areas the Committee may consider for strategic development.

Your involvement in completing the questionnaire will provide important feedback about key aspects of incident management. Please take the time to complete it as accurately as possible, and also take the opportunity to provide written comments where the questions or statements have not allowed you to describe your experiences as clearly as you would like.

Attached to this email should be an information sheet explaining how the questionnaire data will be processed and stored to ensure confidentiality, in compliance with Human Research Ethics procedures. Also attached should be an AIIMS Questionnaire Instructions and Background document. It may be helpful to print this out before proceeding as it will provide you with definitions and other guidance. If you do not have a copy of the Ethics information sheet or Instruction/Background document, please request it from the person within your agency that sent you this email, or alternatively, contact Christine Owen at Christine.Owen@utas.edu.au or phone 03 6226 2555.

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Section 1: Overview

In this section you are asked to provide details about the last major incident you were involved in.

1.1 Where did this incident occur?

- [ ] TAS
- [ ] VIC
- [ ] NSW
- [ ] SA
- [ ] WA
- [ ] ACT
- [ ] NT
- [ ] QLD

1.2 What name/number was given to this event/incident?

- [ ] Can't answer

Name/number

1.3 In which year(s) did this incident occur?

1.4 Was this incident predominately...?
(please tick as many as apply)

- [ ] Grass fire
- [ ] Forest/scrub fire
- [ ] Fire at rural/urban interface
- [ ] Structure fire
- [ ] Structural collapse
- [ ] Hazardous materials
- [ ] Transport (e.g. train, ship)
- [ ] Industrial Rescue
- [ ] Road Rescue
- [ ] Cyclone
- [ ] Flood

Other (please specify)

1.5 How long was the incident going before you attended?

1.6 How long did the incident last?

1.7 Which agencies or groups, other than your own, were involved in the incident? (please tick as many as apply)

	Primary Role	Supporting Role
No other agencies involved	☐	☐
Ambulance	☐	☐
First aid	☐	☐
Fire Local Government	☐	☐
Military	☐	☐
Police	☐	☐
State Emergency Services	☐	☐
Gas or electrical utilities	☐	☐
Technical specialist	☐	☐
Transport companies/agents	☐	☐
Road authority	☐	☐
Water utilities	☐	☐
Port authority	☐	☐
Coroner	☐	☐
Industry based fire service	☐	☐
Aviation	☐	☐
Welfare	☐	☐
Private forestry company	☐	☐
Land management agency	☐	☐
Bureau of Meteorology	☐	☐

Other (please specify)

1.8 Approximately how many people at peak, were involved in the incident when you were in attendance?

☐ Can't answer

Number of people

1.9 What was threatened by this incident? (please tick as many as apply)

- [ ] Life
- [ ] Homes
- [ ] High Rise Structures
- [ ] Commercial Structures
- [ ] Other Structures
- [ ] Forest/Crops/Pastures
- [ ] Waterways
- [ ] Environmental Values
- [ ] Live Stock & Fences
- [ ] Gas
- [ ] Electricity

Other (please specify)

1.10 On a scale of 1 to 7, what level of COMPLEXITY do you think the incident was?

	1 (low)	2	3	4	5	6	7 (high)	can't answer
Complexity of the incident	○	○	○	○	○	○	○	○

1.11 What level was this incident/alarm? (please answer one)

Incident (i.e. ICS level 1,2 or 3)

Alarm

If alarm please indicate....

Agency

Brigade

ARRIVING AT THE INCIDENT

1.12 Prior to your arrival at the incident, were you advised as to the role you predominately performed, or any other role you initially would be performing?

☐ Yes

☐ No

If NO, why were you not advised?

If YES, what role were you advised to perform?

Role:

1.13 Upon arrival, did you perform the role you were advised you would be performing?

☐ Yes

☐ No

If NO, why were you not advised?

1.14 What role did you predominately perform during the incident?

1.15 On a scale of 1 to 7, how ADEQUATE was the information provided to you to perform that role?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Adequacy of information	○	○	○	○	○	○	○	○

1.16 On your arrival, did you report to someone?

- [ ] Yes
- [ ] No

If NO, why not? (then go the question 1.8)

1.17 Did you report to the...?

- [ ] Incident Coordination Centre (State or Regional)
- [ ] Incident Control Centre
- [ ] Staging Area
- [ ] Forward Control Point/Post
- [ ] Directly to Fire Ground or Incident Ground
- [ ] Base Camp
- [ ] Accommodation

Other (please specify)

1.18 Prior to your arrival at the incident was it made clear who you were to report to? (If NO, go to Section 2)

- [ ] Yes
- [ ] No

1.19 On your arrival, were you ABLE to report to this person?

- [ ] Yes
- [ ] No

If NO, why not?

Section 2: Area of Responsibility

In this section you are asked to think about a specific shift during the incident detailed in 'Section 1: Overview'. Please answer the following questions about that shift only.

2.1 In which phase of the incident was this shift?

- ☐ Beginning
- ☐ Escalation (if applicable)
- ☐ Middle
- ☐ Mop up
- ☐ Recovery

ON ARRIVAL AT THE SHIFT

2.2 Did you give a briefing?

- ☐ Yes
- ☐ No

2.3 Were you given a briefing? (If NO, go to question 2.9)

- ☐ Yes
- ☐ No

2.4 Was there an opportunity to ask questions?

- ☐ Yes
- ☐ No

2.5 On a scale of 1 to 7, to what extent do you think your input was VALUED?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Extent to which your input was valued	○	○	○	○	○	○	○	○

2.6 On a scale of 1 to 7, how COMFORTABLE were you in asking questions for clarification?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Level of comfort in asking questions	○	○	○	○	○	○	○	○

2.7 Did the briefing...?
(please tick as many as apply)

- [ ] Explain what had happened
- [ ] Explain the current situation
- [ ] Outline the objectives, strategies and rationale
- [ ] Identify current and expected resourcing at the incident
- [ ] Identify alternative strategies
- [ ] Identify economic, social, public health and environmental risks
- [ ] Identify key operation points (e.g. Helibase, Staging Area, Forward Control)
- [ ] Identify the boundaries of Sectors and Divisions
- [ ] Outline the chain of command including personnel in the IMT
- [ ] Identify the location of IMT personnel
- [ ] Provide information on the communications plan
- [ ] Identify OH&S issues
- [ ] Define shift times
- [ ] Utilise a SMEACS Format

Other (please specify)

2.8 On a scale of 1 to 7, how USEFUL was the information provided by the briefing for you to do your job?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Usefulness of information	○	○	○	○	○	○	○	○

2.9 Did you receive an Incident Action Plan?

- [ ] Yes
- [ ] No

If NO, why not? (then go to 2.15)

2.10 Was your Incident Action Plan written or verbal?

- [ ] Written
- [ ] Verbal

2.11 When did you receive the Incident Action Plan?

- [ ] Prior to arriving at the incident
- [ ] At the briefing
- [ ] Sometime during the shift
- [ ] After the shift
- [ ] Can't remember

2.12 Did the Incident Action Plan include ...? (please tick as many as apply)

- [ ] The overall objectives
- [ ] Strategies for each division and/or sector
- [ ] Information on alternative or fallback strategies
- [ ] The resources allocated to each sector or division
- [ ] A map or site plan of the incident location
- [ ] A medical plan
- [ ] Information and contact details for all the agencies involved
- [ ] A communications plan
- [ ] Predictions of the incidents development
- [ ] An organisational chart
- [ ] Safety considerations

Other (please specify)

2.13 On a scale of 1 to 7, where 1 = poor and 7 = excellent, please rate each of the following in relation to the INCIDENT ACTION PLAN.

	1 (poor)	2	3	4	5	6	7 (excellent)	can't answer
Accuracy	○	○	○	○	○	○	○	○
Timeliness	○	○	○	○	○	○	○	○
Relevancy	○	○	○	○	○	○	○	○
Completeness	○	○	○	○	○	○	○	○
Conciseness	○	○	○	○	○	○	○	○

2.14 On a scale of 1 to 7, how WELL did the Incident Action Plan support the incident objectives?

	1 (poor)	2	3	4	5	6	7 (excellent)	can't answer
Incident Action Plan support of objectives	○	○	○	○	○	○	○	○

Give reasons why, during your shift, the Incident Action Plan did or did not support the objectives.

DURING THE SHIFT

2.15 At most, how many people reported directly to you at any one time (give an approximation if uncertain)?

2.16 Was it clear to whom you were reporting?

- [ ] Yes
- [ ] No

2.17 Were there any factors that prevented you from doing your job?

- [ ] Yes
- [ ] No

If YES, what were these factors?

2.18 On a scale of 1 to 7, to what EXTENT did the communication plans/arrangements enable you to do your job effectively?

	1 (minimal)	2	3	4	5	6	7 (great)	can't answer
Effectiveness of communication plans/arrangements	○	○	○	○	○	○	○	○

2.19 On a scale of 1 to 7, how ADEQUATE were the resources?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Adequacy of resources	○	○	○	○	○	○	○	○

2.20 On a scale of 1 to 7, how CONFIDENT were you that all resources (people and equipment) were accounted for in the resource management system for this incident?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Confidence in resources being accounted for	○	○	○	○	○	○	○	○

2.21 Was there a formal process to identify potential safety issues at this incident?

☐ Yes

☐ No

☐ Can't answer

2.22 Were potential safety issues identified at this incident? (if NO or CAN'T ANSWER, go to question 2.24)

☐ Yes

☐ No

☐ Can't answer

2.23 On a scale of 1 to 7, how ADEQUATELY were you able to address potential safety issues?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Adequacy of addressing potential safety issues	○	○	○	○	○	○	○	○

2.24 On a scale of 1 to 7, how physically SAFE did you feel at this incident?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Physical safety at the incident	○	○	○	○	○	○	○	○

2.25 On a scale of 1 to 7, how psychologically SAFE did you feel at this incident?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Psychological safety at the incident	○	○	○	○	○	○	○	○

2.26 Which of the following risk management tools were AVAILABLE to you at this incident? (please tick as many as apply)

- ☐ Incident Resource Management System
- ☐ Radio repeaters
- ☐ Pro forma briefing checklists
- ☐ Pro forma action checklists
- ☐ Aide memoirs (e.g. watchouts, SMEACS)
- ☐ Deployment of safety officers
- ☐ Immediate feedback from shift change debriefs
- ☐ Use of mentors
- ☐ Deployment of mobile weather station or specialist
- ☐ Access to technical data bases
- ☐ Deployment of technical or industry specialists

Other (please specify)

2.27 During this incident did you work within the Incident Management Team? (If NO, go to question 2.31)

- ☐ Yes
- ☐ No

2.28 Within the Incident Management Team, who was primarily responsible for collating and reporting on progress in implementing the current Incident Action Plan?

- [ ] Incident Controller
- [ ] Deputy Controller
- [ ] Planning Officer
- [ ] Logistics Officer
- [ ] Operations Officer
- [ ] Other
- [ ] Can't answer

2.29 On a scale of 1 to 7, how WELL did the Incident Management Team work?

	1 (not at all)	2	3	4	5	6	7 (very)	can't answer
Incident management Team	○	○	○	○	○	○	○	○

2.30 Were technical specialists used at the incident?

- [ ] Yes
- [ ] No

If YES, what was their area of expertise?

2.31 Did you brief the person that replaced you?

○ Yes

○ No

○ Not applicable (end of shift)

2.32 On a scale of 1 to 7 where 1= low and 7= high, how would you RATE THE FOLLOWING ISSUES in enabling you to do your job on your shift?

	1 (low)	2	3	4	5	6	7 (high)	can't answer
1. Proficiency of personnel	○	○	○	○	○	○	○	○
2. Confidence of the team	○	○	○	○	○	○	○	○
3. Accuracy of information	○	○	○	○	○	○	○	○
4. Timeliness of information	○	○	○	○	○	○	○	○
5. Completeness of information	○	○	○	○	○	○	○	○
6. Relevancy of information	○	○	○	○	○	○	○	○
7. Computer equipment	○	○	○	○	○	○	○	○
8. Phone equipment	○	○	○	○	○	○	○	○
9. Radio equipment	○	○	○	○	○	○	○	○
10. GIS equipment	○	○	○	○	○	○	○	○
11. Critical incident stress debriefing	○	○	○	○	○	○	○	○
12. Appropriateness of food and drink	○	○	○	○	○	○	○	○
13. Sleeping arrangements	○	○	○	○	○	○	○	○
14. Ablution (toilet, shower facilities)	○	○	○	○	○	○	○	○

SUMMARY OF SHIFT

2.33 On a scale of 1 to 7, where 1 = strongly disagree and 7 = strongly agree, please indicate your LEVEL OF AGREEMENT with each of the following statements.

	1 (strongly disagree)	2	3	4	5	6	7 (strongly agree)	can't answer
1. I felt capable undertaking the role and tasks assigned to me.	○	○	○	○	○	○	○	○
2. I felt I made a positive contribution to the work done during the shift.	○	○	○	○	○	○	○	○
3. Overall, personnel on the Fire/Incident Ground performed well during the shift.	○	○	○	○	○	○	○	○
4. Overall, the needs and welfare of all personnel were well catered for.	○	○	○	○	○	○	○	○

Section 3: Teamwork

The questions in this section relate to teamwork during the incident described in 'Section 1: Overview'. Please think about the people you worked most closely with in that incident and answer the following questions.

3.1 Which of the following best describes the TEAM of people you worked with most closely during the incident?

- [ ] State level Coordination Centre Team
- [ ] Regional level Coordination Centre Team
- [ ] Incident Management Team
- [ ] Functional Unit within an Incident Management Team
- [ ] Division or Sector Team
- [ ] Crew Team
- [ ] Strike Team

3.2 On a scale of 1 to 7 where 1 = strongly disagree and 7 = strongly agree, please indicate your LEVEL OF AGREEMENT with each of the following statements.

	1 (strongly disagree)	2	3	4	5	6	7 (strongly agree)	can't answer
1. Team members exchanged information clearly.	○	○	○	○	○	○	○	○
2. Team members exchanged information accurately.	○	○	○	○	○	○	○	○
3. Team members provided helpful advice to each other.	○	○	○	○	○	○	○	○
4. Team members provided constructive feedback to each other.	○	○	○	○	○	○	○	○
5. Team members effectively monitored each other's performance.	○	○	○	○	○	○	○	○
6. Team members exhibited a strong 'we are in this together' attitude.	○	○	○	○	○	○	○	○
7. Team members operated in an open and honest manner.	○	○	○	○	○	○	○	○
8. Team members kept each other well informed about work-related issues.	○	○	○	○	○	○	○	○
9. There were genuine attempts to share information.	○	○	○	○	○	○	○	○
10. Team members shared their individual knowledge to gain a better understanding of the situation at hand.	○	○	○	○	○	○	○	○
11. Team members were able to state and maintain opinions openly.	○	○	○	○	○	○	○	○
12. Team members had the majority of skills needed to effectively perform their respective roles.	○	○	○	○	○	○	○	○
13. Strategies were adjusted in a timely manner as the incident unfolded.	○	○	○	○	○	○	○	○
14. Team members anticipated the needs of others.	○	○	○	○	○	○	○	○

On a scale of 1 to 7 where 1 = strongly disagree and 7 = strongly agree, please continue to indicate your LEVEL OF AGREEMENT with each of the following statements.

	1 (strongly disagree)	2	3	4	5	6	7 (strongly agree)	can't answer
15. Roles were effectively re-allocated as the situation changed.	○	○	○	○	○	○	○	○
16. Team members interacted effectively with stakeholders outside their own team.	○	○	○	○	○	○	○	○
17. Team members had a clear and common purpose for the incident at hand.	○	○	○	○	○	○	○	○
18. Team members trusted each other.	○	○	○	○	○	○	○	○
19. New team members were quickly integrated into the team.	○	○	○	○	○	○	○	○
20. Team members co-ordinated their activities to achieve the best possible outcome.	○	○	○	○	○	○	○	○
21. Team members received clear direction in relation to the tasks at hand from the officer in charge or supervisor.	○	○	○	○	○	○	○	○
22. We effectively achieved our tasks.	○	○	○	○	○	○	○	○
23. The transport arrangements were effective.	○	○	○	○	○	○	○	○
24. The IMT was 'ahead of the game'.	○	○	○	○	○	○	○	○
25. The IMT was consistently playing 'catch up'.	○	○	○	○	○	○	○	○
26. We deliberately sought local expertise.	○	○	○	○	○	○	○	○
27. There were effective provisions used to control fatigue.	○	○	○	○	○	○	○	○
28. The changeover arrangements were effective.	○	○	○	○	○	○	○	○
29. On the fire ground there were too many 'hurry up and wait' type situations.	○	○	○	○	○	○	○	○
30. I felt comfortable approaching members of this team for help if I needed it.	○	○	○	○	○	○	○	○
31. When problems occurred the team was able to recover quickly and get on with the job.	○	○	○	○	○	○	○	○

3.3 On a scale of 1 to 7 where 1= no discussion and 7= regular discussion, to what degree did the team constructively discuss the following potential weaknesses.

	1 (no discussion)	2	3	4	5	6	7 (regular discussion)	8 (can't answer)
Lack of knowledge.	○	○	○	○	○	○	○	○
No continuity of strategic thinking from team to team.	○	○	○	○	○	○	○	○
Unclear information.	○	○	○	○	○	○	○	○
Lack of resources.	○	○	○	○	○	○	○	○
External influences.	○	○	○	○	○	○	○	○
Heavy workload.	○	○	○	○	○	○	○	○

Other (please specify)

3.4 In relation to team members and/or teamwork what improvement do you think could be made?

3.5 Did you EXPERIENCE discrimination of any nature during the incident?

- [ ] Yes
- [ ] No

If YES, was it...? (please tick as many as apply)

- [ ] Racial
- [ ] Sexual discrimination
- [ ] Sexual harassment
- [ ] Sexual orientation
- [ ] Age related
- [ ] Bullying
- [ ] Inter-agency

Other (please specify)

3.6 Did you WITNESS discrimination of any nature during the incident?

- ( ) Yes
- ( ) No

If YES, was it...? (please tick as many as apply)

- [ ] Racial
- [ ] Sexual discrimination
- [ ] Sexual harassment
- [ ] Sexual orientation
- [ ] Age related
- [ ] Bullying
- [ ] Inter-agency

Other (please specify)

Section 4: IMT & Incident Ground/Fire Ground Interaction

The questions in this section relate to interaction between the IMT and the Fire Ground (in fire situations) or the Incident Ground (in non-fire situations) during the incident described in 'Section 1: Overview'. Please answer the following questions about that incident only.

4.1 On a scale of 1 to 7 where 1 = strongly disagree and 7 = strongly agree, please indicate your level of agreement with each of the following statements.

	1 (strongly disagree)	2	3	4	5	6	7 (strongly agree)	can't answer
1. IMT and Fire/Incident Ground personnel exchanged information clearly and accurately.	○	○	○	○	○	○	○	○
2. IMT and Fire/Incident Ground personnel provided helpful advice to each other.	○	○	○	○	○	○	○	○
3. IMT and Fire/Incident Ground personnel provided constructive feedback to each other.	○	○	○	○	○	○	○	○
4. IMT and Fire/Incident Ground personnel effectively monitored each other's performance.	○	○	○	○	○	○	○	○
5. IMT and Fire/Incident Ground personnel exhibited a strong 'we are in this together' attitude.	○	○	○	○	○	○	○	○
6. IMT and Fire/Incident Ground personnel interacted in an open and honest manner.	○	○	○	○	○	○	○	○
7. IMT and Fire/Incident Ground personnel kept each other well informed about work-related issues.	○	○	○	○	○	○	○	○
8. IMT and Fire/Incident Ground personnel made genuine attempts to share information with each other.	○	○	○	○	○	○	○	○
9. In discussion between the IMT and the Fire/Incident Ground, potential weaknesses in what was being undertaken were critically appraised.	○	○	○	○	○	○	○	○
10. IMT and Fire/Incident Ground personnel shared their individual knowledge with each other to gain a better understanding of the situation at hand.	○	○	○	○	○	○	○	○
11. IMT and Fire/Incident Ground personnel were able to state and maintain opinions openly with each other.	○	○	○	○	○	○	○	○
12. I had the confidence that I and others had the skills needed to effectively perform our respective roles.	○	○	○	○	○	○	○	○
13. Strategies were adjusted in a timely manner as the incident unfolded.	○	○	○	○	○	○	○	○
14. IMT and Fire/Incident Ground personnel anticipated the needs of others.	○	○	○	○	○	○	○	○
15. Roles were effectively re-allocated as the situation changed.	○	○	○	○	○	○	○	○
16. IMT and Fire/Incident Ground personnel interacted effectively with external stakeholders beyond the Fire/Incident Ground.	○	○	○	○	○	○	○	○
17. IMT and Fire/Incident Ground personnel had a clear and common purpose for the incident at hand.	○	○	○	○	○	○	○	○
18. IMT and Fire/Incident Ground personnel trusted each other.	○	○	○	○	○	○	○	○
19. The activities of the IMT and Fire/Incident Ground personnel were co-ordinated to achieve the best possible outcome.	○	○	○	○	○	○	○	○
20. When problems arose, IMT and Fire/Incident Ground personnel were able to recover quickly and get on with the job.	○	○	○	○	○	○	○	○
21. IMT and Fire/Incident Ground personnel felt that they contributed to the decision making.	○	○	○	○	○	○	○	○
22. There was a pre-determined frequency for situation reporting from the operations area (Fire/Incident Ground).	○	○	○	○	○	○	○	○

Section 5: Procedures & Processes

The questions in this section relate to the procedures and processes employed during the incident described in 'Section 1: Overview'. Please answer the following questions about that incident only.

5.1 On a scale of 1 to 7 where 1=low and 7=high, how would you rate the following in relation to the EFFECTIVENESS of interoperability of agencies?

	1 (low)	2	3	4	5	6	7 (high)	can't answer
Technological systems	○	○	○	○	○	○	○	○
Policies/procedures	○	○	○	○	○	○	○	○
Culture	○	○	○	○	○	○	○	○

5.2 In terms of your involvement in the incident, on a scale of 1 to 7 where 1=low and 7=high, how would you rate the following?

	1 (low)	2	3	4	5	6	7 (high)	can't answer
1. Your working knowledge of systems in use (e.g. IT systems, communications systems, incident resource management systems).	○	○	○	○	○	○	○	○
2. The effectiveness of the organisational framework for the level of the current incident.	○	○	○	○	○	○	○	○
3. Your training for the incident at hand.	○	○	○	○	○	○	○	○
4. Your level of informal knowledge (experience).	○	○	○	○	○	○	○	○
5. The extent to which external factors inhibited your ability to do the job.	○	○	○	○	○	○	○	○
6. The extent to which you had to go outside normal procedures.	○	○	○	○	○	○	○	○
7. Your level of feeling exposed/at risk for having gone outside the procedures.	○	○	○	○	○	○	○	○
8. Effectiveness of your reporting relationships.	○	○	○	○	○	○	○	○
9. The degree to which you were being asked to do things outside of your chain of command.	○	○	○	○	○	○	○	○
10. Timeliness of requested information.	○	○	○	○	○	○	○	○
11. Your familiarity with the incident management system being used.	○	○	○	○	○	○	○	○
12. Your certainty of what needed to be done.	○	○	○	○	○	○	○	○
13. The level of competing demands you experienced.	○	○	○	○	○	○	○	○
14. Your ability to use your skills to maximum benefit.	○	○	○	○	○	○	○	○

In terms of your involvement in the incident, on a scale of 1 to 7 where 1=low and 7=high, please continue to rate the following.

	1 (low)	2	3	4	5	6	7 (high)	can't answer
15. Your level of inclusion in the decision making process.	○	○	○	○	○	○	○	○
16. The level of contradiction in policies guiding the management of the incident.	○	○	○	○	○	○	○	○
17. Your understanding of policies and procedures used during the incident.	○	○	○	○	○	○	○	○
18. Your access to local knowledge of the incident.	○	○	○	○	○	○	○	○
19. The level of congestion of radio frequencies.	○	○	○	○	○	○	○	○
20. The adequacy of the venue used for your purposes.	○	○	○	○	○	○	○	○
21. The adequacy of resources for your needs.	○	○	○	○	○	○	○	○
22. The level of difficulty in accessing management systems in use during the incident.	○	○	○	○	○	○	○	○
23. The continuity of staff between shifts.	○	○	○	○	○	○	○	○
24. The compatibility of technological systems (e.g. radios, emails etc).	○	○	○	○	○	○	○	○
25. Your understanding of who to contact for information and expertise you needed during the incident.	○	○	○	○	○	○	○	○
26. The adequacy of information provided at changeover.	○	○	○	○	○	○	○	○
27. Your awareness of the proper channels for communicating a safety concern.	○	○	○	○	○	○	○	○
28. Your confidence that any safety concern you communicated would be acted upon.	○	○	○	○	○	○	○	○

Section 6: Individual Profile

Please answer the following questions about yourself.

6.1 In which State or Territory do you reside?

- [ ] TAS
- [ ] VIC
- [ ] NSW
- [ ] SA
- [ ] WA
- [ ] ACT
- [ ] NT
- [ ] QLD

6.2 Are you...?

- [ ] Male
- [ ] Female

6.3 To which age group do you belong?

- [ ] < 20 years of age
- [ ] 20 – 29 years
- [ ] 30 – 39 years
- [ ] 40 – 49 years
- [ ] 50 - 59 years
- [ ] 60 + years

6.4 Identify the main activity(ies) your agency is responsible for (please tick as many as apply)

- [ ] Urban fire
- [ ] Rural fire
- [ ] Land management
- [ ] Emergency Services

Other (please specify)

6.5 In which State or Territory is the agency?

- ☐ TAS
- ☐ VIC
- ☐ NSW
- ☐ SA
- ☐ WA
- ☐ ACT
- ☐ NT
- ☐ QLD

6.6 What was your working relationship with your agency at this incident?

- ☐ Paid employed – Full time (35 hrs or more per week)
- ☐ Paid employed – Part time (incl. Retained staff and Auxiliary)
- ☐ Paid – seasonal employed
- ☐ Unpaid volunteer
- ☐ Seconded to the agency for the incident

Other (please specify)

6.7 How many years of experience have you had in fire and emergency management? (please indicate as many as apply)

Role:

Incident Controller

Planning Officer

Logistics Officer

Operations Officer

Division Commander

Sector Commander

Crew Leader

Please indicate other roles (if any) performed in fire and emergency menagement and include years of experience you have had in these roles.

6.8 How many major incidents have you previously attended in the role you predominately performed during this incident?

- ◯ None (first incident in this role)
- ◯ 1 – 5
- ◯ 6 – 10
- ◯ 11 - 20
- ◯ 20 or more

6.9 Please rate how much training you have received in the role you predominately performed during this incident. (please tick as many as apply)

	None	Moderate	Substantial
Nationally recognised	◯	◯	◯
In-house (not nationally recognised/aligned)	◯	◯	◯
Mentoring/coaching	◯	◯	◯

Other (please specify)

6.10 Have you undertaken training for any of the following functional/operational roles? (please tick as many as apply)

(NOTE: In some agencies some functional training might be incorporated into programs with a different title. If so, please tick any box where your training covers the function listed)

- ☐ IC
- ☐ Planning Officer
- ☐ Logistics Officer
- ☐ Operations Officer
- ☐ Division Commander
- ☐ Sector Commander
- ☐ Crew Leader

Other (please specify)

6.11 In relation to your predominant incident management role please...

a) List 5 of the most relevant learning opportunities/training exercises directly relevant to incident management roles that you have undertaken.

b) Indicate the type of learning opportunity/training exercise i.e. Nationally recognised; In-house (not nationally recognised/aligned); Mentoring/coaching, Other.)

c) The year the learning opportunity/training exercise was undertaken.

d) On a scale of 1 to 7 where 1=very inappropriate and 7=very appropriate, rate the appropriateness of the experience. C/A=Can't answer.

a)Learning/training

b)Type

c)Year

d)Rating (1 to 7)

6.11 continued....(if applicable)

a)Learning/training

b)Type

c)Year

d)Rating (1 to 7)

6.11 continued....(if applicable)

a)Learning/training

b)Type

c)Year

d)Rating (1 to 7)

6.11 continued.... (if applicable)

a)Learning/training

b)Type

c)Year

d)Rating (1 to 7)

6.11 continued....(if applicable)

a)Learning/training

b)Type

c)Year

d)Rating (1 to 7)

COMMENT

Please feel free to add any additional comments about your experiences during the incident you have answered questions about.

Thank you for your assistance and participation in the AIIMS National Questionnaire.

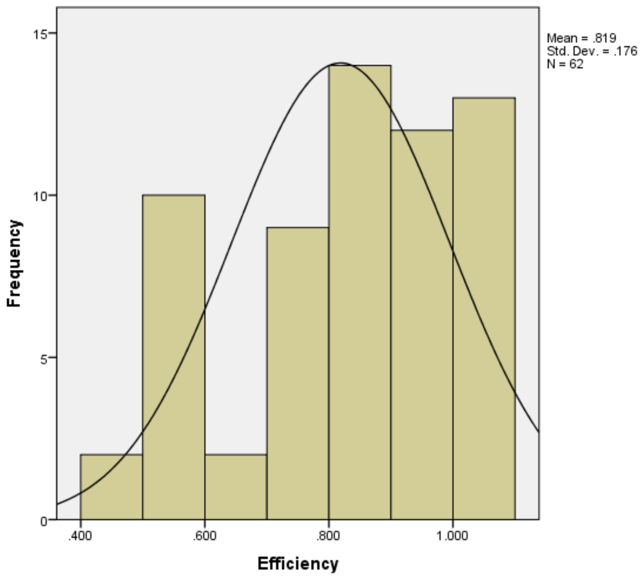
Please return your completed questionnaire in the reply paid envelope marked "Personal and Confidential" to:

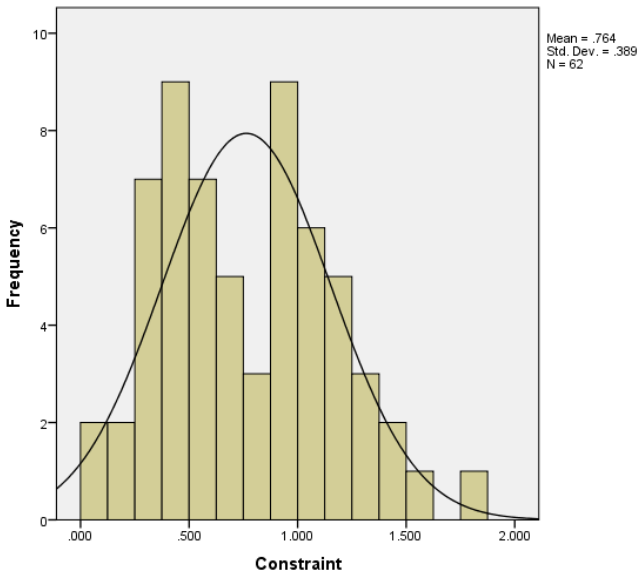
Dr Christine Owen
BCRC Research Project
Faculty of Education
University of Tasmania
Private Bag 66

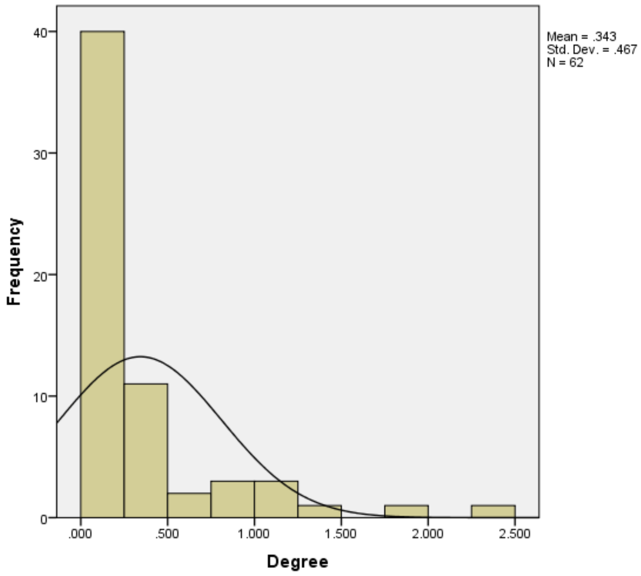
HOBART TAS 7001

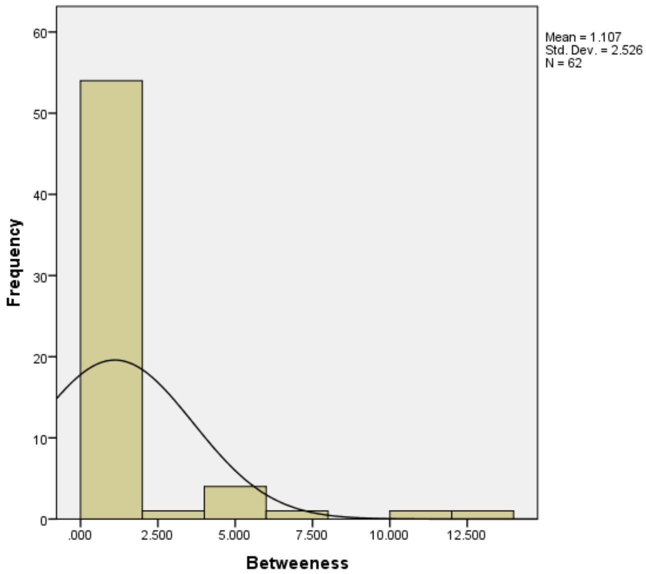
Appendix B (Histograms for Network and Learning Variables)

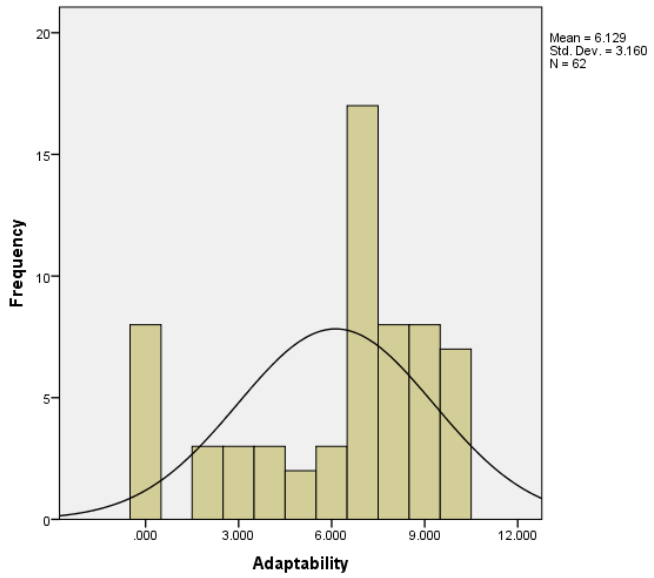
For Actor level Variables of Bunyip Bushfire Network



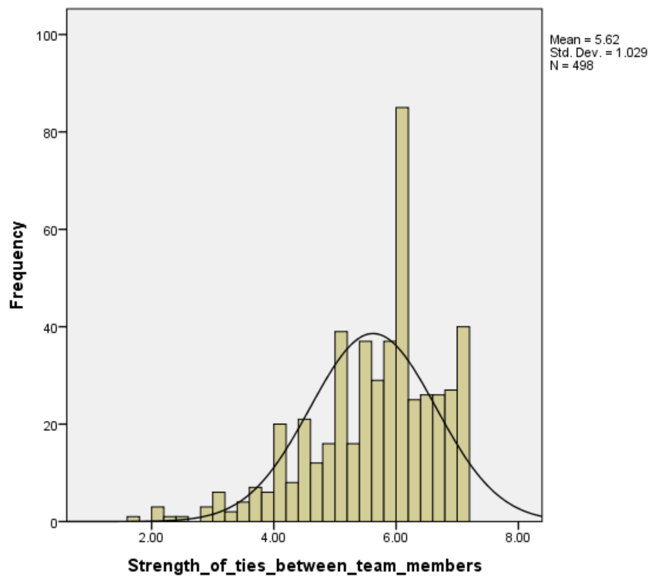


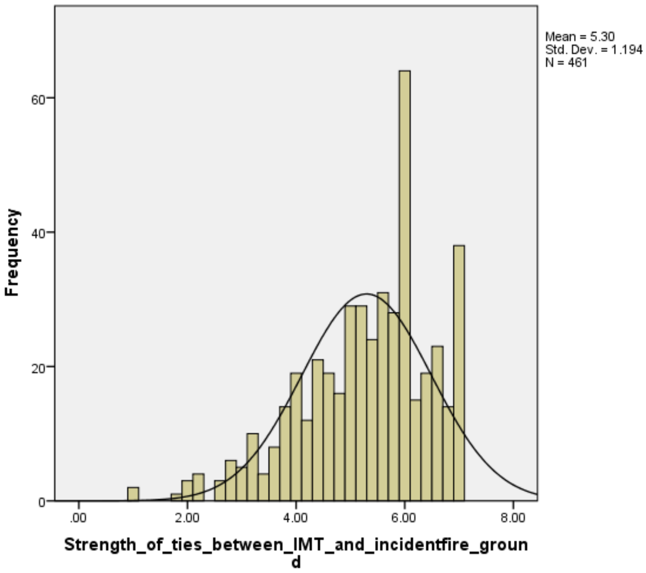

Mean = .343
Std. Dev. = .467
N = 62
Frequency
Degree
40
30
20
10
0
.000
.500
1.000
1.500
2.000
2.500

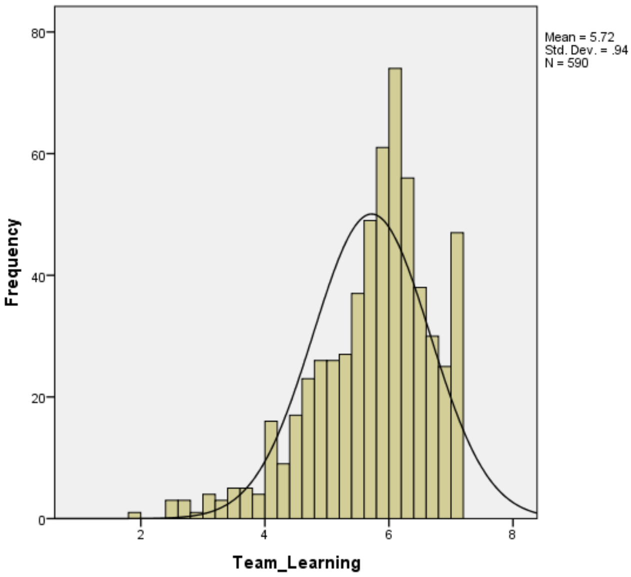

Mean = 1.107
Std. Dev. = 2.526
N = 62
Frequency
Betweeness
60
50
40
30
20
10
0
.000
2.500
5.000
7.500
10.000
12.500



For Dyadic level Variables extracted from AIIMS Survey

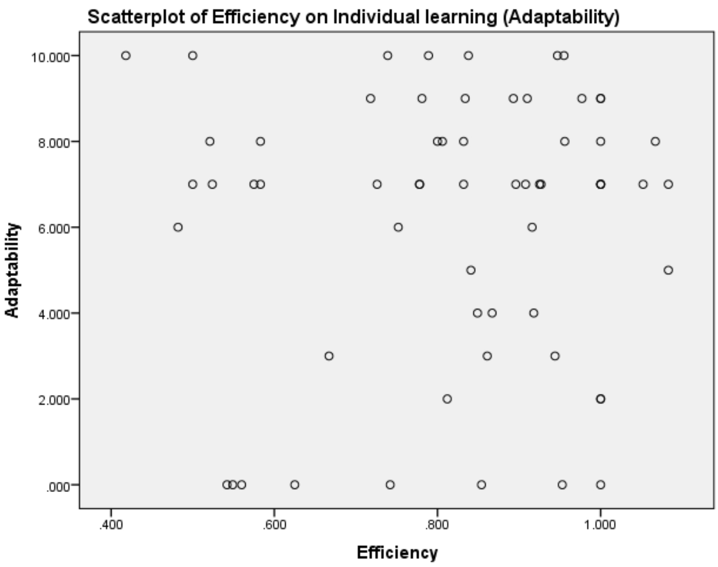


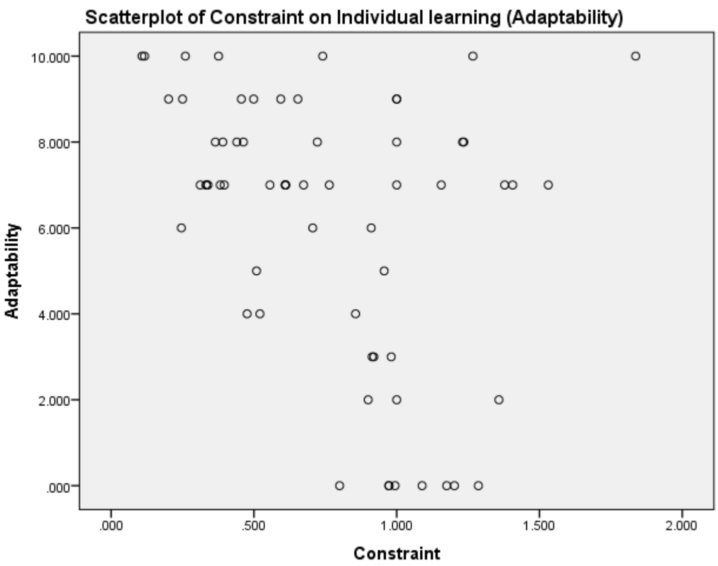

Mean = 5.30
Std. Dev. = 1.194
N = 461
Frequency
0
20
40
60
.00
2.00
4.00
6.00
8.00
Strength_of_ties_between_IMT_and_incidentfire_ground


Mean = 5.72
Std. Dev. = .94
N = 590
Frequency
0
20
40
60
80
2
4
6
8
Team_Learning

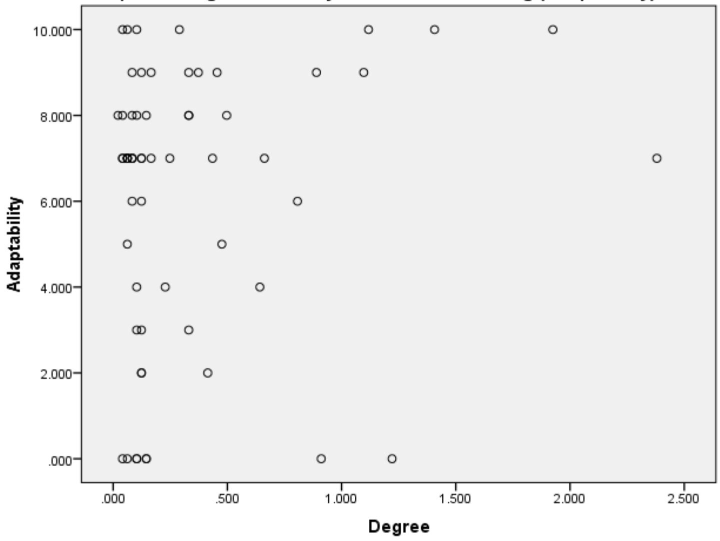
Appendix C (Scatterplots)

For Actor level Variables of Bunyip Bushfire Network

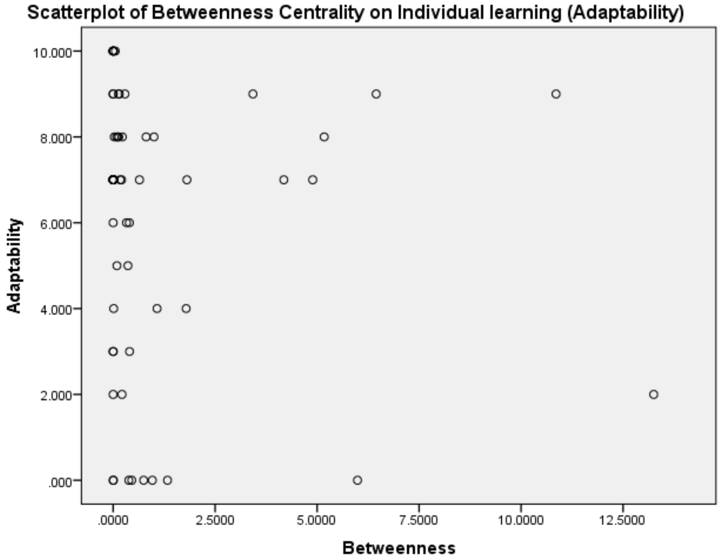




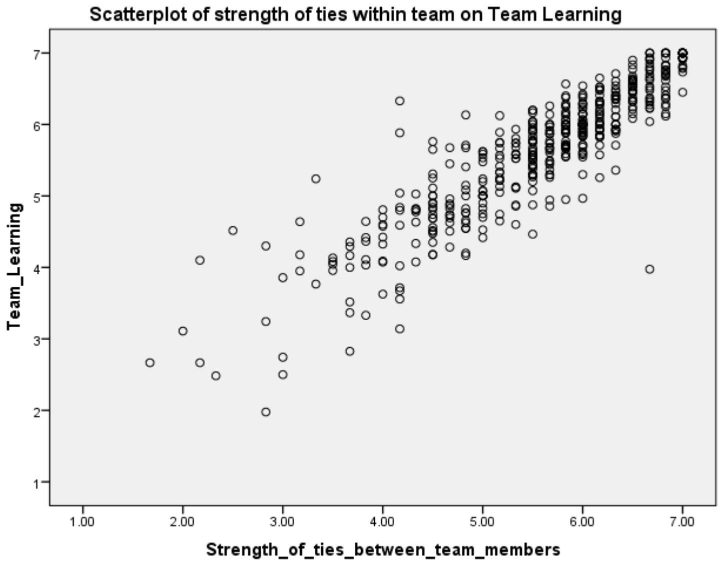
Scatterplot of Degree Centrality on Individual learning (Adaptability)

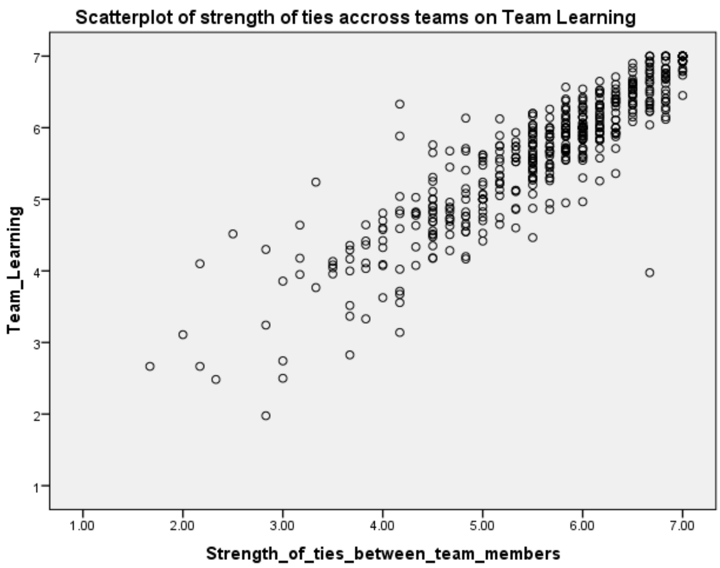


Scatterplot of Betweenness Centrality on Individual learning (Adaptability)



For Dyadic level Variables extracted from AIIMS Survey





Appendix D (Part of a sample statement of an emergency staff member involved in the 2009 Victorian Bushfires)

WIT.3004.030.0001

2009 VICTORIAN BUSHFIRES ROYAL COMMISSION
Letters Patent issued 16 February 2009

WITNESS STATEMENT OF [redacted]

Date of Document: 1 December 2009
Filed on behalf of: The State of Victoria
Prepared by:
Victorian Government Solicitor's Office
Level 25
121 Exhibition Street
Melbourne VIC 3000

Solicitor's Code: 7977
Telephone: +61 3 8884 0444
Facsimile: +61 3 8684 0449
DX 3000077 Melbourne
Ref: PAC 944884
Attention: John Cain

I, [redacted] of 38 Follett Drive, Nyora, Victoria, volunteer Fire Fighter of the Country Fire Authority (**CFA**) can say as follows:

PART 1 – INTRODUCTION

1. My name is [redacted] and my date of birth is 23 January 1945.

2. I am currently a volunteer Fire Fighter with the Lang Lang Brigade of the CFA. Lang Lang Brigade is part of the Cardinia Group of brigades, within CFA Region 8. There are six Groups in Region 8 namely, Casey, Cardina (previously Pakenham), Western Port, Peninsula, South East and Bass Coast.

3. On 5 February 2009, I was tasked to build an operational plan on behalf of the CFA as a contingency plan for 7 February 2009, in relation to the Bunyip fire.

4. On 6 February 2009, I undertook that task in conjunction with other CFA members. We performed the role in a spare office adjacent to the Incident Control Centre (**ICC**) at Pakenham Fire Station.

5. On 7 and 8 February 2009, I undertook the role of Incident Controller (**IC**) for the Bunyip fire when it became a CFA controlled fire.

[5523591: 6688133_4]

PART 2 – CAREER HISTORY AND QUALIFICATIONS

6. I have been a member of CFA for the past 42 years as both a volunteer and an employee.

7. I first joined CFA in 1967 as a volunteer Fire Fighter with the Narre Warren North Brigade. Between 1967 and 1997 I was a volunteer with the Narre Warren North, Pakenham and Pakenham Upper Brigades. During this period I held many ranks within CFA, including Lieutenant, Captain, Deputy Group Officer and Group Officer. Until mid-2008 I had held the positions of either Deputy Group Officer and Group Officer within Region 8 for approximately 25 years.

8. I also took on training and development roles as a CFA volunteer:

   8.1 From 1984 to 1989, I conducted training seminars at the CFA Training College in Fiskville for Group Officers from brigades around Victoria, approximately three times a year. At these seminars, I conducted practical training sessions on strategies and tactics for fighting fires at an urban/rural interface, using a constructed floor map. I trained Group Officers on the development of a fire in this environment and the appropriate tactics and methods to fight such a fire.

   8.2 In recognition of my experience as a CFA volunteer and in addition to my involvement in fighting the Ash Wednesday bushfires I formed part of a CFA delegation, which travelled to Canberra in 1989 to participate in the final stages of development of the Australasian Inter-service Incident Management System (**AIIMS**). I developed a high level of expertise in AIIMS and, in 1994, I was made a national accredited instructor in AIIMS by CFA.

   8.3 I continue to run AIIMS training courses on behalf of CFA, both internally and externally.

   8.4 In 1995, I was contracted by CFA to develop and deliver a pilot training course for Level 3 Planning as part of the CFA Learning & Development program.

9. I continued as a CFA volunteer until September 1997, when I moved laterally to take up a position as an Operations Officer in Region 8. I continued as a full time CFA employee until I retired in July 2004.

10. In addition to my work as an Operations Officer for CFA, between 1997 and 2004 I acted as a mentor for both volunteers and career staff at CFA in relation to wildfire fire fighting operations. This role involved supervising and reviewing the operations of Level 1 and Level 2 endorsed Fire Fighters 'on the job' at fire incidents on hot days. I was required to review the structure implemented to fight the fire, ensure the strategies and tactics employed were sound, monitor the flow of information and progress reports, ensure utilisation of all available resources and identify any Occupational Health and Safety issues.

11. On resigning as Operations Officer in July 2004, I rejoined Pakenham Upper Brigade as a volunteer. Since that time I have been a volunteer with the Pakenham Upper Brigade, and Lang Lang Brigade, and was also the Cardinia Group Officer until mid-2008.

12. Since my retirement, I have continued to undertake contract work for CFA. My contractual roles with CFA have mainly involved conducting training sessions as detailed below:

    12.1 the development and delivery of an AIIMS course for State Emergency Service (**SES**) staff. I have delivered this course to SES volunteers and career staff, employees from the Yarra Ranges Shire Council, Banyule City Council and Cardinia Shire Council and Victoria Police (**VicPol**) employees; and

    12.2 the development and delivery of AIIMS training courses for metropolitan water utilities

13. Since first joining the CFA I have completed numerous training courses including:

    13.1.1 AIIMS [Incident Control];

    13.1.2 Certificate II in Fire Fighting;

13.1.3 Wildfire Fire Fighter and Wildfire – Low Structure Fire Fighter;

13.1.4 Crew Leader – Wildfire, Strike Team Leader – Wildfire and Sector Commander – Wildfire;

13.1.5 Personal Protection 1, Safety Advisor – Wildfire and Field Safety Advisor – Wildfire;

13.1.6 Wildfire Behaviour 1, 2 and 3;

13.1.7 Wildfire Suppression 1, 2 and 3;

13.1.8 Operations Officer Level 3;

13.1.9 Staging Area Manager, Incident Management Skills; Planning Management and Logistics Management;

13.1.10 Fire Weather, Map Reading;

13.1.11 Communication Systems and Computer Skills;

13.1.12 Workplace Communications, Workplace Trainer and Workplace Assessor;

13.1.13 Mentoring Skills; and

13.1.14 Project Management.

14. I am currently endorsed as a Level 3 Planning Officer, Level 3 Operations Officer, Level 3 IC and as a Level 3 Logistics Officer.

PART 3 – EXPERIENCE IN MAJOR INCIDENTS

15. I have undertaken numerous roles in connection with major incidents on behalf of CFA, including as a Level 3 IC, Level 3 Operations Officer, Level 3 Planning Officer and as a Level 2 Logistics Officer. I have also performed the roles of Strike Team Leader, Sector Commander and Division Commander.

16. I was first deployed as a Strike Team Leader during December 1972 in connection with fires in Churchill Park. Over the ensuing years I was deployed on many

occasions as Sector Commander, Division Commander and IC in connection with fires in the Mornington Peninsula and bordering areas of Region 13.

17. The major incidents I have attended include:

17.1 the Ash Wednesday fires, where I undertook several roles as a CFA volunteer including IC, Operations Officer and Division Commander for a period of three weeks over the duration of the fire in both Cockatoo and Upper Beaconsfield;

17.2 the 1997 Dandenong fires, where I performed the role of Planning Officer overnight in connection with a fire at Ferny Creek;

17.3 the 1998 Caledonia Creek fire, where I performed the role of CFA Liaison Officer to the Department of Sustainability and Environment (**DSE**) for 4 days;

17.4 the 2002-2003 Victorian Alpine fires. My involvement in fighting these fires lasted for a period of approximately eight weeks, during which time I undertook roles as Deputy IC, Operations Officer and Planning Officer; and

17.5 the Black Saturday fires, where in addition to the roles I undertook as detailed in this statement, I also acted as Operations Officer for two days at the Woori Yallock ICC in connection with fires burning in the South Murrindindi complex about two weeks after Black Saturday.

18. I have also participated in interstate deployments for CFA. In 2001, I was deployed to assist the NSW Rural Fire Service in connection with fires burning out of control near the towns of Waterfall and Heathcote in the Royal National Park, south of Sydney. I acted in the capacity of both Operations Officer and Planning Officer in connection with these fires for a period of nine days, until the fires were brought under control. In the same period I was deployed to assist as Operations Officer for a further two days in relation to a second fire burning at Mittagong.

PART 4 – EMERGENCY RESPONSE RESOURCES IN REGION 8

19. The following is a list of the emergency resources in Region 8 extracted from the Region 8 contact details book:

    19.1 70 brigades which are a mixture of rural, urban and industry (eight are career staff brigades);

    19.2 30 pumpers;

    19.3 74 CFA owned tankers;

    19.4 14 brigade owned tankers;

    19.5 42 support vehicles;

    19.6 35 other types of vehicles including Mobile Communications Vehicles and Hazmat vehicles;

    19.7 10 slip-ons; and

    19.8 six quick fills.

PART 5 – PREPARATION FOR 7 FEBRUARY

4 February 2009

20. During the week leading up to 7 February, I was aware that there were a number of fires burning in the Bunyip State Park, and that these fires were being controlled by DSE. I understand that the majority of these fires were thought to have been the result of lightning strikes. I have since been advised that these fires had been burning for several days, and possibly for more than a week prior to 4 February.

21. I was also well aware of the weather predictions and general forecasts for the week leading up to 7 February. Due to my experience in fulfilling key Incident Management Team (**IMT**) roles on behalf of CFA, I have a pager at home tuned to the Cardinia Group which provides constant updates on current and predicted weather conditions. This information, together with radio broadcasts, television reports and frequent reviews of the Bureau of Meteorology's website (particularly the

wind information) enabled me to stay informed of the impending weather conditions for Saturday 7 February. I was also aware that it was going to be a Code Red day.

22. During the late afternoon of 4 February 2009, I was informed via pager messages that one of the fires which had been burning in the Bunyip State Park, usually referred to as the Bunyip Ridge fire, was continuing to be difficult to control. I was already aware of the fire as I have a clear and distinct distant view of the Bunyip State Park from my home. Throughout the day I received several telephone messages from concerned CFA members.

23. As the fire was still burning on public land, DSE remained the control agency for the fire.

5 February 2009

24. I have also been advised that DSE had initially been managing these fires from the ICC in Belgrave, however during the week prior to 7 February they relocated to the Pakenham ICC. It is my understanding that the DSE relocated to the Pakenham ICC on 5 February, following forecasts of strong winds and with awareness that the fire would not be readily contained in the Bunyip State Park.

25. On 5 February at approximately 1200 hours, I received a telephone call from Trevor Owen, the Operations Manager for Region 8, requesting that I assume a strategic operations role as Team Leader of the Operational Contingency Planning Team based at Pakenham ICC.

26. I accepted the role, and was tasked with putting together a team and building an operational plan for a possible fire that might move out of the Bunyip State Park, and threaten private land on 7 February. To this end, I photocopied the relevant pages from the CFA map book, and started making preliminary plans in my mind as a fore runner to formulating an Operational Contingency Plan.

27. During our telephone conversation, Trevor also informed me that a ground observation team, comprised of three CFA members, had been deployed that day. The Ground Observers had been tasked with identifying defendable and non-defendable properties north of the Old Princes Highway, that would be directly

affected by the fire running south, or south east, under the influence of predicted strong winds. They had also been asked to identify all available water resources, both static (dams) and reticulated sources.

28. It was my understanding, based on my conversation with Trevor Owen, that should the Bunyip fire move out of the Bunyip State Park and become a CFA controlled fire, I would be allocated the role of IC.

29. After I spoke to Trevor I contacted Phil Craig, the Cardinia Group Officer. I informed Phil of the role Trevor Owen had requested I perform, and asked that he and Steve Hicks, Cardinia's Deputy Group Officer, support me as part of the Operational Contingency Planning Team for 7 February. I asked Phil to attend the Pakenham ICC for a meeting on Friday, 6 February 2009 at around 0830 hours.

30. After the telephone request I received from Trevor Owen to build a Operational Contingency Plan, I did not place any requests for DSE support as all DSE personnel were already fully committed in IMT roles at the Pakenham ICC.

31. During my conversation with Phil Craig, I also requested that I be provided with suitably qualified people on 7 February to man the key IMT roles of Operations, Planning and Logistics, as well as Field Commanders (Division Commanders, Sector Commanders and Strike Team Leaders). As the Group Officer, it was part of Phil's role to arrange this resourcing.

32. I then contacted Steve Hicks. I had a similar conversation with him, and asked that he be available to be my Strategic Operations Officer on 7 February if required. I also asked him to attend the Pakenham ICC from 0830 hours the following day to participate in the planning process.

33. I understand that Trevor Owen also contacted a number of other people to attend on the Friday and participate in the planning meeting scheduled for 0830 hours.

34. Preplanning the IMT was a normal response to a Code Red day, but the predictions for 7 February were so dire that I considered we must have our absolute best team in place, and be ready to respond quickly. During my conversations with Phil Craig on Thursday, I specifically requested that he and Steve Hicks be available to be in

attendance on Saturday morning from 0800 hours. I considered that whatever happened, we were going to need to be there early on Saturday for a briefing to assess the current situation, and also to consider any information that may not have been available while we were planning on Friday.

6 February 2009

35. I arrived at the ICC at Pakenham at approximately 0830 hours on 6 February, for the scheduled Operational Contingency Plan meeting to plan for management of the Bunyip fire. The following people were present at that morning meeting:

35.1 Trevor Owen (Operations Manager Region 8);

35.2 David Sherry, (Operations Manager Region 9);

35.3 Brian Dalrymple – Lieutenant for Longwarry Fire Brigade (Gilbert Mynard, Captain of Longwarrry replaced Brian at 1100 hours);

35.4 Phillip Craig (Cardina - Group Officer);

35.5 Steve Hicks (Cardina - Deputy Group Officer);

35.6 Dave Ellams (CFA Field Officer - Ground Observation Leader); and

35.7 Jim Dore (Cardina - Operations Officer).

36. During this meeting, we discussed the likelihood that the fire would spread from Region 8 into Region 9 if it broke its containment lines. David Sherry and I agreed that even if this were the case, Region 8 would take control of the Bunyip fire on 7 February. This was largely because Region 9 resources were fatigued from their efforts fighting the Delburn Complex fires during the previous week. I asked David if there were any personnel from Region 9 with the requisite skills that he wanted directly involved. David offered Gilbert Mynard, the Captain from the Longwarry Brigade, to assist with providing local knowledge of the area. Phil Craig and Steven Hicks were also allocated to my team for the purpose of developing an Operational Contingency Plan.

37. It was requested by the Operation Managers, Trevor Owen and David Sherry, that the Operational Contingency Plan take into account weather and wind predictions across both Regions 8 and 9.

38. At this stage, DSE remained the authorised control agency, and there was still no formal CFA involvement in the IMT working at the Pakenham ICC.

39. During the morning of 6 February, I reviewed the maps that the ground observation team had compiled of assets in the potential path of the fire. The team had marked points on the map such as "W" for water point, a green dot for a defendable house, and a red dot for non-defendable houses. Whether or not an asset is determined to be defendable or non-defendable is usually based on the surrounding terrain, the proximity to, and quantities of fuel types conducive to the propagation of wildfire. I paid particular attention to the markings on the map referring to the location of various water points. Attached to my statement as **Annexure 1** are copies of the 5 maps finalised by the ground observation team on 6 February.

40. In total there were six members of the Operational Contingency Planning Team. The team worked from 0830 hours until 2300 hours. I left approximately a few hours before 2300 hours and I understand that when I was not in attendance that the team continued to refine the plan details by producing the final GIS map as set out in **Annexure 3**.

41. The preplanning that was completed on 6 February was enormously beneficial on 7 February. The pre-planning that was done was assisted from knowledge we possessed as to where the fire was likely to run on 7 February.

42. After a review of the information provided by the Ground Observers, an operational analysis was undertaken by the Operational Contingency Planning Team based on the combined experience of those in the team, the expected fire behaviour, weather predictions from the Bureau of Meteorology, input from Gilbert Mynard, the Longwarry Brigade Captain, and information provided by Brian Dalrymple, a Lieutenant with Longwarry Brigade. Brian provided further detail in relation to the key life and infrastructure exposures, and the level of fuel loads expected across the area already under consideration in the draft plan.

Appendix E (Sample of incident management log filled by an emergency staff member involved in the 2009 Victorian Bushfires)

DSE.0075.0625.0032

INCIDENT MANAGEMENT LOG

Date: 6/2/09 Sheet: 2.

Name: R Pidduck. Function: Ops. 2 Location: Toorumbuk. Bunyip Ridge

Time	TO / FROM	T / R / V	Name	Notes	Action
				Andrew Forrest.	
Ring 1hr prior to arrival.				0417 928 338.	
				59662731.	
				Yarra Valley Catering.	
1920	F	V	Greg Marry.	Melb central (20)	
				Francis Mines	
				East sector	
				West Cupps (20)	
				Wayne Beaton.	
				West sector.	
NE			TP	Wards west sector – 2000 start.	
				Mulch away west sector. 2000 start.	
East.			D6. Vince.	Marchese – 2000 start.	
			TP	Moran – 1600 start.	
10.30	Knock off.		D5.	Custanio east sector – noon start.	
				Dozer operators started	
				Powelltown D6	
				~~Ode~~ 4 D4.	
2245	T	R	FH	896 000 spot over.	
				dozer working on it	
2230	F	R	ICC.	1 dozer BR tk.	
				Strengthen containment lines.	
				Push back elevated stuff.	
				1hr relays.	
				Troy Southern, P'town, D6 -	
				w/ Marchese from Quickfill south along	
				east sector.	

T = Telephone R = Radio V = Verbal

INCIDENT MANAGEMENT LOG

Date: 6/2/09 Sheet: 3

Name: Rob Rifield Function: Ops 2 Location: Bunyip Ridge

Time	TO/FROM	T/R/V	Name	Notes	Action
1117	F	R	Pedro	Security for floats.	
1118	T	R	FH.	Spot fire (Burning in Nthern Section	
				~~[illegible]~~ 885 999 trickling into gully,	
				burning back into black. Do not believe	
				crossed creek.	
				Weather 24° RH 38 Wind O Var –	
			FH	Quiet Sector	
				Dozer tidying up Nth area.	
				. Bunyip Ridge track / aim to	
				get around fire.	
1130	T	R	ICC	Request recurity.	
				Line recon 878 005 (didn't bother)	
				(not found inburn) 880 007	
				(~~[illegible]~~ tracked) 883 008 –	
				884 004.	
				Wards. 886 998.	
				879 999	
				OK to go w/ my plan of resource deployment	
				candles to come down.	
1145	T	R	Grant	Implement resource plan.	
1147	T	R	FH.	P'town D6 + Marchese movements	
			(Hifield)	~~Brad~~ ~~[illegible]~~ F'town D4 to FH. w/ 504 from H'field.	
				Adam Kleen w/ Jim Cameron.	
1205	F	R	G4	875 996 Moran.	
				Mulch Away → Blue R Tk.	
				1412 Meals	

T = Telephone R = Radio V = Verbal

DSE.0075.0625.0034

INCIDENT MANAGEMENT LOG

Natural Resources and Environment

Date: 7/2/09 Sheet: 1

Name: Rob Pitcher. Function: ? Ops 2 Location: Bunyip Ridge.

Time	TO FROM	T R V	Name	Notes	Action
1230	F	R	GS	Moran 15 mins	
1234		V	FH.	D4 Passing bays etc east sector.	
				Grant + Moran @ #6.	
				Seb to check #1, 2 + 3.	
				#5 Ward.	
				#4 OK.	
				Safety. – crews into black.	
				– limited 4x4 exp.	
				Eats.	
0100	T	R	ICC	29.4 R/H 33 Wind 0.	
0113.	T	V		Fill dozers	
				Get ready to move them out.	
0123	T	R	~~Sudrie~~ Grant.	Turn Mulch Away around + park @ top of fire. ✓	
0200	T	R	ICC	T 29 35% 2 Km/h NW.	
				Mt Town D6? ✓	
				" D4 ✓	
				Moran ✓	
				Marchese ✓	
				Mulch Away ✓	
				Wards. ✓	
0300	~~R~~	R	FH	Start to move out.	
0300				31.4 32 5 NW est 15g.	
				?	
				Sudrie out numerous	
				70 m in	

T = Telephone R = Radio V = Verbal

INCIDENT MANAGEMENT LOG

Date: 7/2/09 Sheet: 2

Name: Rob Patrick Function: Ops 2 Location: Bunyip Ridge.

Time	TO / FROM	T / R / V	Name	Notes	Action
0400	T	R	ICC	22.5 47% 12	
				874 979.	
0430	T	R	ICC	22.3 55 5	
			Floats to	Gembrook Tonimbuk. GR. 780951	
				Tynong Nth exit. (ALEX)	
			Not	Blackwoods Ck Tk + 839 993	
			on	Anderson.	
			float -	- Moran D7. Gary.	
				- Mulch away. Gary. Lay.	
				- P'town. D6 Troy. Southam.	
				Mike - Aqueduct Tk.	
0514 GR	T	R	ICC.	GR 30.5 34 3 8g W	
				WARDS TD 15 EDMONSON x LOCKED.	
				P'TOWN D4 . DSE	
TO 780951.				MARCHESE D6 MARCHESE.	
				COSACHIO D5 COSACHIO. x NOT LOADED.	
				~~FRG~~ DREW ISAAC. + WOODDUCK (BRAD).	
				JIM + 4 ADAM (D4 FLOAT).	
0530	T	R	ICC	22 47% 5/10g SSE.	
GR.	867 981.			Dozers walking out	
0545				Dozers on floats x 2 left.	
				Marchese 4x4 gone as well.	
0600				24 49% 0	
0603	T	R	Alex	Turn dozers around	

T = Telephone R = Radio V = Verbal

INCIDENT MANAGEMENT LOG

Date: 7/2/09 Sheet: 3

Name: Rob Roberick Function: Ops 2 Location: Murrindindi Bridge.

Craig Bray.

Time	TO / FROM	T / R / V	Name	Notes	Action
0644			At fire	25 44 0	
0700	GR 867 981			24 50 0	
0716	T	R	ICC	Request road closures.	
				Change over?	
				Marchuke dozer will require escort.	
				" " off rider w/ fresh operator	
				Plan road route - 4 Ton load limit	
				. Gembrook - Tonimbuk Rd.	
0730			ICC	23 51 0	
				Steve Emerson on the way - Gembrook crew.	
0741	F	R		No ground crews going in.	
			Bombing	345 south to north.	
				2 more on way 40 mins.	
				2 cranes.	
				1 medium.	
				Quiet behaviour.	
				Troy to ~~float~~ & take P'tn D6 to Blacksnake Ck.	
				Simon Summer float coming.	
				ICC tell Lex about no resources on line.	
0830	T	R	ICC	27 47 0	
				142? 1 channel of 136 is no good.	

T = Telephone R = Radio V = Verbal

DSE.0075.0625.0037

INCIDENT MANAGEMENT LOG

Date: 7/2/09 Sheet: 4

Name: Deb Patrick. Function: Ops 2. Location: Bunyip Ridge.

Time	TO/FROM	T/R/V	Name	Notes	Action
0846	F	T	ICC	10 hr.	
				Trevor Mc Intosh.	
			Mike M.	0429397721.	
0905	T	R	ICC	Ground contact for aircraft?	
				Mark Stevens 147	
				ICC	
				Greg Harry, Gembrook. 107. LEX	
				136 WADE	
				10.30 crew knock off	
				11.00 " " "	
				29.00 start time / pick up.	
				Logistics. ~~59454704~~ ~~59454704~~	
				59454720	

T = Telephone R = Radio V = Verbal