

**Online Social Networks and
Subjective Well-being of Older
Australians: Network Homogeneity,
Social Capital and Negative
Interactions**

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Declaration

Except where otherwise indicated, this thesis is my own original work.

Mahin Raissi
28 October 2016

To my husband Mahmoud,

To our daughter Yalda,

And to my parents.

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Abstract

This thesis studies the personal networks of older Australians and their associations with subjective well-being (SWB) by focusing on three main characteristics of social networks: homogeneity (connecting with similar people), social capital (access to resources) and negative interactions. Using an innovative purpose-built Facebook application, data on personal networks of 105 Australians aged 50 years and over is collected in two parts. This application collected data on personal networks from Facebook and then loaded them into a visual survey enabling participants to provide information on each relationship (e.g. closeness) and SWB.

There are three main findings of this thesis. First, it characterises the personal networks of the sample. In general these networks are loosely-knit, diverse, geographically dispersed and yet, composed of several homogeneous and densely-knit clusters. Further, while there are some negative relationships, they are mostly positive and provide access to a diverse set of resources. Social network scholars have provided a similar view based on limited data collected by conventional methods. This thesis provides a much more detailed characterisation based on the rich data set collected in this research.

Second, it provides new insights into the associations between personal networks and SWB. In particular, this study shows that network size is unrelated to SWB, density is negatively associated with SWB, and measures of homogeneity and social capital exhibit either a lack of or a negative association with SWB. Further, a strong detrimental effect of negative interactions on SWB, that has been commonly found in previous research, is not confirmed in this study.

Third, this thesis examines whether the above findings are an artefact of the source of personal network data. This view is not supported by the fact that participants' Facebook personal networks considerably overlap with personal networks in real life. Rather the associations between personal networks and SWB were found to be more related to how personal networks have been constructed than whether they are on Facebook or in real life. It is proposed that previous research has been based on personal networks limited to core network members. Limiting personal networks to close relationships produced a positive association between density and SWB; it is the inclusion of not-close relationships that results in the negative association between density and SWB.

The sample used in this study is small and not representative of the target population, thus the findings may not be generalised. However, it provides fresh insights into personal networks and their associations with SWB, by employing a research framework based on social network analysis, utilising advanced methods such as multilevel analysis and benefiting from a rich data set. This thesis provides a basis for future research that is expected to improve our understanding of social networks and their associations with well-being by using more representative samples.

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Introduction

The Australian population is ageing; the proportion of people aged 65 years and over was 14% in 2012 and is projected to increase to at least 22% in 2061 (Australian Bureau of Statistics, 2012). The ageing of a population is positive as it indicates increased life expectancy resulting from improved health. However, with the increasing number and proportion of older people, Australia is facing major challenges relating to economic output, infrastructure requirements and the provision of aged care facilities. Maintaining health and well-being in later life are the central issues contributing to these challenges. Although on average older Australians have good health and well-being, a substantial proportion has a physical or mental illness (Australian Institute of Health and Welfare, 2012). In response, much attention is focused on promoting healthy ageing through preventing the onset of diseases, encouraging productivity and removing barriers to workforce participation of older people (Australian Government, 2010). However, making sustainable, long-term plans needs further understanding of health and well-being and their determinants, especially social factors that have gained little attention in this regard.

Traditionally, health and well-being were studied based on personal characteristics, such as sex, age, education, lifestyle and physical environment. Recently the role of social environment in health and well-being has gained attention. The contribution of one's social relationships to health and well-being can equal or exceed that of established factors such as economic status or education. This is particularly the case among older people because the importance of social relationships gains more weight in later life as the number of relationships decreases due to death of the partner or friends.

Research on social relationships and their associations with well-being are extensive, especially research on older people. Yet our knowledge in this area is limited in two ways. First, findings of the previous studies are mainly based on partial and inconsistent conceptual frameworks focused on specific target populations (i.e. vulnerable people). Second, previous studies are

mostly based on limited data on social networks.

First, the existing literature is based on inconsistent conceptual frameworks that all seem to be derived from "Social Network Analysis" (SNA) approach. While SNA provides a comprehensive framework with well-defined sets of concepts and measures, the existing literature tends to use it partially and inconsistently. In this regard, researchers have used many terms and concepts loosely and interchangeably and often defined and measured them differently. Moreover, some of the most important concepts of SNA including "structure" (structure of relationships among people) has been almost absent in the current literature to the extent that individuals' social networks are diminished to the help and aid that family and friends can provide ("social support"). In accordance with focusing on social support, studies tend to focus on specific target populations that are often at risk of social isolation or suffering from poor well-being. The inconsistent use of SNA approach that has been mostly studied based on specific target populations has led to the existing partial and inconsistent findings in this area, while the power of social networks in explaining health and well-being is overestimated.

Second, previous studies have often limited and oversimplified individuals' social networks to a small number of "dyadic" relationships with the core (i.e. close) network members; individuals' social network, known as "personal" or "ego-centric" network, refers to the network of relationships according to the focal individual called "ego". As a result, researchers fail to capture the wide range of social relationships, most notably the relationships that connect individuals with the wider society and are vital for accessing resources. Defining personal networks to include "dyadic" relationships between ego and her "alters" ignores the relationships among alters and hence do not adequately reflect the complex structure of the network within which the dyadic relationships are embedded. For example, social support is often studied based on the resources that each alter can provide. But scholars have pointed out that availability of those resources does not only depend on the existence of resources and characteristics of relationships (e.g. closeness) through which resources are accessible, but also on the structure relationships among alters (Walker et al., 1993).

For older Australians, there is a major lack of research on social networks. Literature has perceived social networks of older people even more limited to the extent that the focus of attention has been shifted from social relationships to "lack of social relationship" or social isolation. The common stereotype of "the lonely old person" is evident from the title of many scholarly works:

"Nowadays you don't even see your neighbours': loneliness in the everyday lives of older Australians" (Stanley et al., 2010), "Preventing social isolation in later life: findings and insights from a pilot Queensland intervention study" (Bartlett et al., 2013) or "Social isolation: Its impact on the mental health and well-being of older Victorians" (Pate, 2014). This emphasis on social isolation has been at the expense of studying the social networks of older people and their well-being.

This thesis studies the personal networks of older Australians and the association between personal networks and well-being. In this study, the personal network is composed of three parts of information: "structure", "composition" and "function". For each participant, "structure" refers to the set of her relationships with her alters and the relationships among her alters. "Composition" refers to the composition of characteristics of alters. "Function" refers to the provision of resources as well as being a source of emotional interactions.

This thesis has two aims. First, it aims to describe personal networks to provide a view of the personal networks of participants of this study. In particular, it attempts to answer the following questions. What do these personal networks look like? How large are these personal networks? How connected are the members of these personal networks? What are the characteristics of the members of these personal networks? How similar are the participants with the members of their networks? What resources can networks' members provide? How positive or negative are the relationships within these personal networks? How strong are the relationships? Which relationships provide more resources? Which relationships are more positive or negative?

The second aim of this thesis is to determine the associations between personal networks and subjective well-being. Subjective well-being is measured using two indicators: psychological well-being and life satisfaction. To achieve this aim three important aspects of personal networks are studied: homogeneity (connecting with similar people), social capital (access to resources) and negative interactions.

In studying personal networks, one of the main practical issues is related to collecting data. Relying on the ego to provide information about her network can impose an undue burden especially when it comes to reporting connections among alters. Moreover, data about alters especially on connections among alters reported by ego is less reliable. Many scholars do not collect data on connections among alters or if they do it, they limit the network to a small number of alters that ego knows well. There are other approaches to construct personal networks such

as observing individuals' interactions, using contact diaries or more recently using records of technology-mediated interactions. The ubiquitous use of Online Social Networks (OSNs) makes it much more viable to collect data on personal networks. However, OSNs have not been effectively employed by social researchers due to the methodological challenges in obtaining data as well as the methodological and ethical concerns in the use of these data for social research.

The data for this study were collected on personal networks of 105 Australians aged 50 years and over using a purpose-built Facebook¹ application² called AuSON (Australian Seniors' Online Networks). Using this application, data were collected in two parts. For any participant of this study who has installed AuSON, it first automatically collected data on the personal network and socio-demographic characteristics of the participant from Facebook. Then, it loaded the personal network data into a visual survey that enabled the participant to add more information on subjective well-being, social capital and negative interactions.

This study considers Facebook personal networks as proxies for personal networks in real life. The extent to which this is true is examined, particularly as the models for testing the associations between personal networks and subjective well-being are guided by theories based on personal networks in real life. This study checks the validity of data on personal networks collected from Facebook for the purpose of this study by ascertaining the overlaps between participants' personal networks on Facebook and in real life. Results of this validity checking are used in explaining the findings of this study on the associations between personal networks and subjective well-being and further, provide new insights into the use of OSNs for social research.

The structure of this thesis is as follows. It begins with a review of the literature on social networks and well-being with a focus on online personal networks in later life. Chapter 2 provides a conceptual framework for the analysis of this study. This conceptual framework focuses on three features of social networks: homogeneity, social capital and negative interactions.

Chapter 3 provides a review of research methods used in this study, as well as a description of the sample. In this chapter, I explain how the data for this research been collected from Facebook and combined with the information provided by participants. The ethical and methodological challenges are discussed as well as suggested solutions. Some of the concepts and measures that are used in the analysis are defined in this chapter. The final section of chapter 3 de-

¹Facebook.com was the most popular Social Network Site (SNS) at the time of this study

²Interactive software applications developed to utilise the core technologies of the Facebook social networking platform (Stroud, 2016)

scribes the sample in terms of socio-demographic characteristics, subjective well-being and the structural characteristics of personal networks. By describing the structural characteristics this chapter provides a preliminary view of the typical personal network of participants of this study.

In chapter 4, I study homogeneity in personal networks and its relation with subjective well-being. Homogeneity is measured based on network structure and socio-demographic characteristics of network members including age, education and geographical location (location of residence). The analysis in chapter 4 improves the view of personal networks provided in chapter 3 by describing how homogeneous are the personal networks. This chapter also studies how the structural characteristics correspond with the homogeneity based on socio-demographic attributes of network members. Finally, this chapter examines how homogeneity is associated with subjective well-being.

Chapter 5 focuses on social capital defined on the basis of network structure and function (access to resources). By describing social capital this chapter further improves the view of personal networks provided in chapters 3 and 4. This chapter then examines how the structure of the personal networks is related to its function in facilitating access to resources. Finally, chapter 5 studies the associations between measures of social capital and subjective well-being.

Chapter 6 describes positive or negative emotional interactions and examines their associations with subjective well-being (happiness and life satisfaction). The positive and negative emotional interactions are defined as the extent to which each alter can make ego feel happy or unhappy (reported by participants via the online survey). The analysis of this chapter provides new insights into the associations between emotional interactions and subjective well-being by considering the interconnections among alters.

Facebook personal networks are somewhat different from the personal networks in real life. Chapter 7 examines this further by studying the overlap between participants' personal networks on Facebook and in real life. It further studies how *important* relationships can be identified in Facebook personal networks based on the measures developed in chapter 4, 5 and 6. Finally, chapter 7 attempts to answer the question about the validity of data on personal networks collected from Facebook for this research and more generally for research in the context of well-being.

Chapter 8 summarises the findings of this research in three sections. It first characterises the personal networks of the sample of this study in terms of network structure, homogeneity, social capital and emotional interactions (illustrated in chapters 3 to 6). Second, this chapter summarises and explains the main findings on the associations between personal networks and subjective well-being. Third, this chapter discusses the validity of findings of this study based on findings of chapter 7. This chapter concludes with discussion on the use of data from OSNs for social research (in the context of well-being in later life) as well as the limitations of this research and suggestions for future research.

Literature review and conceptual framework

2.1 Introduction

Over the past few decades, there has been an extensive amount of research on social networks and individuals' health and well-being. The powerful impact of social networks on health and well-being is now widely understood by scholars as well as the wider public. Several researchers have shown that social connectedness has a vital role in individuals' health even to the extent of affecting mortality (Berkman and Syme, 1979). However, there are some major limitations and gaps in the literature. Most importantly, the current literature uses social networks metaphorically and barely employs the formal approach of social network analysis. There are so many terms and concepts broadly referring to social networks such as social connectedness, social integration, social support, social isolation and social inclusion, but they do not really capture social networks.

This chapter provides a conceptual framework for the thesis based on the social network perspective. To do so, it reviews the most relevant literature on social networks and well-being. It first provides an overview of social network analysis as a comprehensive approach to studying social structure. It then reviews the literature on social networks and health and well-being by focusing on three main aspects of networks: structure, composition and function. This chapter also reviews how Online Social Networks haven been used in the context of health and well-being. It further reviews the literature on social networks in later life. This body of literature is mostly based on practical research, but it will be discussed in relation to the theories of social relationships in later life. Limitations, gaps and challenges- mostly methodological- are discussed as well as some solutions developed in this research. This chapter finishes with a summary and presents the conceptual framework that is used in this study.

2.2 Social networks

Theories of social networks have been developed by some of the classical sociologists such as Emile Durkheim (1897) and George Simmel (Simmel and Wolff, 1950). However social network analysis (SNA) was not systematically employed until 1960 (Elizabeth, 1957; Barnes, 1971). The fundamental difference between social network and other sociological theories is shifting the view of social structure from the sum of individual actors' attributes to the "actual" structure of relations among them (Wellman, 1988). Actors can be individual persons, organisations or nations. Social network analysis takes relations between actors as units of observation, while traditionally, social science has been mainly focused on the actors themselves. Therefore the social network approach aims to provide social explanations based on how actors are connected to each other in reality rather than through categorising them in groups defined by their attributes such as gender, age, socio-economic status or social class. Certainly, the social network approach considers the categorical attributes of actors, but does so through relations between actors and not their abstract and conceptual relations.

SNA studies social structure as relations between actors and in this way provides a framework with a comprehensive set of concepts, measurements and analytical tools. It uses a more abstract terminology to refer to actors and relations, mostly taken from graph theory. An actor is interchangeably called a "node" or "vertex" and a relation is interchangeably called a "tie" or an "edge". These terms are also used in the present research interchangeably.

Social networks have been studied in two main ways: as whole (socio-centric) and personal (also called ego-centric) networks (Wasserman and Faust, 1994). The whole network approach examines a set of nodes and ties between them as a whole which is usually bounded in some defined way (e.g. organizational membership). Personal network approach focuses on the focal actor who is called ego and the relations of that actor with others who are called alters.

From the SNA point of view, these two approaches are not essentially different (although they have roots in different disciplines as sociology and anthropology), but they have been employed in different areas of study. The main focus of the whole network approach is examining the structural patterns emerging from relations as a whole and its associations with the outcomes such as the flow of power, resources or information. On the other hand, personal network approach examines networks of relationships from individuals'(egos) standpoint and aims to provide generalisations about how such networks are associated with their behaviour such as

voting behaviour or well-being.

Personal networks

Personal networks are social relationships according to the focal person known as ego (Mitchell, 1969; Laumann, 1973; Fischer, 1982). Personal networks have been also used in various contexts from studying social support of single mothers (D'Ercole, 1988) to occupational status attainment (Lin et al., 1981). One of the central themes in studying personal networks has been related to how the macro-level changes such as the process of urbanisation impact the social life of individuals (at the micro-level).

Understanding personal networks has been central to studying the nature of community. This understanding has important implications for studying the associations between personal networks and well-being. The positive effect of community engagement on health and well-being is widely acknowledged in the literature, as communities are sources of resources, sense of belonging and confidence (Berkman, 2003). However, as I explain in the next paragraphs, since the meaning of community is changed over the time, studies often fail to adequately capture how individuals are involved in communities. This may lead to conclusions that people lack social relationships, as many do not even know people in their localities (Stanley et al., 2010). Social network scholars prefer to use "personal communities" (Maas et al., 2009) rather than communities, which implies that the definition of community has changed from "spatially-defined" to "relationally-defined". In this notion, communities are defined from the point of view of ego as people who are connected to ego who are usually connected to each other as well. This community is not necessarily physically bounded, but it can rather be distributed in space.

Community that traditionally preserved (and still does) the special meaning of social cohesion has always been perceived to be bound to the local neighbourhood interactions. In the 1970s with the mass urbanisation, scholars started to study the common fear of losing communities (Wellman, 1979; Fischer, 1982). In examining the "community question" (see (Wellman, 1979)), scholars concluded that the community is not "saved", it not either "lost", but it is "liberated". It means that communities are now "personal" that they are parts of personal networks and not bound to any physical location. The idea of liberated personal communities argues that the essence of community is its social structure, not its spatial structure (Wellman, 1988, p. 86). Unlike the societies of old or in small rural areas, individuals' relationships in contemporary societies are not bound within the physical neighbourhood; people even do not know their neigh-

bours. Rather, social relationships are liberated in a sense that individuals form and maintain relationships at distance. The advent of transportation, as well as communication technologies, made personal communities more liberated by affording individuals to form and maintain relationships at distance

As it is discussed in research by Wellman and his colleagues (Wellman and Hall, 1988; Boase, 2006; Wellman, 2007; Maas et al., 2009) the "social world is composed of social networks and not of groups" (Wellman, 2002). The way in which individuals and institutions are connected has changed from "little boxes" to "glocalization" and then "networked individualism". The notion of little boxes refers to the time when individuals were linked together through their organising institutions (family or village). Individuals were bounded within their organization such as family, club, church or work place. Little boxes refer to having door-to-door communication such as with their physical neighbour (in cities) or with almost everyone in a village.

"Glocalization" refers to the emergence of groups which are less dependent on their geographical boundaries. Transition from little boxes to glocalization occurred along with advancements in communication technologies (i.e. telephone) as well as transport technologies (i.e. fast trains and affordable air flights). So, the transition from little boxes to glocalization can be seen as transition from door-to-door to place-to-place connectivity. "Glocalization is a neologism meaning the combination of intense local and extensive global interaction" (Wellman, 2002, P. 13).

"Networked individualism" refers to person-to-person connectivity. With the advent of new communication technologies such as internet, email or mobile phones, individuals can connect to each other directly independent of their physical location. So, the transition from glocalization to networked individualism is actually the transition from place-to-place to person-to-person connectivity.

The popular growth of new communication techniques further weakens boundaries and expands personal communities. Accordingly, the present study takes the view that individuals in the contemporary societies are "networked individualists" managing their social relationships across different traditionally defined boundaries such as kinship or neighbourhood. Therefore, personal networks include people from different social groups and institutions associated with the focal persons. This eliminates the need for searching beyond the personal networks for links between individuals (at the micro level) and between individuals and the larger communities,

institutions and society (at the macro level), as these links are all contained within personal networks.

2.3 Social networks and well-being

In studying health and well-being, traditional social science mainly focuses on the attributes of individuals and societies and tries to explain the phenomenon by grouping them in categories. For example, it is well-known that on average, women live longer than men (Waldron and Johnston, 1976; Waldron, 1983; Austad, 2006; Barford et al., 2006; Oksuzyan et al., 2008), or people with better socio-economic status and education have a better physical and psychological well-being (Larson, 1978a; House et al., 1990; Winkleby et al., 1992; Ross and Wu, 1996; Berkman and Gurland, 1998; Meeks and Murrell, 2001).

The social network approach argues that the inequalities in health and well-being can be better explained by considering the differences between individuals' social networks (Hawe and Shiell, 2000; Cattell, 2001; Song and Lin, 2009) rather than their personal attributes. Therefore, SNA explains the inequalities in health and well-being as a result of "social distribution of possibilities: unequal availability of resources" (Wellman, 1988). In other words, rather than the direct associations between individuals' attributes and outcomes, SNA *explains* the process through which differences in such attributes (e.g. gender or education) are linked with the differences between outcomes (i.e. health and well-being). The underlying proposition is that if individuals' attributes are linked with outcomes, it is because of the links between social networks and outcomes and the fact that people with different attributes have different social networks.

Research on social networks and well-being has its origins in some of the first sociological research done by Emile Durkheim on suicide. Durkheim (1897) examined how "social integration" is associated with the suicide rate, categorised by individual level characteristics such as gender, marital status, education and religion. He concluded that higher rates of suicide happen in societies with either a lack of or a very high level of social integration. Although it has some limitations and critics (see (Berk, 2006)), Durkheim's work on suicide is acknowledged as having created new insights into the social determinants of well-being.

Although Durkheim did not study suicide using the social network framework (and he did not even use the term network), his study put this phenomenon into a larger context which was beyond the individuals' personal and psychological environment. One of the core concepts in

his study was "social integration", which refers to the extent to which individuals are attached to groups and society. By observing patterns of suicide in different societies and groups, he explained how suicide increases when social crises or rapid social changes disturb social integration.

As one of the first empirical studies into social relationships and health, Berkman and Syme (1979) published results which clearly indicated the vital role of social connectedness for health, even to the extent of affecting mortality. They studied the 1965 Human Population Laboratory survey of a random sample of 6928 adults in Alameda County, California and a subsequent nine-year mortality follow-up. They found that people with few social contacts were systematically more likely (1.9-3.1 times) to die in the follow-up period than those who had more social contacts. Moreover, their analysis revealed that associations between social relationships and mortality was independent of self-reported physical health status, year of death, socio-economic status, and health-related behaviour such as smoking, alcoholic beverage consumption, obesity and physical activity.

Several similar studies on different populations (Orth-Gomer and Johnson, 1987; Kaplan et al., 1988; Sugisawa et al., 1994; Avlund et al., 1998; Ellwardt et al., 2015a) confirmed that the likelihood of death was higher among people who had too few contacts or no social relationship. In Australia, Giles et al. (2005) did a similar analysis using data from the Australian Longitudinal Study of Aging (Luszcz et al., 2014) on adults aged 70 years and above who lived in the community and in residential care facilities. The study found that in general social network was protective against mortality, in 10 year follow up. However, when differentiating between types of relationships, better social networks with friends and confidants (the existence of confidants and whether the confidant was a spouse) were significantly related with survival, while there was no significant effect for having relationships with children or relatives.

Holt-Lunstad et al. (2010) conducted a meta-analysis of 148 studies focused on social relationships and mortality. Their analysis indicates that social connectedness is vital to individuals' health, and social integration (defined based on social roles as active participation in broad range of social relationships and social roles) was found to have the strongest association with lower risk of mortality (among 10 measures including perceived and received social support, network size and density or feeling of loneliness and social isolation). They conclude that "the influence of social relationships on risk for mortality is comparable with well-established risk

factors for mortality."

Further studies have attempted to understand the mechanisms through which social relationships affect individual health and well-being with a special attention to causality (House et al., 1988; Goldman, 2001; Berk, 2006; Berkman et al., 2000; Yuasa et al., 2012).

It is now well-known, that networks are related to well-being through two main mechanisms: *direct or main effect* and *stress-buffering*. The main effect model suggests that social networks can directly impact individuals' health and well-being just because they are connected to others. Connections with individuals and groups exposes individuals to various effects either at the level of interpersonal relationships (dyadic) or networks which act above of each of their interpersonal relationships. Networks can have different effects such as social control, social influence, peer pressure, sense of identity, belonging and self-worth, predictability and stability, of purpose and of meaning (Cohen, 2004).

The stress buffering model suggests that social relationships can benefit well-being by providing the material and emotional resources needed to cope with stress (Farmer and Sundberg, 2010; Cohen and Wills, 1985). This model has been employed extensively in research on associations between social networks and health and well-being (Matthews, 1984; Wethington and Kessler, 1986; D'Ercole, 1988; Gilles et al., 2015).

Cohen (2004) identifies three aspects of social relationships which are related to health: social integration, social support and negative interactions. Social integration refers to the extent that "an individual participates in a broad range of social relationships" (Brissette et al., 2000) and has been measured by active participation in 12 roles including being married, being a parent, being a parent in law, being a fellow volunteer, etc. (see Cohen et al. (1997) for the complete list). Cohen and his colleagues have used concepts of "social integration" and "social diversity" to refer to the extent to which individuals are involved in various types of relationships. They have defined social support as the provision of resources through social networks which is intended to improve an individual's ability to cope with stress. This definition explicitly takes into account stress buffering as the mechanism through which social support is related to health. Negative interactions are measured based on whether individuals have experienced enduring social conflict. Similarly, Berkman (2001) identified four primary aspects of social relationships that are related to well-being: provision of social support, social influence, social engagement

and attachment, access to resources and material goods.

Although, the current literature provides insights into the relation between social networks and health and well-being, it has a number of limitations that I discuss in three main categories. Some of the limitations are common to the three categories.

First, a significant body of the research in this area has been undertaken by scholars from other fields of research than sociology. The prevalence of epidemiological and psychological studies in both theoretical and empirical research is evident. This body of literature has a special focus on the exact mechanisms and the casual associations between social connections and health and well-being. As stated by Cohen (2004), these studies are more interested to know how social connections "get under the skin" (Uchino, 2006). Although, this body of literature is invaluable for understanding social factors of health and well-being, it does not adequately address social factors using sociological frameworks. This literature has been mainly dominated by views, questions and research methods used in fields other than sociology. It therefore, diminishes the social dimensions of relationships to some specific aspects which are responsible for biological or psychological influences. And the broader social context through which social relationships influence health and well-being are either not covered or have been used only as contextual factors.

Relatedly, this literature has mostly defined social networks as a set of "dyadic" relationships. By doing so, they are able to examine how social relationships influence health and well-being. In particular, the number of relationships, their characteristics and function (e.g. strength or negative interactions) and the amount and types of support received are the main determinants of individuals well-being. However, social network analysis has not been used appropriately. As has been stated by Berkman (2001), "Hall and Wellman have appropriately commented that much of work in social epidemiology has used the term social networks metaphorically since rarely have investigators conformed to more standard assessments used in network analysis."

Second, researchers have defined and used many concepts loosely and interchangeably such as social networks, social connectedness, embeddedness, social integration, social attachment, social isolation, social support, social capital and so on. Such varied use of concepts and terms make the studies and their findings incomparable. Moreover, use of various terms (which are usually from different fields of study) make it difficult to reach agreement on them and create one framework for future studies.

While social network analysis provides a framework with a comprehensive set of terms, concepts, measurements and tools, they have not been used consistently. Scholars use different terms to refer to concepts that have already been defined by social network scholars. For example, from the social network point of view, social relationships are the actual channels to access resources. However, instead of examining how individuals are connected to each other and how their connections provide them with resource, scholars have sought to measure individuals' perception of social support as social networks. Of course, individuals' perception of their social environment can play an important role in their well-being, but an individual's perceived social support is not his or her social network. As another example, the term social integration has been extensively used to study how individuals are linked to the larger society for example through membership in groups or communities. However, this term is quite broad and includes a vast range of concepts. This makes it difficult to measure in a way that can be comparable across studies. Using the social network analysis approach, scholars can study the extent to which individuals (or groups or organizations) are actually connected to each other. This makes the studies and their findings more comparable.

Third, the literature has mainly focused on specific target populations who are characterised as vulnerable (e.g. people with mental health problems) or the general population at a particular point in their life course (e.g. older age), creating the impression that social relationships are the cause or cure for everything, and a lack of social relationships means deprivation of everything. With the original aim of understanding the role of social factors in well-being among other factors, the power of networks have been over emphasised and somehow exaggerated. This has happened at the same time that social network analysis, as noted above, has not been used appropriately.

In particular the stress buffering mechanism, as one of the main ways through which social networks are related to well-being, is based on stressful life events. In this way, social support is helpful when there are stressful events. Since such events are more likely to happen when people are in their difficult time or when they experience transition in life (e.g. bereavement or parenthood), social support is mainly helpful for people during difficult times. Moreover, findings on the negative or positive impacts of social relationships is confounded, not only because of existence of several other factors (which are not often possible to control) but mainly because of the data on social relationship itself. For example, people usually tend to perceive

themselves as "more alone in their emotional difficulties than they really are" (Jordan, Monin et al. 2011), or on average, people's friends have more friends than they do (Feld, 1991; Hampton et al., 2012). So, the impact of social networks on well-being may have been overestimated as a result of focusing on specific target populations.

In the context of the Australian population, the literature is very limited and can also be characterised by the main limitations noted above. Among those who have paid attention to social factors of well-being in Australia, there has been much emphasis on either physical well-being (McCallum et al., 1994; Andrews et al., 2002; Booth et al., 2000; Giles et al., 2004, 2005) or mental health issues (Butterworth et al., 2006; Vanderhorst and Dr, 2005). Social networks have been mostly studied as social support (Kendig et al., 1999; Huang et al., 2010) and very limited attention has been paid to other aspects of social networks such as social capital (Alexander et al., 2008).

The conceptual framework of the present study is based on three prominent features of social relationships which are consistently found to be important. Social relationships are found to be highly homophilous (love of the same), they are found to be the main way to get access to resources and they are the main source of stress (as social strain). These three aspects have been identified by Cohen (2004) and have been used in many studies, but mainly at the level of dyadic relationships.

The present research studies these three features from a broader sociological point of view. It studies how personal networks are homogeneous, how such homogeneity is reflected in the structure of personal networks and how it is related to well-being. It also expands the second feature by studying social capital rather than social support as the mechanism through which personal networks facilitate access to resources structurally and functionally, and how it is related to well-being. In studying negative interactions, this research expands the current approach by considering how others with whom an individual has positive and negative interactions are connected to each other. In this way, it is not only about the volume of positive or negative interactions that can determine well-being, but it is also about where are each of such interactions located in the structure of personal network. The literature on each of these three features is reviewed briefly in the three following sections and in more detail in Chapters 4, 5 and 6 respectively.

Network homogeneity and well-being

One of the most striking characteristics of personal networks is homogeneity. The form and level of connecting with similar others varies across societies and has changed over time (Smith et al., 2014) as we have transited from living in pre-modern societies, to modern societies with institutions which are highly segregated in many aspects and then the recent decades with the remarkable advancement in communication technologies. So on the one hand, modern society has facilitated connecting with diverse people by providing more opportunities to meet new people, but it has also facilitated connecting with people with similar attitudes and interests (Popielarz and McPherson, 1995). For example, homogeneity based on gender has decreased in time as more women work outside the family (Smith et al., 2014), but the advent of new communication technologies may have allowed people to connect with similar others based on other dimensions, such as with those who share attitudes and interests (Lewis et al., 2012)

Surprisingly, the literature on homogeneity of personal networks is limited to a few prominent studies (Marsden, 1988; McPherson et al., 2001). The current literature has mostly focused on describing and explaining homogeneity (Feld, 1982; Mark, 1998; Louch, 2000; Schaefer et al., 2011) and less attention has been paid to the implications of homogeneity, especially in relation to health and well-being. Moreover, those studies that have focused on homogeneity in personal networks, have often limited them to a small number of core social relationships. The core social relationships are very likely to be homogeneous, thus showing less variance in attributes of network members.

There are also limitations of the existing literature in measuring homogeneity in personal networks. Homogeneity has been mostly studied based on types of relationships (referred to as role diversity) (Cohen et al., 1997, 2000) and attributes of alters (Marsden, 1987, 1988; McPherson et al., 2001; Seder and Oishi, 2009; Lewis et al., 2012) and there is almost no attention to the structural dimension. By the structural dimension, I refer to what is actually present in the structure of personal networks (this is related to but, is different from what Feld (1982) means by structural dimensions). In this way, a personal network which is segmented by separate clusters of relationships among alters can clearly indicate diversity as different clusters represent different contexts. With no view of such segmentation in the structure of network, one may discover a high level of homogeneity based on the attributes of alters. In other words, similarity between the attributes of alters can show only a part of homogeneity. A complete characterisation of homogeneity also requires analysis of the structure of relationships.

The present research studies homogeneity in personal networks by considering both the (socio-demographic) attributes of network members and the structure of relationships between them. It also studies how these two dimensions are related to each other. More details are provided in Chapter 4.

Social capital and well-being

Social capital is a broad theory in social science and has been used in various fields from economics to politics. However, it has less been employed in research on individuals' health and well-being. In the following paragraphs, I briefly review and discuss social capital in relation to other theoretical views used in the context of social networks and well-being. Chapter 5, will further review this theory as well as the relevant empirical studies of individual health and well-being.

Social capital was originally developed in sociology to address phenomena mainly at macro level such as explaining why some societies are more successful in modern democracy (Tocqueville, 1945). It is argued that social capital could explain inequalities between nations or groups in a way that was not been achieved by other fields such as economics or politics (Woolcock, 1998). However, social capital has been less used to explain inequalities at the level of individuals. With the more recent developments in social network analysis, scholars have provided an analytical framework for social capital (Borgatti et al., 1998; Lin, 1999).

At the level of individuals, social support has been substituted for social capital. From the social network point of view, social capital and social support are similar as the underlying assumption is that social relationships are the main way to access resources. But in applied research, they have been employed in different areas. Social capital has been used mostly in relation to instrumental outcomes and economic actions (e.g. finding a new job) (Burt, 1995; Woolcock, 1998; Burt, 1999; Burt et al., 2000; Ooka et al., 2006; Agneessens and Wittek, 2008), while social support has its main focus on aid and support received via interpersonal relationships mostly emotional aid with expressive outcomes (Matthews, 1984; Slevin et al., 1996; Penninx et al., 1999; Lin et al., 1999; Seeman TE, 2001; Neville and Alpass, 2002; Stone, 2003; Chan and Lee, 2006; Gow et al., 2007; Lakey, 2008).

Many studies in the area of health and well-being have studied social support and social capital

as separate concepts (Cooper et al., 1999; Fram, 2003; Ryan et al., 2008; Leal et al., 2011). In this way, social support has been defined based on help and support that individuals receive from their social contacts, while social capital has been defined by their involvement in larger groups and communities. While these provide a good understanding about individuals' involvement in their local social environment as well as in the global society, they do not capture what is really linking individuals to their local or global structure. In studying social support and depression, Lin et al. (1999) argues that social ties are structured in three layers as "belongingness" (community participation), "bonding" (network relations) and "binding" (intimate personal relations). He further explains how these three levels act as a continuum in that "the inner layer is contingent on upon the outer layer and each outer layer of linkage affords the opportunity to construct inner-layer linkages" (Lin et al., 1999, pg. 346). This is what social network scholars emphasise about an infrastructure of relationships linking individuals at the micro level to groups and communities and the whole society at the macro level.

Lin (1999) explains how SNA provides a new approach to study social capital which is not confounded between these levels by capturing access to resources embedded within social networks. He proposes the "position generator" model that focuses on individual links to the hierarchical positions. This model measures social capital at the level of individuals, but is more appropriate for measuring social capital for instrumental actions rather than expressive. More recently Van der Gaag and Snijders (2004) have developed a survey instrument called "resource generator" that combines two aspects of social capital as "social support" and "social leverage" (Lin, 2000), by explicitly measuring individuals direct access to resources rather than inferring it from position of network members in the social structure. Using this survey instrument, one can measure social capital based on access to a diverse set of resources rather than being mainly focused on either instrumental or emotional support. Resource generator is also compatible with other methods used in collecting network data such as the "name generator" and in this way enables researcher to collect data on network structure as well. However, in the resource generator survey employed by Van der Gaag and Snijders (2004), resources are finally aggregated as assets of ego and are not linked with the data on network structure, hence does not provide any information on how resources are distributed in personal networks.

The present research studies the social capital of individuals using the resource generator survey instrument with some modifications. In addition to measuring social capital for individuals, it studies how resources are distributed in personal networks, who provides which type of re-

source, and how access to resources is related to the structure of networks (Chapter 6).

Negative interactions and well-being

Social relationships are mostly studied as positive, being the main ways to access help and support and hence having a protective role in cases of stressful life events. As acknowledged by many scholars, social relationships are not always positive and enabling; they can also be negative and hence have negative impacts on well-being (Levitt et al., 1996; Ingersoll-Dayton et al., 1997; Rook, 2001). However, negative relationships and their effects on well-being have been less studied (Rook, 1984). Moreover, those studies who have considered negative interactions in relation to well-being have mostly focused on the existence and the number of interactions and some other important aspects have remained unclear.

Most notably, the current literature has paid only limited attention to the structure of personal networks in which positive and negative interactions are embedded (Kalish et al., 2009). Positive and negative interactions are regarded as dyadic relationships between ego and her alters, thus assuming that they can affect ego's well-being entirely independently. Some recent studies have pointed out that characteristics of positive and negative interactions such as type (e.g. kinship or friendship), intimacy or intensity of contact can further explain the links between positive and negative interactions and well-being (Cheng et al., 2011). However, the impact of a positive and negative interaction does not only depend on how close or intimate the alter is to ego, but also depends on how connected is the alter to other alters by the fact that alters can influence each others' relationships with ego. In this way, the effect of having a positive or negative interaction with an alter who is highly central in the network structure is different from having the same type and amount of interaction with another alter who is less central. This thesis studies positive and negative emotional interactions by going beyond the existence and number of positive and negative interactions to include their importance in relation to ego and with the rest of the network (Chapter 6).

2.4 Structure of personal networks and subjective well-being

While SNA pays special attention to the structure of relations, structure is largely absent in studying of personal networks that personal networks are not assumed to be networks anymore (they are usually not represented as relational matrix data). Instead personal networks are conceived as a set of dyadic relationships which are mainly important for providing help and support, and can be aggregated to ego's attribute. In this way, social networks are utilised to

describe ego with some more attributes in a similar way as the categorical attributes such as the number of social relationships (representing structure), types of relationships (composition) as well as the type and volume of help and resources they can provide (function).

The structure of relationships between alters acts as an infrastructure for transfer of help, support and information without direct interaction with ego. For example, the extent to which alters are connected to each other can be related to network's capability in arranging for providing help (Hurlbert et al., 2000). Since most studies take only relationships with ego and not relationships between those who are connected to ego, almost everything is determined by the number and quality of relationships with ego. In this way, alters who usually have different roles can contribute to ego's well-being differently (e.g. parents may have more important role in someone's life than colleagues). But, as noted by scholars, it is not only the presence and quality of ties (dyadic) that determines well-being, but it is also about the patterning of relationships and the way that alters with different roles are connected to each other (Walker et al., 1993).

There are three main concepts used for the structural characteristics of personal networks and their association with SWB: "*social integration*", "*network cohesion*" and "*network segmentation*".

Social integration refers to the extent that individuals are integrated with the society and is rooted in Durkheim's work on suicide (Durkheim, 1952). Durkheim's research and the following studies on individuals' well-being showed that people who are socially integrated are less likely to commit suicide (Vanderhorst and Dr, 2005) and generally have a better physical and psychological well-being (Holt-Lunstad et al., 2010). The existing literature has defined social integration based on three measures: the number of social relationships (network size), the type of social relationships (roles, see (Cohen et al., 1997)) and the frequency of contacts (House et al., 1988). Among these three measures, the number of social relationships which is basically network **size** has been used the most. This thesis uses only network size to measure social integration. The associations between network size and SWB is further explained in the following paragraphs.

It has been found that network size is associated with well-being (Cohen, 2004; House et al., 1988; Windsor et al., 2012). In terms of psychological well-being, other researchers found that having many friends is related to improved mood (Lin et al., 1999). Burt (1987) also found that happiness increases with the number of people with whom ego can discuss important matters.

Chan and Lee (2006), found that personal network size is positively associated with the happiness of elderly Chinese and that it is more important than income. Network size has usually been measured implicitly using related concepts such as social isolation or loneliness. In this way, it is consistently found that a lack of social contacts is highly related to poor well-being. However, few studies have actually measured network size by counting the number of social contacts and if they did, they have usually limited the network size to the few network core members. Moreover, scholars have pointed out that it is not only the presence, but more so the pattern of relationships that contribute to well-being (Seeman, 1996; Kalish et al., 2009). This gives the motivation for use of more sophisticated measures for network structural characteristics.

Network cohesion refers to the extent of interconnections among network members. In the context of personal networks, cohesion indicates the extent to which alters are connected to each other. Cohesive networks are commonly found to facilitate the flow of resources and corporations for the provision of support (Coleman, 1990; Hurlbert et al., 2000). There are three ways to measure cohesion. First, by comparing the existing number of ties to the ideal number of ties needed to have the fully cohesive network (total number of possible ties for the given number of nodes). Second, by taking the average of the number of ties for each node in the network. Third, by measuring the extent to which the network is formed as a community (Friggeri et al., 2011). The first way is actually the measure of **density**, the second way provides the measure that is referred as **average degree** and the third way measures network **transitivity**. Further details on these three measures are provided in section 3.3.2.

There is strong evidence that network cohesion is associated with well-being. In particular, denser networks contribute to well-being by maintaining social identity and providing access to social support. According to Coleman (1990), dense networks consisting of "strong ties" (relationships with family and close friends) can facilitate the efficient transmission of useful information to network participants, and can also increase trust and reduce the probability of free riding or malfeasance. However, sparse networks consisting of "weak ties" (social relationships with acquaintances) can improve an individual's access to new resources such as novel information, for example about a new job, that may not exist within the close network of strong relations (Granovetter, 1983).

Burt (1987) examined the associations between social networks of discussion partners (people

with whom ego discussed important matters) and happiness using a sample of the data collected in the 1985 General Social Survey in the US (Burt, 1987: pg 314). This study found that it is the negative impact of strangers (discussion partners who did not know each other) rather than the positive impact of close relations (discussion partners who knew each other) that determines expressions of happiness. According to this study, respondents with large networks (five or more discussion partners) containing one or more strangers were about as happy as social isolates, the respondents with no discussion partner. Respondents with two discussion partners who were strangers to one another were actually less happy than the social isolates.

When personal networks are large and include a wide range of relationships from very close to far acquaintances, it is not clear that the dense or sparse networks are better related to well-being as each of them can be a source of benefits as well as detriments (Lin, 1999, 2001). Focusing specifically on subjective well-being, dense networks are the main source of social support and should, therefore, have a positive impact on well-being (Kadushin, 1982; Ashida and Heaney, 2008, pg 147), but they also have the potential for creating a strain on relationships and hence a negative impact on well-being (Rook, 1997; Walen and Lachman, 2000). On balance, in the context of the well-being of older people, I regard the impact of network density will be positive for well-being.

Transitivity measures the extent to which alters form triads. Simmel and Wolff (1950) introduced and conceptualised the idea of triads and distinguished it from dyads in their characteristics in a way that compared with dyads, the ties in a triad are fundamentally different in terms of quality, dynamics and stability over time (Krackhardt, 1998).

The associations between network transitivity and well-being are studied based "balance theory" (Heider, 1946, 1985; Cartwright and Harary, 1956). According to this theory, people tend to have balanced networks to avoid psychological distress. Social relations tend to be transitive as a result of balance theory or a desire to make social ties cognitively consistent (Feld, 1981). Research on friendship networks and suicide in America by Bearman and Moody (2004) concluded that teenage females whose social relationships are intransitive are at higher risk of contemplating suicide than those who are embedded in more transitive friendship networks.

Network segmentation refers to the patterning in networks such that they are composed of smaller groups. Scholars have used different concepts to refer to the small groups such as

communities, modules, clusters, densely-knit or cohesive sub-groups (given that the personal networks are not overall cohesive). (Snijders and Spreen, 1997, pg. 28), provide a theoretical definition of segmentation in personal networks as:

Segmentation is the degree to which, within the set of actors directly connected to ego (the "alters"), there is for each alter a gap between the other alters to whom he is himself directly connected, and the other alters to whom he is not directly connected.

This notion defines segmentation as a function of distance between alters. If they are within groups are close to each other, if they are between groups the distance can be long or there may not even be a link between them. This thesis measures segmentation as the number of groups that a personal network can be divided to that is referred to as "**number of groups**". Further details on this measure is provided in section 3.3.2.

Segmentation can explain a lot about one's personal network and can be associated with well-being in many ways. People with segmented personal networks may have more opportunities and freedom in their networks as their groups of alters do not know each other. The existence of multiple groups within personal networks indicates the presence of multiple social settings Feld (1981). Multiple settings can represent diversity in a personal network and hence diversity in the available resources through different settings. But being involved in different social settings also indicates being involved in different roles that can create role strain and have detrimental effects on well-being (Pearlin, 1983).

2.5 Personal networks in later life

One of the most highlighted findings about social networks of older people is that network size decreases with age. On average, older people have fewer social relationships (Palmore, 1981; Marsden, 1987) as a result of inevitable loss of social associates due to several factors such as retirement or death (Cumming and Henry, 1961) and low rate of replacement for the lost relationships (Broese van Groenou et al., 2013).

However, the literature has greatly emphasised social isolation and loneliness in later life (Lowenthal, 1964; Wenger et al., 1996; Penninx et al., 1999; Victor et al., 2000; Findlay and Cartwright, 2002; Findlay, 2003; Vanderhorst and Dr, 2005; Cattani et al., 2005; Cornwell and Waite, 2009) which has led to change the focus from the importance of social relationships to the implications of lack of them, and much attention has been paid to the policies and programs to tackle isola-

tion of older people.

A recent comprehensive study (Cornwell et al., 2008) provided insights about social connectedness of older adults which are contrary to the popular notion of social isolation in old age. Using data from a population based study of 3005 Americans aged 57-85 collected in 2005-2006 (the National Social Life, Health, and Ageing Project), they examined social connectedness based on networks of interpersonal relationships (network size, density and composition, volume of interactions and closeness of relationships) and community involvement (socializing with neighbors, attending religious services, volunteering and organized group involvement). The authors found that although age is negatively related with network size (15% decline in network size for each ten years), closeness of relationships and the number of non-primary network members (not from family), other aspects of social connectedness such as socializing with neighbors and religious and voluntary involvement increased with age.

While many researchers have found that social networks shrink in older age, this decrease is more related to the total number of social relationships. Considering other aspects of social networks such as composition and function, the literature suggest a complex association between age and social networks. Socio-emotional selectivity theory (Carstensen, 1993, 1995; Carstensen et al., 1999) argues that as people understand that time is limited, they become more selective in their social relationships.

Many studies have confirmed socio-emotional selectivity theory, finding that the number of core members is stable, while the number of peripheral contacts decreases with age (van Tilburg, 1998; Helene H. Fung and Lang, 2001). Older adults tend to maintain more intimate, supportive, emotionally close and rewarding core social contacts and detach from negative or conflicting relationships (Lansford et al., 1998; Fung et al., 2001; Lang, 2001; Windsor and Butterworth, 2010; Luong et al., 2011). There is less agreement about the frequency of contacts: some researchers have found decreases in the amount of interaction (Cornwell, 2011) as people age, while others have found either an increase, no change or a complex relationships. For example, Cornwell et al. (2008); Cornwell (2011) found a nonlinear (U-shape) relation between age and volume of interaction with network members, with the lowest amount between 65 to 75.

Such complex association can be partly explained based on life course events in later life (Cavan et al., 1949) such as retirement and spouse loss. Retirement can change the network composition,

reducing the number of non-kin relations, especially from the work environment, and increasing relations with neighbours as well as those from volunteering and religious services. The death of a spouse or partner or friends has been found to be the greatest challenge of all in later life, where there is less opportunity for adaptation (compared to such loss in younger age). Such events can have major impacts on social relationship and well-being of older adults (Bowling and Cartwright, 1982; Arbuckle and de Vries, 1995; Johnson et al., 2000; Manzoli et al., 2007; Stroebe et al., 2008; Utz et al., 2011; Lee et al., 2001; Das, 2013).

In addition to the important life events in later life, sociological perspectives emphasise the experience of people in their older age. In his work with the title "I don't feel old", Paul Thompson (Thompson et al., 1990; Thompson, 1992) argues that people experience a different daily life in their later life. One aspect of this difference is related to the fact that compared to other age groups, they are not limited in daily routines such as going to school or work. In this way, they have more time for socialising, leisure and enjoying family-related social activities such as grandparenting. Later studies have found older people are more likely to participate in volunteering, attending social activities such as religious or cultural events (Moberg, 1953) or spending more time with family and friends (Larson et al., 1986; Huxhold et al., 2013).

In summary, despite the extensive literature on social relationships in later life, our knowledge in this area is still limited. The literature is mostly driven by and confirmed the view consistent with what has been commonly perceived as "lonely older people". While acknowledging that social relationships are subject to many changes in later life –most notably changes in size and composition– this does not necessarily lead to a significant level of social isolation in this age group. Similar to other characteristics, social relationships change during life and as a result, people gain experience to adapt to changes (though it might be more challenging in later life). Thus, there is no reason why we should consider social relationships in later life differently from earlier life. Moreover, the 50+ age group is more heterogeneous than what has been commonly viewed as a homogeneous socially vulnerable group (Cwikel et al., 2006). The social network approach, takes into account the heterogeneous nature of a group by considering the heterogeneity in social relationships.

For example, (Cwikel et al., 2006) studied never-married childless older women in Australia (Older cohort of the Australian Longitudinal Study on Women's Health) and found that these women were more likely to be involved in volunteering and social groups than married women

with children. Authors have stated that this group have significantly higher level of education than other women which is associated with less financial difficulty.

2.6 Online social networks and well-being

I review the literature on Online Social Networks (OSNs) and in particular Social Networking Sites (SNSs) in the context of health and well-being. The literature in this area can be categorised in two main themes: researchers who have studied OSNs itself (e.g. its associations with health and well-being) and those who have utilised OSNs for research on health and well-being. OSNs refer to online social networks of individuals, while SNSs refer to social networking sites that allows individuals to articulate their social networks online. In other words, SNSs are platforms for OSNs.

Of the first group, literature has an special focus of attention on how use of SNSs can influence individuals' health and well-being. For example "Facebook can make us miserable" (Gulati, 2011) via different ways such as "creating a den of comparison", "distracting constantly" and "decline of close relationships". Photo updates on Facebook can have negative impact on users' psychological well-being as people usually show images of their happy times that may create feeling of sadness or depression for friends.

Kross et al. (2013) found that Facebook use is negatively related to subjective well-being. Using an experimental study of eighty young adults, they found that the more respondents use Facebook, the worse they feel (i.e. worrying and loneliness) and the worse their life satisfaction. A recent study of 229 college students found that anxiousness, alcohol use and marijuana use predicted emotional attachment to Facebook (Clayton et al., 2013). Scholars have also studied the negative effects of using Facebook when people terminate their relationships (Bevan et al., 2012).

There are also many studies that found OSNs can improve well-being in various ways such as expanding social networks, facilitating access to more diverse resources, reducing social barriers for some people (i.e. low self-esteem students) and well-being (Ellison et al., 2007; Steinfield et al., 2008; Valenzuela et al., 2009). In most of these studies the positive impact of OSNs on well-being are because of improving "bridging" social capital (connecting with acquaintances who can link them to wider social circles).

OSNs are also found to improve "bonding" social capital (connecting with close social contacts) by strengthening close relationships. The Pew Internet and American Life project (Hampton et al., 2012), shows that people use Facebook to connect with their social contacts in real life. Moreover, Facebook users have more close relationships, receive more social support, more likely to trust other people and are more politically engaged than their counterparts who do not use Facebook. Therefore, Facebook may improve well-being by facilitating the maintenance of social relationships (acting as new ways of communication) and hence by decreasing depression and anxiety and improving life satisfaction (Grieve et al., 2013).

However, researchers suggest that the effects of Facebook on well-being can be better explained by studying the way that individuals use it rather than by considering whether they use it or not (Burke et al., 2010). Analysis of users' activities on SNSs showed a positive association between having direct communications (i.e. sending private messages) and bonding social capital and a negative association with the feeling of loneliness. But the amount of content use (e.g. reading posts or clicking on photos) showed a negative association with social capital (both bonding and bridging) and a positive association with the feeling of loneliness.

The second group of studies have utilised SNSs for research on health and well-being. Focusing on Facebook, some scholars have used it to recruit participants by running online surveys within groups or pages (Bhutta, 2010). Many studies have used it as a source of data which has been already articulated by people in SNSs as either directly provided from company (Golder et al., 2007; Lampe et al., 2007) or collected by research teams (Seder and Oishi, 2009; Brooks et al., 2014).

There have also been different approaches for collecting data: collecting data using conventional methods (i.e. survey and interview) or collecting data with no interaction with participants by employing new methods and techniques (i.e. data mining from SNSs). Each of these approaches has its advantages and limitations.

The first approach has been widely used in social science for several years. However, the disadvantage of this approach is that it can be demanding on participants to provide the required information. The second approach is better suited to collecting data from SNSs as it significantly decreases the demand on participants to provide information. However, this approach is also limited in some ways such as in collecting information that are not either available online or not

adequate for the purpose of research such as information on well-being or the resources that individuals' online social networks can provide.

While each of the two above approaches can be utilised to collect data from SNSs, depending on the purpose of a research, each of them or a combination of both approaches may be employed (Gilbert and Karahalios, 2009). However, only few studies have used the combination of two approaches. Even studies that have done so, have not actually linked the parts of data collected using each approach. For example, Brooks et al. (2014) collected data on personal networks of participants from their Facebook and data on their social capital (in real life) via an online survey which has been attached to the first part. These data have been used to study how the structural characteristics of Facebook personal networks are associated with social capital in real life. This research has linked the two parts of information through the conceptual framework of research and not by the "internal link" between them. In this way, a participant may have high score in social capital, but the data do not provide any information on how many of that participant's Facebook friends provide resources or which friends can provide what resources. The present study combines the two approaches and extends them by linking network data (i.e. structure and composition) collected from Facebook with the complementary information (i.e. function: closeness of relationship, social capital and emotional interactions) provided by participants.

Relatedly, although the literature increasingly advocates utilising SNSs for social research (Lenhart and Madden, 2007; Boyd, 2007; Wilson et al., 2012), there are still many debates and challenges about the validity of SNSs for social research. In particular, while some scholars have taken the view that Facebook can be used to study social behaviour in its naturalistic way (Lewis et al., 2008), this is the subject for several research examining how people represent themselves on Facebook and more generally online (to what extent they perform their real life roles online) (Marwick, 2005; Ellison et al., 2006; Boyd, 2008; Zhao et al., 2008; Hum et al., 2011; Chen and Marcus, 2012). For the purpose of the present study, the main challenge in use of data collected from an SNS is the fact that it considers the Facebook personal networks as proxies for personal networks in real life, while, Facebook personal networks can only partially overlap with their real life networks. This challenge and the devised solutions are studied in Chapter 7.

2.7 Summary and the conceptual framework

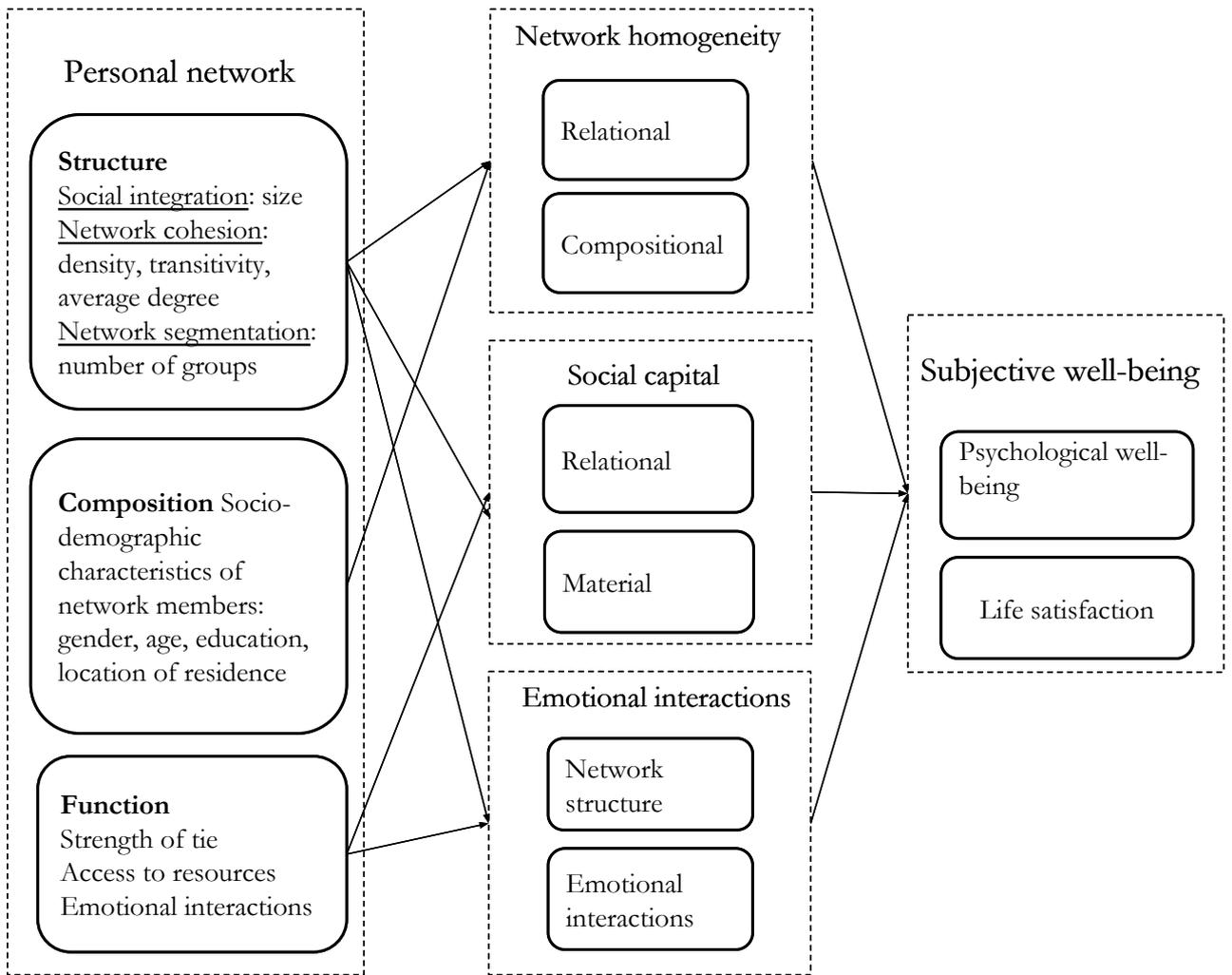
Research on social networks and well-being is extensive. However, there are major gaps in this body of literature that have been discussed in this chapter. The conceptual framework of this

research is shown in Figure 7.1, and is based on three main features of personal networks: homogeneity, social capital and emotional exchanges. This is very similar to the framework provided by Cohen (2004), where three features of social networks are identified: social integration, social support and negative interactions. Social integration refers to the extent that participants are involved in a broad range of social relationships measured by types of relationships (i.e. kin or non-kin). Social support is the provision of resources through social networks. Negative interactions are measured based on whether individuals have experienced enduring social conflict.

The framework developed in this thesis is based on similar features but from a broader sociological perspective. In this way, homogeneity provides a broader view of social integration by considering the diversity of characteristics of network members. Social capital provides a broader view of networks' function in facilitating access to resources compared to social support, by broadening the types of resources, the range of relationships through which resources may be accessible (not only close alters but also acquaintances) and by considering the relational aspect of networks in this regard. Negative interactions defined by Cohen (2004) can also be defined as a type of emotional interactions (positive or negative).

This conceptual framework is built upon three main components of personal networks: *structure* (relations between network members), *composition* (characteristics of network members) and *function* (resources provided by network members). In this regard, the study of homogeneity involves the combination of network structure and composition ("relational" and "compositional" see Chapter 4), while the study of social capital ("relational" and "material" see Chapter 5) and negative interactions ("network structure" and "emotional interactions" see Chapter 6) involves network structure and function.

Figure 2.1: Conceptual framework of the thesis



Research methods, and a description of the data

3.1 Introduction

The data for this research is a combination of data collected from Facebook profiles and the complementary information provided by participants. The first part includes information about the structure of personal networks, socio-demographic attributes of ego and her Facebook friends and type of relationships (e.g. family or close friends). The second part includes information about types of relationships as reported by ego, strength of relationships, social capital, positive and negative emotional interactions and ego's subjective well-being (SWB).

In order to collect this, a Facebook application was designed and developed, called AuSON (Australian Seniors' Online Networks). Once a participant installs AuSON and approves access to the requested information, it collects the first part of data from Facebook and then loads it into a visual survey that enables the participant to add more information (the second part).

This research is based on the data collected from 105 Australians aged 50 years and over who participated in this research by using AuSON during one month in December 2012. Of the initial 108 participants, three were excluded from the analysis. Two participants had no friend on Facebook resulting in non-valid network measures and one participant had more than 1,000 friends on Facebook which was identified as an outlier in the sample of this study. The choice of this target population (aged 50 years old and over) is because the present study is a part of a larger Social Networks and Ageing Project (SNAP¹) with the industry partner National Seniors Australia (NSA). Since eligibility for NSA's membership starts from the age of 50 years old, accordingly, the present study focuses on this age group.

¹For further information see this URL: <http://demography.anu.edu.au/groups/ageing/snap>

Participants were recruited using a combination of conventional methods and snowball sampling such as sending invitation messages to the target population via public media (i.e. radio and newspapers) as well as asking participants to invite their Facebook friends via AuSON. Participants did not receive any incentive, but they were able to view the graph of their own Facebook personal networks via AuSON.

The sample used in this thesis is not representative for the target population and hence the findings are not expected to be generalised unless stated. However, as it will be explained throughout the thesis, participants of this study are from different parts of Australia (i.e. see chapter 4) and have a diverse set of demographic characteristics. To put the sample in context, age group 50 years and over are often found to be the least active age group in the use of Internet and social media globally and in Australia (McAndrew and Jeong, 2012; Pew Research Center, 2014; Wong, 2015). There are less statistics showing the accurate number of older Australians who use Facebook and the existing statistics only show the approximate numbers. According to Australian Bureau of Statistics (2014a), only around 40% of age group 55+ with Internet access at home use it for online social networking (compared with more than 80% for age group 15-34); older persons use Internet mostly for paying bills or online banking. The approximate number of Internet subscribers in Australia at the end of December 2013 was 12 million and around 80% of the age group 55-64 and 46% of age group 65+ use Internet (Australian Bureau of Statistics, 2014b). These mean that of the approximate number of 6 million Australians aged 50 years old and over (AIHW, 2007), 4.8 million use Internet (considering 80% use) and then 1.9 million use social networking sites. The number of people from this age group who use Facebook is estimated to be less than 1.9 million.

This chapter provides more detail about the data, the specific methods and tool (AuSON) used to collect the data, the recruitment process and the ethical and methodological considerations. It also defines some of the concepts and measures that will be used in the next chapters. The chapter concludes with a descriptive analysis of the data used for this study.

3.2 Data collection

The data for this research has been collected in two phases: First AuSON collects data from Facebook profiles and second, loads into an online survey where participants are asked to add more information. The data collected from Facebook has many advantages, especially regarding

the structure of personal networks that is otherwise very difficult to collect. However, for the purpose of present research, a major limitation is the lack of data on subjective well-being as well as other aspects of personal networks such as social capital or negative interactions which are either not available on Facebook or else are not adequate for the purpose of this study. Considering these limitations and the need for linking network data with the outcomes (i.e. subjective well-being), this research is designed to collect all of the required data using one integrated tool.

3.2.1 Part 1: collecting data from Facebook profiles

Once a participant installs AuSON, it automatically collects publicly-available information from the participant's Facebook profile using the Facebook APIs (application programming interfaces). AuSON is developed using the Facebook "Graph API" which is the primary way to get data in and out of Facebook's social graph. A Facebook API can be accessed using a language provided by Facebook as FQL (Facebook Query Language) which is a limited version of SQL (Structured Query Language). FQL enables developers to directly access Facebook database tables².

The following data are collected from Facebook profiles:

- Socio-demographic characteristics of ego, where they are publicly available through ego's profile on Facebook. These characteristics are: gender, age, relationship status, education and location of residency (latitude and longitude, country/state/city) as ego has reported in her profile.
- Structure of 1.5 degree personal network: the list of ego's friends and ties among friends; with whom ego is friend in Facebook, and whether each pair of them are each other's Facebook friends. Note that in accordance with the restrictions of the Facebook APIs, AuSON does not collect connections among ego's friends if either of the alters has made his or her friendship list private. Further, AuSON cannot collect the 2.0 degree networks by discovering friends of friends (see Hogan (2008) for a complete discussion about collecting data using Facebook APIs). Shown in Figure 3.1, AuSON collects the second graph which is the 1.5 degree personal network.

²Documents on developing a Facebook application is available at the following URLs <https://developers.facebook.com/docs/> and <https://developers.facebook.com/docs/graph-api>

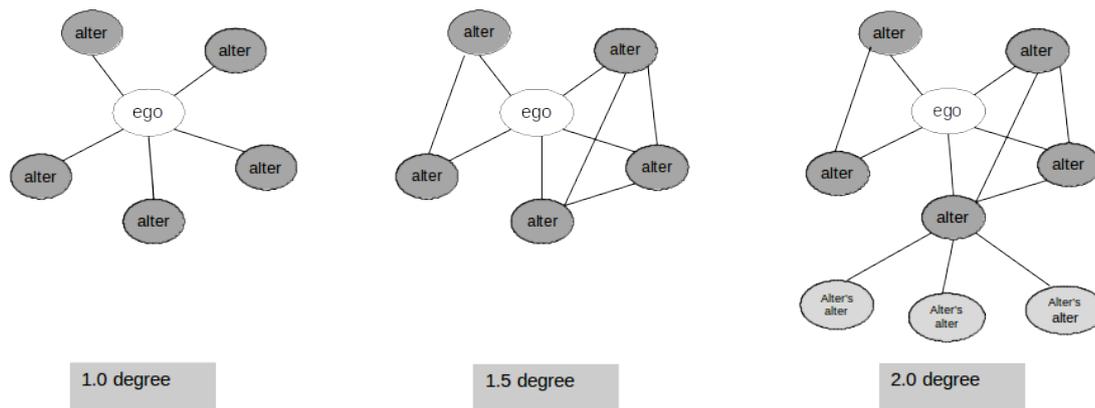


Figure 3.1: Personal networks - by degree

- Socio-demographic characteristics of ego's friends where they are publicly available. These characteristics are: gender, age, relationship status, education and location of residency (latitude and longitude, country/ state/ city) as each friend has reported in her profile.
- Type of ego's relationships with her friends on Facebook, as reported in ego's profile. Facebook allows users to define the way that they know their friends by assigning a type to their relationships. For example, the ego may have defined her relationship with her sister as "sister" or "sibling" or "family member". As ego labels a relationship with one of her friends, that label would be displayed in the ego's profile only when it is approved by that friend. In this way, the type of relationship is not just declared by ego, but it is also confirmed with the friend. The present research uses this section of data only to distinguish between kin and non-kin relationships.

Once AuSON successfully completes collecting the first part of data, it saves a copy of it into the database designed for this research, which is located at the Australian National University. It then allows ego to view the graph of her own Facebook network. After viewing their Facebook personal networks, participants can continue their participation by undertaking the survey. To verify that the recruited participants meet the eligibility criteria of this study, AuSON asks a few questions about being Australian and 50 years old. For those participants who want to continue their participation and are eligible, AuSON starts the second part of data collection by loading the first part into a graphical survey.

3.2.2 Part 2: collecting data via online survey

The designed online survey has 7 steps. The online survey is visual and participants can see the photos of their Facebook friends. In most of the questions, participants are able to drag and drop the photos of their friends into boxes (see Appendix A). The survey is designed in this way for the purpose of making it easier and more enjoyable for participants.

The following 7 steps were involved in the second part of data collection:

1. Subjective well-being: The first step includes a few questions about subjective well-being (see section 3.3.1).
2. Grouping Facebook friends. In this step participants are asked to categorise their Facebook friends into groups in a way that is meaningful to them. To ease this task, AuSON provides some groups which are defined based on the structure of the networks. Using a community detection algorithm ("Louvain" method; see section 3.3.2), AuSON classifies network members into groups and asks participants to modify them in a way which is meaningful to them. Participants can modify the name of groups, delete a group, create new groups and modify members of groups.
3. Adding important alters who are not on Facebook. Ego can add up to 10 important alters who are not on Facebook into the network collected for this research. These alters who are not on Facebook are included in ego's personal network, similar to the Facebook friends. Ego is asked to provide some information about each added alter including name (real name, nickname, initials or anything she likes), gender and age. Ego is also asked to nominate the groups that each alter belongs to and up to 10 Facebook friends who know that alter.
4. Strength of tie. Ego can rank each alter based on how close her relationship is with that alter, from "very close" to "very far" (see section 3.3.2).
5. Potential social capital. Ego is asked to nominate alters who have particular skills or resources. In response to the question: "Do you know anyone who has ...", ego can nominate any of her alters for any of the ten listed resources/skills. For each resource, ego can nominate up to ten alters. In addition, ego is also asked whether she has the resource/skill

herself (yes or no). (see section 5.3.1)

6. Actual social capital. Ego is asked to nominate those alters from whom she can easily ask for help on the list of 10 resources/skills. For each resource, ego can nominate up to 10 of her alters from whom she can easily ask for help. In addition, for each resource, ego is also asked to nominate those contacts to whom she can easily provide help (see section 5.3.1).
7. Emotional interaction. Ego is asked about alters with whom she has positive or negative interactions. In response to the question: "Who makes you feel happy or unhappy?" ego can nominate her alters from making her "very happy" to "very unhappy" (see section 3.3.2).

At the end of the survey, participants are encouraged to send our invitation message to their Facebook friends. To do so, AuSON shows the list of participant's Facebook friends and the message that will be sent to them: "This is an invitation message for you to participate in a research project about Online Social Networking and Successful Ageing, carried by researchers at the Australian National University". The invitation message also includes a link to AuSON.

3.2.3 Target population and recruitment process

The target of this study was Australians aged 50 years and over who were using Facebook at the time of data collection (December 2012). AuSON is an online Facebook application and it was open to the public, but only Australians aged 50 years and over were included in the analysis. After installing AuSON and viewing their personal networks, users were asked to answer two questions: "Are you eligible to vote in Australia?" and "What is your year of birth?". Although all users were able to view and complete the survey, only those users who had answered "yes" and were 50 years or older, were included in the analysis.

The sample was recruited in three ways. First, an email was sent to a list of Australians aged 50 years old and over who had participated in the SNAP survey and had reported that they use Facebook and are happy to participate in the present study. From this list, only around 10% participated in this study.

Second, an invitation message was sent to the target population via public media such as radio, national and organizational print, online newspapers and mailing lists. Third, in parallel with other methods, snowball sampling was used; participants were able to invite their Face-

book friends to participate in this study via AuSON.

It is not very clear from which source each participant has been recruited. However, the sharp increase in the number of participants after publishing in the public media, particularly radio and newspapers, indicates the important role of public media in finding participants for this study in comparison with personal and organizational emails invitation messages. This is because mainstream media such as radio and newspapers have broader coverage compared with emails, especially among older people who may not often check their personal emails. Invitations through public media which are better known can create more legitimacy than personal emails. It is more likely that people trust an invitation message delivered through national radio or newspaper than emails. However, interconnections among some personal networks, although few, and the time of their participation, implies that some of the participants have been invited by their Facebook friends.

3.2.4 Ethical considerations and methodological challenges

There are several ethical and methodological issues in doing social research using social media in general, and Facebook in particular (Zimmer, 2010a). In the following paragraphs, I discuss some of the most important issues and the ways these have been addressed in this research.

Ethical issues: There are many debates regarding the ethics of using social media for research (Zimmer, 2010a,b; Vallor, 2010, 2012). One of the most important ethical issues relates to collecting information about people without their consent (Zimmer, 2010a). The use of data collected from social media without obtaining individuals' consent is commonly accepted, partially due to the fact that this media is regarded as being public. However, some scholars argue that information shared by individuals on social media are not intended to be collected and analysed even in the case of broadcast platforms such as Twitter. For example, Zimmer (2010b) argues that people share information in order to be viewed and read by other users, and not by researchers to archive them or analyse them. Social networking sites (i.e. Facebook) usually record personal information that makes their users identifiable. Such information is considered sensitive, especially due to their considerable overlap with individuals' identity in real life. For example, it is not unusual that Facebook users report detailed information about their life, from educational levels and work experience to information about types of relationships with each friend or photos or videos of social gatherings. Such a set of detailed information can make each user unique and identifiable. The ethical issues and the potential risks or harms should be considered very

carefully and addressed in any research using data from social media, in particular, Facebook.

The present research has considered the ethical issues seriously and has addressed them to minimise the potential risks in several ways. First, the identifiable pieces of data which were required for the purpose of research or data collection have either not been saved into the database -they were obtained only for the purpose of collecting data (the visual survey)- or have been coded (encrypted) in a way that is not possible to link the data back to the user. For example, for the purpose of collecting data, participants were able to view their own personal networks as well as some information about their friends, such as name and profile photo. This information that could be viewed by participants was removed from the database at the completion of participation. One piece of information which is unique to Facebook users and is instantly identifiable is the Facebook ID (which is an internal identifier). Facebook IDs were automatically converted to encrypted codes which were neither identifiable by human nor convertible to the original IDs. Second, no personal information or network data has been described or displayed in publications in a way that can be identifiable; the cases illustrated in publications are slightly modified and presented as graphs with no name or identifiable information.

In addition to the devised solutions, participants were provided with a comprehensive set of information about this study as well as how to participate or withdraw from it (see Appendix A). AuSON also provided tutorials designed to show which steps and activities are included in using AuSON (see Appendix A). Participants needed to provide consent before participating via giving access to AuSON. Since collecting each part of data from Facebook needs a specific set of permissions, AuSON needed participants' permissions to access their Facebook data. To do so, AuSON showed the list of information that would be collected from the profile and participants could approve access to each part of the data by selecting it³. Finally, participants were informed that they could withdraw their participation at any stage by following a URL that automatically removed them from this study and cleaned their data from the database⁴. This research has obtained the ethics clearance from The Australian National University Human Research Ethics Committee (HREC) under protocol number 2012/650.

Methodological challenges

Facebook limits the amount of data that can be obtained in total (per application) and per access (API call). The rules are applied in two main ways: first, by limiting the number of accesses per

³Facebook has a clear term of condition for developers that are explained at the following URL: <https://developers.facebook.com/policy/>

⁴It is notable that there was only one case of withdrawal from this study.

application and second, by limiting the amount of data that can be read in each access.

Depending on the size of a personal network, these limiting rules can cause problems in using APIs to collect data. Only considering the network structure, even collecting data of a relatively small network (less than 100 friends) may fail if the amount of data including alter-alter ties exceeds a given number of records (4000 at the time of data collection). As a solution, AuSON uses an algorithm which is able to collect a large amount of data (i.e. large networks with more than 1000 nodes) by doing iterations. The algorithm starts with an initial size which is estimated based on the number of friends and network density. After reading the first part of data, it sets the size for the second iteration based on the result of the iteration.

Another issue was that the Facebook API and the policies regarding access to data were changing because of the ongoing development of Facebook. As a result, it was challenging to use an application over time. Another challenge was that AuSON was designed to work with standard computers and internet browsers. A number of participants who attempted to use AuSON on touch-based technologies such as iPad reported difficulties in completing the survey.

3.3 Defining key concepts and measures

In this section I define some of the key concepts that will be used throughout this thesis.

3.3.1 Subjective well-being

Well-being is a broad term referring to a set of concepts. According to the Webster dictionary, it means: "The state of being comfortable, healthy, or happy". Subjective well-being refers to individuals' evaluation of the own quality of life (Angner, 2008; Barwais, 2011); "Subjective well-being consists of a person's cognitive and affective evaluations of his or her life" (Diener et al., 2009). Compared with the objective measures of well-being such as health and economic status, subjective well-being proved to be an indicative measure of the overall status of an individual's well-being (Dupuy, 1984; Ware and Gandek, 1998; Friedman et al., 2005; Diener and Ryan, 2009) and has been used in numerous studies in the context of various correlates (Larson, 1978a; Butterworth et al., 2006). The present study uses two measures of SWB: psychological well-being (PWB) and life satisfaction (LS) which are two important aspects of mental health developed in McDowell (2006, p. 588), Ware et al. (1994), Manocchia (1998) and Deci and Ryan (2006).

Psychological well-being: is measured based on responses to the following questions: "How much of the time in the previous 4 weeks have you ...?"

1. Been a very nervous person
2. Felt so down in the dumps that nothing could cheer you up
3. Felt calm and peaceful
4. Felt downhearted and blue
5. Been a happy person
6. Felt pressured
7. Felt competent at what you do

Participants were asked to choose from the following options:

- All of the time
- Most of the time
- A good bit of the time
- Some of the time
- A little of the time
- None of the time

For each participant, PWB is the average of the scores for the above questions that ranges from 1 to 5 showing the lowest to the highest level of PWB. The scores for questions 3, 5 and 7 have been reversed before aggregating. The average score for PWB is used in the analysis of Chapters 4 and 5. The analysis in Chapter 6 uses only one dimension of PWB: "been a happy person" and examines how it is associated with the emotional interactions with alters (how alters can make ego feel happy or unhappy).

Life satisfaction: is measured based on response to the question: "All things considered, how satisfied are you with your life?". Participants were asked to choose from "Totally dissatisfied" to "Totally satisfied", scored from 1 to 10. This measure has been used in the analysis of Chapters 4, 5 and 6.

3.3.2 Personal networks

A personal network refers to a set of social relationships according to the focal person called "ego". Theoretically, this set encompasses all of the social relationships ego may have, attributes of those relationships and characteristics of those with whom ego has relationships (alters) and

social relationships among them. In practice, a study may capture a subset of ego's personal network depending on the focus of research. A personal network in the present research is constructed as the part of ego's personal network that is articulated on Facebook; it is assumed that ego's personal network is a complete set of her relationships composed of those who are articulated on Facebook as well as those who are not. Although participants could add up to 10 of their non-Facebook important alters to their personal network included in this study, only a few of participants did this and when they did, only few alters were added. In this way, the personal networks included in this study are considered to be only captured from Facebook. As explained earlier in this chapter (section 3.2), personal networks include ego's set of relationships on Facebook (called friendship), the type of each relationship (kin or non-kin), socio-demographic characteristics of alters and the existence of relationships among alters (whether each two alters are friends on Facebook). In the following paragraphs, I define three main features of personal networks that will be used in the present research: "structure", "composition" and "function".

Structure

Network structure generally refers to the construction of relations among network members. By network structure, I refer to the key structural characteristics of the networks as size, density, transitivity, average degree and the number of groups.

Size: indicates how large the ego's personal network is and is equal to the number of alters including Facebook friends and non-Facebook important alters. Since, the number of non-Facebook alters is very small and negligible, the size of ego's personal network is equal to the number of Facebook friends.

Density: refers to the extent that ego's alters are connected to each other and is equal to the proportion of all possible ties among alters that are actually present (Riddle and Mark, 2005). Density provides a basic measure of network cohesion.

Transitivity: or "clustering coefficient", measures the probability that the pair of alters with a mutual friendship (not with ego) are connected to each other (Wasserman and Faust, 1994). In other words, transitivity measures the probability of observing the third relationships among three alters in the presence of the already existing other two relationships. In applying this measure to Facebook personal networks, it shows the extent to which ego's Facebook friends who

have a common friend among ego's friends, are each other's Facebook friend. Note that similar to the other structural properties, transitivity captures the transitivity of relationships among alters and hence is constructed after removing ego from her personal network.

Average degree: indicates the mean number of mutual friendships all alters have with ego. This measure simply calculates the "degree centrality" (the number of connections) for each alter in the network and then takes the average of these results. The average degree represents network cohesion as it shows the degree of alters' involvement in the network. Compared with the density, which is highly sensitive to network size, the average degree provides a better measure of network cohesion of personal networks (Brooks et al., 2014).

Number of groups: shows the number of groups included in a personal network and is computed using a community detection algorithm. Personal networks are often composed of multiple groups representing different spheres of activity; such spheres are termed as Foci by Feld (1981). Different algorithms use different methods in finding communities (Lancichinetti and Fortunato, 2009). This research employed the widely used "Louvain" community detection algorithm (Blondel et al., 2008). This method provides one of the most efficient techniques in decomposing the network structure into mutually exclusive groups. The number of groups in a personal network represents the number of different contexts which are densely knit inside and weakly connected to each others. In this way, this measure indicates network diversity (see Chapter 4) as well as bridging social capital (see Chapter 5).

For analytical and methodological reasons, ego is removed from her personal network before calculating the network structural measures. This decision is taken based on the excellent discussion provided by McCarty and Wutich (2005) about including or removing ego from structural analysis of personal networks and its implication for the calculated measures.

Composition

Network composition refers to the attributes of alters in the personal networks including gender, age, educational level and location of residence (country/state/city). This part of data has been collected from Facebook profiles and will be mainly used in the analysis of Chapter 4.

Function

By function, I refer to the functional aspect of social relationships. It is composed of three mea-

asures: the strength of tie, social capital, and emotional interactions.

Strength of tie: is usually measured based on a combination of indicators: duration of the relationship and frequency of contact, intimacy of relationship and provision of reciprocal services within the tie (Granovetter, 1973). Using these indicators one can measure the strength of tie in a range from the most recent, frequent, very close and involved in the provision of reciprocal services/help to the most old, least frequent and very weak relationship and not involved in the provision of reciprocal services/help. In this multi-dimensional scale, relationships can be described in many ways such as "old, far and weak", "old but frequent and close", "recent, but weak and non-reciprocal" or "recent, close and reciprocal".

As discussed by Marsden and Campbell (1984), among all of the indicators for the strength of ties, intimacy is the best predictor for the strength of tie, while some indicators such as the type of relationship (e.g. kinship), are not strongly related to the concept. The present research measures the strength of tie using only one indicator: intimacy or closeness of the relationship. In response to the question: "How close do you feel to each of your Facebook friends?", participants are asked to rank their Facebook friends (are visually represented) in five categories labeled as "very far" to "very close" and scored from 1-5.

Social capital: indicates the amount of resources that ego has access to via alters (Van der Gaag and Snijders, 2004). The two questions: "Do you know anybody who has this skill/ resource?" and "From whom you can easily ask for help" provide data for measuring "potential" and "actual" social capital (see 5.3.1 for more details). For each of 10 listed skills/resources, the ego can nominate up to 10 alters who have that skill/resource. Thus, each alter can be nominated to have at most 10 skills/resources. Social capital and its related concepts and measures are defined in Chapter 5.

Emotional interactions: refer to the positive or negative interactions that ego may have with her alters. Negative emotional interactions is a general and broad concept and can be defined in various ways (Rook, 1984; Cohen, 2004). In response to the question: "Who makes you feel happy or unhappy", participants are asked to nominate their network members who can make them "Very happy", "Happy", "Neither happy nor unhappy", "Unhappy" or "Very unhappy". So, each tie has a score from 1 to 5 indicating the emotional interaction from very negative to very positive respectively.

3.4 Characteristics of the sample: socio-demographic, subjective well-being and personal networks

3.4.1 Socio-demographic characteristics

The sample consists of 105 Australians aged 50 years old and over with an average age of 65 years and a maximum of 85 years. Figure 3.2 shows the age distribution of our participants.

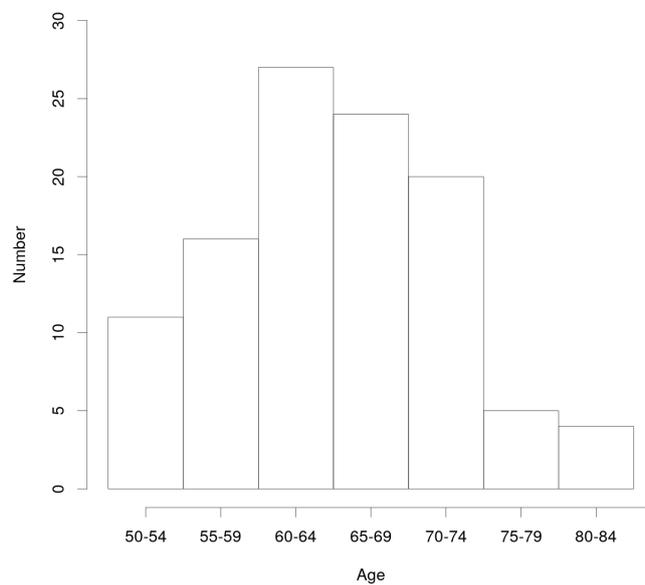


Figure 3.2: Age distribution of participants

Of the 105 participants, 66 are female, 37 are male and the gender of 2 participants is unknown. Figure 3.3 depicts the frequency distribution of the participants based on their marital status. Married participants constitute the largest group with 45% (47 participants), 9% are single (10 participants), 3% are separated, 2% are in a relationship and 2% are widowed. A large proportion of participants (39%) did not report their relationship status. In terms of education, 35% (37 participants) reported their education as graduate school, 25% as college and 22% as high school.

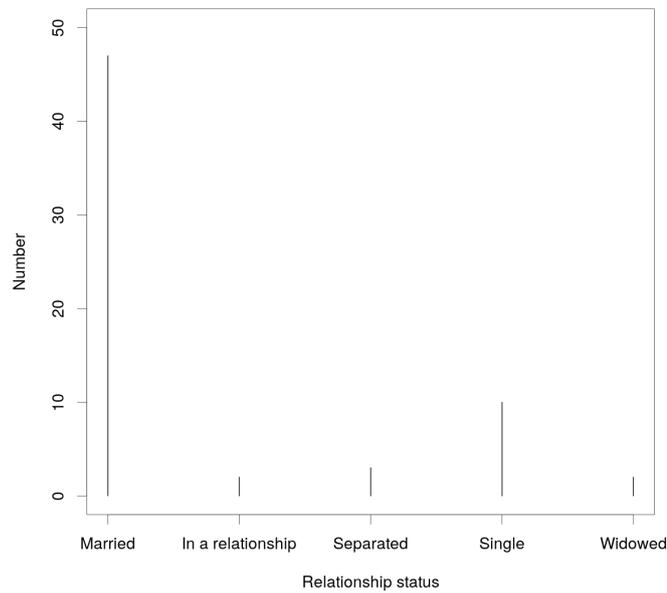


Figure 3.3: Relationship status of participants

3.4.2 Subjective Well-being

Overall, data on well-being shows that participants are relatively satisfied with their life and reported their psychological well-being above 3, which is the midpoint. The average score of psychological well-being is 3.7 and the average score of life satisfaction is 7.7 (see table 3.1). Figure 3.4 represents the distribution of psychological well-being and life satisfaction. Both of the distributions are highly left-skewed indicating that the majority of participants have good psychological well-being and are satisfied with their lives.

Table 3.1 Descriptive statistics of subjective well-being (N=76)

	min	mean	median	max	sd	Q1	Q3
PWB (1-5)	1.9	3.7	3.7	4.9	0.66	3.33	4.1
LS (1-10)	1.0	7.7	8	10.0	1.63	7	9

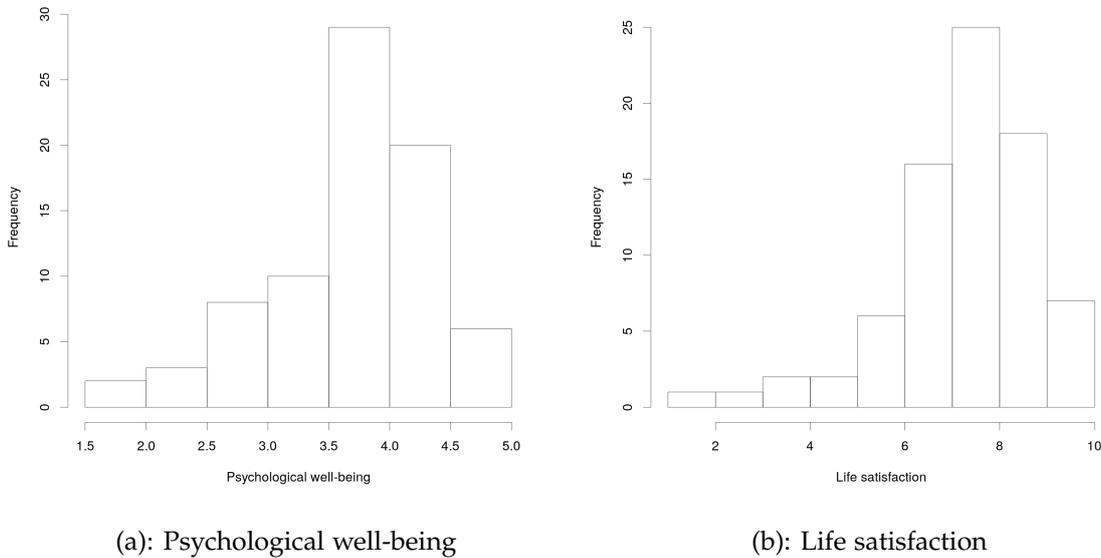


Figure 3.4: Subjective well-being of participants

3.4.3 Personal networks

In this chapter, I only describe structural characteristics of personal networks that are used in the following chapters. Other feature of personal networks will be studied in the next chapters; the composition is the main focus of Chapter 4, function of personal networks will be studied in Chapters 5 (strength of ties and social capital) and 6 (positive and negative emotional interactions).

Structure of personal networks: two cases Figure 3.5 show the graphs of personal networks for two participants. The right side graphs show the personal networks when the ego is removed from her personal network (before calculating the measures of structural characteristics). As shown in the graphs, the personal networks of participants A and B are similar in some ways and different in some other ways. Perhaps the most visually evident fact about these personal networks is that they are overall sparse, but nodes are concentrated in clusters in a way that both personal networks are made up of groups which are loosely connected to each other, but tightly knit inside.

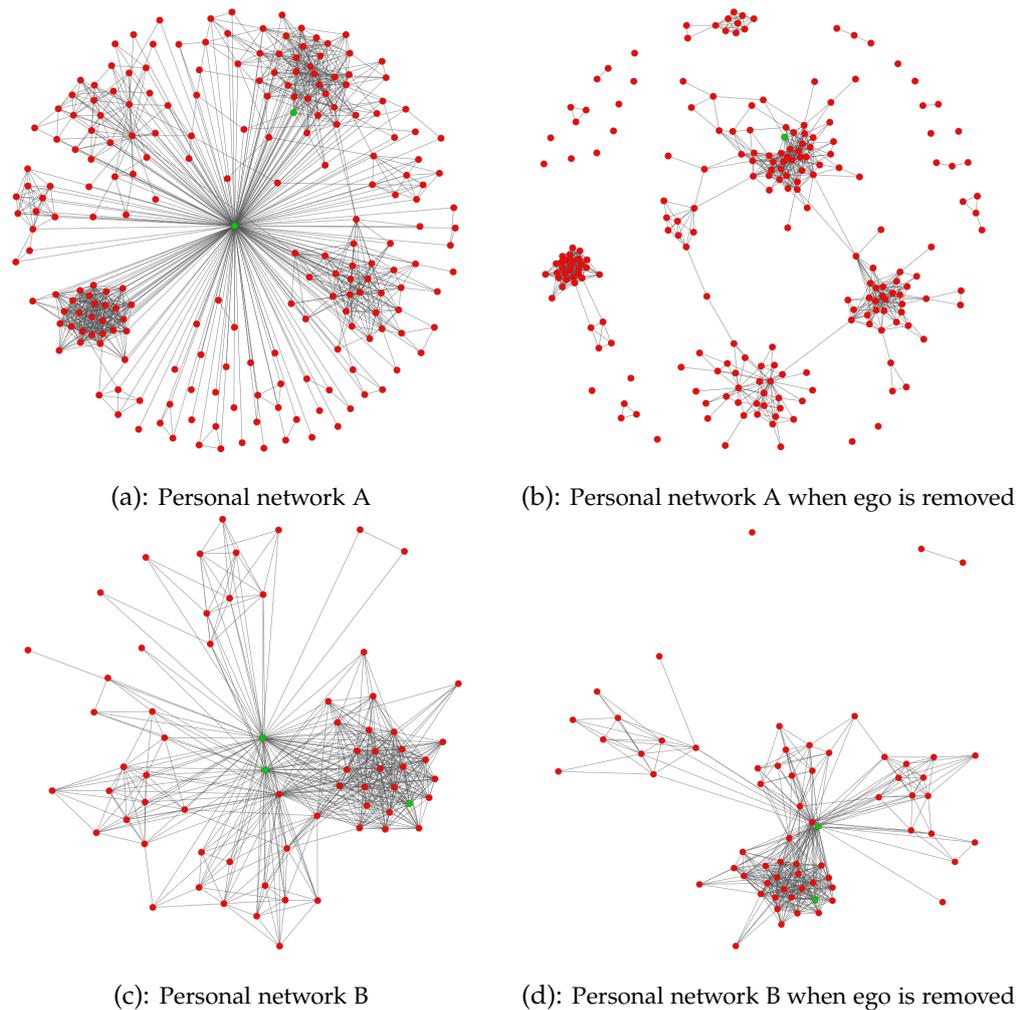


Figure 3.5: Graphs of personal networks: two cases

However, comparing these two personal networks shows that overall, personal network B is more cohesive and less segmented than personal network A. Although both are segmented among groups, the groups are more distinguishable in the first network than the second. In the first network, the groups are very loosely connected to each other via a shared friend or only a few mutual friendships across groups, while in the second network, there are considerably more ties between groups, mainly via some alters who are shared between groups. The graph of the first network represents a social environment in which ego has a distinct position from the rest of her network, she is in the centre of her network with almost the same distance to all of her friends. The situation is somehow different in the second network, in which ego does not have an equal distance to her friends. There are a couple of nodes in her personal networks who are very close to her in a way that is difficult to distinguish, and the layout of the graph does not change much when the ego is removed from her network. This is because of the role of a few central alters who are connected to many other alters from different groups.

Table 3.2 summarises the structural characteristics of personal networks A and B based on the five main measures. The personal network A is larger (three times) than network B. But the density of network A is considerably lower (one-fifth) than the density of network B. Network A is more transitive, has higher number of groups, but lower average degree than network B. Comparing these measures also confirms what was evident from the network structure visually. Network B is more cohesive than network A while network A is better segmented between more groups.

Table 3.2 Structural characteristics of personal networks: two cases

Participant	size	density	transitivity	number of groups	average degree
A	213	0.04	0.70	15	8.79
B	67	0.2	0.65	7	13.3

Some of the differences between these two personal networks can simply be because of their differences in their sizes. For example, when the number of alters increases, the chance of them knowing each other would decrease or the chance of them being from different groups (contexts) would increase. These are not specific to personal networks in which the interconnections among alters is influenced by the ego to some extent, but they are general rules applicable to any type of social network. The correlations between network structural measures will be further explained later in this section. The differences between personal networks can be explained in many other ways such as differences in personalities that can result in different networking behaviour (Kalish and Robins, 2006), differences inherent in the social structure of activities which network members are from (Feld, 1981). Whatever the reasons, the differences between personal networks can be used to explain the differences between well-being that are further studied in next chapters.

With the purpose of understanding the general patterns in personal networks included in this study, table 3.3 summarises the structure of personal networks according to the five defined measures.

Table 3.3 Structural characteristics of participants' personal networks

measure	min	mean	max	sd
size	5.00	79.02	404.00	72.93
density	0.01	0.15	0.67	0.12
transitivity	0.00	0.54	0.85	0.14
number of groups	1.00	5.62	15.00	2.85
average degree	0.78	7.39	23.60	4.31

On average, personal networks of participants are smaller than the average network on Facebook; 79 compared with 338 (Smith, 2014). Figure 3.6 depicts the ranked network size. There is a large variation in network size, as some participants have less than 10 friends while some have more than 300. However, only a small number of participants have more than 200 friends and the majority of them have fewer than 100 friends. Other studies have found that people aged 50 and over have on average a smaller number of relationships on social media compared with other age groups. Wong (2015) reported that Australian users of social media (Facebook, LinkedIn and Twitter) who are 50-64 years old had, on average, 190 relationships (friends in Facebook, contacts in LinkedIn or followers on Twitter) in 2015, and users 65 years and over had on average 60 social relationships, while the average number of relationships for other age groups was at least 281. This report did not distinguish between the number of relationships based on the type of social media.

Note that the number of friends on Facebook is usually accumulated as people tend not to remove their friends (un-friend) even if the relationship is "decayed". As discussed by Burt (2000a), relationships are expected to weaken over time and this is not specific to social media or Facebook. However, when the network is collected using traditional methods (e.g. name generator via interview), respondents usually do not elicit the decayed relationships. Such weakened relationships may still exist in someone's Facebook friends list. Some studies show that on average, only a small proportion of individuals' Facebook friend are "actual" and "maintained" (Marlow, 2009; Ellison et al., 2011) in terms of having communication. However, compared to other studies (which mostly focus on young people) participants of the present study have relatively small networks on Facebook, and this might be because older people are less likely to add acquaintances into their Facebook networks. In this way, it is expected that the personal networks of participants of this study have a considerable overlap with their real life networks. This will be further studied in Chapter 7.

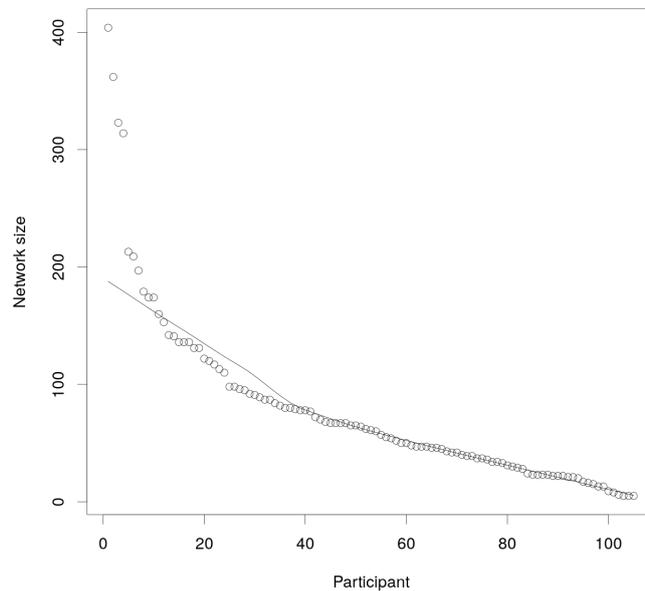


Figure 3.6: Personal network size: rank plot

Note: The curve fitting line is calculated based on LOESS (Locally wEighted Scatter-plot Smoother) methods (Cleveland and Devlin, 1988)

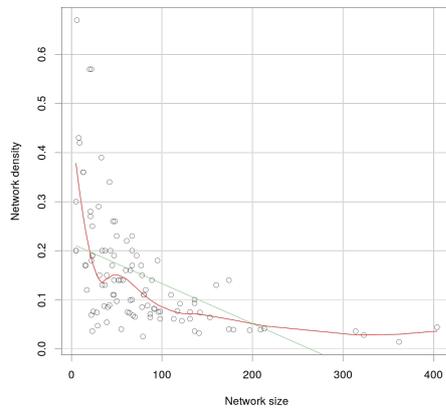
The average density of personal networks is 0.15 indicating that of each 100 possible connections between alters only 15 of them exist. In other words, of each 5 ego's Facebook friends, only two of them are each others friend on Facebook (1.5 ties for 5 alters). This indicates that the personal networks of participants are sparsely knit. In the absence of any standard for comparison, there is no expected density, theoretically or empirically. Different studies have reported different values for the density of personal networks, depending on the size of networks as well as the types of relationships included. Among the early studies on personal networks Wellman (1979) found that the mean density of East Yorkers' intimate networks (up to six alters) was 0.33 which means of all possible ties among intimates, only one-third of them existed. In a later study done in northern California, Fischer (1982) found an average density of 0.44 in personal networks composed of 5 alters.

The transitivity of participants' personal networks ranges from 0 to 0.88, with an average of 0.53, indicating that of 100 potential triads (open triads), 53 of them have been formed (are closed). For social networks, transitivity between 0.3 and 0.6 is quite common (Snidjers, 2012). Compared with density, transitivity signifies the presence of local clustering. So, while the average density of personal networks is low, the average of transitivity is relatively high that means ties among alters tend to be more involved in triads that can lead to highly dense clusters.

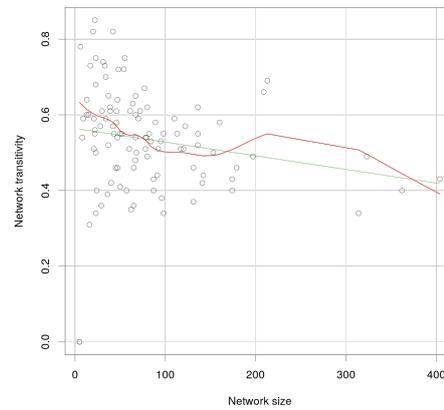
On average, participants have 7.4 mutual friendships with their Facebook friends. In other words, of 79 egos friends (average network size in this study), each friend knows only 7 other friends. Consistent with what was found for density of personal networks, the personal networks of the participants are less cohesive than what has been found in other studies. For example, participants of a recent study (Brooks et al., 2014) of 3149 non-faculty staff from a large U.S. university who use Facebook, had on average 14 mutual friendships with their Facebook friends; this is twice the average degree for participants of the present study.

On average, the personal networks of participants are made up of 5.6 groups. Different groups (clusters) represent the different contexts. Considering family, close friends and acquaintances as three groups which are usually included in personal networks, our participants have on average, two more groups in their networks. Depending on the community detection algorithm and the target population, scholars have found different numbers of groups in Facebook personal networks. Using the "Louvain" method (Blondel et al., 2008), Brooks et al. (2014) found that on average, personal networks are composed of 6.5 groups. Wolfram (2013) also found that the average number of groups is 3. Therefore overall, the personal networks of participants of this study are relatively diverse in terms of including alters from a large number of different groups.

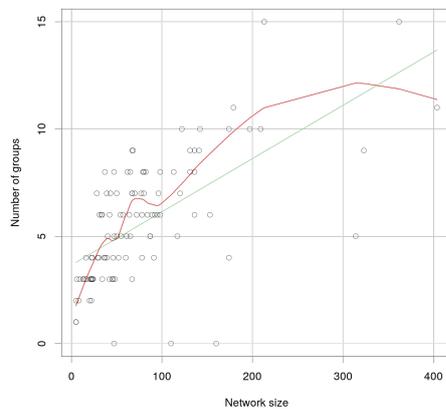
As discussed earlier in this section, to some extent, the patterning of interconnections among alters can be explained by network size. Although the correlations between network structural measures have often been assumed, they have rarely been tested. This is beyond the aims of the present research, but I briefly review these correlations for the personal networks used in this study. Shown in figure 3.7, although the relations are non-linear, size shows an overall negative correlation with density and transitivity and an overall positive correlation with the number of groups and average degree.



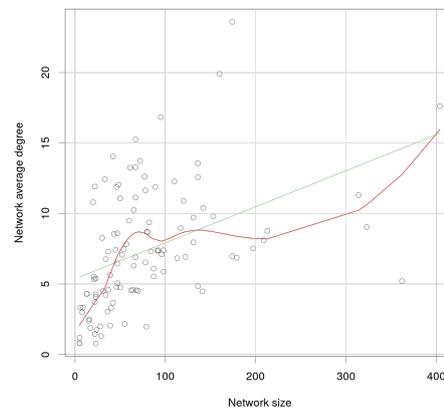
(a): Network density by size



(b): Network transitivity by size



(c): Number of groups by size



(d): Average degree by size

Figure 3.7: Network structural characteristics by size

Perhaps the clearest is the negative correlation between network size and density indicating that larger personal networks are sparser than smaller ones. The correlation between size and transitivity is also notable. The non-linear correlation suggests that transitivity declines with network size to a limit and then increases with it and then again decreases when a network becomes very large. The correlation between network size and the number of groups is pretty clear and positive, indicating that larger networks are generally made up of more groups. This simply shows that when networks grow in size, they also grow in the number of contexts included in them. This can be because of the way people manage their personal relationships with many people or because larger networks are already constructed based on many different contexts which are again because people who have larger networks know more people from different contexts.

The positive correlation between network size and average degree also shows that overall, alters'

engagement in ego's personal network increases with network size. Both density and average degree indicate cohesion in personal networks but have different relations with network size. It can be explained by considering the way that these two measures capture the cohesion. Network density measures the ratio of existing ties to the all possible ties among alters, while average degree measures the average of alters' ties to other alters. In this way, the average degree is influenced by network size by the prevalence of large and densely knit clusters in large networks, while network density decreases with network size as the number of all possible ties among alters increases disproportionately with it. So, overall, size has an important role in explaining the other structural characteristics of personal networks. Larger networks tend to be sparser and less transitive, but they are composed of more groups and have higher levels of alters' engagement in the network.

3.5 Discussion and conclusion

This chapter provided details of the data used in this research, methods used to collect the data and a summary of characteristics of the sample.

The data for this research are collected using a Facebook application which is developed for this research. Using SNSs in general and Facebook in particular to collect data for social research has advantages as well as limitations and challenges. The main advantage is obtaining data that are already been collected by SNSs. Therefore, it can help researcher by reducing the cost associated with collecting network data, lifting the huge response burden and obtaining a network which includes a wider range of social ties (i.e. weak ties as well as strong). However, depending on the focus of study, such data can be limited in certain ways. For the purpose of this research, the data collected from Facebook was not adequate to measure well-being as well as some aspects of personal networks such as social capital and emotional interactions. As a solution, the data collected from Facebook was combined with the information provided by participants.

In addition to the technical challenges involved in collecting data from Facebook, one of the major challenges was related to the recruitment process and this resulted in a limited number of participants. Some of challenges and reasons were related to the fact that the target population has the lowest use of Facebook. Older people are also more likely to have many concerns regarding sharing information online as well as allowing a Facebook application to access to their information. Although potential risks related to participating in this research have been iden-

tified and fully addressed and the related information provided through several documents, concerns about the privacy of data was an important barrier to participation in this research.

The sample included in this study is 105 Australian aged 50-85 years with more females than males (66 and 37). The age of participants is almost normally distributed and 60-70 is the largest age group. On average, participants have good psychological well-being with the mean value of 3.7 (ranging from 1-5) and are relatively satisfied with their lives with the average of 7.7 (ranging from 1-10). However, there are cases (13) who had a psychological well-being score below the midpoint, as well as some who had life satisfaction below the midpoint (6).

The structural characteristics of personal networks indicate that in general, they are sparse and segmented. The average density of personal networks in this study is 0.15 and on average each alter knows only around 7 other alters (of the average of 79 friends). However, the average of 0.54 for network transitivity, and the average 5.6 number of groups indicate the local clustering within personal networks. The personal networks have a similar structure to the two cases illustrated in this chapter. The structure of personal networks depicts a social environment that is not a cohesive network in which everyone is connected to everyone. Instead, personal networks are composed of several components that are loosely connected to each other. Each of these components can be viewed as networks of relationships representing a context in real life (Feld, 1981). These components that are often densely-knit are structurally suited for coordinating activities even though ego is not included in the network.

The structural characteristics of personal networks described in this chapter resemble the view of personal networks provided by other social network scholars (Wellman, 1979; Fischer, 1982; Wellman and Hall, 1988; Maas et al., 2009). However, the personal networks in this study are much sparser than the previous studies based on personal networks in real life. For example, Fischer (1982) found the average density of 0.44 for personal networks of northern Californians. The average of density was 0.79 for the personal networks in Israel (Fischer and Shavit, 1995), it was 0.46 for personal networks in France (Grossetti, 2007) and it was 0.33 for East Yorkers (Wellman, 1979). The density of personal network can be explained based on various factors. For example, network density is found to increase with the prevalence of kin ties (Fischer, 1982; Wellman, 1979). However, the more contexts involved in personal networks, density decreased. The personal networks in this study are highly sparse and segmented mainly because they are relatively large and include different contexts. It can be also explained based on the extent to

which networks of relationships within contexts are dense. This may be itself explained based on the structure of social institution (e.g. family structure) in Australia as well as the social norms and culture that encourages sparsity or density of relationships within different contexts.

Being involved in different contexts can have different implications for health and well-being. The segmented network can provide more freedom of action and opportunities and facilitate access to a diverse set of resources. But at the same time, it needs ego to manage her relationships in different settings which itself requires ego to allocate different sets of resources (e.g. time and attention) for different contexts. In addition, it means that ego will be involved in different roles for different contexts (e.g. being a mother in one group and being a co-worker in the voluntary association) which can be rewarding and beneficial (e.g. by learning different skills) but also, may create role strain. Therefore, having sparse and segmented networks can be beneficial and positive or detrimental and negative for well-being. This will be studied further in the next chapters.

Network homogeneity and subjective well-being

4.1 Introduction

Personal networks are commonly found to be homogeneous, which means they are often composed of people who are similar to each other (Marsden, 1988). Homogeneity in personal networks leads to clustering in our social world, which has important implications for almost every aspect of our life, from the spread of information, to the provision of social support to the transmission of disease.

Although scholars have highlighted the importance of homogeneity of social relationships for individuals and societies, it is one of the least studied aspects in relation to well-being. The existing literature has mainly focused on describing homogeneity and explaining the reasons and the processes leading to this phenomenon. Yet, our knowledge about two questions is limited: "how homogeneous are personal networks?" and "how is homogeneity in personal networks related to well-being?". Due to the difficulties in collecting network data, the literature in this area has mostly limited personal networks to a small number of core network members who are by construction expected to be similar to each other. While the data on social networks and individuals' attributes articulated in online social networks provide a unique opportunity to approach these questions surprisingly, only very few researchers have used social media to study homogeneity in personal networks and further, those few exceptions have not paid attention to the implications of homogeneity for well-being.

This chapter studies homogeneity in personal networks and its implications for subjective well-being (SWB). To do so, it studies homogeneity based on two main features of personal networks: "structure" and "composition". The former feature refers to the structural characteristics

of personal networks (e.g. size, density and transitivity), while the latter refers to the socio-demographic attributes of network members (i.e. gender, age, education and geographical location). This chapter defines and operationalises homogeneity as the opposite of diversity.

The previous chapter studied the first feature and found that the structural characteristics of personal networks of participants of this study exhibit a high level of "diversity", that I refer to this as "relational diversity". The present chapter includes the second feature that is based on socio-demographic attributes of network members and I refer to this as "compositional diversity". It also studies the combination of these two features which has been referred to as "assortative mixing" or the extent to which network members with similar attributes are connected to each other.

Diversity is basically defined on the bases of the attributes of network members. However, social network scholars have commonly found that diversity can be deduced from structural characteristics of networks (Burt et al., 1983). For example, if someone has many friends, she is more likely to have a diverse network than someone who has few friends. Or networks that are highly dense are less likely to link individuals with diverse sets of resources (Granovetter, 1983). Although examining the validity of these ideas is beyond the scope of this research, it is of interest to test the extent to which they are applicable to the data set for this research. Therefore, in addition to examining the associations between network diversity and SWB, this chapter aims to better understand how relational diversity is related to compositional diversity.

This chapter has three aims. First, it aims to describe homogeneity/diversity of personal networks based on relational and compositional diversity and assortative mixing. Second, it examines how relational and compositional diversity are related to each other. Third, it studies associations between homogeneity/diversity of personal networks and SWB.

The rest of this chapter is structured as follows. The first section provides a review of the literature. The second section defines concepts and measures used in this chapter. The third section presents results of the analysis and findings. The discussion and conclusion are provided in the last section.

4.2 Literature review

The literature on homogeneity in personal networks and its association with well-being can be categorised in three main themes. The first theme focuses on homogeneity in personal networks itself in order to provide new insights into the question of how homogeneous or diverse personal networks are (McPherson et al., 2001). Research falling under this theme is usually based on large samples and findings can be compared across groups and societies. The second theme is interested in explaining the reasons and processes leading to homogeneity (and more broadly in patterning) in networks (Feld, 1982; Kossinets and Watts, 2009). Research in the third theme focuses on the implications of homogeneity for health and well-being. This theme has mainly focused on health and diversity in types of relationships rather than attributes of network members (Cohen et al., 1997). In this section, I selectively review the literature mostly from the first and third theme. The literature of the second theme is not the focus of the present chapter and hence is only reviewed when relevant to the first and third themes.

The existing literature provides clear evidence on homogeneity in personal networks based on socio-economic attributes from gender (Fischer and Oliker, 1983; Marsden, 1988; Shrum et al., 1988; McPherson et al., 2001) to age (Fischer, 1982; Marsden, 1988; McPherson et al., 2001), education (Verbrugge, 1979; Marsden, 1988; McPherson et al., 2001) and place of residence (Fischer and Oliker, 1983; Hampton and Wellman, 2000; Preciado et al., 2012), especially among non-kin (Marsden, 1988). For example, Fischer (1982) found that non-kin alters were separated by only six years of age, compared to 24 years for non-siblings kin alters. However, the pattern of homogeneity is different for each attribute and for each group based on that attribute. For example, women are found to have more homogeneous personal networks than men (Volkovich et al., 2014). Older people are consistently found to have more diverse social networks compared with other age groups, which is because of the prevalence of kinship ties in their networks (Burt, 1990, 1991; Uhlenberg and de Jong Gierveld, 2004). Marsden (1988) found an interesting pattern in the age of alters with whom one "discussed important matters". The 60 and over age group was the only one for which there was significant tendency toward connecting with different age groups. Some researchers have found a severe deficit of younger non-kin in personal networks of older people (Uhlenberg and de Jong Gierveld, 2004; Schaie and Uhlenberg, 2007). In regard to education, research by Marsden (1988) revealed that all levels of education are homogeneous, while homogeneity is stronger among the extreme groups of education that is either college level or 1-6 years of school education.

Although this body of literature has provided new insights into homogeneity, it has some limitations. Most notably, the research has been done on personal networks that often include only a small number of core network members. When personal networks are limited to few people who are usually recalled in response to specific questions, network members are by construction expected to be similar to each other. For example, the studies using data from the General Social Survey (Burt, 1984) such as Marsden (1988), McPherson et al. (2001) and Smith et al. (2014) are based on personal networks that include only 5 members with whom individuals have discussed important matters in last six months. The average network size was 18.5 in the study by Fischer (1982). Therefore, homogeneity in personal networks may have been over-stated. In fact, personal networks are expected to be more diverse if respondents are not limited to reporting only a small number of alters.

Homogeneity of personal networks is potentially an important correlate of well-being. However, it is one of the least studied characteristics in this regard. Moreover, findings of research in this area are not consistent. A major body of literature on this topic is based on research from an epidemiological point of view, which uses the term "diversity" and defines it as diversity in the types of relationships included in personal networks (e.g. kinship, friendship or work-related). This body of literature has commonly found that network diversity is beneficial for health and well-being as diversity increases individuals' exposure to diverse biological environments which can consequently enhance well-being (Cohen et al., 1997). However, psychologists highlight the benefits of having homogeneous personal networks for well-being, in which individuals experience psychologically balanced and consistent social environments (Heider, 1985). Research from sociology although, mostly uses the term homogeneity. The findings of sociological research shows that homogeneity in personal networks can have both positive and negative impacts or even a complex association with well-being (Walker, 2015). So, in reviewing the literature from each field, this section uses both terms of diversity and homogeneity.

Diversity in networks is found to be positively associated with health, mainly by increasing the level of exposure to people with different attributes. In a line of research on health, Cohen et al. (1997) examined how the characteristics of individuals' personal networks are related to the chance of being affected by the common cold virus and found that individuals with more diverse social networks were less susceptible to infectious illnesses. In their research, Cohen et al. (1997) introduced a measure for diversity called the "Social Network Index" (SNI), which was based on participation in 12 types of social relationships, mainly including intimate rela-

tionships. Similar research by Barefoot et al. (2005) confirmed that having a greater variety of social contacts especially with intimate alters, had a protective role for health (ischemic heart disease and total mortality). Using data from the Longitudinal Aging Study Amsterdam (LASA) in 1992 and six follow-ups, Ellwardt et al. (2015b) found that a lower level of network diversity measured by SNI was associated with a reduction in cognitive functioning. Fiori et al. (2006) also examined diversity in personal networks of older adults (60+) from the Americans' Changing Lives study and found that individuals with diverse networks, including both family and friends, had the lowest level of depressive symptoms, while depressive symptoms were highest among individuals in the non-friends (only family) networks.

Network homogeneity has also been found to be positively related with well-being in several ways. In a homogeneous network, relationships are more likely to be consistent, stable and involving less conflict and thus more likely to create a convenient social environment and reduce psychological distress (Heider, 1985). Such networks can create a strong sense of group identity and belonging, which enforces trust, sanctions and norms of behaviour that may result in enhanced well-being. Homogeneous networks are also usually the best source of social capital as everyone in the network can be quickly and efficiently provided with useful resources (Coleman, 1990). A study on friendship networks using data from the General Social Survey of Canada (2003), indicates that homogeneity of friendship networks is positively related to higher levels of social trust, less stress and better health, while diversity increases the chance of receiving help from friends (Van der Horst and Coffé, 2012). They measured homogeneity based on a variety of demographic and socio-economic attributes including, ethnicity, mother tongue, gender, family income level, level of education and age.

However, being embedded in a homogeneous set of relationships may have a negative impact on well-being by limiting and localizing the individuals' social space, increasing the impact of undesirable social influence, in particular on unhealthy behaviour and by amplifying the impact of social strain in the presence of negative interactions (Rook, 1997). From a social capital point of view, social networks act as the main means of accessing resources (Wellman and Gulia, 1993). Insights from social network analysis highlight the important role of having diverse relationships in accessing novel information and resources. Information and resources are usually localized, limited and redundant in homogeneous networks (Granovetter, 1983; Burt, 2000b) which can create barriers to accessing novel information such as innovations in health. Moreover, homogeneity can influence well-being indirectly through its broader impact on reproducing inequality

or creating barriers for developing trust ("generalized trust" (Putnam, 2007)) by clustering societies based on socio-economic attributes or cultural status (Coffe and Geys, 2007; Garip and DiMaggio, 2011).

In summary, there is no final agreement on the direction of associations between homogeneity and well-being. The existing literature provides strong evidence for both negative and positive associations between network homogeneity and well-being. Perhaps the literature on diversity and health provides the most consistent findings on the protective impact of diversity on health. However, some studies have found evidence that conflict with results of Cohen et al. (1997). For example, Hamrick et al. (2002) examined the association between network diversity and health mediated by "stress" and found that diversity in personal networks is beneficial for health of individuals who could handle it- those with lower level of stress. One of the main differences between their study and the study of Cohen et al. (1997) is that they define networks based on a broader set of social contacts including both supportive and non-supportive others with the idea that interactions with non-intimate (e.g. members of fellow volunteers) social contacts can have an equal impact on health in carrying different viruses as the intimate ones. Thus, given the lack of agreement on the direction of association between homogeneity of personal networks and well-being, this chapter studies it through a research question rather than a hypothesis: what are the associations between homogeneity in personal networks and subjective well-being?

Network structural characteristics and well-being

Research findings on the direction of associations between network structure and well-being are also conflicting. Many researchers have found that network size is positively related to well-being and at least a lack of social contacts has constantly been shown to be strongly related with poor psychological well-being (Burt, 1987; Chan and Lee, 2006; Tyler et al., 2009; Zhu et al., 2013) and physical well-being (Seeman, 1996; Cohen et al., 2000; Berkman et al., 2000) and even affects mortality (Berkman and Syme, 1979). Baumeister and Leary (1995) argue that the need to belong is fundamental to human beings and it is strongly linked to well-being such that having no social contact can be highly detrimental to psychological well-being.

However, maintaining a large number of social relationships needs time and effort, which can also have detrimental effects on well-being. Having many social relationships increases the number of different roles in which ego is involved and fulfilling the obligations of each role can create role strain that consequently become detrimental to well-being (Pearlin, 1983; Eder, 1985).

Findings on associations between network density and well-being are even more conflicting. Studies have found that people who are located within densely-knit social networks experience lower levels of stress (Kadushin, 1982, P. 157-58) and are more likely to feel pleased with the overall situation of their life (Eder and Enke, 1991; Fischer, 1982, P. 393-94). Other researchers have reported either a negative relationships or no significant association between network density and well-being (Israel and Antonucci, 1987; Haines and Hurlbert, 1992) or complex associations mediated by other factors such as gender (Falci and McNeely, 2009) or socio-economic status (Fischer, 1982). Walker (2015) found that the association between network density and well-being is rather complex, depending on the nature of interactions occurring within the personal networks and the extent to which individuals are affirmed to the social environment. This research found that network density increases self-esteem and self-efficiency when individuals belong to self-affirming social environments, but reduces self-efficiency and has no association with self-esteem in dis-affirming environments.

Falci and McNeely (2009) investigated the associations between network size, density and depression among young girls and boys and found that either having too few or too many friends can have a negative impact on psychological well-being. More interestingly, they found that having too many friends with low density is associated with higher levels of depression among girls and with high levels of density among boys.

Apart from network size and density, other characteristics of network structure have gained little attention from researchers. For example, the extent to which a personal network is fragmented between groups of alters can also be negatively related to well-being (Burt, 1987). Networks which are segmented between groups may have a negative impact on well-being as different groups represent different context and ego may have different roles for each context (e.g. being a member of family and a group of colleagues) (Krackhardt, 1998). If the groups are not connected to each other each needs a separate allocation of time and effort and hence can exacerbate the role strain. But on the other hand, a fragmented network with many groups represents diverse contexts which can provide multiple sets of resources in a way that ego does not need to rely on only one group for getting access to resources.

Assortative mixing

Several studies have documented that social relationships are "assortative" in many ways (Mars-

den, 1987; McPherson et al., 2001; Yuan and Gay, 2006; Volkovich et al., 2014). Assortativity also called "homophily" and refers to the tendency to connect with similar others (Newman, 2003). Most studies on personal networks have only considered the relationships between the ego and her alters, and assortativity among alters has gained little attention (Kalmijn and Vermunt, 2007). As one of the possible reasons (or processes), assortativity can lead to clustering among alters based on their attributes. Although such clustering is identifiable from the structure of personal networks, the role of attributes of network members in such a clustering is not evident, neither from the structure nor the composition. Examining the actual reasons or processes (homophily is one of these processes) that have led to clustering among alters is beyond the scope of this chapter. However, this chapter will study the patterning of personal networks on the bases of attributes of alters. Therefore, in this chapter, assortative mixing refers to the product and not the process.

Homogeneity in online personal networks

Data collected from online social networks provide a unique opportunity to study homogeneity in personal networks. Surprisingly, the number of studies in this area is limited to a few prominent studies (Lewis et al., 2008; Wimmer and Lewis, 2010; Lewis et al., 2012; Volkovich et al., 2014). Ugander et al. (2011) studied the structure of networks among 149 million Facebook users (almost half of the population who are eligible to use Facebook) and found interesting patterns based on age, gender and country of origin. Most notably, they observed a strong tendency to connect with others in the same age group and this tendency decreases by age. Thus, older users (60+) had the most diverse networks based on age. They also found clear evidence of a preference for connecting within a country, while there was no evidence for assortativity based on gender. The existing literature in this area has mainly described homogeneity and then explained the reasons/processes leading to homogeneity, and there is a major gap in studying the implications for well-being. Among those who studied the implications, there is a lack of attention to demographic attributes such as gender or age. For instance, Seder and Oishi (2009) studied homogeneity of Facebook friendship networks of the first-year college students based on ethnic/racial background and its associations with their subjective well-being. Their analysis revealed a positive association between network homogeneity and subjective well-being among European American participants, while no significant association was observed among non-European American participants.

4.3 Definitions and measurements

4.3.1 Relational diversity

Relational diversity is measured based on five indicators: size, density, transitivity, average degree and number of groups (see section 3.3.2 for definitions).

4.3.2 Compositional diversity

Compositional diversity is measured by either the standard deviation of attributes of alters for continuous variables (i.e. age) or by the index of qualitative variation for categorical variables (i.e. gender and education) (Marsden, 1987; Knoke and Yang, 2008) which is defined for ego i as:

$$IQV_i = \frac{1 - \sum_{j=1}^K p_j^2}{\frac{(K-1)}{K}} \quad (4.1)$$

where the alters can be classified into K discrete or ordered categories and p_j is the proportion of alters in the j th category. The IQV is standardized between 0, indicating that all alters are in one category and 1, indicating that the alters are equally spread over the K categories. This measure therefore indicates the extent to which attributes of the network members are different from each other.

4.3.3 Assortative mixing

Assortative mixing in personal networks refers to the extent to which alters with similar attributes are connected to each other. For example, assortative mixing based on gender refers to the extent that alters with same gender are connected to each other.

Newman (2003) defined the assortative mixing coefficient as:

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} \quad (4.2)$$

In mixing matrix e , each element e_{ij} refers to the fraction of ties in the network that connect a node of type i to one of type j . $a_i = \sum_j e_{ij}$ and $b_j = \sum_i e_{ij}$ are the fractions of ties in the network which end in nodes of types i and j respectively. Since the ties (Facebook friendship) in this study are undirected, the mixing matrix is symmetric and thus for any attribute, $e_{ij} = e_{ji}$.

The measures discussed in this section indicate the homogeneity of relationships between al-

ters (from ego's point of view). So, ego has been removed from her own personal network before calculating any of these measures.

4.4 Analysis

The analysis is presented in three parts. First, I will describe the homogeneity/diversity in personal networks of participants based on the measures defined in the previous section. Second, I will examine associations between relational and compositional diversity. Third, I will provide results of multiple regression analyses between measures of homogeneity/diversity and SWB. Ego's personal characteristics including gender, age and marital status (having spouse or not) are included in the analyses as control variables.

4.4.1 How homogeneous are personal networks of participants of this study?

Descriptive analysis

Measures of relational diversity have been described in the previous chapter (see section 3.4.3). The present section focuses on measures of compositional diversity which are summarised in Table 4.1.

Table 4.1 Summary of measures of compositional diversity (N=105)

		min	mean	median	max	sd	Q1	Q3
Gender	diversity	0.31	0.73	0.74	1	0.17	0.60	0.82
	assortative mixing	0.90	0.99	0.99	1	0.02	0.98	0.99
Age	diversity	4.04	16.17	16.28	28.7	3.30	14.45	17.83
	assortative mixing	0.75	0.99	0.99	1	0.03	0.98	0.99
Education	diversity	0.03	0.85	0.88	1	0.15	0.85	0.91
	assortative mixing	0.89	0.99	0.99	1	0.02	0.98	0.99
Geographical location (country)	diversity	0.49	0.75	0.73	1	0.10	0.69	0.79
	assortative mixing	0.00	0.98	0.99	1	0.10	0.98	0.99

Gender: The average of gender diversity is 0.73 with a minimum of 0.31 and maximum of 1, indicating that on average, egos have a high level of diversity based on gender. The observed range of gender diversity from a minimum of 0.31 to maximum of 1, indicates that there is no personal network with perfect imbalance based on gender, but there are cases of perfect balance. For the assortative mixing coefficient, the average is 0.99 which indicates that alters are connected with other alters of the same gender to a substantially greater degree than one would expect in a randomly mixed network.

Comparing diversity in personal networks of men and women indicates that men have more

diverse and less assortative networks based on gender than women (see table 4.2). The average gender diversity is higher for men (0.81) than for women (0.68), while women have more assortative networks based on gender.

Table 4.3 shows gender composition of networks of male and female egos. On average, net-

Table 4.2 Average of homogeneity/diversity for females and males

	Sex	N	Mean diversity	Mean assortativity
1	Male	41.000	0.811	0.985
2	Female	67.000	0.680	0.990

works of female egos are composed of 70% women and 27% men (gender is not identified for 3% of egos). Men have on average 50% men and 48% women in their networks (2% are not identified).

These two findings indicate that on average, women have more same gender alters in their

Table 4.3 Percentage of ego-alter connections based on gender

	female	male
female	0.70	0.27
male	0.48	0.50

personal networks, while men have a balanced composition of both same and opposite gender alters. Since kinship networks are often found not to be homogeneous based on gender, the observed homogeneity in women's personal networks reflects the prevalence of non-kin relationships (Marsden, 1987). This finding seems to contradict the expectation that women have networks which are roughly as homogeneous as the general population, as women are more involved in childcare and family responsibilities (Moore, 1990). Investigating the exact reasons for this contradicting finding is beyond the scope of the present research, but, a brief explanation is provided. Firstly, on average women live longer than men (Austad, 2006) which increases the chance of observing women in personal networks of both older men and women egos. Secondly, studies have found that women tend to have larger friendship networks (more alters who are "just friends") in later life (Fischer and Oliker, 1983) than men, which increases the number of same gender alters in women personal networks; unlike kinship, friendship networks are found to be homogeneous based on gender (Marsden, 1987). Thirdly, men are more likely to connect with their wives' social contacts than women to connect with their husbands' that increases the number of opposite gender alters in personal networks of men (Fischer and Oliker, 1983). Fourth, it has been commonly found that the tendency toward connecting with same gender is higher for women than men (Volkovich et al., 2014). In conclusion, a large proportion of opposite gender alters are from kinship networks for both men and women, but men may have more opportunities to connect with non-kin opposite gender through their work as well as their wife's

social contacts, while women are more likely to connect with women through their membership in communities or volunteering roles especially in all-women groups (Popielarz, 1999).

Age: Table 4.1 shows that average diversity index for age is 16.17, meaning that on average, there is a standard deviation of 16.17 between the ages of alters is within personal networks. Fischer (1982) found that non-kin friends are separated only by six years, while non-sibling kin alters are separated by 24 years. Comparing with these findings, average standard deviation of 16.7 indicates a wide range in alters' ages, that can be because of inclusion of different types of relationships (kin and non-kin) in the networks. The average assortative mixing coefficient for age is 0.99 which indicates that alters are highly likely to connect with other alters in the same age group.

The summary of homogeneity within age groups (see Table 4.4) shows that age diversity increases with the age of ego. This can be interpreted in three ways. First, overall, kinship ties in personal networks of older people are more likely to be present than non-kin ties (i.e. peers) due to the loss of friends and peers (i.e. because of death). As kinship networks are usually composed of a wider age range compared with friendship networks, prevalence of kinship relationships results in higher age diversity in personal networks.

Table 4.4 Homogeneity based on age by ego's age group

Age of ego	N	Mean diversity	Mean assortativity
50-59	23	15.398	0.995
60-69	50	16.344	0.992
70+	32	17.207	0.978

Second, the increase in age diversity with age can be explained by the life transitions that people experience from 50 years to 60 to 70 and above such as retirement. Such transitions can influence the composition of personal networks; people who are retired may invest more in neighbourhood and family relationships compared with when they have many relationships with peers from work.

Third, increased age diversity with age can be explained by the attitude of different age groups regarding the use of online social networks. Older people are often found to be the least active age group in using online social networks and they use it mainly to connect with their family and close friends (McAndrew and Jeong, 2012) which increases the chance of having kin in their networks.

Meanwhile, assortative mixing based on age steadily and slowly decreases with age from 0.995 to 0.978. This decrease can result from decreased proportion of non-kin relationships compared with the increased (or stable) proportion of kinship relationship in personal networks of older participants, due to the loss of peers at older ages.

However, assortative mixing based on age is high for all age groups indicating a higher prevalence of within age group connections than between age groups. Table 4.5 shows the composition of age groups in personal networks based on age group of egos. For all age groups, the proportion of connections (ego-alter) within groups are higher than between groups. This part of data is entirely collected from Facebook profiles and a considerable proportion of people have not reported their age, resulting in relatively small numbers as elements of the matrix.

Table 4.5 Age composition of personal networks by ego's age group

Age of ego	N	<20	20-29	30-39	40-49	50-59	60-69	70+	Unknown
50-59	23	0.016	0.079	0.084	0.067	0.113	0.054	0.021	0.566
60-69	50	0.014	0.059	0.068	0.077	0.075	0.121	0.037	0.549
70+	32	0.008	0.058	0.057	0.075	0.051	0.094	0.094	0.562

Education: Average diversity for education (table 4.1) is 0.85 and this indicates that participants of this study have highly diverse networks based on education. This measure ranges from 0.03 to 1 and represents a range from almost perfect homogeneity (diversity=0.03) in which all alters have the same education and perfect diversity (diversity=1) in which no two alters have the same level of education. The average of assortative mixing is 0.99 which indicates that it is very likely that alters with the same educational level are connected to each other.

Comparing measures of diversity and assortative mixing based on education among participants with different levels of education (see table 4.6) shows that diversity of alters' education increases steadily with increases in the level of egos' education. Egos with high school education have less diverse personal networks based on education. All groups are highly assortative based on education, indicating a high level of clustering based on education.

Table 4.6 Homogeneity based on education by ego's education

Education of ego	N	Mean diversity	Mean assortativity
Graduate School	15	0.872	0.988
College	37	0.849	0.989
High School	19	0.838	0.985
Unknown	32	0.857	0.989

The composition of egos' personal networks based on education shows that egos with a high school degree have the highest proportion of alters with a high school degree in their networks (see table 4.7). The second group in terms of connecting with the same alters is college, and then graduate school. This clearly shows that network homogeneity based on education increases as egos' educational level decreases.

Table 4.7 Education composition of personal networks by ego's education

Education of ego	N	Education of alter			
		Graduate School	College	High School	Unknown
Graduate School	15	0.044	0.287	0.209	0.460
College	37	0.107	0.279	0.164	0.450
High School	19	0.040	0.209	0.293	0.458
Unknown	32	0.061	0.237	0.223	0.480

Geographical location: As shown in table 4.8, on average, alters live in six different countries (country of residence at the time of data collection), 11 states (Australia comprises six states and two territories) and 24 cities. Average geographical distance between ego and her alters is 3557 kilometers which indicates the presence of many long-distance connections in personal networks of participants.

Table 4.8 Geographical distance in personal networks (N=67)

	min	mean	median	max	sd	Q1	Q3
Average distance (KM)	26	3375	2153.6	13762	3207.3	1205.4	4178.8
Number of countries	2	6	5	29	4.0	4	8
Number of states	2	11	8	58	8.5	6	12
Number of cities	2	20	15	128	17.7	10	24

Figure 4.1 depicts the ranked average geographical distance in personal networks. The graph shows that despite the high average distance, many personal networks (around 40) have an average distance of less than 2000 kilometres and only a small proportion have on average long distance connections (more than 4000 kilometres).

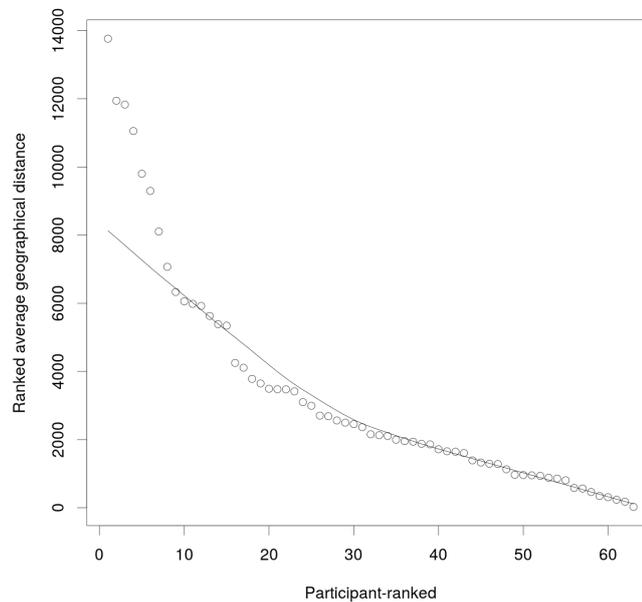


Figure 4.1: Average geographical distance in personal networks

The diversity index and assortative mixing have also been calculated using names of countries, states and cities included in each personal network and summarized in table 4.9. Assortative mixing has only been calculated for country due to the computational difficulties in calculating this measure for attributes with many categories.

Table 4.9 Homogeneity based on geographical location

	min	mean	median	max	sd	C
Diversity index based on country	0.56	0.75	0.73	1.00	0.096	0
Diversity index based on state	0.56	0.76	0.76	1.00	0.077	0
Diversity index based on city	0.56	0.77	0.76	0.95	0.072	0
Assortative mixing based on country	0.00	0.98	0.99	1.00	0.101	0

These measures indicate that on average, egos have geographically diverse personal networks, more than what would be expected by chance. It also reveals a high level of clustering among alters who live in the same country, which means that egos have many connections from different countries, but alters from the same country are very likely to be connected to each other. One way to explain clustering based on country of residence is that egos' Facebook personal networks connect them with clusters of alters who live in other countries and are perhaps family members or friends who live in same countries.

4.4.2 What are the associations between relational and compositional diversity? Bivariate analysis

The summary of the bivariate analysis is provided in table 4.10. In the following paragraphs I review the most notable findings.

There is a weak positive correlation between being male and diversity based on gender ($r=0.37$, $p<0.001$) which means male egos are slightly more likely to have opposite-gender alters than female egos. This has been found in the previous section by studying gender diversity and composition of personal networks for men and women (see section 4.4.1).

Ego's age is positively correlated with diversity based on gender, while age and country of residence are negatively correlated with assortative mixing based on age. It also has a positive correlation with network density. This indicates that older participants have denser personal networks in which alters are more likely to be diverse based on gender and age and less clustered. These characteristics are more often found in kinship networks compared with networks of peers (Marsden, 1988), which indicates that the ratio of kin to non-kin relationships increases slightly with age.

Network size is positively correlated with measures of relational diversity (most notably with number of groups) and is negatively correlated with measures of compositional diversity. There is a negative correlation between network size and diversity based on gender, country and state of residence. On the other hand, network size is positively correlated with measures of assortative mixing. It is positively correlated with average degree and number of groups, while negatively correlated with density. It can be concluded that larger personal networks are less diverse based on socio-demographic attributes, are more sparse, are composed of more contexts and exhibit a higher level of clustering among alters with same attributes.

Network density is negatively correlated with relational diversity and positively correlated with compositional diversity. Network density is positively correlated with network diversity based on age and geographical location (country and state) and is negatively correlated with measures of assortative mixing. Unlike network size, density is negatively correlated with number of groups. The interpretation is that denser personal networks are more likely to be smaller and hence are less likely to include different groups. The positive correlation with age diversity may be because of prevalence of kin relationships within smaller personal networks.

The correlation between transitivity and measures of network diversity are not consistent with each other. Transitivity is positively correlated with age and geographical diversity, but negatively correlated with assortative mixing based on gender and education while, positively correlated with assortative mixing based on age and country of residence. Transitivity indicates alters' overall tendency to cluster, and its positive correlation with age and geographical diversity can be interpreted by prevalence of kin who live in different countries.

Network average degree is negatively associated with measures of compositional diversity - although it is only significant for gender and geographical diversity - and positively associated with assortative mixing. Since average degree represents the extent to which alters share friends with ego, it is expected that the more diverse the attributes of network members, the less the number of shared friendships. The negative correlation with diversity based on gender can be because of the greater prevalence of peers than of kin and thus a high level of assortative mixing. Average degree is subject to influence by large and dense clusters in which alters have many connections with each other. Another explanation is based on network size. Average degree tends to be higher in larger networks ($r=0.43$, $p<.001$), with a greater prevalence of peers than kin and hence a greater level of assortative mixing.

Table 4.10 Pearson correlation coefficients among egos personal attributes, measures of relational and compositional diversity (N=103).

	1 ^a	2	3	4	5	6	7	8	9	10	11
1. gender											
2. age	0.03										
3. size	-0.05	-0.18									
4. density	0.08	0.26**	-0.49***								
5. transitivity	0.12	-0.07	-0.19	0.35***							
6. average deg.	-0.05	-0.02	0.43***	0.09	0.16						
7. divers. gender	0.37***	0.23*	-0.20*	0.15	0.13	-0.21*					
8. divers. age	0.11	0.20*	-0.11	0.32**	0.38***	0.04	0.18				
9. divers. edu.	-0.19	-0.04	-0.02	0.04	-0.09	-0.05	-0.13	-0.12			
10. num. group	-0.06	-0.17	0.77***	-0.54***	-0.11	0.00	-0.09	-0.12	0.01		
11. assort. gender	-0.11	-0.12	0.42***	-0.28**	-0.22*	0.53***	-0.06	-0.28**	0.01	0.20*	
12. assort. age	-0.17	-0.34***	0.27**	-0.21*	0.23*	0.36***	-0.29**	-0.07	-0.08	0.16	0.22*
13. assort. edu.	-0.15	-0.16	0.39***	-0.25*	-0.22*	0.51***	-0.07	-0.31**	-0.02	0.19	0.96***
14. assort. country	0.08	0.08	0.19	-0.11	0.27**	0.27**	-0.14	0.07	-0.05	0.14	0.05
15. divers. country	0.07	0.26**	-0.37***	0.29**	0.28**	-0.24*	0.24*	0.27**	0.05	-0.26**	-0.48***
16. divers. state	0.03	0.12	-0.26**	0.22*	0.28**	-0.22*	0.22*	0.28**	-0.08	-0.16	-0.35***
17. divers. city	0.14	0.00	-0.06	0.10	0.21*	-0.06	0.11	0.14	-0.05	-0.05	-0.27**

	12	13	14	15	16
13. assort. edu.	0.26**				
14. assort. country	0.08	0.04			
15. divers. country	-0.23*	-0.45***	-0.25*		
16. divers. state	-0.07	-0.32**	-0.26**	0.66***	
17. divers. city	0.02	-0.23*	-0.14	0.42***	0.79***

Note: *: p<0.1 **: p<0.05 ***: p<0.01
^a: Male=0

4.4.3 Multiple regression analysis: personal networks and subjective well-being

This section examines associations between homogeneity of personal networks and SWB. The dependent variable is measured by PWB (psychological well-being) which ranges from 1 to 5 and LS (life satisfaction) which ranges from 1 to 10 (see Section 3.4.2)

For each dependent variable, six models are developed. Models 1-5 are exclusive and only model 6 has all variables (except for measures of assortative mixing). Model 1 tests the role of the control variables (gender, age and having a spouse/partner) in explaining SWB. The second model examines the associations between size and number of groups and SWB. The third model includes network density, transitivity and average degree. Models 4 and 5 examine associations between diversity and assortative mixing and SWB respectively. The final model (model 6) includes all of the variables except for assortative mixing as these measures did not improve the models.

Psychological well-being: The results are shown in table 4.11. Among all included explanatory variables for PWB, only four variables show significant associations: egos' age and having a spouse/partner, network transitivity and diversity based on education. These four variables are all positively related with PWB.

Older participants and those who had a spouse/partner have reported better PWB. The small positive coefficient for age ($\beta=0.03$, $p<0.05$) indicates that older participants have a slightly better PWB. Having a spouse/partner increases the level of PWB by 0.43.

Among the measures of relational diversity, only network transitivity is significantly associated with PWB. This positive association indicates that when relationships between alters are transitive, ego has a better PWB. To better understand this association, consider a personal network in which there are two relationships between three alters. The existence of the third relationship between them is positively related to the ego's PWB. This is not a causal relationship in a way that increasing transitivity will necessarily lead to an improved PWB. This positive association can be because participants with better PWB tend to have a transitive relationship around them. It also can be the result of other factors of social structure contributing to transitivity in personal networks (Feld, 1981) such as being from a same context (e.g. transitive relationships among family members).

Among measures of compositional diversity, only diversity based on education is significantly related to PWB ($\beta=2.54$, $p<0.10$). Compared with age and gender, diversity based on education reflects a level of diversity in personal networks which can facilitate access to diverse resources. As descriptive analysis (see section 4.4.1) shows that diversity based on education is higher than other attributes, and the fact that it has a significant relation with PWB indicates the important role of education in personal relationships. The role of education of network members on ego's well-being will be further investigated in Chapter 5 through the concept of social capital.

Table 4.11 OLS regression of homogeneity of personal network and psychological well-being

	Model1	Model2	Model3	Model4	Model5	Model6
gender	0.01 (0.16)					0.01 (0.17)
age	0.03** (0.01)					0.03** (0.01)
hasSpouse	0.35** (0.16)					0.43** (0.17)
size		-0.00 (0.00)				-0.00 (0.00)
number of groups		0.02** (0.01)				0.02 (0.01)
density			-1.00 (0.68)			-1.05 (0.84)
transitivity			1.01 (0.65)			1.19* (0.67)
average degree			-0.02 (0.02)			0.01 (0.03)
gender diversity				0.11 (0.50)		-0.31 (0.54)
age diversity				0.02 (0.03)		0.02 (0.03)
education diversity				1.89 (1.34)		2.54* (1.31)
geo diversity (country)				-0.32 (0.89)		-0.51 (0.92)
gender assortativity					18.91 (14.31)	
age assortativity					-0.71 (2.40)	
education assortativity					-14.56 (12.15)	
Constant	1.65** (0.74)	3.60*** (0.11)	3.43*** (0.34)	1.83 (1.32)	0.07 (5.18)	-1.30 (1.61)
Observations	76	76	76	75	75	75
Log Likelihood	-71.64	-74.81	-74.71	-74.00	-74.29	-63.22
Akaike Inf. Crit.	151.29	155.63	157.42	158.01	156.57	152.45

Note:

Standard errors in parentheses

*: p<0.1 **: p<0.05 ***: p<0.01

Life satisfaction: As shown in table 4.12, across the six models only few variables are significantly related to LS, and the only significantly related variable in the final model (model 6) is having spouse/partner. The positive association between having a spouse/partner and LS ($\beta=1.12$, $p<0.05$) indicates that participants who have had a spouse/partner have reported greater LS by more than one level than those who did not have a spouse/partner.

Age exhibits a weakly positive relation with LS in model 1, but it becomes non-significant in the final model in the presence of other variables. Similarly, diversity based on gender shows a positive relation with LS ($r=2.09$, $p<0.1$) which is only significant in model 4 and not in the final model.

The associations between measures of homogeneity and LS are qualitatively different from their associations with PWB. One of the notable differences is in the association with network transitivity and diversity based on education which both had important power in explaining PWB, but not with LS. This difference can be partly explained by the difference between these two measures in capturing SWB. While PWB captures a temporary SWB based on egos' experience during the last four weeks, LS shows a broader picture of SWB that can be based on egos' recent experience and their overall satisfaction with life.

Table 4.12 OLS regression of homogeneity of personal network and life satisfaction

	Model1	Model2	Model3	Model4	Model5	Model6
gender	-0.08 (0.39)					0.27 (0.46)
age	0.05* (0.03)					0.03 (0.03)
hasSpouse	0.91** (0.41)					1.12** (0.45)
size		-0.00 (0.00)				0.00 (0.01)
number of groups		0.01 (0.03)				0.00 (0.03)
density			1.40 (1.69)			0.14 (2.22)
transitivity			1.63 (1.63)			1.06 (1.78)
average degree			-0.03 (0.05)			0.02 (0.07)
gender diversity				2.09* (1.23)		1.88 (1.43)
age diversity				0.11 (0.07)		0.13 (0.08)
education diversity				-0.73 (3.27)		1.71 (3.47)
geo diversity (country)				0.21 (2.18)		-0.22 (2.42)
gender assortativity					12.47 (36.01)	
age assortativity					-4.70 (6.04)	
education assortativity					-15.90 (30.56)	
Constant	3.82** (1.84)	7.81*** (0.29)	6.80*** (0.85)	4.93 (3.22)	15.69 (13.04)	-1.01 (4.25)
Observations	76	76	76	75	75	75
Log Likelihood	-141.37	-145.28	-144.22	-140.83	-143.47	-136.11
Akaike Inf. Crit.	290.73	296.56	296.45	291.65	294.95	298.21

Note:

Standard errors in parentheses

*: p<0.1 **: p<0.05 ***: p<0.01

4.5 Discussion and conclusion

This chapter has three main findings. First, it was found that personal networks of participants of this study are highly diverse based on socio-demographic attributes. Second, relational and compositional diversity provide divergent pictures of diversity in personal networks. Third, overall measures of diversity are only partially associated with SWB; only network transitivity and diversity based on education show positive associations with PWB.

Overall, the personal networks in this study exhibit a higher level of diversity based on socio-demographic attributes than what would be expected by chance. The scores for diversity based on gender indicate that there are perfectly diverse personal networks, but there is no case of perfectly homogeneous personal network. The average diversity based on age is 16 (the average standard deviation) and it indicates a wide age range among alters, which may be explained by including both kin and non-kin relationships in personal networks. Diversity based on education has the highest value and may be explained based on the wide age range included in personal networks which increases the chance of having different levels of education. Measures for geographical diversity also indicate the presence of many long distance connections and to a diverse set of countries. It is important to note that the high level of diversity found in this chapter may be the result of including all types of relationships in personal networks. The existing literature emphasises that relationships tend to be homogeneous among non-kin. The present chapter did not distinguish between kin and non-kin to provide a broad view of relationships in personal networks including all types of relationships from very close ones to relationships with people who are in the ego's Facebook friends list and ego may have never met them in real life. The present chapter was interested in such a broad view, but distinguishing between kin and non-kin relationships can provide new insights using the similar analysis employed in this chapter.

The findings of the bivariate analysis indicate that overall, measures of diversity deduced from network structural characteristics do not correspond with the diversity derived from socio-demographic attributes of network members. Network size is negatively associated with measures of compositional diversity, while network density and transitivity are positively related to measures of compositional diversity. Networks that exhibit higher levels of age diversity are more likely to be made up of kinship relations, which are usually more homogeneous based on other attributes (e.g. cultural tastes) and resources. So, measures of diversity based on socio-demographic attributes provide a basis for diversity in personal networks in a way that

individuals have access to the basic levels of help and support. For example, if networks of older individuals are highly homogeneous based on age, including mostly same aged others, it indicates a clear age segregation that may affect their well-being. On the other hand, diversity measures based on network structure better represent egos' access to more diverse resources. Therefore, consistent with other research (Smith et al., 2014), this chapter suggests considering other attributes such as racial background, cultural preferences or occupations for future research on diversity in personal networks.

The associations among measures of relational diversity also provide new insights into the nature of diversity in personal networks. Network size is strongly and positively correlated with number of groups, while network density has a strong negative correlation with these measures. Since the number of groups indicates diversity (relational aspect), network diversity increases with size and decreases with density. Because the networks of people with similar attributes tend to be denser than the networks of people with diverse attributes, this indicates the increased local integration and decreased global cohesion (Marsden, 1988). In this way, density measures the global cohesion while number of groups indicates the prevalence of local density within clusters of relationships. These associations which have also been identified by other social network scholars, can be explained in several ways. First, the time and resources that individuals can devote to social contacts is limited. Therefore people manage their networks in a way that they can spend time with groups of alters simultaneously. Second, groups are mainly developed as foci independently from individuals' personal networks. Larger networks are more likely to represent different foci, which can lead to groups in the network (Feld, 1981). Third, individuals cognitively tend to have a balanced network that needs similar alters to be connected to each other (Heider, 1985). Another factor that can increase transitivity in Facebook personal networks and consequently number of groups is the fact that Facebook suggests new friends from the friends list of egos' friends.

Older participants and those who had a spouse/partner had reported a better SWB. Having a spouse had a consistent positive association with both PWB and LS, which confirms the vital role of having a spouse in later life found in other studies (Larson, 1978b; Lawton et al., 1984; Manzoli et al., 2007). Age is only weakly associated with PWB which indicates that older participants have slightly better psychological well-being. This finding is also consistent with the findings of previous research (Walker, 2005; Jivraj et al., 2014). However, there is no significant difference between older and younger participants in the level of their life satisfaction.

Overall, lower levels of relational diversity and higher levels of compositional diversity are related to better psychological well-being. The network transitivity and diversity based on education are positively associated with PWB. Bearman and Moody (2004) also found the protective role of transitivity in friendships networks on suicidal ideation among young American girls. To the best of my knowledge, previous researchers have not examined the role of transitivity of relationships among alters in well-being using personal network data. Those who have paid attention to the connections between alters (Burt, 1987; Kalish et al., 2009), have actually examined the extent to which alters know each other (dyads) and not the extent to which pairs of alters with a shared friend know each other.

The positive association between diversity based on education and well-being may be explained in several ways. First, education can better describe homogeneity/diversity in networks than demographic attributes such as age or gender and hence reflect ego's access to a diverse set of resources. This will be further studied in Chapter 5 through the concept of social capital. Second, the association between higher level of diversity based on education and SWB may be mediated by the role of education of ego. It was found that diversity based on education increases with egos' level of education. So, egos' education may have a positive impact on both diversity of network as well as well-being. This chapter was not focused on the exact reason for this positive association, but it is recommended for future research.

Measures of diversity had different associations with LS than PWB. None of the associations with PWB are statistically significant in relation with LS. It can be partially explained by the fact that PWB captures a temporarily subjective well-being based on the ego's experience during the last four weeks, while LS shows a broader picture of SWB that can be a mixture of recent experience and the ego's overall perception of own life. In this way, egos with a higher level of transitivity in relationships among alters have a better PWB, but the level of their LS is not significantly different. This difference indicates that characteristics of personal networks may have different impacts on different aspects of well-being. Egos experience lower levels of stress or higher levels of happiness when relationships between their alters are more transitive, but they may not be necessarily more satisfied with their life.

As discussed in the literature review of this chapter (section 4.2), findings on the impact of size and density on well-being are conflicting. The analysis in this chapter has found that net-

work size and density are unrelated to well-being which is contrary to what has been found by some scholars (Burt, 1987; Chan and Lee, 2006; Zhu et al., 2013) and is consistent with the findings of others (Israel and Antonucci, 1987; Haines and Hurlbert, 1992). The lack of significant association between network size, density and SWB in the analysis of the present chapter can be attributed to two factors. First, personal networks include all types of relationships from kin and close friends to acquaintances and people who ego has never met in real life. Findings of studies confirm that characteristics of different sets of relationships can have different impacts on well-being (Kalish et al., 2009; Huxhold et al., 2013). Second, the present chapter considered all Facebook relationships as equally important to the ego, which is not realistic. Recent research (Helliwell and Huang, 2013) found that the number of Facebook friends is largely unrelated to well-being, while the number of "actual" friends is positively related to well-being. The present chapter has focused on the homogeneity of personal networks on Facebook including all types of relationships. However, examining the role of homogeneity on well-being by distinguishing between different sets of relationships is highly recommended for future research. This will be partially studied in Chapter 6. Chapter 7 will also further study the differences between relationships on Facebook and the extent to which they are important to the ego in real life.

Social capital and subjective well-being

5.1 Introduction

The two previous chapters studied personal networks with the purpose of better understanding how personal networks are related to SWB. In particular, the previous chapters focused on the network diversity by examining both network structure and composition. The results of analysis indicated that personal networks included in this study exhibit a higher level of diversity than what would be expected by chance. Such personal networks are assumed to facilitate access to diverse resources due to their structural and compositional characteristics.

This chapter further studies personal networks as actual means of access to resources and how this aspect of personal networks relates to subjective well-being. Networks' function of providing access to resources is conceptualized as "social capital". It is widely known that social capital has an important role in the life of individuals and societies. However, researchers have mostly focused on the collective values and our knowledge about social capital for individuals and its role in outcomes is limited especially in well-being. According to the early conceptualisation of social capital as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" Bourdieu (1985, p. 248), it is composed of two components: network structure and the embedded resources.

While social network scholars have shown that network structure and embedded resources are inherently related to each other, they are often studied separately in relation to different types of outcomes. Very little research has studied them jointly especially in the area of well-being.

Moreover, the relations between the two components of social capital are mainly demonstrated theoretically and have rarely been tested empirically. This chapter tries to fill the gaps in the current literature by studying social capital at the level of individuals based on a framework including both network structure and resources embedded within the structure. It further studies how these two components are associated with each other and with subjective well-being.

This chapter is organised as follows. First, a review of the literature on social capital focusing in particular at the level of the individual and its relation to SWB is provided. Second, concepts used in the analysis of this chapter are defined. The third part presents results of the descriptive, bivariate and multiple analyses. The chapter finishes with the discussion of the results and the main findings.

5.2 Literature review

Social capital is a relatively new theory in social science, but it is "fast becoming a core concept in business, political science and sociology" (Burt, 2000b). However, there are several limitations in this area of research especially in relation to individuals' health and well-being. First, although scholars agree on the central elements of social capital, there are significant differences in meaning, measuring and applications of this concept. One of the most discussed challenges in studying social capital is that this concept is so broad that it can cover almost every question in social science. Such broadness often leads to ambiguity of this concept, making it difficult to define and measure (Kadushin, 2004). Second, much of the research has focused on social capital at the level of groups or communities and little attention has been paid to it at the level of individuals (Van der Gaag and Snijders, 2004). Third, the existing literature is even more limited in employing the recently developed models to measure social capital for individuals and its implications for well-being.

This section selectively reviews the literature with the main focus on social capital of individuals based on its two components: relational and material. This review of the literature is concerned with clarifying the measures and concepts that will help in developing the conceptual framework used in this chapter. The literature on the implications of social capital for individuals' well-being was briefly reviewed in Chapter 2 and a more in-depth review is provided in this section.

Social capital has been studied at two levels: group and individual (Borgatti et al., 1998). At

the group level, social capital is conceived as the asset of groups and the whole society. The main focus of attention in this perspective is socio-cultural processes such as social integration, trust, norms and rules to produce and maintain the collective asset (Bourdieu, 1985; Coleman, 1990; Putnam, 1995). Social capital at the individual level can be traced back to the social support literature and has been reformulated as "social resource theory" (Lin, 1986). This approach focuses on individuals' relationships as the source of informational, material and emotional aid (Bourdieu (1985); De Graaf and Flap (1988); Marsden and Hurlbert (1988); Burt (2000b); Lin (1999, 2001).

Bourdieu (1985), provided the first contemporary analysis of social capital and made it clear that it is made up of two components: "relational" and "material". He defined social capital as:

"the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition - or in other words, to membership in a group - which provides each of its members with the backing of the collectivity-owned capital, a 'credential' which entitles them to credit, in the various senses of the word." Bourdieu (1985, p. 248).

As noted by Portes (1998), Bourdieu provides an instrumental definition of social capital in which networks are not a natural given or even a social given. Networks are "the product of investment strategies, individual or collective, consciously or unconsciously aimed at establishing or reproducing social relationships that are directly usable in the short or long term" (Bourdieu (1985, p. 249). The relational component of social capital refers to the network of social relationships in which individuals' membership can create opportunities to access resources while, the material component relates to the amount and the quality of those resources (Portes, 1998).

A more recent social network approach to social capital is based on the concept of embedded resources (Burt, 1995; Lin, 1999, 2001). This approach defines social capital as "access to" and "use of" embedded resources in social networks. Lin (1999) argues that this approach helps to solve the problem of confusion between micro (individual) and macro (community) level outcomes. Consistent with Bourdieu, the social network approach emphasizes that social capital is not an outcome or a goal per se, but a means of achieving outcomes in other forms (e.g. economic capital) and this is what links social capital to well-being at the level of individuals.

Thus, in response to the question of "how is social capital associated with well-being?", it can be

said that it is simply by facilitating access to resources. Given that social capital is defined as "investment in social relations with expected returns" Lin (1999, p. 30), individuals invest in social relationships with the expected return of better well-being. However, depending on various factors such as the type of relationships or the amount of resources accessible through relationships, there is a vast variation in the expected returns (Wellman and Wortley, 1990). This is what explains the inequalities in the amount of social capital and outcomes (Song and Lin, 2009). For example, two individuals with the same number of relationships may have access to different numbers and sets of resources suited to facilitate different actions and returns. Generally, there are two types of outcomes for social capital as 1) returns to "instrumental" actions and 2) returns to "expressive" actions (Lin et al., 1999). For instrumental actions, social capital is a means to obtain resources which are not possessed by individuals and returns are exemplified by money, power and status. For expressive actions, social capital is a means to maintain resources which are already available to individuals and the returns are exemplified by physical health, mental health and life satisfaction (Lin, 1999). In this way, resources embedded in networks can facilitate instrumental actions such as accessing information to find a new job (Granovetter, 1983; De Graaf and Flap, 1988) or expressive actions such as maintaining the functional or emotional resources during difficult events in life (Krause, 1986; Fram, 2003).

It is commonly found that different types of outcomes are linked to different types of social capital (Lin, 1999). The two types of actions as instrumental and expressive actually represent the two types of social capital as "bridging" and "bonding" which were introduced by Putnam (1995). Bonding social capital refers to individuals' strong ties such as connections with close associates such as family and close friends. Thus, it is often associated with values of being bonded in homogeneous groups of people such as shared values, trust, sense of belonging and easy and efficient access to social support. Bridging social capital refers to individuals "weak ties" (Granovetter, 1983) such as connections with acquaintances and friends of friends. This type of social capital is associated with values of heterogeneous groups of people, linkage to external assets/information, sense of being as a part of a broader group and diffuse reciprocity with a broader community (Williams, 2006). By definition, it is expected that bonding social capital suits expressive actions and in return improves health and well-being while, bridging social capital is more expected to facilitate instrumental actions and hence occupational or financial attainment. There is an extensive literature on returns of expressive actions (Lin, 1986; House et al., 1988; Hall and Wellman, 1985; Kadushin, 1983; Chan and Lee, 2006; Gow et al., 2007; Lakey, 2008) as well as on returns of instrumental actions (De Graaf and Flap, 1988; Ooka

et al., 2006; Huang and Western, 2011)

However, the literature on social capital and well-being is overwhelmingly dominated by the role of bonding social capital and expressive actions. While there is an extensive literature on effects of social support and bonding social capital on various aspects of individuals health and well-being, only a few researchers have examined the role of bridging social capital in this regard. It is undeniable that having strong and meaningful relationships with family and friends plays a crucial role in individuals' well-being (see discussions in Chapter 2). Nevertheless, there is plenty of evidence on the importance of weak ties that bridge individuals to larger social environments for different aspects of an individual's life. As one form of capital, social capital can be transformed or used to reproduce other forms of capital such as economic or human capital. When there are strong links between other types of capital and well-being (i.e. economic capital and well-being), social capital as whole can be linked to well-being as well as its types and components. Using data from the Taiwan Social Change Survey collected in 1997, Song and Lin (2009) examined the impact of social capital and social support on individuals' well-being measured by depression and self-reported health status. They defined social capital as network members' capabilities to link ego to resources via their occupational position and social support was defined as the percentage of kinship ties and average of ties' intimacy. Song and Lin (2009) found that social capital impacts health over and above social support. So, while acknowledging the commonly found associations between bonding social capital and well-being, this chapter argues that bridging social capital can also have an important role in explaining well-being.

Social capital as network structure: relational component

Clearly, resources do not flow in a vacuum. Social connections act as the infrastructure through which people access various resources. Social network scholars have commonly shown that different characteristics of network structure can be used to study accessibility to different types and amount of resources for actors, as well as the possible outcomes (Coleman, 1990; Burt, 1995). For example, Lin (1999, p. 34) expresses that "for preserving or maintaining resources (i.e. expressive actions), denser networks may have a relative advantage ... On the other hand, for searching and obtaining resources not presently possessed (i.e. instrumental actions), accessing and extending bridges in the network should be more useful"

Among all the network measures, network density has gained special attention in relation to social capital. Density is commonly found to be associated with bonding social capital. Coleman

(1990) states that "The fact that everyone knows everyone, creates obligations within the network, which in turn increases trust and reduces the chance of free riding or malfeasance". However, network density is found to be not a careful measure because of its high level of sensitivity to network size; larger networks need disproportionately more ties per alters. Scholars have shown that other measures such as average degree (see section 3.3.2) better represent network cohesion (Gilbert and Karahalios, 2009; Brooks et al., 2014). However, average degree does not substitute for density as a measure for bonding social capital and both of these measures will be used in the analysis of this chapter.

Transitivity indicates the extent to which network members tend to cluster and is measured as the ratio of closed triads to open triads. High levels of transitivity indicate prevalence of closed triads in the network. This happens when the network is composed of multiple densely-knit clusters with lack of connections between them (low number of open triads). Although, clustering among alters indicates a high level of density within clusters which represent bonding social capital, a lack of open triads indicates a low level of global cohesion in the network. Therefore, transitivity can better indicate bridging social capital than bonding. Brooks et al. (2014) found that bonding social capital is less tied to local clustering than to global cohesion, as open triads better indicates the global cohesion than closed triads.

In this research, I develop a new measure for bridging social capital as *global average degree* and to avoid confusion, I rename average degree as *local average degree*. Bridging social capital is defined as the network's capacity in linking ego to others (friends of friends) and hence provides access to diverse resources which are not embedded within ego's personal network. Network size provides a crude indicator of bridging social capital; it implies that the more people that ego knows, the more likely that the ego has access to diverse resources. However, this measure assumes that all alters have the same capability in linking the ego to others, which is not true. For more clarification, if we have two egos e1 and e2 with network size of 4 and 8 respectively. We also know that each of e1's alters have five other friends who are not directly connected to e1 and each of e2's alters have two friends who are not directly connected to e2. Using network size we can say that e2 has a higher level of bridging social capital than e1. But considering how many people e1 and e2 are connected to via their direct connections (friends of friend), bridging social capital is higher for e1 than e2. Global average degree measures the average number of people who are connected to the ego via personal network (see section, 5.3.2).

Social capital as access to resources: material component

This chapter uses the social network approach to study the social capital as it provides an appropriate framework for defining, measuring and analysing social capital for individuals. This chapter measures social capital using a survey instrument called "resource generator" (RG) developed by (Van der Gaag and Snijders, 2004, 2005; Van der Gaag and Webber, 2008). This instrument is based on the original ideas of (Lin, 1999) about resources embedded in networks and it aims to measure social capital at the level of individuals. This instrument has been used extensively by many researchers (view the completed list compiled by Bartelski (2011)).

RG measures an individual's social capital as the sum of all resources/skills that are accessible through their network. Availability of each resource depends on the strength of ties with the network member who owns it. Strength of tie is measured based on the type of relation. In this way, if an individual knows more than one person who has one resource (e.g. good computer skills), it is assumed that the resource is available through the strongest relation. Family relationships have the highest strength followed by friends and then acquaintances. Van der Gaag and Snijders (2004) identified categories of social capital as: "prestige and education related", "political and financial skills", "personal skills" and "personal support". However, these resources and categories can be modified to fit the target population for the purpose of study. A list of resources (see Van der Gaag and Snijders (2005)), which are commonly used in different studies in some countries (Bartelski, 2011), can be modified for a target population in another country.

Although potential social capital indicates the amount of resources available to each ego, further detailed measures shows how potentially available resources are actually exchanged if needed. As noted by Lin (1999), knowing someone who has a resource does not necessarily mean that that resource is accessible to the ego. The two important factors determining accessibility are whether the ego asks for resource and whether the resource owner is willing to provide if requested.

Although RG provides a comparative measure for individuals' social capital, it has also some limitations. First, it assumes a positive association between closeness of relations (inferred from type of relation) and accessibility of resources to individuals. For example, if an individual knows two people who have a resource and one is a family member and the other is a close friend, RG assumes that the family member provides that resource. While it is commonly found that resources are more available through strong ties (family members) than weak ties (acquain-

tances), some studies have noted that it is not always true (Small, 2013). This study extends the use of RG by identifying the exact alters a personal network who have specific resources. Thus, a resource may be available through different alters who have different types of relationships with ego.

Second, the RG does not capture the distribution of resources in individuals' networks; it is effectively assumed that one source for each resource is adequate in measuring individuals' social capital and other sources are redundant. However, capturing different sources for resources reveals how resources are distributed among alters and can be used for some more indicative measures. Alexander et al. (2008) employed data on multiple sources of resources to calculate a measure called "multi-strandedness" that has been previously introduced by Fischer and Shavit (1995). Multi-strandedness provides a measure for social control by the fact that it indicates the extent to which ego needs to rely on a limited number of alters to access to resources; higher levels of multi-strandedness indicate higher levels of social control. Data on multiple sources for each resource enables us to have a better view of how social capital is distributed in personal networks.

Third, RG measures social capital based on individuals' direct access to resources embedded within their personal networks. In this way, the RG overcomes the undue response burden which is the main limitation of other methods for collecting network data such as "name generator" namely, . However, combining RG with other methods such as name generator can create a more precise view of an individual's social capital. Depending on the focus of the study, a combination of RG and name generator approaches can provide information on the amount of resources available in a personal network as well as the characteristics of alters who provide resources and the type of relationships between ego and alters. The present research uses this combination. It benefits from the data on network structure and characteristics of alters collected from Facebook, and in this way the potential response burden of using name generator approach has been avoided.

5.3 Concepts and definitions

5.3.1 Material component of social capital

Potential social capital

Potential social capital indicates the amount of resources in a personal network that are po-

tentially accessible to ego. This measure is calculated based on two indicators or concepts: *availability* of resources through direct links to alters (ego-alter tie) and *accessibility* to resources measured by strength of ego-alter ties.

Information on *availability* of resources are provided by ego in response to the question of "Do you know anybody who has this skill/resource?". For each of 10 resources, ego can nominate up to 10 alters as her alters who have that resource. Thus, each alter can be nominated to have at most 10 resources.

The ten resources are:

- Give advice about financial matters
- Can speak a foreign language
- Give advice or help using computer or internet
- Give advice on matters of law (e.g. in relation to your landlord, your employer or government regulations)
- Could help your family or yourself to get a job (including part time, casual or voluntary jobs)
- Give advice, information or reference about health problems
- Help when moving house
- Give advice concerning a conflict with family members
- Owns a holiday house
- Has university education

Accessibility to resources is measured by strength of ego-alter ties; this information is provided by ego in response to the question: "How close do you feel to each of your social contacts?". Strength of each tie in a personal network is scored from one to five (see section 3.3 for more details).

Potential social capital is measured by the summation of all alters' potential resources multiplied by the strength of tie. Define G_e as the personal network for ego e , and further:

- n_e is the size of the network G_e .
- \mathbf{r}^e is the vector of potential resources in G_e :

$$\mathbf{r}^e = \begin{bmatrix} r_1^e & \dots & r_i^e & \dots & r_{n_e}^e \end{bmatrix} \quad (5.1)$$

where $r_i^e \in \{1...10\}$ = "number of resources that each alter has"; The list includes only ten re-

sources. Thus, each alter can be nominated at most ten times. Further, \mathbf{w}^e is the vector of strength of ties between ego and her alters which are scored from one to five.

$$\mathbf{w}^e = \begin{bmatrix} w_1^e \\ \vdots \\ w_i^e \\ \vdots \\ w_{n_e}^e \end{bmatrix} \quad (5.2)$$

and $w_i^e \in \{1, 2, 3, 4, 5\} = \{\text{"Very far"}, \text{"Far"}, \text{"Neither far nor close"}, \text{"Close"}, \text{"Very close"}\}$. Potential social capital for ego e is calculated as:

$$\tilde{s}^e = \sum_{i=1}^{n_e} (r_i^e \times w_i^e) \quad (5.3)$$

Actual social capital

Actual social capital refers to the amount of potential social capital that is actually obtained if needed. Information on actual social capital are provided by ego in response to two questions of "From whom you can easily ask for help" and "To whom you can easily give help?". In response to each of these two questions, for each of 10 resources, ego can nominate up to 10 alters who can provide that resource or ego can easily provide that resource to alters. Thus, each alter can be nominated to actually provide or receive at most 10 resources.

Received social capital: is measured as summation over all received resources (resources that ego can easily ask for from her alters) multiplied by the strength of tie. Received resources refer to the social exchanges from alters to ego in which ego is the receiver of resources.

$$\mathbf{r}^{e+} = \begin{bmatrix} r_1^{e+} & \dots & r_i^{e+} & \dots & r_{n_e}^{e+} \end{bmatrix} \quad (5.4)$$

where $r_i^{e+} \in \{1...10\} = \text{"number of received skills/resources from alter } i \text{ to ego } e\text{"}$.

Received social capital is therefore:

$$s^{e+} = \sum_{i=1}^{n_e} (r_i^{e+} \times w_i^e) \quad (5.5)$$

Provided social capital: is measured as summation over all provided resources (resources that ego can easily provide to her alters) multiplied by the strength of tie. Provided resources refer to the social exchange from ego to alters in which ego is the provider of resources.

$$\mathbf{r}^{e-} = \begin{bmatrix} r_1^{e-} & \dots & r_i^{e-} & \dots & r_{n_e}^{e-} \end{bmatrix} \quad (5.6)$$

where $r_i^{e-} \in \{1...10\}$ = "number of provided skills/resources from ego e to her/his alter i ".

Provided social capital is calculated as:

$$s^{e-} = \sum_{i=1}^{n_e} (r_i^{e-} \times w_i^e) \quad (5.7)$$

Resource diversity

Diversity in resources refers to the extent to which network members have a diverse set of skills/resources. I measure resource diversity as the number of distinct skills/resources available in a personal network. So, for each type of resources, this measure removes the redundancies. For example, if a personal network contains 10 resources composed of three types A, B and C, the number of distinct resources will be three.

Help circle

Help circle refers to the number of alters who are nominated by the ego as having any of the listed resources and are willing to provide them if needed. In other words, help circle is equal to the number of alters from whom the ego can easily ask for help.

Multi-strandedness

Multi-strandedness is the average number of times an alter is nominated for having skills/resources (Alexander et al., 2008). It is calculated by dividing the total number of network resources by the number of alters who are named to have those resources (help circle). For example in a particular personal network, if 4 alters are providing 14 resources in total, multi-strandedness will be $14/4 = 3.5$. Thus on average, each alter provides 3.5 resources.

5.3.2 Relational component of social capital

Types of social capital: bonding and bridging

Bonding and bridging social capital can be measured based on both components: relational and material. The material components of bonding and bridging social capital is often measured according to the type of resources. For example, having good computer skills is related to bridging

social capital, while giving advice concerning a conflict with family members indicate bonding social capital. The types of resources used in this study were not designed with the purpose of measuring bonding and bridging social capital separately, and hence data on the material component of social capital is not adequate to distinguish between these two types of social capital. Therefore, this chapter only uses the relational measures for bonding and bridging social capital.

Bonding social capital. This is defined using 2 measures. Density (the extent to which alters are connected to each other) and average local degree (average of alters' degree within the personal network). More details on these measures are provided in sections 3.3.2 and 5.2.

Bridging social capital. This is defined using 4 measures: size, transitivity, number of groups and average global degree. More details on these measures are provided in sections 3.3.2 and 5.2.

For each ego, average global degree is equal to the average of number of friends of ego's alters who are not ego's friend on Facebook. For example, if ego e1 has 3 alters and two of her alters have 4 friends and one has 7 friends (assuming that they are not ego's friends), the average global degree for e1 is $(4+4+7)/3=5$. For each alter in personal network of ego e1, the number of friends refers to the number of that alter's friends on Facebook who are not friend with ego e1. Data on the number of alters' Facebook friends has been collected from Facebook.

5.4 Analysis

There are three parts to the analysis. First, I will describe social capital of egos in regard to the concepts defined in this chapter. Note that this section will only focus on measures of social capital based on the material aspect; measures for the relational aspect have been described in Chapter 3, sections 3.4.3. Second, results of bivariate analysis will be provided that show how various measures described in the first section are related to each other. The main focus of this section of analysis is the associations between the relational and material components of social capital. Third, I will provide results of the multiple regression analysis examining the associations between social capital and SWB.

5.4.1 Descriptive analysis

As summarised in table 5.1, participants on average have access to 8.5 resources in their personal networks (including the redundancies) and 2.4 distinct resources (out of the maximum of 10

resources). They receive these resources from an average of 5 alters (help circle). The average of multi-strandedness is 1.8 which means on average, each alter provides 1.8 resources. Comparing with other studies (Fischer and Shavit, 1995; Alexander et al., 2008), the average of 1.8 for multi-strandedness is relatively high and indicates that our participants rely on a limited pool of alters who have multiple types of resources. On average, the number of resources that participants own (mean=4.1) is greater than the number of resources that they have access to via their alters (2.4). All together, these findings show that egos have access to a relatively small number of the skills/resources listed in this research and through a limited number of alters. Moreover, their personal networks facilitate access to even less resources than what they have themselves.

Table 5.1 Descriptive characteristics of social capital (N=42)

	min	mean	median	max	sd	Q1	Q3
Potential resources	0	8.5	20	61.0	14.70	6	29
Actual received resources	0	8.4	0	57.0	14.64	0	15
Actual provided resources	0	7.4	0	67.0	13.16	0	11
Potential social capital	0	33.3	76	266.0	59.24	19	118
Actual received social capital	0	38.3	0	257.0	65.85	0	65
Actual provided social capital	0	34.0	0	323.0	61.61	0	52
Own resources	0	4.1	4	10.0	2.78	2	6
Multi-strandedness	1	1.8	1.50	4.7	0.74	1.35	2.11
Help circle	0	5.0	0	36.0	8.68	0	7
Number of distinct resources	0	2.4	0	10.0	3.25	0	4

Overall, egos can actually receive almost all of the potentially available resources in their personal networks. On average, egos have 8.5 resources in their personal network and they can easily ask for 8.4 resources. They are also willing to provide on average 7.4 resources to their alters; however these resources can be duplicated that ego may provide 1 resource to several alters. Comparing the average number of received and provided resources indicates that on average egos receive more than they provide, but the difference is small.

The average of actual social capital is higher than potential social capital (33.3); the average for received social capital is 38.3 and the average for provided social capital is 34. Since the average number of potential resources (8.5) is higher than the average number of actual resources (8.4 and 7.4), the actual social capital is higher than the potential social capital because of the strength of ties involved in actual social capital relative to the ties involved in potential social capital. In other words, egos may actually receive fewer resources than the total number of resources that alters have (potential resources), but they receive those few resources from alters who are closer to them.

Figure 5.1 plots the availability of different types of resources in personal networks. Since for

each resource, each participant can nominate up to 10 alters who have that resource, values are plotted between 0 to 10. So, this graph plots the number of alters who have each resource. Knowing someone who has university education is the most frequent resource in participants'

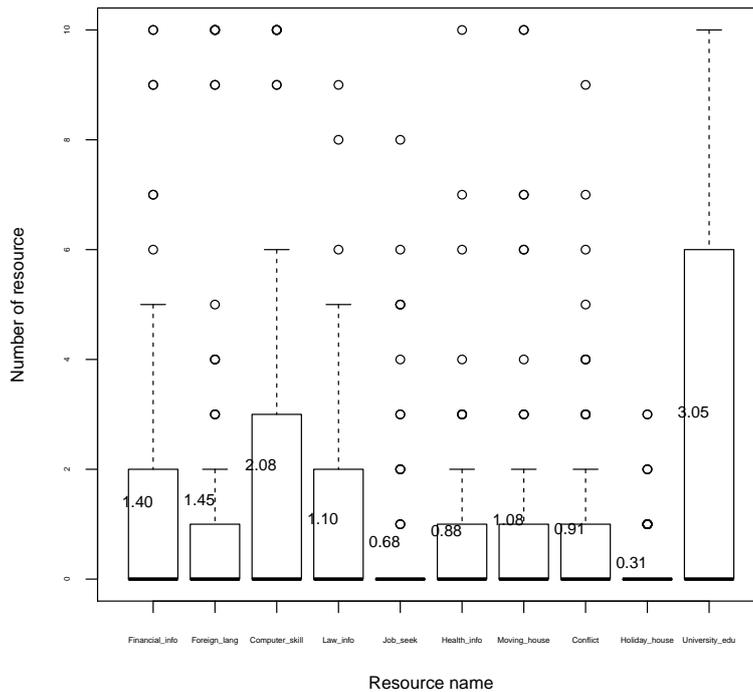


Figure 5.1: Distribution of potential resources by type of resource

Note: the numbers shown in this box-and-whisker plot, indicate the average values.

personal networks (average=3.05). The second most popular resource is good computer skills (average=2.08). Information about financial matters is the third available resource to our participants with the average of 1.40 followed by information about law with an average of 1.10. Owning a holiday home and helping in getting a job for ego or her/his family are the least frequent resources with average of 0.31 and 0.68 respectively. We can partially explain the abundance of resources such as university education or good computer skills by the fact that such resources may be generally more frequent than some more specific resources such as information about health issues. Another explanation is that participants of this study are people who use Facebook. So, it is very likely that themselves or someone in their network is educated and has computer skills. In particular, most older people would have someone from their family (i.e. children or grandchildren) who have these skills even if they don't have themselves.

Figure 5.2 plots the percentage of participants who own each resource. The most frequent re-

source among participants is having good computer skills (48.2% of egos have reported that they have this resource), followed by having financial information with 42%. Interestingly, having university education is the third least frequent resource with 25.9 percent.

Figure 5.3 maps resources based on being owned by participants and being accessible via social

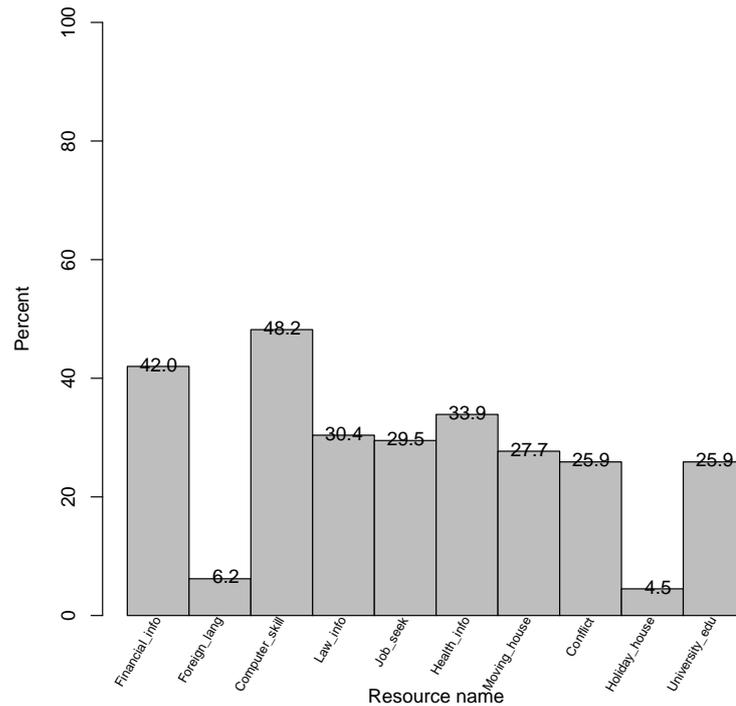


Figure 5.2: Distribution of resources owned by participants by type of resource

contacts (that are depicted in Figures 5.2 and 5.1) in a two-dimensional space. As shown in the graph, there are four regions and each region represents the extent of owning resources versus knowing someone who owns resources. For example, the right-top region shows high chance of owning a resource as well as knowing someone who has that resource. The majority of resources are in the bottom-right region of the graph. This indicates that for the majority of resources, the participants are more likely to have resources themselves than knowing someone who has them. There is only one resource in the left-top region: university education. It means that participants are more likely to know someone who has a university education than to have it themselves. There is also one resource in the top-right region: good computer skills which indicates that participants are very likely to have good computer skills as well as to have social contacts with good computer skills. But the likelihood of owning this resource is even more than knowing someone who has it. There are three resources in the bottom-left region: owning a holiday house, being able to speak a foreign language and can give advice concerning a conflict with family mem-

bers. The likelihood of owning these three resources is low as is knowing someone who has them; however, they are slightly different. While the chance of owning a holiday house is as low as having a social contact who owns it, the likelihood of knowing someone who knows a foreign language is slightly higher than having this skill and the likelihood of knowing someone who can give advice on family conflicts is less than having this skill.

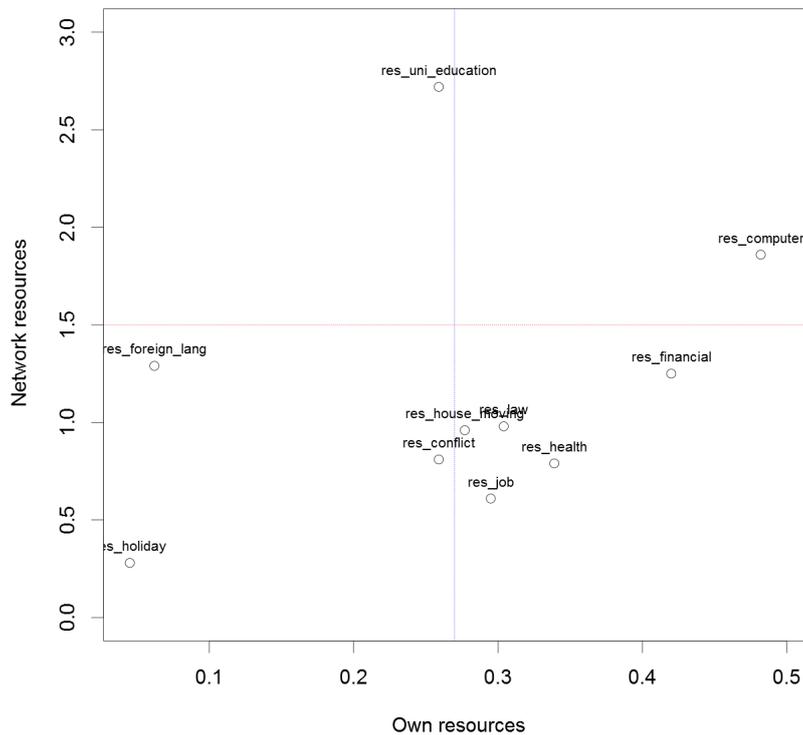


Figure 5.3: Potential resources versus resources owned by participants

5.4.2 Associations between relational and material components of social capital: Bivariate analysis

This subsection provides new insights into the associations between the two components of social capital: relational and material. Table 5.2 shows the Pearson correlation coefficients among the variables of interest. The most notable findings are reviewed in the following paragraphs.

Table 5.2 Pearson correlation coefficients among relational and material components of social capital

	size	density	transitivity	local degree	global degree	number of groups	potential sc	actual sc (received)	actual sc (provided)	multi-stranded	help circle
potential sc	-0.11	0.16	0.15	0.26	-0.04	-0.02					
actual sc (received)	-0.17	0.08	0.02	0.09	-0.17	-0.01	0.92***				
actual sc (provided)	-0.17	0.08	0.01	0.08	-0.13	0.00	0.68***	0.88***			
multi_stranded	-0.33*	0.51***	-0.15	-0.14	-0.14	-0.44**	0.12	0.12	0.00		
help circle	-0.09	0.03	-0.01	0.24*	-0.13	0.08	0.89***	0.89***	0.80***	-0.21	
number of resources	-0.19	0.15	-0.04	0.12	-0.18	-0.05	0.80***	0.85***	0.77***	0.28	0.85***

Note:

N=76

*: p<0.1

** : p<0.05

***: p<0.01

Network size and multi-strandedness have a negative correlation, which means that the larger the network, the larger the pool of alters from which ego may receive resources (potentially accessible). So, in a larger network ego experiences a slightly lower level of social control as ego does not rely on few alters to get access to resources/help.

As expected, network density is positively correlated with multi-strandedness ($\beta=0.51$, $p<0.001$), which means that egos who live in a densely-knit set of relationships are more likely to experience social control as the number of alters who provide help are small. Considering the direction of correlations between density and the measures of material social capital (although are not statistically significant), we can say that overall, denser networks provide more resources. However, the positive significant correlation between density and multi-strandedness indicates that even though egos in denser networks receive more resources from more alters, multi-strandedness increases with network density. Therefore, though denser networks provide more resources, social control is higher in such networks compared with sparser networks.

The correlation between average local degree and the number of potential resources is positive ($r=0.32$, $p<0.05$), meaning that the higher the level of alters' engagement in ego's personal network, the greater the chance of ego knowing someone who has a resource.

Similarly, average local degree is (weakly) positively related to help circle ($r=0.24$, $p<0.05$), which indicates that egos who have many mutual friends with their alters are more likely to know someone in their network who has resources/skills. These two positive associations can result from egos who share many friends with their alters, are more likely to know their alters and this knowledge may help them to know about who has what resources. Examining the exact reason for these correlations is beyond the scope of this chapter, but will be further studied in Chapter 7.

The number of groups is negatively correlated with multi-strandedness ($r=-0.44$, $p<0.01$). It means that the more groups ego has in her personal network, the less likely is that she relies on a small number of alters who have resources. This correlation reveals that personal networks that are structurally diverse provide more opportunities for ego to access resources via a larger pool of alters, compared to those networks composed of few groups.

5.4.3 Associations between social capital and subjective well-being: Multiple regression analysis

This section provides the results of multiple regression analysis of the associations between social capital and SWB. Personal attributes of ego (gender, age and having a spouse) are used as control variables.

Tables 5.3 and 5.4, present six models. The first model tests the role of personal attributes on SWB. Models 2 and 3 include relational measures of social capital: measures of bridging are included in model 2 and measures of bonding are in model 3. In model 4 the impact of material-based measures of social capital are tested. Model 5 includes all of the variables except for material based social capital. Model 6 is the full model and includes all variables.

Psychological Well-being (PWB). The results of the analysis for PWB are summarised in table 5.3. In the following paragraphs, I review the most notable findings.

Age has a small but consistently significant association with PWB ($\beta=0.05$, $p<0.05$) indicating that older participants have a slightly better PWB than younger ones. This positive association was also found in chapter 4 (see section 4.4.3) in studying homogeneity of personal networks. Thus, from both the perspective of homogeneity of personal networks and social capital, age is positively associated with psychological well-being.

The coefficients for the relational measures of social capital change across the models and only three relations are significant in the final model: average global degree ($\beta=-0.001$, $p<0.1$), density ($\beta=-0.83$, $p<0.05$) and transitivity ($\beta=2.29$, $p<0.05$). The coefficient is quite small for average local degree and indicates that having social contacts who have more social contacts beyond ego's network is not related to better well-being. Such social contacts may facilitate access to resources that are not available in ego's network, but the findings of this chapter do not confirm it. The large negative coefficient for network density indicates that a higher level of connectedness among alters is related to a lower level of ego's PWB. But, the positive association between transitivity and PWB means that having personal networks in which alters tend to form triads is beneficial for PWB and can be explained in this way. Transitivity indicates bridging social capital thus, personal networks with higher levels of transitivity can better facilitate access to resources. Compared with density that indicates the overall connectedness among alters, transitivity captures the tendency toward local clustering. The negative coefficient for density and

the positive coefficient for transitivity indicates the positive role of bridging social capital over bonding for PWB. The positive role of transitivity on PWB was also found in Chapter 4 in studying homogeneity of personal networks on SWB (see section 4.4.3). We can conclude that overall, participants with transitive relationships among alters have better PWB.

The network size, the number of groups and the local degree are unrelated to PWB across models. The lack of significant associations between size and SWB was also found in Chapter 4 and was discussed there (see section 4.4.3). Average local degree and the number of groups have been found in other studies to be important indicators for bonding and bridging social capital (Brooks et al., 2014) respectively and hence are expected to have significant relation with SWB. However, the analysis of this chapter does not support it.

None of the relations between PWB and material based measures of social capital are significant. One reason for this lack of significant association is that the sample is small and it is even smaller when including material component of social capital because not many participants have reported their social capital.

Table 5.3 OLS regression of social capital on psychological well-being

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gender	0.01 (0.16)				0.01 (0.15)	-0.09 (0.27)
age	0.03** (0.01)				0.03*** (0.01)	0.05** (0.02)
hasSpouse	0.35** (0.16)				0.36** (0.16)	0.34 (0.28)
size		0.00 (0.00)			0.00 (0.00)	0.01 (0.01)
transitivity		0.71 (0.62)			1.56** (0.64)	2.29** (0.94)
number of groups		-0.01 (0.04)			-0.04 (0.04)	-0.11 (0.08)
global average degree		-0.00* (0.00)			-0.00* (0.00)	-0.00* (0.00)
density			-0.60 (0.63)		-1.87** (0.81)	-0.83** (0.15)
local average degree			-0.02 (0.02)		-0.01 (0.02)	-0.03 (0.04)
potential sc				0.00 (0.00)		0.00 (0.00)
actual sc(received)				0.00 (0.02)		-0.00 (0.02)
actual sc(provided)				-0.02 (0.01)		-0.00 (0.01)
multi-strandedness				-0.09 (0.15)		-0.20 (0.21)
Constant	1.65** (0.74)	3.55*** (0.40)	3.88*** (0.18)	3.87*** (0.33)	1.10 (0.92)	-0.27 (1.82)
Observations	76	76	76	42	76	42
Log Likelihood	-71.64	-74.53	-75.96	-43.95	-65.26	-36.15
Akaike Inf. Crit.	151.29	159.06	157.92	97.91	150.51	100.30

Note:

N=76

*: p<0.1

**: p<0.05

***: p<0.01

Life satisfaction (LS): results of the analysis for LS are summarised in table 5.4. In the following paragraphs, I review the most notable findings.

None of the associations between personal attributes and LS are significant. The coefficient for age is significant only in the first model. Having spouse is also significant in models 1 and 5 but not in the final model.

Among all measures of social capital, the only significant relation is between potential social capital and LS which is positive (0.02, $p < 0.1$). This positive association indicates that participants with higher amount of social capital are more likely to be satisfied with their lives. This positive association is not necessarily because of the higher number of available resources or the number of alters who have those resources. Potential social capital is composed of the number of resources and strength of ties between ego and alters who have those resources. Therefore, participants who are more satisfied with their lives may know more people who have resources or may know few people who have resources, but feel close to them that can easily ask for help or they may have both.

Interestingly, across the models none of the measures for relational social capital are significantly related to LS. Although the sample for analysis of the present research is limited and findings are not generalisable, this finding suggests that compared to other factors, the relational component of social capital has a limited power in explaining LS. Further research based on a larger sample may provide better insights into the role of the relational component of social capital on individuals' well-being.

Table 5.4 OLS regression of social capital on life satisfaction

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
gender	-0.08 (0.39)				-0.01 (0.40)	-0.46 (0.58)
age	0.05* (0.03)				0.04 (0.03)	0.05 (0.05)
hasSpouse	0.91** (0.41)				1.00** (0.42)	0.89 (0.59)
size		0.00 (0.00)			0.00 (0.00)	-0.00 (0.01)
transitivity		2.15 (1.54)			2.58 (1.70)	1.96 (2.01)
number of groups		-0.11 (0.10)			-0.13 (0.10)	-0.05 (0.16)
global average degree		-0.00 (0.00)			-0.00 (0.00)	0.00 (0.00)
density			2.05 (1.55)		0.04 (2.14)	-1.85 (4.38)
local average degree			-0.02 (0.05)		-0.03 (0.06)	0.02 (0.10)
potential sc				0.02** (0.01)		0.02* (0.01)
actual sc(received)				-0.05 (0.04)		-0.05 (0.04)
actual sc (provided)				-0.02 (0.02)		0.01 (0.03)
multi-strandedness				-0.02 (0.30)		-0.07 (0.44)
Constant	3.82** (1.84)	7.26*** (0.99)	7.52*** (0.44)	7.42*** (0.64)	3.43 (2.43)	2.88 (3.89)
Observations	76	76	76	42	76	42
Log Likelihood	-141.37	-143.77	-144.74	-71.88	-139.17	-68.15
Akaike Inf. Crit.	290.73	297.54	295.49	153.76	298.33	164.29

Note:

Standard errors in parentheses

*: p<0.1 **: p<0.05 ***: p<0.01

5.5 Discussion and conclusion

This chapter measured and described social capital for participants of this study and its association with their SWB. The following paragraphs discuss the main findings of this chapter.

Overall, egos have access to a relatively small number of resources via a small number of alters. The number of resources accessible through alters is even smaller than the number of resources that egos own themselves. However, this small number of resources is diverse that covers all types of resources included in this study. Moreover, egos can easily ask for almost all of the resources they know their alters have in case of need. The list of resources owned by egos was somewhat different from the list of resources available through alters. Having university education, good computer skills and information about financial matters were the most abundant resources accessible via alters while, having good computer skills, information about financial matters and information about health were the mostly owned by egos themselves. However, egos who own a resource themselves were more likely to have that resource in their networks which indicates that resources are localised in individuals interpersonal environments. This can be explained in many ways. People with similar skills are more likely to be connected with each others (rule of homophily), or friends become similar to each others (social influence) or it reflects the impact of homogeneous shared foci in which people share similar resources (i.e. co-workers). Either of these mechanisms, this finding supports the idea of inequalities in access to resources. From a social capital point of view, it shows the role of networks that act as invisible bounded social environments which are durable in time (Bourdieu, 1985) and provide members with a backup of maintained resources.

The bivariate analysis did not support the assumed associations between relational and material aspects of social capital. For example, larger or denser personal networks do not provide more social capital. Among all of the included measures, only average local degree had a positive relation with help circle which means that egos who have more mutual friendships with their alters, know more of their alters who have resources. This positive relation can be explained in this way that cohesive personal networks provide more opportunities for ego to know alters and the resources they may have. Such knowledge can be better acquired as a result of having mutual friendships as they ties to be more durable and stronger in triads (Feld, 1997). Note that the association found in this chapter is based on the average degree (aggregated at the level of personal network) and does not provide any indication about the ties involved in the mutual friendships and how they are identified to have resources. This will be further studied in

Chapter 7. The measure of multi-strandedness exhibits indicative relations with characteristics of network structure, thus confirms findings of other studies that multi-strandedness provides a fruitful measure for social capital (Alexander et al., 2008). Multi-strandedness decreases with relational measures of bridging social capital and increases with relational measures of bonding social capital. Egos with larger and more diverse networks receive resources from a larger pool of alters, while in a more cohesive personal networks, egos are more limited to a small number of alters who have resources.

Overall, the material component of social capital does not show significant associations with SWB, except for the weak relation between potential social capital and LS. For the relational component, measures of bridging social capital better explain SWB than measures of bonding. The negative relation of density and the positive relation of transitivity with PWB indicate that egos with better PWB have sparse but clustered personal networks. In spite of what has been commonly found in the literature, that denser networks are better sources of (bonding) social capital and are better for expressive actions and hence for subjective well-being, the analysis of this chapter revealed that sparser networks associated with better SWB. This could be because density is negatively associated with bonding social capital or because bonding social capital is negatively associated with SWB. Similarly, the positive association between network transitivity and PWB indicates the positive role of bridging social capital on SWB; The literature suggests that the relational measures of bridging social capital are better suited for instrumental actions and the related outcomes such as power or money. Because of the lack of information on material measures of bonding or bridging social capital, this chapter was not able to examine the pathways through which density and transitivity are associated with SWB. This is recommended for future research. In addition to the inherent complexity in these associations, the contradictory findings of this chapter may be because the personal networks that are collected from Facebook are different from those commonly captured by researchers in real life (i.e. are larger or more diverse). This chapter did not aim to disentangle the mechanisms, but this is partially addressed in Chapter 7 and strongly recommended for future research.

Finally, I acknowledge that the findings of this chapter are limited by the non-representativeness of the sample of older Australians who use Facebook. The sample used in this research is small and the data on social capital is limited for several reasons. First, participants of this study would have access to more resources which are not captured in this study due to either difficulties in working with computer on this survey, or because of the length of the survey and the

fact that questions on social capital were asked in later steps. Second, the list of resources was limited to 10 selected resources. The resources were chosen from Van der Gaag and Snijders (2004) and tried to cover a range of main categories of social capital identified by Van der Gaag and Snijders (2004) and Van der Gaag and Snijders (2005). Participants may know alters who have many other skills or resources, but those resources are not in the list used in this research. Moreover, participants of this research may had and needed specific resources which might not be included in our survey. A more comprehensive list including more resources would provide a better view of social capital.

Emotional interactions and subjective well-being

6.1 Introduction

The previous chapter (5), studied personal networks as the main way people access resources in later life, and their associations with subjective well-being (SWB). However, personal networks are not always positive and enabling. They can be also negative and limiting in various ways. Social networks that can provide individuals with resources and improve SWB, can also be a source of social strain and hence have a detrimental impact on well-being (Rook, 1997; Walen and Lachman, 2000)

This chapter further studies personal networks and their role in explaining SWB, by focusing on positive and negative emotional interactions. SWB is defined slightly differently from previous chapters: instead of psychological well-being, it uses only one variable of this component to measure overall happiness (see section 6.3). The emotional interactions between ego and her alters (the explanatory variables) indicate the extent to which alters can make ego feel happy or unhappy (see section 6.3).

The literature is extensive on how negative social relationships affect the well-being of people in general, and especially in later life. However, researchers have mostly focused on the existence and the number of positive and negative interactions and their associations with well-being, while other aspects of this phenomenon have remained relatively unexplained. The intensity or sources of these interactions have gained little attention, while the structural characteristics of personal networks have been largely absent in current studies. In this regard, positive and negative interactions are considered as mere isolated relationships between ego and her alters that do not depend on each other or on the structure of the personal network in which they

are embedded. This chapter broadens the debate on the role of positive and negative emotional interactions in explaining SWB by going beyond the existence and number of positive and negative interactions to include their importance in relation to ego and with the rest of the network.

This chapter has three aims. First, it provides a conceptual framework for research into negative interactions at the level of personal networks. The main advantage of this framework is that it integrates the structural characteristics of personal networks with emotional interactions. Second, to better understand (online) personal networks in later life, this chapter describes them in terms of emotional interactions. Third, it studies the associations between emotional interactions and SWB by utilising the framework developed in this chapter.

The structure of this chapter is as follows. First, I review the related literature. Then, I provide the conceptual framework and define the concepts used in this chapter. In section 6.4, analysis and findings will be presented. The final section discusses the findings and provides the conclusions.

6.2 Literature review

Positive and negative emotional interactions are studied under a broad concepts of "positive and negative social exchange" or "positive and negative ties"; emotional interactions are considered as a type of social exchange or more generally as ties. The literature has defined and measured positive social exchange as social support (i.e. emotional and instrumental). Negative social exchange however, has been generally defined as conflicting social relationships and has been measured based on various aspects such as criticism, hostility, unwanted demands (Rook, 1984) or taking advantage of, breaking promise of help or provoking feelings of conflict or anger (Finch et al., 1989) or giving unwanted advice or intrusion, failure to provide help and unsympathetic or insensitive behavior and rejection or neglect (Newsom et al., 2005). This way of defining the positive and negative ties enables distinguishing between ties which are exclusively positive, exclusively negative or a mixture of positive and negative referred to as "ambivalent". However, being supportive and problematic are different aspects of social relationships and are measured differently. Therefore, being negative is not the opposite of being positive as they do not show the distance in one spectrum. Hence, it is not possible to describe positivity of a tie with a single measure.

Positive and negative ties can also be defined based on the concept of "like-dislike". Affective

relations (e.g. making someone happy or unhappy) are mostly studied using the well-known social psychology theory known as "balance theory" (Heider, 1946). This theory explains how people feel uncomfortable if they have positive sentiments towards two entities (i.e. two persons) who do not have a positive sentiment towards each other. Heider (1946) has noted that like and agreement can represent positive sentiment and dislike and disagreement represent negative sentiment. According to this conceptualisation, a tie can be positive or negative or something in between. For example, in the context of personal networks, ego can like an alter (+1) or dislike her (-1) or in a more nuanced way, ego can give a score to her alter showing her sentiment towards her from "dislike so much" to "like so much".

Although researchers point to the importance of distinguishing between positive, negative and ambivalent relationships (Rook, 1997; Fingerman et al., 2004; Uchino et al., 2004; Rook et al., 2012), because of their different implications for well-being, the present chapter uses the definition in which each tie can be either positive or negative or something in between. In this way, ego may have an alter who makes her feel "very unhappy" (negative) but also provides her with resources thus making the relationship overall, ambivalent. However, this chapter only considers the first characteristic of this relationship and hence would classify the relationship as negative.

Positive and negative ties in later life and associations with well-being

The literature has mainly focused on the supportive aspect of social networks for older people. More recently, however, negative social relationships in later life and their role on well-being has gained greater attention. One of the most highlighted findings from various studies on negative interactions in later life is that older adults generally experience less negative and more positive social relationships compared with their younger counterparts (Andrews and Withey, 1976; Hansson et al., 1990; Akiyama et al., 2003; Windsor and Butterworth, 2010), in part due to the fact that through a lifetime of experience, older people can acquire the social expertise and strategies that allow them to successfully avoid conflict with others (Luong et al., 2011). However, given the reduction in network size in later life, the negative ties that *do* exist can have significant effects on well-being.

The literature has consistently found that negative social exchange, while relatively infrequent (Rook, 2001), has a greater impact on well-being than positive social exchange (Rook, 1997, 2003; Newsom et al., 2005). In other words, it has been found that it is the detrimental impact of negative social exchange that determines well-being rather than the protective impact of posi-

tive social exchange. However, there is debate about the validity of this striking finding, mostly related to the limitations in the existing studies including incomplete sampling and the fact that studies compare positive and negative social exchanges from different sources and unequal intensities (see Rook (1997) for the full discussion.).

Scholars have pointed out that it is not only the presence and amount of the positive or negative interactions that determine SWB, but there are also two other factors that play important roles in this regard: the sources of those interactions and the structure of relationships in which the positive and negative interactions are embedded.

The first factor refers to the nature of relationships and how positive or negative interactions with different sources are associated with well-being (Okun and Keith, 1998; Walen and Lachman, 2000; Fingerman et al., 2004; Adams and Blieszner, 1995). The nature of relationships is basically studied as type (e.g. kin or non-kin) and strength (i.e. closeness). However, researchers have focused more on the types of relationships by distinguishing between family and friends and moreover between different types of relationships within family (parents, siblings, children and so on) than strength. Those studies who have paid attention to strength of relationships in regard to well-being, have found that having positive and negative interactions with close and intimate alters has a differentiated association with well-being, compared with interactions with non-close alters. Cheng et al. (2011) studied the effects of closeness of positive and negative relationships on well-being of older Chinese, finding that positive and negative exchanges with close alters had a greater impact on well-being than exchanges with non-close alters.

The second factor, structure of personal networks, has received very limited attention (Kalish et al., 2009). The structure of personal networks can be used to explain well-being at two levels: relationships ("dyad") and network ("supra-dyad"). As discussed earlier in this thesis (see section 2.4), network structure can be used to explain SWB by examining various characteristics including size, level of network cohesion and segmentation. For example, people with larger or more cohesive personal networks are expected to have better well-being (Kadushin, 1982; Burt, 1987).

Network structure can also be related to SWB by weighting the positive or negative relationships according to the location of alters (with whom ego has the interactions) in the structure of the network. In this way, positive and negative interactions do not have absolute values regardless of

the location of alters within the network structure. Instead, the final effect of each alter in being positive or negative depends on their connections with other alters. So, alters not only directly affect ego's happiness through their direct relationships with her, but also indirectly through their potential influence on other alters' relationships with ego. For more clarification, consider an alter who is well connected with other alters (i.e. she is central in the network structure), and has a high level of emotional interaction (either positive or negative). It is expected that the role of this alter's interaction with ego on ego's well-being (i.e. happiness) is more important than the role of an alter with the same level of emotional interaction, but who is not central in the network structure as the central alter can have greater indirect effect and hence greater overall effect on ego's well-being than the non-central alter. Considering the relative importance of the location of alters in explaining SWB indicates that the positive or negative interactions are not independent from each other nor from the rest of ego's personal network. Relationships are instead embedded within the structure of ego's personal network and in this way can have both direct and indirect effects on ego's SWB.

In sum, the importance of studying the negative side of social relationships for health and well-being has recently been highlighted. The literature in this area has commonly found that the number of negative interactions is significantly less than the number of positive interactions. Older people are consistently found to report more positive and fewer negative relationships. However, the negative impact of these fewer negative interactions on well-being is greater than the positive impact of positive interactions. To understand this striking finding, researchers have considered various factors. For example, it is been found that the two types of interactions have independent impacts on well-being and through different pathways: positive interactions are directly related to well-being, while negative interactions can affect well-being both directly and indirectly by exacerbating the impacts of psychological distress on well-being (Finch et al., 1989; Newsom et al., 2005). However, much less is known about the role of closeness of relationships and the structure of personal network. As explained above, network structure operates at two levels: dyad and network. At the level of the network, well-being can be explained with regard to the network structure as a whole. At the level of the dyad, network structure determines the importance of each positive or negative interaction based on its location (i.e. centrality) within the personal network. The present chapter uses measures based on both levels; further details are provided in section 6.3.

Structure of relationships among close alters

Many studies have examined the associations between structural characteristics of personal networks and SWB (see section 2.4). However, these studies are mostly based on personal networks composed of strong relationships or they distinguish strong from weak ties. Therefore the structure of relationships among close alters can have different associations with well-being from the structure of relationships among non-close alters (Kalish et al., 2009). With the aim of examining the associations between social networks and mental health, Kalish et al. (2009) used a novel framework that considered the structural characteristics of personal networks. To do so, they defined "strong-tie triadic closure" that referred to the proportion of strong-tie partners (up to 48 people who were important in their life in that they felt close to them and/or could count on them for help or advice) who knew each other (see Kalish et al. (2009) for the details of the developed measures). The present chapter employs the idea of "strong-tie triadic closure" to measure the structural characteristics of the "sub-network" that includes only ego's close alters. Thus the present chapter includes three measures: the number of close alters, the extent to which they know each other (are each others friend on Facebook) and the extent to which they tend to cluster among themselves. The conceptual basis of associations between these measures and SWB are the same as what has been discussed in Chapter 2.4 in regard to the structural characteristics of personal networks. These three measures are actually network size, density and transitivity which have been used for the personal networks in this and the previous chapters; the only difference is that here these measures are based on a subset of ego's personal network which include only close alters. Further details are provided in section 6.3.4.

6.3 The conceptual framework used in this chapter, concepts and definitions

Two sets of variables are used in this chapter. The first set is the structural characteristics of personal networks: both the Facebook network and the sub-network including only close alters. The second set of variables is the amount of positive and negative interactions with alters. The first set refers to the size, density and transitivity of Facebook personal networks that includes all of ego's alters and a sub-network that includes only ego's close alters (close or very close). I refer to this sub-network as "close sub-network" which is further defined in section 6.3.4.

The second set of variables measure the amount of positive or negative interactions in a personal network as a whole. In this regard, two personal networks with equal numbers of positive and negative interactions (e.g. 3 positives and 1 negative), may not have equal amount of pos-

itive and negative emotional interactions. In a given personal network, each alter's *valence* in affecting ego's happiness is her capacity in making ego feel happy or unhappy, scored from 1 to 5. This score is defined based on ego's response to the question of "who makes you feel happy or unhappy?" (see section 3.3.2).

To measure the amount of positive and negative interactions in a personal network, we need to measure the amount of positivity or negativity of ego's interaction with each alter by considering the importance of that interaction. The importance of the interaction with each alter that I refer to as "happiness inducement" can be measured using one of two attributes: closeness of relationship with that alter and centrality of that alter in the structure of the personal network. Therefore, the happiness inducement for each interaction depends on two factors: alter's valence and alter's importance. These provide two sets of measures which I refer to as *closeness-weighted happiness inducement* and *centrality-weighted happiness inducement*.

The following pages define these two sets of measures. It also defines the measures related to strong triadic closure. Note that for each concept, there are two names. The first is the notation that defines the measure in the equations and the second is a variable name used in the analysis and discussion.

6.3.1 Measures based on closeness-weighted happiness inducement

Overall happiness index

The "overall happiness index" shows the amount of positive and negative interactions in a personal network according to closeness of relationships. This measure is calculated as summation over the alters' "closeness weighted happiness inducement" which is calculated as the alter's valence multiplied by the closeness of relationship with that alter.

Define G_e as the personal network for person e , and further:

- n_e is the size of G_e network.
- \mathbf{h}^e is the vector of happiness inducement in G_e :

$$\mathbf{h}^e = \begin{bmatrix} h_1^e & \dots & h_i^e & \dots & h_{n_e}^e \end{bmatrix} \quad (6.1)$$

where h_i^e is the valence of alter i for ego e which is defined as:

$$h_i^e \in \{1, 2, 3, 4, 5\} = \{\text{"Very unhappy"}, \text{"Unhappy"}, \\ \text{"Neither happy nor unhappy"}, \text{"Happy"}, \text{"Very happy"}\}$$

Define w^e as the vector of closeness of relationship between ego and alters, which are scored from one to five (see section 3.3.2):

$$w_i^e \in \{1, 2, 3, 4, 5\} = \{\text{"Very far"}, \text{"Far"}, \text{"Neither far nor close"}, \text{"Close"}, \text{"Very close"}\}$$

$$w^e = \begin{bmatrix} w_1^e \\ \vdots \\ w_i^e \\ \vdots \\ w_{n_e}^e \end{bmatrix} \quad (6.2)$$

Then

$$\tilde{h}^e = \sum_{i=1}^{n_e} (h_i^e \times w_i^e) \quad (6.3)$$

Then \tilde{h} is the vector of overall happiness indexes of all N participants.

$$\tilde{h} = \begin{bmatrix} \tilde{h}^1 \\ \vdots \\ \tilde{h}^i \\ \vdots \\ \tilde{h}^N \end{bmatrix} \quad (6.4)$$

The overall happiness index (h^e) that is the overall happiness index for ego "e" is also called as **OHI** which will be used in the analysis of this chapter.

Positive and negative happiness indices

Although the overall happiness index provides a comparative measure for the overall amount of happiness received from a personal network, it does not show the differences between personal networks in terms of the number of each type of interaction. For more clarification, consider two

egos e_1 and e_2 who have reported different numbers of positive and negative ties. For example e_1 has three positive interactions and e_2 has reported 2 positive and one negative. Depending on the exact valences and closeness scores, the overall happiness index for these two egos can be equal, while having only positive ties can be qualitatively very different from having both positive and negative ones. In order to better distinguish between personal networks with different compositions of positive and negative interactions, I define two more measures, the "positive happiness index" for only positive and the "negative happiness index" for only negative interactions.

The positive happiness index (\tilde{h}^{e+}) is constructed the same way as \tilde{h}^e , but only includes the reported positive ties ("happy" and "very happy"). Negative happiness index (\tilde{h}^{e-}) is also constructed the same way as \tilde{h}^e , but only includes the reported negative ties ("unhappy" and "very unhappy").

Note that these measures are called **PHI**, **NHI** in the analysis respectively.

$$\tilde{h}^{e+} = \sum_{i=1}^{n_e} (h_i^e \times w_i^e) \quad \text{if } h_i^e \geq 3 \quad (6.5)$$

$$\tilde{h}^{e-} = \sum_{i=1}^{n_e} (h_i^e \times w_i^e) \quad \text{if } h_i^e < 3 \quad (6.6)$$

Similar to the overall happiness index (\tilde{h}), the positive happiness index can be represented as a vector for all N participants (the negative happiness index is similarly defined based on \tilde{h}^{e-}):

$$\tilde{h}^+ = \begin{bmatrix} \tilde{h}^{1+} \\ \vdots \\ \tilde{h}^{i+} \\ \vdots \\ \tilde{h}^{N+} \end{bmatrix} \quad (6.7)$$

Although a positive relation between overall happiness index and SWB is expected, this index will not be included in the multiple regression analysis. As suggested by the literature, people report a considerably lower amount of negative interactions than positive (Hansson et al., 1990; Windsor and Butterworth, 2010). Therefore the overall happiness index is highly influenced by the amount of positive interactions and it is very close to the positive happiness index (see

section 6.5.1).

6.3.2 Measures based on centrality-weighted happiness inducement

Similar to the measures developed above, network centrality scores can be used to construct "centrality happiness indices" for the total, positive and negative interactions. These three measures are constructed in the same way as the measures based on closeness-weighted happiness inducement, but instead of closeness of relationships, centrality of the alters are included in these measures.

The centrality happiness index for ego "e" (\tilde{h}^e) is similar to \tilde{h}^e , but includes alters' measure of centrality instead of closeness of their relationships to ego. Thus,

$$\tilde{h}^e = \sum_{i=1}^{n_e} (h_i^e \times c_i^e) \quad (6.8)$$

where c_i^e is the centrality measure of alter i in the personal network e , and is calculated as *degree* centrality. Degree centrality for an alter is equal to the number of other alters that alter knows. The normalized score of this measure controls for network size and ranges between 0 (no connection with any other alter), to 1 (connection with all of the alters).

Defined, for each personal network G_e , \mathbf{c}^e is the vector of centrality measure for her alters:

$$\mathbf{c}^e = \begin{bmatrix} c_1^e \\ \vdots \\ c_i^e \\ \vdots \\ c_{n_e}^e \end{bmatrix} \quad (6.9)$$

Similar to the overall happiness index (\tilde{h}^e), the centrality happiness index shows the overall amount of happiness received from alters based on their position in the personal network. However, as noted above this measure is very likely to be influenced by the amount of positive interactions rather than the negative interactions and hence does not show the real differences between personal networks with different amount of positive or negative interactions. Therefore, two measures of positive and negative centrality indices are developed and used in the analysis in this chapter.

Positive centrality index is defined as:

$$\tilde{h}^{e+} = \sum_{i=1}^{n_e} (h_i^e \times c_i^e) \quad \text{if } h_i^e \geq 3 \quad (6.10)$$

Since only degree centrality has been included in this measure, it is also named **PHI_deg**.

Negative centrality index is defined as:

$$\tilde{h}^{e-} = \sum_{i=1}^{n_e} (h_i^e \times c_i^e) \quad \text{if } h_i^e < 3 \quad (6.11)$$

Since only degree centrality has been included in this measure, it is also named **NHI_deg**.

6.3.3 Number of positive and negative interactions

The number of positive ties (\bar{h}^{e+}) in each personal network G_e is:

$$\bar{h}^{e+} = \sum_{i=1}^{n_e} (\tau_i^e) \quad (6.12)$$

where

$$\tau_i^e = \begin{cases} 1 & \text{if } h_i^e \geq 3 \\ 0, & \text{otherwise} \end{cases}$$

The number of negative ties (\bar{h}^{e-}) in each personal network G_e is:

$$\bar{h}^{e-} = \sum_{i=1}^{n_e} (\tau_i^e) \quad (6.13)$$

where

$$\tau_i^e = \begin{cases} 1 & \text{if } h_i^e < 3 \\ 0, & \text{otherwise} \end{cases}$$

These two measures are only used in the descriptive and bivariate analysis. The variable names for them are **count_PHI** and **count_NHI** respectively.

6.3.4 Measures based on relationships among close alters

With the purpose of understanding the role of interconnection between close alters on ego's SWB, sub-networks of the 1.5 degree personal networks are constructed by excluding the non-

close friends and ties between them from the original personal networks. These constructed sub-networks are referred to as "close sub-network"s. As a result for each 1.5 degree personal network, there is another 1.5 degree personal network that includes only alters who are close to ego, ties between ego and those alters and ties between those alters (if there is such tie in the original network).

I define three measures which are the structural characteristics of the newly constructed sub-networks: "close size", "close density" and "close transitivity". These three measures indicate the structure of relationships among close alters. Therefore, "close size" is size of the "close subnetwork", "close density" is density of the "close subnetwork" and, "close transitivity" is transitivity of the "close subnetwork".

6.3.5 Subjective well-being

is measured based on two components: happiness and LS (see section 3.3.1 for more details). Happiness of ego has been measured by asking participants to respond the question "How much of the time in the previous 4 weeks have you been a happy person?", with the following responses: "All of the time", "Most of the time", "A good bit of the time", "Some of the time", "A little of the time" and "None of the time". Happiness is scored from 1-5 indicating the level of ego's happiness.

6.4 Positive and negative interactions illustrated by two cases

To better understand the role of the various measures developed in this chapter in explaining positive and negative interactions in personal networks, they are illustrated by two cases. Figure 6.1 shows the graph of personal networks A and B, with the valence of interactions indicated as vertex values. These two personal networks have the same size of 67 and similar numbers of positive and negative interactions; A has 10 positive and 1 negative, while B has 13 positive and 1 negative. However, the structure of personal networks as a whole and the distribution of positive and negative interactions over the structure, makes them different in several ways. As it is clear in the graphs, the positive and negative interactions are all from one cluster who are mostly family members (green ties)¹. In personal network B, the positive interactions are also mostly from one cluster, but there are some positive interactions with alters in other clusters.

¹Note that the type of relationship as family or non-family has only been used in these graphs for better comparison, but have not been included in the analysis of this chapter.

In both personal networks, the positive interactions mostly involve close alters. However none of the negative interactions are with close alters. Comparing the position of alters with whom ego has positive or negative interactions shows that the positive interactions are more central in both personal networks and the only negative interactions are less central than the positive ones. The alter with negative interaction knows more alters on average in personal network A than in network B, due to being located in the density knit cluster. The alter with the negative interaction in personal network B, knows only one alter. But that alter has a very positive interaction with ego, is very close to her and is central in her personal network ².

Also shown in Figure 6.1, are the close sub-networks of personal networks A and B. Both of these sub-networks are composed of only one component (for each pair of nodes, there is a path between in the network). This means that in both personal networks, close alters are directly or indirectly connected to each other even when ego is removed. The close sub-network is better connected for ego A in which almost all alters know each other, while close alters of ego B are grouped in clusters which suggests that close sub-network A is denser than close sub-network B.

²How alters with the positive or negative interactions are connected to each other, is beyond of the scope of this chapter, but is recommended for future research.

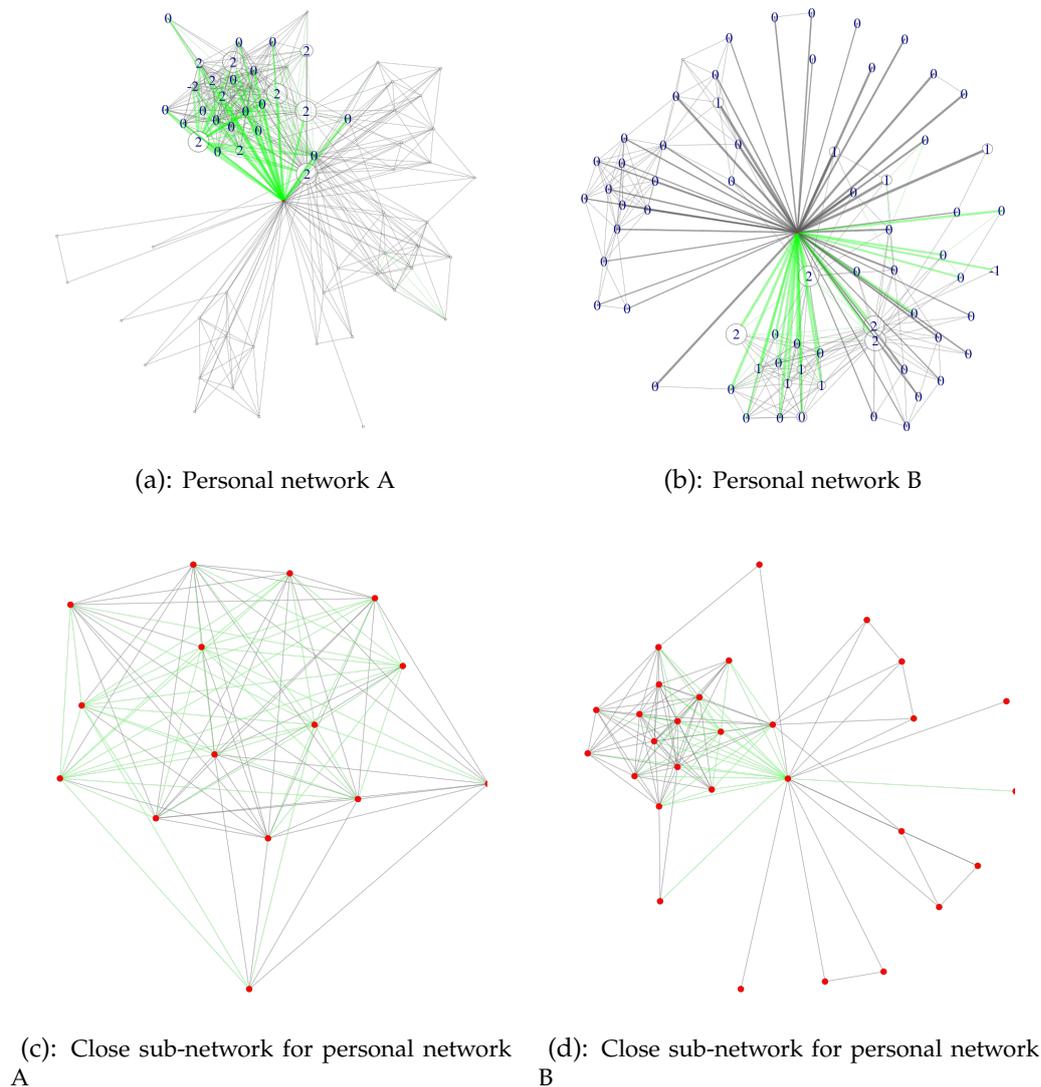


Figure 6.1: Positive and negative interactions for two personal networks

Note: in graphs (a) and (b), size of nodes show their happiness inducement as the "overall happiness index", the labels of nodes show their valence and for a better visualisation it ranges from -2 to 2 and the thickness of ties show their strength.

Although the visual representation of personal networks and their close sub-networks provides some intuitive understanding of positive and negative interactions, the measures defined in the previous section can provide a more precise view of it. While the number and amount of positive and negative interactions based on closeness of relationships are almost the same for both personal networks, the amounts are different when considering centrality of alters with whom ego had the interactions (Table 6.1.). This shows that position of alters with whom ego has positive or negative interactions can provide more indicative measures than closeness of relationship. Measures of close sub-networks are also indicative. Although both personal networks include 67 alters, the number of close alters in personal network B is as twice that of personal network A. The difference of two sub-networks is even greater in density and transitivity of two sub-

networks. Based on this a preliminary conclusion is that when considering only the number of interactions or the types of relationships with whom ego has those interactions (i.e. family or non-family), the two personal networks explained here would be very similar. However data on the closeness of relationship, the number of close alters, the structure of relationships among close alters and the position of alters with whom ego has positive and negative interactions reveals difference between them that are expected to explain the difference in their SWB. These measures will be further used in the next section to describe the positive and negative emotional interactions in personal networks and their associations with SWB.

Table 6.1 Positive and negative emotional interactions for two personal networks

	OHI	PHI	NHI	PHI count	NHI count	PHI degree	NHI degree	close size	close density	close tran- sitivity
Personal network A	1.11	1.17	0.03	10	1	29.61	0.67	14	0.26	0.79
Personal network B	1.14	1.19	0.04	13	1	16.45	0.04	28	0.88	0.91

6.5 Analysis and findings

The analysis has three parts. First, the measures of positive and negative interactions will be described, as well as happiness of ego. Second, the correlations between network structure, measures of positive and negative interactions and SWB will be assessed using bivariate analysis. Third, the associations between positive and negative interactions and SWB (happiness and LS) will be tested, using ordinal logistic and ordinary least squares regression analysis respectively.

6.5.1 Descriptive analysis

Table 6.2 summarises the variables used in this chapter. On average, the amount of reported negative interactions is considerably lower than the positive interactions. The average overall happiness index is very close to the average positive happiness index and has a very large distance from the average negative happiness index. The average number of positive interactions (count_PHI) is 5.74, while the average is 0.32 for the negative interactions (count_NHI).

On average, participants have 17 alters to whom they feel close or very close. The average density of the close sub-network is 0.38 which is higher than the average density (0.15, see sec-

tion 3.4.3) of their Facebook network (including both strong and weak ties). On average, the close sub-network also has a higher level of transitivity than the Facebook personal networks (0.68 compared with 0.54). In terms of SWB, on average participants have been relatively happy in the four weeks prior to the time of data collection; the average happiness is 3.31 which is above the midpoint of 3.

Table 6.2 Positive and negative emotional interactions in personal networks (N=42)

	min	mean	max	sd
OHI	0	33.70	140	45.21
PHI	0	34.70	142	46.16
NHI	0	1.01	18	2.78
count_PHI	0	5.67	21	7.23
count_NHI	0	0.32	6	0.88
PHI_deg	0	405.32	3146	670.80
NHI_deg	0	12.70	222	42.41
close size	0	16.91	46	11.11
close density	0	0.38	1	0.27
close transitivity	0.25	0.68	1	0.19
happiness	1.00	3.31	5	1.07

6.5.2 Bivariate analysis

Results of the bivariate analysis are presented in Table 6.3. Overall, the negative correlation between measures of negative interactions and happiness (NHI: $\beta=-0.26$, *NHI_deg*: $\beta=-0.26$), and lack of significant correlation between measures of positive interactions and happiness, indicate that the negative impact of negative interactions on SWB is larger than the positive impact of positive interactions. This is consistent with findings of previous research (Rook, 1997; Newsom et al., 2005) and will be further examined in the next section using multiple regression analysis. Happiness is negatively related with measures of negative interactions. However, there is no evidence of a protective impact of positive interactions on ego's happiness.

Overall, "close size" shows positive correlations with the measures of positive interactions as well as with LS, while there is no significant correlation between network size and these measures. This indicates that while the total number of Facebook friends (network size) is unrelated to measures of emotional interactions and happiness, the number of Facebook friends who are close to ego (close size) provides an indicative measure in this regard. Similar results have been found by other researchers. For example, Khan et al. (2014) found that the number of "actual" friends (Facebook friends who are actual friends in real life) was positively associated with

class-related academic collaboration among high school students, while the number of Facebook friends was unrelated. The associations between network size and "close size" with ego's SWB will be further examined in the next section using multiple regression analysis. "Close size" is not only positively correlated with the number of positive interactions, but it is also positively correlated with the number of negative interactions ($C_PHI: \beta=0.39$, $C_NHI: \beta=0.27$). The fact that the number of both positive and negative interactions increases with the number of close alters, indicates that both of these types of interactions are more common in close relationships. In other words, it suggests that close alters are not only sources of positive interactions (which is expected), but also they are the source for the negative interaction as well. The association between closeness of relationship and the type of emotional interaction will be further examined in Chapter 7.

Among the socio-demographic characteristics of ego, age shows a weak negative correlation with the number negative interactions ($\beta = -0.24$) and weak positive correlation with happiness ($r=0.23$). Having a spouse or partner is also correlated (weakly) with happiness and life satisfaction. These mean that older participants and those who have spouse are slightly happier than their counterparts. Those who have a spouse also reported a higher level of LS, while there is no significant difference between older and younger participants in this regard. Older participants also reported slightly fewer negative interactions.

Table 6.3 Pearson correlation coefficients among personal attributes, structural characteristics and measures of emotional interactions

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. male																
2. age	0.05															
3. hasSpouse	0.22	-0.04														
4. size	-0.10	-0.26*	-0.02													
5. density	0.08	0.28*	-0.01	-0.51***												
6. trans	0.08	-0.06	0.04	-0.22	0.39***											
7. PHI	-0.17	-0.08	-0.03	-0.09	0.01	-0.02										
8. NHI	-0.21	-0.21	-0.07	-0.03	-0.09	-0.13	0.36**									
9. PHI_deg	-0.07	-0.13	-0.05	0.00	0.06	0.00	0.83***	0.41***								
10. NHI_deg	-0.19	-0.18	-0.06	-0.02	0.00	0.00	0.30**	0.91***	0.39***							
11. count_PHI	-0.17	-0.10	-0.07	-0.11	0.01	-0.01	0.98***	0.36**	0.80***	0.28*						
12. count_NHI	-0.18	-0.24*	-0.09	0.00	-0.10	-0.15	0.45***	0.94***	0.51***	0.80***	0.44***					
13. close size	-0.07	-0.22	0.08	0.13	-0.18	0.11	0.46***	0.21	0.45***	0.22	0.39**	0.27*				
14. close density	0.17	0.26	-0.17	-0.31*	0.54***	-0.06	-0.16	0.05	0.00	0.09	-0.17	0.02	-0.58***			
15. close trans.	0.10	0.13	-0.04	-0.44**	0.52***	0.59***	0.13	0.02	0.13	0.09	0.17	0.03	-0.34*	0.60***		
16. happiness	0.02	0.23*	0.25*	-0.02	-0.05	0.12	0.03	-0.26*	0.01	-0.26*	-0.02	-0.21	0.09	0.01	0.14	
17. LS	0.09	0.20	0.25*	-0.08	0.15	0.15	0.09	-0.21	0.14	-0.21	0.03	-0.16	0.34**	-0.12	0.09	0.65***

Note: N=75
 * p<0.1; ** p<0.05; *** p<0.01

6.5.3 Multiple regression analysis

Tables 6.4 and 6.5 provide a summary of analysis for ego's happiness and LS. There are seven models for each dependent variable. The first model includes only personal attributes: gender, age and relationship status (1=have spouse/partner, 0=otherwise). Model 2 tests the role of network structure in explaining SWB. In model 3, measures of the positive and negative interactions based on closeness-weighted happiness inducement are included. Model 4 includes measure of the positive and negative interactions based on centrality-weighted happiness inducement. Model 5 includes measures of strong triadic closure. Model 6 includes all variables except for measures of strong triadic closure and the final model includes all of the variables.

Happiness: Based on analysis presented in Table 6.4, the following are the main results. Happiness is negatively associated with the density of the Facebook network ($\beta=-12.47$, $p<0.05$) while, it is positively associated with the density of the "close sub-network" ($\beta=4.13$, $p<0.1$); For each unit increase in density of Facebook network, the odds ratio of one level increase in happiness is $\exp(-12.47) = 3.84e^{-6}$, while for each unit increase in density of "close sub-network" the odds ratio of one level increase in happiness is $\exp(4.13) = 62.18$. These results indicate that happier participants have sparser Facebook networks, but the network of relationships among their close alters is denser. This finding indicates that network density has a positive effect on ego's happiness only when it includes close relationships. When network include both close and not-close relationships, density has a negative effect on happiness.

Happiness is also negatively associated with measures of negative interactions in models 3 and 4 (NHI in model 3 and *NHI_deg* in model 4), while none of the relations with the measures of positive interactions are significant in these models. The potent negative effect of negative interactions on well-being has been consistently reported (Rook, 1997; Newsom et al., 2005). However, when other variables are included (model 6) the coefficient for negative interactions becomes non-significant. Instead, among all measures of positive and negative interactions, only the association with positive centrality index (*NHI_deg*) is significant, though the coefficient is relatively small. These changes across the models, in sum, indicate that positive interactions can have an equal to or even greater effect than negative interactions in explaining well-being. Considering the fact that the sample used in these analysis is small and the associations between happiness and measures of either positive or negative interactions are weak, the findings cannot be generalised. However, these findings do show that the detrimental effect of negative interactions is subject to change if the research framework takes account of various factors including

network structural characteristics.

None of the associations between happiness and network size or the number of close alters are significant. However, the direction of coefficients, supported by the results of bivariate analysis suggests that size of Facebook personal network can be negatively associated with SWB, while the number of close alters can be positively related to SWB.

Overall, older participants and those who have spouse or partner are happier than their counterparts; though the coefficient for age is only significant in models one and six and not in the full model. This finding is supported by previous chapters (see sections 4.4.3 and 5.4.3) where it was found that age and having spouse were positively related to psychological well-being.

Table 6.4 Ordinal logistic regression analysis of positive and negative emotional interactions and happiness

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
male	-0.12 (0.46)					-0.37 (0.49)	-0.74 (0.71)
age	0.07** (0.03)					0.09** (0.04)	0.06 (0.05)
hasSpouse	0.75 (0.51)					0.91* (0.53)	2.12** (0.85)
size		-0.00 (0.00)				-0.00 (0.00)	-0.00 (0.01)
density		-2.81 (2.28)				-5.34** (2.53)	-12.47** (5.85)
transitivity		1.57 (1.68)				2.84 (1.92)	4.88 (4.45)
PHI			0.01 (0.01)			-0.00 (0.01)	-0.01 (0.01)
NHI			-0.20** (0.08)			-0.18 (0.22)	-0.15 (0.29)
PHIA_deg				0.00 (0.00)		0.00* (0.00)	0.00* (0.00)
NHIA_deg				-0.01** (0.01)		-0.00 (0.01)	-0.01 (0.02)
close size					0.00 (0.03)		0.06 (0.04)
close density					0.60 (1.67)		4.13* (2.25)
close transitivity					0.67 (1.73)		0.81 (2.50)
Observations	75	75	75	75	49	75	49
R ²	0.10	0.03	0.09	0.08	0.01	0.24	0.38
χ ²	7.08*	1.96	6.78**	6.01**	0.68	18.65**	21.17*
	(df = 3)	(df = 3)	(df = 2)	(df = 2)	(df = 3)	(df = 10)	(df = 13)
AIC	210.11	215.23	208.41	209.18	143.38	212.54	142.89

Note:

Standard errors in parentheses

*: p<0.1 **: p<0.05 ***: p<0.01

LS: Results of the analysis of LS is presented in Table 6.5. The main findings are discussed in the following paragraphs.

Most notably, the associations between LS and measures of negative interactions change across models, while the positive centrality index has a consistently positive association with LS. The negative index of happiness (*NHI*) has a negative association with LS in model 3 ($\beta=-0.16$, $p<0.05$). This association becomes positive and non-significant in model 6. The negative centrality index has also a negative relation with LS in model 4 that becomes non-significant in model 6. Although the coefficient for the positive centrality index is very small ($\beta=0.001$, $p<0.05$), it indicates that having positive interactions with alters who are central in the personal network can have a positive impact on ego's life satisfaction. Therefore, if everything else is the same, participants who are more satisfied with their lives, gain higher level of happiness from alters who are central in their networks.

Comparing the coefficient for measures of positive and negative interactions reveals that the position of alters (centrality score) who are involved in such interactions provides indicative measures that should be considered in the analyses. When we compare two sets of measures based on closeness-weighted happiness inducement (*PHI*, *NHI*) and the centrality-weighted happiness inducement (*PHI_deg*, *NHI_deg*), the number of positive or negative interactions and the level of each interaction (scored 1-5) is the same. The fact that only the positive centrality index is significant in the full model indicates that the position of alters with whom ego has positive or negative interactions can better explain ego's LS than the extent to which ego feels close to those alters.

The second notable result is that network density is negatively associated with LS ($\beta=-6.73$, $p<0.1$). This large negative coefficient means that participants who are more satisfied with their life have sparser personal networks. The adverse effect of network density has also been found on happiness (see Table 6.4). However, unlike happiness, LS does not show any significant association with the density of close sub-network. In sum, Facebook personal networks are more favourable for SWB (both happiness and LS) when they are sparse while the networks of close alters are more favourable for happiness when they are denser.

Similar to happiness, having a spouse or partner has a consistently positive association with LS. Age also exhibits a positive relation with LS, but it is not significant in the final model.

Table 6.5 OLS regression of positive and negative emotional interactions and life satisfaction

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
male	0.08 (0.39)					-0.14 (0.40)	-0.20 (0.41)
age	0.05* (0.03)					0.05* (0.03)	0.01 (0.03)
hasSpouse	0.91** (0.41)					0.94** (0.40)	1.20** (0.46)
size		-0.00 (0.00)				-0.00 (0.00)	-0.00 (0.00)
density		1.34 (1.92)				0.13 (1.92)	-6.73* (3.35)
transitivity		1.45 (1.61)				2.09 (1.61)	2.52 (2.58)
PHI			0.01 (0.00)			-0.01 (0.01)	-0.01 (0.01)
NHI			-0.16** (0.07)			0.04 (0.17)	0.02 (0.16)
PHIA_deg				0.00** (0.00)		0.00* (0.00)	0.00** (0.00)
NHIA_deg				-0.01** (0.00)		-0.01 (0.01)	-0.01 (0.01)
close size					0.03 (0.02)		0.04 (0.03)
close density					-0.78 (1.18)		0.34 (1.24)
close transitivity					1.69 (1.27)		1.79 (1.54)
Constant	3.79** (1.76)	6.71*** (0.92)	7.61*** (0.23)	7.58*** (0.21)	6.57*** (0.99)	2.58 (2.30)	4.18 (2.72)
Observations	76	76	76	76	49	76	49
Log Likelihood	-141.37	-144.40	-142.70	-141.52	-83.26	-135.60	-70.21
Akaike Inf. Crit.	290.73	296.81	291.40	289.05	174.51	293.20	168.41

Note: Standard errors in parentheses
 *: p<0.1 **: p<0.05 ***: p<0.01

6.6 Discussion and conclusion

This chapter studied the associations between personal networks and SWB by focusing on the role of positive and negative emotional interactions. It utilised a conceptual framework that combined the structure and function of personal networks in the context of emotional interactions. The framework aimed to broaden our view of the interactions between individuals and perceive it as a part of a structure surrounding them. I argued that it is not only the personal characteristics of ego and the nature of relationships between ego and her alters, but also the context in terms of the structure of relationships within ego's personal network, that determines ego's SWB. The analysis in this chapter supports this argument.

It has been found that participants reported a considerably fewer negative than positive interactions which is commonly found especially among older people (Hansson et al., 1990; Luong et al., 2011). However, the bivariate analysis provided evidence of the negative effects of negative interactions on SWB and no evidence of a positive effect of positive interactions on SWB. Participants who gained more feelings of unhappiness from their alters, were less happy. Many scholars have found that it is the impact of negative interactions - although usually few - that determines well-being rather than positive interactions (Rook, 1997).

However, including other independent variables in multiple regression analysis reduced the effect of negative interactions in explaining SWB compared with positive interactions. None of the associations between measures of negative interactions and SWB are significant in models 6 and 7 for happiness. These results are echoed in the analysis of LS which indicates that the negative effect of negative interactions on SWB is subject to change depending on the variables included in analysis. Moreover, the findings of analysis in this chapter indicate that the amount of positive interactions can better explain SWB than the amount of negative interactions. Analysis also revealed that the position of alters who are involved in positive and negative interactions is more important in explaining SWB than closeness of relationships between ego and those alters. This indicates that the associations between emotional interactions and SWB are subject to change when the structure of relations among alters is considered in the analysis.

In terms of association between network structure and SWB, analysis shows that there is no significant relation between the number of Facebook friends and SWB. Bivariate analysis, also shows no significant relation between network size and either the amount of positive or negative interactions or the number of each interaction. These findings indicates that neither ego's SWB,

nor the amount of positive and negative interactions depend on the number of Facebook friends. However, bivariate analysis shows that the number of close alters is positively correlated with amount of positive and negative interactions (more strongly for the positive interactions) and with life satisfaction. Similar results has been found by other researchers. For example, research by Helliwell and Huang (2013) on 5,000 Canadians revealed that there is a positive association between number of real-life friends and subjective well-being, but size of online network is uncorrelated with subjective well-being.

The density of the personal network is negatively related to SWB (both happiness and LS), but the density of relations among close alters has a positive association with SWB (but this is significant only for happiness). This can be explained in two ways. First, it is important to consider the differences between the structure of Facebook and that of close personal networks. As explained in Chapter 3 (section 3.4.3), Facebook personal networks are large, sparse and locally clustered (less cohesive and more segmented). Since density considers all of the possible connections among network members as an ideal networks (for density), it may not an appropriate measure for Facebook personal networks in which many connections are very unlikely to exist for being involved in separate groups (clusters) - by definition, there are very few connections between groups - that is partly the function of network size. In comparison, close sub-networks explained in this chapter (section 6.5.1) are relatively small and dense representing a cohesive set of relationships. In this way, density may be a more meaningful measure for close sub-network than the Facebook personal network. It suggests the need for other meaningful measures for density in networks with similar structural characteristics to Facebook ones. One idea can be use of "local density" that is calculated based on density of groups rather than based on the personal network as a whole. Second, it is also important to consider the nature of relationships on Facebook that may be considerably different from relationships with close alters. The close sub-network includes only those relationships on Facebook that are close to ego in real life, thus resembles the personal networks in real life. This can explain why the commonly found positive effect of network density on SWB is only shown for close sub-networks. This will be further studied in Chapter 7 by examining the overlap between participants' personal networks on Facebook and in real life.

The analysis of this chapter showed that positive and negative interactions are not isolated dyadic relationships. They are instead embedded within the structure of the personal network as a whole. Considering this fact significantly improved our understanding of the levels of

positive and negative interactions experienced by ego and their association with SWB. Scholars have pointed out the importance of the sources of positive and negative interactions (e.g. with family or friends) and their role in explaining SWB (Cheng et al., 2011). The present chapter discussed this feature of relationships in the literature review and used it briefly in explaining the two cases studies, but did not include it in further analysis as it is beyond the scope of this chapter. This chapter also assumed that the central alters and those who are closer to ego make a greater contribution to the amount of positive and negative interactions experienced by ego. These assumptions are however not tested and could influence the findings. In the next chapter (section 7.5.2), I will study the associations between strength of tie, position of alter in the personal network and positive or negative interaction. This will help to better understand whether strength of tie is related more strongly to emotional interactions or the position of alters in the structure of personal network. Findings can be used in future studies using the methods used in this chapter, by providing more precise measures.

To what extent Facebook friends are actual and how might actual friends be identified?

7.1 Introduction

In studying personal networks in later life and their associations with SWB this thesis has so far, considered Facebook personal networks as proxies for personal networks in real life. However, these two types of personal networks are arguably different by the fact that not everyone in real life uses Facebook and not all Facebook friends are considered as social contacts in real life. The previous chapters also considered all the relationships included in a (Facebook) personal network equally "important", reflecting the fact that Facebook has only one name for all of the relationships: "friend".

This chapter has two aims. First, it ascertains the extent to which personal networks on Facebook overlap with the personal networks in real life. This examines the validity of data on personal networks from Facebook for the purpose of studying the associations between personal networks and SWB. In other words, it studies whether the findings on the associations between personal networks and SWB as discussed in this research are the artefacts of data on personal networks collected from Facebook. The overlap between personal networks on Facebook and in real life is examined in two ways. First, the proportion of family and close friends who are on Facebook is examined. Second, the extent to which Facebook relationships are identified (based on the information provided by participants on their relationships) for the closeness of relationship, are involved in exchange of resources or emotional interactions is examined.

Second, it explains the "importance" of (Facebook) relationships based on characteristics of rela-

tionships (social similarity, type and centrality) as well as the network (structure) in which they are embedded. "Importance" of relationships is measured based on three attributes: closeness, the number of exchanged resources and the level of emotional interactions. In particular it answers the question: "Who is important to ego?". This question is composed of smaller questions: are alters who are more similar to ego (in terms of socio-demographic attributes) are important to her? Are kin more important to ego than non-kin? Are the more central alters within the personal network more important to ego than other alters? Are relationships more important if they are located in larger or denser personal networks?

The structure of this chapter is as follows. First, this chapter reviews the literature related to both aims. This is followed by the conceptual model used for the second aim. Second, it defines the concepts and explains how they are measured. Third, it reviews the methods used in this chapter with the main focus on multilevel analysis. Fourth, it provides analysis in two parts in accordance with the two aims of this chapter. This chapter finishes with a discussion and conclusion.

7.2 Literature review

This section reviews the relevant literature in three parts. First, research on studying individuals' social networks online and in real life is reviewed. This part will help to define the concepts for both the descriptive and multilevel regression analysis. Second, I discuss how the current literature explains the importance of relationships in personal networks based on social similarity, geographical proximity, type of relationships, centrality (the extent to which alters are central in the network structure) and structural characteristics of the personal network as a whole. Based on this I develop a conceptual framework for examining the importance of relationships. Finally, I provide the conceptual framework which links the aspects of social relationships discussed as independent variables to the concepts developed as dependent variables.

7.2.1 Online and real life social networks

It is well known in social science that humans are cognitively limited in the number of stable social relationships that can be "maintained". The anthropologist Robin Dunbar (Dunbar, 1992) found that on average humans can maintain only 150 stable relationships; this is called the "Dunbar number". With the advent of new technologies, especially the rise of social media, on average

people have networks which are arguably much larger than the Dunbar number. Apart from the use of new technologies, social network scholars argue that individuals in modern societies have larger networks (see Wellman (2011)). The use of communication technologies have further reduced the costs of maintaining social contacts (Wang and Wellman, 2010), thus enabling people to have large networks.

Even though new communication technologies enable individuals to have very large networks (individuals can have up to 5000 friends on Facebook) and facilitate communication with many at the same time (talking to a group rather than an individual), the number of relationships that people can actively maintain is still quite limited. Using data from Facebook, Marlow (2009) found that there is a significant difference between size of personal networks measured by number of Facebook friends, and the number of *maintained relationships* measured by online interactions with Facebook friends (ego has clicked on a news feed story or visited friends' profile more than twice). The difference is even greater when considering friends with whom ego has actually communicated or where the communication has been reciprocal. For example, of 500 friends, 40-50 are maintained, 15-25 involved one-way communication and only 10-16 involved two-way communication.

More recently, Ellison et al. (2011) distinguished between the total number of Facebook friends and "actual" friends, defined as relationships rooted in some kind of offline connection. In particular, participants were asked to report the number of actual friends in response to the question: "Approximately how many of your TOTAL friends do you consider actual friends?". Khan et al. (2014) also examined how the total number of friends and the number of actual friends on Facebook can predict students' class-related informal collaboration on Facebook. They measured the total number and the number of actual friends on Facebook based on the information provided by participants (690 high school students) via a pen and paper survey. Their analysis showed that the number of actual friends on Facebook is a significant predictor for class-related academic collaboration, while there was no significant association between the total number of friends on Facebook and class-related academic collaboration.

In the context of well-being, Helliwell and Huang (2013) compared the effect of "online" with "real friends" on individuals SWB for a sample of 5000 Canadians drawn randomly from an online pool of respondents. The number of real and online friends was measured based on participant responses to two questions: "how big is your real-life social network?" (1-5: "less

than 10 friends" to "more than 50 friends") and "how big is your online social network?" (0-5: "no online social network", "less than 100 friends", "100-300", "300-500", "500-700" and "more than 700"). They found a positive significant association between number of real friends and SWB, while the number of online friends was not related with SWB.

There are two main shortcomings of the existing literature in this area. First, studies have mainly relied on either the information reported by participants or the information collected from users' online communications. Relying on participants memory to provide information can lead to bi-ased data. Such studies then use basic measures such the number of Facebook friends or just the number of real friends, which do not provide adequate insight into personal networks either online or in real life. They have usually found either a positive or negative association between the number of online or real friends and other characteristics such as social capital or well-being, but they have not examined the reasons. Also, they do not tell us about who are the real or online friends or what are the characteristics of each type of relationship; and more importantly do not explain the overlaps between individuals' online with real life networks which is relevant to the extent to which online social networks can be used for social research.

Second, the literature is inconsistent and incomparable because several terms and concepts are used for the same concepts such as "online versus real" friend, "total versus actual" number of friends, "all versus maintained or reciprocal" and stable relationship. For a long time, social network scholars have used similar terms such as "important alter" to refer to individuals with whom ego feels close, discusses important matters (e.g. family issues), receives emotional or instrumental support or simply is important to ego (McCallister and Fischer, 1978; Fischer, 1982; Laumann et al., 1983; Burt, 1984; Straits, 2000).

Among all of the terms suggested by the literature, I chose to use two terms: "actual friends" and "important alters" and I distinguish between them. The definitions are provided in section 7.3.1.

7.2.2 Characteristics of important relationships in personal networks

For the second aim of this chapter, this section reviews the literature on the characteristics of relationships and personal networks in relation to the importance of relationship. The current literature suggests that importance of relationship can be explained by two sets of characteristics: characteristics of the relationship and characteristics of the personal network. I review

the first set by focusing on social similarity (based on age, gender and education), geographical proximity, type of relationship (kin/non-kin) and centrality of the alter (degree, betweenness and eigenvector). For the second, I review the literature on network structural characteristics by focusing on only network size and density. The review of literature in this section will result in the conceptual framework used in analysis of this chapter (see section 7.5.2).

Social similarity and geographical proximity

Social relationships are multiplex in that each relationship can convey multiple contexts (Verbrugge, 1979). For example, a colleague can be a neighbour as well as a team-mate in football. In addition to overlap in roles (context), social relationships tend to be homophilous in many ways especially among core members of personal networks (Marsden, 1987; McPherson and Smith-Lovin, 1987; Marsden, 1988; McPherson et al., 2001; Wimmer and Lewis, 2010; Smith et al., 2014). Close relationships are usually among people with similar socio-demographic characteristics, with less geographical distance and are usually the main source of companionship and emotional support (Berscheid et al., 1989; Blumstein and Kollock, 1988; Waring, 1985; Reagans, 2011).

Gender: Several researchers have documented the strong tendency to connect with same-gender others especially among non-kin (Marsden, 1987) in different age groups from children (Eder and Hallinan, 1978; Shrum et al., 1988) to young adults (Ennett et al., 2006) or older adults (Marsden, 1987) and such tendency varies across different life stages (Fischer and Olicker, 1983). However the implications of connecting with same gender for strength of relationship, exchange of resources or emotional interactions have been usually examined indirectly through considering the types of relationships. For example, several studies have examined the role of spouse (which is usually an opposite-gender intimate relation) in providing social support or creating social strain (Walen and Lachman, 2000; Fingerman et al., 2004). As also discussed in Chapter 4, the literature suggests that overall, similarity based on gender is positively related to the importance of relationship, but mostly among non-kin. The proxy role of kin in the association between similarity based on gender and importance of relationship will be tested in the analysis.

Age: The literature suggests that age similarity is the most powerful factor in explaining close relationships especially among non-kin (Fischer, 1977; Verbrugge, 1979; Fischer, 1982; Reagans, 2011, pg. 93-98). However, for exchanges of resources, age similarity is not important due to the important role of kin which are often heterogeneous based on age (Feld, 1984; Marsden,

1987). While it has been found that compared with other age groups, older people have the most diverse personal networks based on age (Marsden, 1987; McPherson et al., 2001), similarity based on age can have a double contribution on the importance of relationship in later life. First, similar to other age groups, older people are expected to have more in common with same-age others as they have similar life history or because they are in similar life stages. Second, in contrast to other age groups, relationships have more chance of being long and hence being especially strong (Granovetter, 1973). Overall, relationships with similar age others are expected to be important to ego especially among non-kin. The proxy role of kin will be tested in the analysis of this chapter.

Education: Most social institutions are segregated based on educational level, providing more opportunities for connecting with others with similar educational levels. Education is found to have a more significant role in explaining the importance of alters compared with demographic attributes such as gender or age (Smith et al., 2014; Marsden, 1988). A recent study (Gilbert and Karahalios, 2009) of Facebook friends, found similarity based on education to be one of the most powerful predictors of strength of tie among 17 variables including 3 for social similarity based on education, occupation and political affiliation. However, the authors have noted that this finding may be influenced by the fact that participants were recruited from a university community. Although, the personal networks included in the present study are highly diverse based on education (Chapter 4), it is expected that similarity based on education is positively related to the importance of relationship.

Geographical proximity: The literature suggests that geographical distance matters for strength of relationship (Reagans, 2011; McGee et al., 2011) and for the overall relationship even in the age of Internet (Mok et al., 2010). However, different types of relationships and different modes of communication are differently sensitive to geographical proximity. For example, Mok et al. (2010) found that relationships with the core network members (including intimate kin) remains strong even at a distance, with the help of communication technologies such as Email. Other researchers have also found that the way that geographical proximity is related to relationships depends on what is involved in them. Fischer (1982, p. 175) argues that geographical proximity is important, but it depends on the social exchange: "... there is indeed nothing mystical about proximity. Nearby associates are preferred when nearness is critical." Wellman and Wortley (1990) and Mok and Wellman (2007) found similar results: people seek help from neighbours in matters of minor need (e.g. borrowing a cup of sugar), but when they need something which

involves confiding (e.g. borrowing a large amount of money), they turn to intimates wherever those people live. In sum, while there is no final agreement, overall it can be said that geographical distance is related to the importance of the relationship.

Type of relationship

In their East York study, Wellman and Wortley (1990) provided one of the most comprehensive analyses on social relationships and social support. They found that family provide a diverse range of support, but among all types of family relationships (parent-adult child, sibling and extended kin), the parent-adult child relationship is the most supportive of all intimate and active ties, while siblings mainly provide emotional support. Similar patterns have been found in the Australian population (D'Abbs and the Institute of Family Studies in Australia, 1982) and among older Australians (Stone, 2003). Using data from the Living in Queensland survey in 2008, Huang et al. (2010) examined the support networks and well-being of 4000 individuals. One of the main findings of this study was that kin plays an extensive role in providing support: kin come first in providing each of 10 types of support including financial, practical and emotional support, while friends take second place.

Although kin relationship have been widely found to be supportive, they are also more likely to exhibit "ambivalence" (mix of being positive and negative) compared with other relationships such as friendship (Fingerman et al., 2004; Huxhold et al., 2013). It has been found that friends are better than family in providing companionship (Messeri et al., 1993; Rook and Ituarte, 1999), enjoyment and socialization (Pinquart and Sörensen, 2000). While researchers have different findings on how family relationships are associated with strength of tie as well as emotional interactions, overall, it is expected that family members are important in individuals' personal networks.

In addition to the main role that family relationships play in individuals' personal networks in providing help and support, this type of relationship has another role, which is integrating across socio-demographic lines. While there is an strong tendency to connect with same gender and age, family relationships are usually heterogeneous on these attributes. Thus if it is expected that important alters are socially similar to ego, this needs to be adjusted when alters are family members. For example, we may expect that ties with same age alters tend to be stronger, but not among kin. As a result, the interactions between family and social similarity will be controlled as well as the interactions between family and geographical proximity.

Centrality

In another line of research, it has been found that compared with other attributes of relationships, the position of alters in the structure of personal network can better determine the importance of relationships. For example, Feld (1997) argues that in comparison with other measures such as closeness of relationship or frequency of interaction, "structural embeddedness" is better at indicating strength of tie for two main reasons: 1) the more embedded the tie is in the network structure, the less the tie is under the individuals' control and therefore 2) tend to be more stable. Structural embeddedness has been measured as the number of shared alters. Using social network terminology this measure is equal to the degree centrality of alter. Feld concludes that ties that are highly embedded in the network structure are durable in time, thus are more capable of being strong.

An earlier study on personal networks by Fischer (1982) also found a positive relationship between the extent to which an alter is central in the network structure and being important to ego. "Among the associates of our respondents, the more central they were, the more involved they were with the respondent in a variety of ways. For example, the chances that an associate was named as a supporter two or more time- that is, had a multi-stranded relationship - went up from 0.22 for associates who knew none of the others to 0.37 for those who knew a few of the others, to 0.47 for those who knew at least two-thirds of the others. ... central associates were indeed close associates." (Fischer, 1982, p. 152). This early research used the number of shared partners between ego and each alter (alter's degree centrality) to indicate the extent to which alter is located within a set of relations with ego. According to Foci theory (Feld, 1981), the higher the number of shared partners between ego and a given alter, the more likely they share activities and the more likely that they have same origins (e.g. family). Shared activities or same origins indicate having similar attributes and access to similar resources. Thus an alter with a high degree centrality is more likely to be close to ego, involved in exchange of resources and emotional interactions.

A more recent branch of social network analysis research emphasizes the important role of "brokers" in providing access to novel information and resources. The idea of the strength of weak ties or ties which connect otherwise disconnected groups has gained a lot of attentions in studying of personal networks, especially in the context of online social networks (Granovetter, 1973; Friedkin, 1980; Granovetter, 1985; Burt, 1995, 2000b; Haythornthwaite, 2002). Due to their

structural position in the network structure, brokerage roles cannot be embedded in a set of relations and hence are less restricted in shared Foci, less under partners' control and less likely to be durable in time. Therefore in contrast with structural embeddedness, brokers are more likely to represent weak ties, are less involved in exchange of resources and emotional interactions. However, the notion of strength of weak ties (Granovetter, 1973), suggests that alters who are located in brokerage role can provide ego with resources which are less likely to be available through their strong ties.

Moreover, it has been found that usefulness of the relationship in terms of possessing resources better determines the exchanges of resources than closeness of relationship between ego and an alter (Small, 2013, pg. 427); "the utility of the tie, rather than its effective character, is what primarily motivates ego". In this way, ego seeks support from those alters who have resources (and ego knows this) and such alters are not necessarily closest to ego. Strength of tie is one of the factors that contribute to exchange of resources among individuals, but there are more other factors such as whether the alter has a resource/skill or the extent to which ego is aware of it in case of need. Small (2013) concludes that people usually ask for resources from others who are available than those who are close to ego. It suggests that alters who have brokerage roles in personal networks are important to ego. Brokerage role is measured based on the extent to which an alter is located between other alters who are not directly connected to each other. This role has been quantified using a node level measure called "betweenness centrality" which is defined as the sum of proportion of times that each node falls on the shortest path between others (Freeman, 1977).

Degree centrality and betweenness centrality describe the local structure around each alter. Another approach to identify the location of important alters is based on how central is the alter in the global structure of the network. This concept has been quantified using a measure called "eigenvector" centrality. Degree centrality says that important alters are those who know many other alters, but how about if those many other alters are isolated themselves (only connected to ego)? So, rather than taking alters who have many connections (high degree centrality), eigenvector centrality considers central alters as those who are connected to other central alters. In this way, the measure of degree centrality provides the point of departure for calculating eigenvector centrality. Given that alters with the highest degree centrality are the most central alters, eigenvector centrality identifies the influential alters as those who are attached to the central alters. The most influential actors in a network are the highly connected individuals within highly

interconnected clusters, or "big fish in big ponds". Nodes with high eigenvector centrality are not necessarily high in betweenness centrality; they are usually embedded within the highly interconnected set of relations and not well-suited for brokerage role in the network.

Structure of personal network

The structure of personal network as a whole can also add to our understanding of the importance of relationships between ego and alters. For example, apart from the fact that the strength of tie between ego and an alter depends on how central is that alter in ego personal network, it also depends on how many alters ego has or how connected are alters with each other. This is important, since the relationship between ego and her alters are assumed to be mutual. So, it is not only about how alters can allocate time and attention to their relationship with ego, but it is also about how ego can maintain her relationships. If ego has many connections, it is less likely that she can devote enough attention to each of them.

Theoretically it is expected that ties are weaker in larger personal networks, as ego's attention is limited (Binder et al., 2012; Pollet et al., 2015). However, this does not mean that people with fewer social relationships have stronger ties. Some studies show that people who have more friends are usually more social and able to keep their social relationships active compared with those who have fewer friends (Wang and Wellman, 2010). Similar statements can be made about exchange of resources or the emotional interaction between ego and her alters. On one hand, larger personal networks usually have a wide variety of resources and hence, it is more likely that each alter can provide at least one resource (Wellman and Gulia, 1993). But, on the other hand, ego's knowledge is usually limited about what kinds of resources are available through which alter and ego needs to rely on a small pool of alters to get help. Emotional interactions are very similar to strength of tie; network size can be both negatively and positively associated with it.

Fischer (1982) found an interesting paradoxical rule about the interaction between network density and strength of ties. His analysis revealed that despite our expectation, ties become weaker when network density increases. "The more interconnected a network, the weaker the ties to any specific member. This is paradoxical, given that total network density tended to go with feeling content about one's relations." (p: 155).

Fischer explains this paradox by considering the role of a few crucial and significant alters within

dense networks (rather than each tie). "Dense networks may be felt as supportive because they necessarily include a couple of particularly supportive individual relations. The availability of one or two crucial and central associates may also explain the greater overall sense of well-being that low-income respondents with dense networks had compared with those with low-density networks. It is the availability of a few strong ties, not the whole network, that makes the difference." (p: 155)

While there is no agreement on how network size is related to attributes of ties, on balance, the first point of view (that ego's attention is limited) seems to better explain the relation between network size and importance of relationships. So, the hypotheses are developed based on the negative effect of network size on ties attributes (in terms of being important to ego). Regarding network density, I chose to develop a hypothesis based on Fischer (1982) findings and test them in this research.

7.2.3 Conceptual framework and hypotheses

The previous section reviewed the literature on actual and important relationships online and in real life by looking at different components. Linking all of these components leads to the conceptual framework shown in figure 7.1. Note that this model is developed for the second aim of this study (studying the importance of relationships). I explain the model and link it to the hypotheses derived from literature review.

As shown in the model, the importance of relationship is measured using three dependent variables: strength of tie (closeness of relationship between ego and alter), exchange of resources (number of resources that each alter can potentially provide to ego) and emotional interactions (the extent to which an alter makes ego feel happy or unhappy) which are further defined in section 7.3.1. The independent variables are organised in two levels: attributes of relationships (relationship level) and attributes of networks (network level). In the first group the variables are organised in four categories namely, social similarity (section 7.3.2), geographical proximity (section 7.3.2), type of relationship (section 7.3.3) and centrality (section 7.3.4). In the second group there are only two variables: network size and density. The hypotheses are listed below in the same order as shown in the conceptual model.

Hypothesis 1 *Social similarity is positively related to importance of relationship.*

Hypothesis 2 *Geographical proximity is positively related to importance of relationship.*

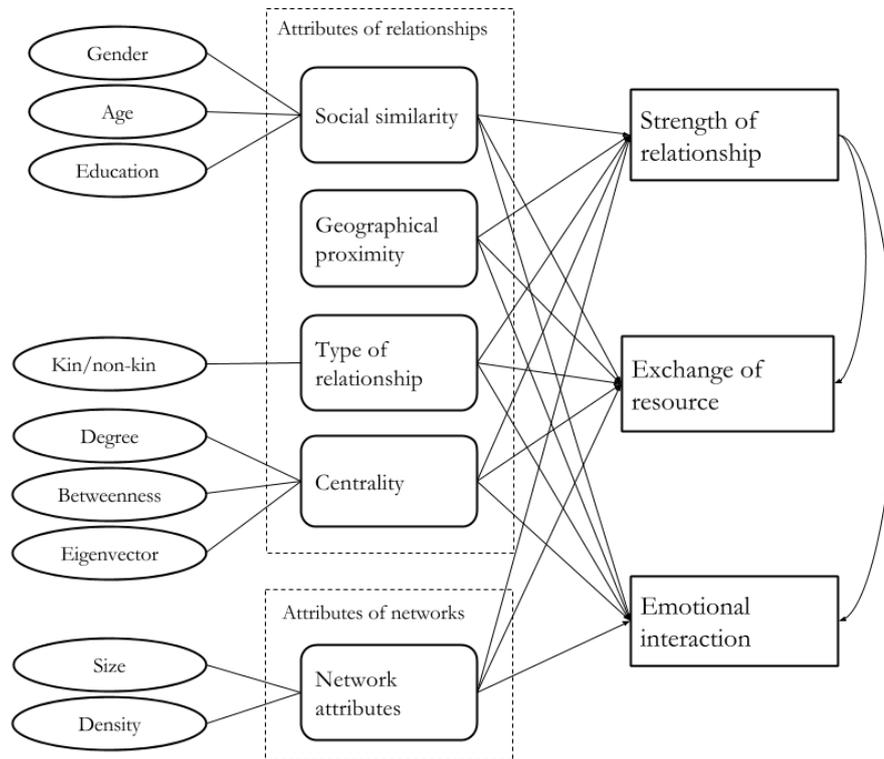


Figure 7.1: Explaining the importance of relationship: the conceptual framework

Hypothesis 3 *Type of relationship (kin/non-kin) is positively related to importance of relationship.*

Hypothesis 4 *Centrality is positively related to importance of relationship.*

Hypothesis 5 *Network size is negatively related to importance of relationship.*

Hypothesis 6 *Network density is negatively related to importance of relationship.*

Hypothesis 7 *Closeness of relationship is positively related to exchange of resources.*

Hypothesis 8 *Closeness of relationship is positively related to positive emotional interaction.*

This conceptual framework can explain only a part of the variation of importance of relationships. A part of the unexplained variation may be associated with differences between personal networks. Personal networks are different in many ways that can be partially seen as the way individuals manage their relationships differently. For example, men and women tend to have different personal networks conditional on the stage in the life cycle (Fischer and Oliker, 1983; Marsden, 1987) and young and old people tend to have different network structure and composition (Marsden, 1987). Moreover, it has been commonly found that individuals' personal characteristics play an important role in their networking behaviour (Burt et al., 1998; Kalish and

Robins, 2006). Using the suggested model, we may be able to explain a part of variation in the dependent variable (i.e. importance of relationships) and the remaining part may be explained by considering the difference between personal networks. This part can be explained in two ways: by considering the average variance of the dependent variable between personal networks and by considering the fact that associations between explanatory variables (i.e. type of relationship) and dependent variable can vary between personal networks. For example, some individuals may be overall better in maintaining their close relationships (the average of variance), while some individuals may feel a special closeness with their family compared with non-family (the association between family and closeness of relationship can vary between individuals). These are considered in the analysis of this chapter by employing multilevel models (see section 7.4).

7.3 Definitions and measurements

7.3.1 Actual friend and important alter

Actual friends and important alters are defined based on three dimensions: closeness of relationship, exchange of resources and emotional interactions.

Strength of ties: is measured based on closeness of relationship between ego and her alters and scores from 1-5 (very close to very far). See section 3.3.2 for more details. Note that since, closeness of the relationship is the only dimension for strength of tie, these two terms may be used interchangeably.

Exchange of resources: refers to the number of skills or resources that ego can potentially receive from an alter. This is equal to the number of times that alter has been nominated by ego to have a skill or resource. Each alter can be nominated to have up to 10 skills or resources, so this measure has a value between 1 and 10.

Emotional interactions: refers to the level of emotion in a tie between ego and her alter and shows the extent to which that alter can make ego feel happy or unhappy. This variable ranges from -2 (very negative interaction) to 2 (very positive interaction).

I define *actual friend* as someone that ego knows in real life and I measure it based the three above mentioned dimensions. So, an actual friend is a Facebook friend who is nominated for closeness of relationship (at any level from very far to very close), or a Facebook friend who is

nominated as having at least one resource or a Facebook friend for whom ego has rated the level of emotional interaction (any level either negative or positive).

Important alters are a subset of actual friends. An important alter is an actual friend who is "close" or "very close" to ego, or has been nominated to have at least one skill or resource or has either negative or positive interaction with ego in making her feeling "very unhappy", "unhappy", "happy" or "very happy".

For more clarification, actual friends are all of Facebook friends who have been ranked by ego based on their closeness of relationship from "very far" to "very close" that means ego knows each of them and can recall the closeness of relationship with them. However, only those actual friends are important to ego who are "close" or "very close". In this way, Facebook friends who have been identified to be "very far", "Far" or "Neither far nor close" are not important to ego. In terms of having skills or resources, the two concepts are same because if a friend has been nominated to have at least one resource, that friend is actual and at the same time is important. For the last criteria, actual friends are all of those who can make ego feel "very happy", "happy", "Neither happy nor unhappy", "unhappy" and "very unhappy". But only those are important who can make ego feel either unhappy or happy and not those who can make ego feel "neither happy nor unhappy".

7.3.2 Social similarity and geographical proximity

Social similarity of a tie between ego and her alter shows the extent to which characteristics of ego and an alter are similar. This concept has been quantified as difference between characteristics of ego and alter. Socio-demographic characteristics include gender, age and education. So, for a particular tie (between ego and a particular alter) and a particular characteristic (e.g. gender), social similarity refers to the difference between the values of that characteristic for ego and her particular alter. For gender and education, the distance is equal to 0 if the values for the attribute is the same for both nodes and is equal to 1 if the values are not the same. For age, the distance is the absolute difference between the ages of nodes. For education, it shows the difference between educational level of nodes. Since education has been measured at three levels (high school, college and graduate school), the difference can be 0 (same level of education), 1 or 2.

Geographical proximity is calculated based on the geographical distance between where ego and

alter live (identified by latitude and longitude). Data on the geographical location is collected from Facebook profiles as ego and her alters have reported their current location of residency. This measure shows the distance between ego and her alters in kilometers.

7.3.3 Type of relationship

Type of relationship between ego and her alters is defined as kin (1) or non-kin (0). This data is collected from Facebook profiles and completed (if missing) with the information that participants have provided via the online survey (step 2- grouping social contacts).

7.3.4 Centrality

Centrality for an alter in the personal network of ego, shows the relative importance of that alter in the structure of personal network. Centrality can be measured for both ties (e.g. showing how embedded is a tie within other ties) and nodes; this chapter uses node centrality. So, for a tie between ego and one of her alters, centrality has been calculated for the alter and is assigned to the tie.

Centrality is measured based on three indicators which are called node level centrality measures: degree, betweenness and eigenvector (Freeman, 1979; Knoke and Burt, 1983; Faust and Wasserman, 1992; Wasserman and Faust, 1994; Marsden, 2002). These measures have been extensively used in social network analysis. Degree centrality, refers to the number of ties that a node has. In the context of personal networks, degree centrality for an alter is equal to the number of other alters that alter knows. The normalized score of this measure, controls for network size and ranges between 0 (no connection with any other alter), to 1 (connection with all of the alters).

Betweenness centrality shows the extent to which a node is located in the (shortest) path between other nodes (Freeman, 1977). Being highly central in terms of betweenness can be favourable, as other nodes need to rely on them to connect to each other. In the context of personal networks, alters with high betweenness centrality are those who are among many other alters. Such alters are usually represented as those who connect groups. The score is normalised by definition as the proportion of all shortest paths that include the node by calculating betweenness of the node in ratio to the total betweenness that does not involve the node.

Eigenvector centrality, which is used as measure of influence, shows the prominence of a node in the global structure of the network (as opposed to local). This measure, considers central alters

as those who are connected to other central alters. The most influential nodes in a network are the highly connected individuals within highly interconnected clusters, or "big fish in big ponds".

In personal networks, ego will be the most central node as she is connected to everyone. So, ego is removed from her personal network (see McCarty and Wutich (2005)) and the central alters are identified based on the remaining network.

7.4 Research methods

This section reviews the research methods for this chapter, and is mainly focused on multilevel analysis. It provides a brief explanation of multilevel analysis; for further details of the use of this method when applied to personal networks see Snijders et al. (1995). The section then reviews the five models which are developed based on the conceptual framework presented in section 7.2.3.

Personal or ego-centric networks have usually been studied by aggregating over the entire network (Walker et al., 1993). Depending on the focus of study, we can aggregate the attributes of nodes or ties for each personal network and then use the aggregated values (e.g. average closeness of relationship), along with characteristics of network (e.g. size), as well as ego (e.g. ego's age) in statistical analysis.

However, when the dependent variable is an attribute (or a function) of ties, the data cannot be aggregated. Applying statistical analysis on ties can be invalid, because the independence assumption is violated as ties of each personal network (as for any kinds of relational data) are inherently dependent. The nested data structure is not specific to personal networks and has been studied in social science as multilevel analysis (Goldstein, 1995; Snijders and Bosker, 1999) and employed in various studies (Rice and Jones, 1997; Duncan et al., 1998; Diez-Roux, 2000; de Alencar Ximenes et al., 2009). The use of multilevel analysis for personal networks was introduced by Snijders et al. (1995), and it has been employed by social network scholars (van Duijn et al., 1999; Kalmijn and Vermunt, 2007; Lubbers et al., 2010; de Miguel Luken and Tranmer, 2010).

Hierarchically structured data are often exemplified by data on students who are nested within schools (that are then nested within suburbs or regions). If a researcher interested in studying factors associated with students' educational achievements and applies statistical models to the

cases at the level of students, there is an implicit assumption that students from the same school do not "resemble" each other more than students from other schools which is not true. Students from one school are more likely to have similar attributes than from different schools for several reasons. Students are the unit of analysis, thus in multilevel terminology they constitute level one and schools level two. Similarly, ties are nested within personal networks and ties are more likely to share similar attributes within personal networks than between them due to their inherent similarity; ties within personal networks are highly expected to be homogeneous (McPherson et al., 2001). Since, ties are nested within personal networks, ties are at level one (level of tie), while personal networks (level of network) are at level two.

Including attributes which are based on the relational structure of network data such as centrality makes uni-level analysis even less valid. Measures of node level centrality are sensitive to other parameters of networks such as size (see Badham (2013)), are not comparable across networks (independent from their personal networks). In addition, by focusing on attributes of ties we can explain only a part of the variation in the dependent variable (e.g. strength). As discussed earlier in section 7.2.2, attributes of ties also depend on attributes of personal network structure as a whole such as size and density. Therefore, it is not only social similarity or centrality of alters, but it is also the overall structure of personal network that determines strength of the tie.

Multilevel models jointly consider two levels, taking into account variability between ties (at level one) as well as difference between personal networks (at level two). One of the advantages of using multilevel analysis is that the effect of level one variables on the dependent variable can be different across personal networks. For example, the way that kin is related to strength of relationship could be different from one personal network to another (in theory, for some people, kinship relationships may be very strong while for some people they may not). Multilevel models take this variance into account using two effects called "fixed" and "random". The fixed effect of this variable is the average effect in the entire population of personal networks. The random effect for the independent variable is the part which varies across personal networks and has one value for each personal network. The fixed effect is expressed by the fixed term regression coefficient and the random effect is reported by the variance of the random effects across the population (Snijders, 2005). In applying multi-level models to personal networks, it is required that there be no or minimum overlap between them (Snijders et al., 1995). The overlaps between personal networks included in the multilevel analysis in this chapter is very small and negligible.

Theoretically, any variable from these two levels can be included in models. For example, one may consider characteristics of ego (e.g. gender or age) in explaining strength of her ties with her Facebook friends. However, the analysis of this chapter is limited to include only attributes of ties and personal networks. The models and included variables are explained in more detail in the following paragraphs.

As shown in figure 7.1, there are three dependent variables: strength of relationship, exchange of resources and emotional interaction. There are 10 explanatory variables: type of relationship (kin/non-kin), social similarity (gender, age and education), geographical proximity, centrality (degree, betweenness and eigenvector) and attributes of network structure (size and density). The eight first variables are from level one (ties level) and the last two variables are from level two (network level). Strength of relationships which is the first dependent variable, becomes the explanatory variable for the second and third dependent variables and is categorized with level one variables as it is a characteristic of tie. The dependent variables are all ordinal, thus, multi-level models are used which are appropriate for this type of variable (Christensen, 2012). These models are analogous to the ordered logit regression models (see Snijders and Bosker (1999)), and the coefficients are interpreted as odds ratios.

For each dependent variable, five models have been developed by adding groups of variables. The first model is called the null model (model 0) and is empty. This model includes only the intercept (overall mean change in dependent variable if all independent variables are 0) and will be used as the starting model.

Model 1 includes the 8 level-one variables and the interactions among them. It is expected that adding these variables considerably improves the model; these variables are expected to explain a large proportion of the variance of the dependent variable. The number of possible interaction terms among variables can be many, making it difficult to judge whether to include them in the model. Therefore, inclusion of interaction terms is guided by theoretical considerations rather than their importance in the models. For closeness of relationship, only interactions with the type of relationship are included. For exchange of resources and emotional interaction, the interaction between type and closeness of relationship is added. To better understand the effects, main and interaction terms are added separately (model 1.a and model 1.b respectively).

In model 2, level-two variables are added. Size and density represent network level variables and are expected to improve the models considerably by explaining a proportion of variance of dependent variable which has not been explained using tie level variables. Network size and density are systematically correlated as density decreases when size increases which suggests adding the interaction between them. However, there is no theoretical reason for the effect of this interaction on dependent variables. For example, while ties are expected to be weaker in larger or denser personal networks, there is no assumption about closeness of relationships in larger networks when density increases (or decreases). Moreover, when the interaction term was added, it did not improve the models.

Model 3 includes cross-level interaction terms; interactions between network size and density with level one variables. Again, interactions are included based on theoretical insights; for example it is expected that the impact of age difference on closeness of relationship will be unrelated to the size of network. Thus, only interactions with measures of centrality are included which are aimed at controlling for the systematic relation between structural attributes of networks and node level centrality measures. For example, it is expected that a closeness of relationship between ego and a highly connected alter differs by network of different sizes. This model has the complete list of variables proposed in the theoretical framework (see 7.1).

The final model (model 4) includes random slopes. The Associations between dependent and level one variables can vary between personal networks. A part of the variance of dependent variable can be explained using this variation which is called random slopes. This model, controls for random slopes of any of the level one variables. However, only one variable is included in this model: degree centrality. In order to test whether this model is significantly different from the previous model, the log-likelihood ratio test has been used (Casella and Berger, 2002). This test compares the log-likelihood of the two models and determines, whether the difference is significant by using chi-squared test.

7.5 Analysis and findings

The analysis is in two parts. The first part is a descriptive analysis addressing the first aim of this chapter. Analysis of this part are based on two approaches: describing the proportion of participants' real life network who are on Facebook and describing the proportion of Facebook ties which are actual. The second part uses multilevel analysis to address the second aim on explaining the importance of relationships based on characteristics of relationships. The second

part of analysis has three parts itself which are based on three dimensions of the definition for important alters (see 7.3.1).

7.5.1 Descriptive analysis

What proportion of participants' real life networks are on ego's Facebook personal network?

The overlap between participants' real life and Facebook networks is represented in figure 7.2. Around 73% of participants reported that almost half or more of their family members are on Facebook; 23% have some but less than half and only 3.3% have none of their family members on Facebook. This finding is consistent with the literature that older people use online social networks mainly to connect with their family members, children and grandchildren especially if they live at distance (Madden, 2010; Bell et al., 2013).

Similarly, almost 60% of participants have reported that almost half or more of their close friends are on Facebook. 33.3 percent have some but less than half and only 6.7 percent had none of their close friends on Facebook. Moreover, the majority (73%) of participants have less than 5 friends on Facebook they have never met in real life. Overall, participants have almost half or more of their family member or close friends on Facebook. This indicates participants personal networks in real life have a moderate overlap with their personal networks on Facebook.

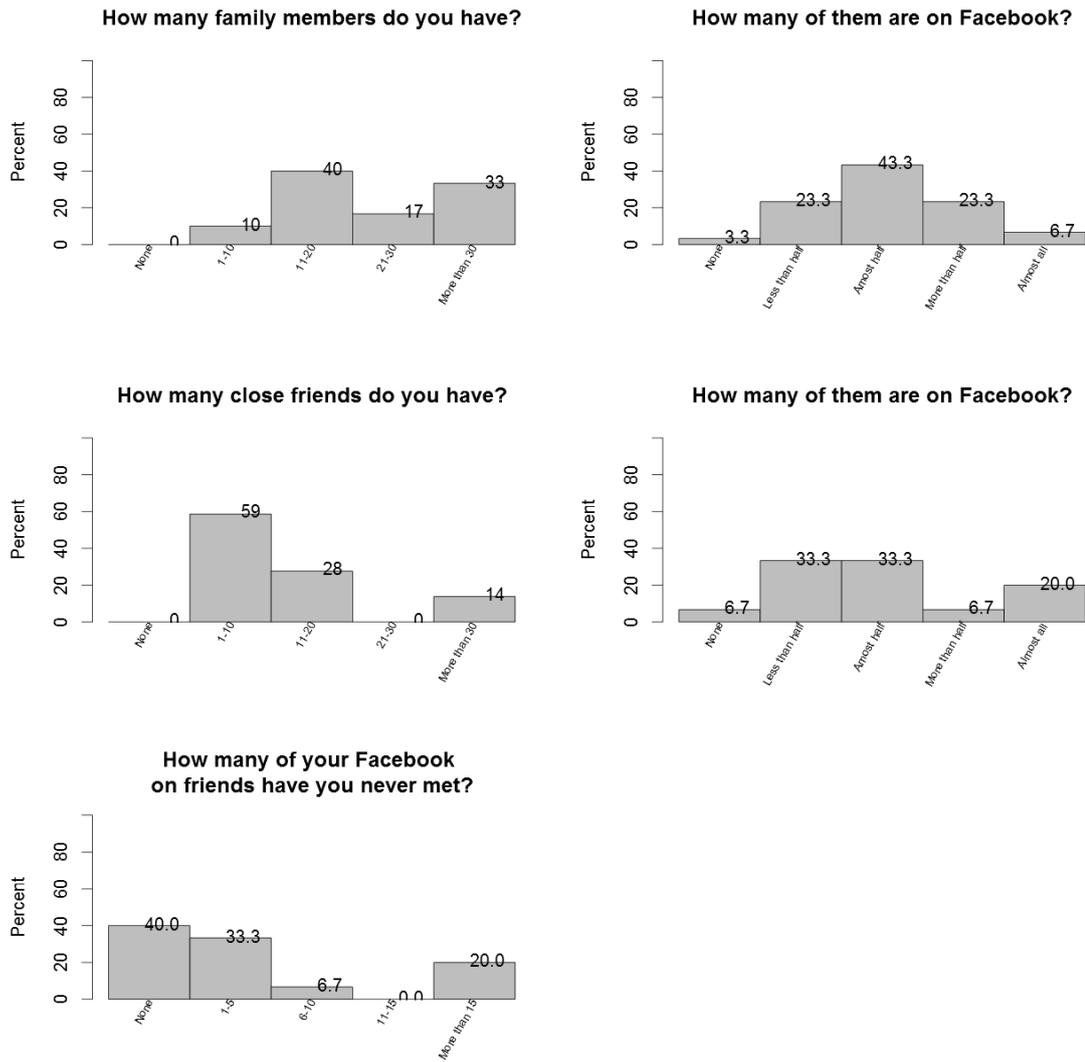


Figure 7.2: Number of family and close friends in real life and the proportion of them who are on Facebook.

What proportion of individuals' Facebook network are actual and important?

Overall, almost all of participants' Facebook friends are actual; participants know on average 89% of their Facebook friends by identifying how close do they feel to each of them. Table 7.1 summarises the proportion of Facebook relationships based on closeness, exchange of resources and emotional interactions. Across all personal networks, only 11% (sd=0.19) of relationship were not identified for closeness of relationship. However, only 51% of relationships are identified to have a resource and 46% are involved in emotional interactions.

While almost all of the ties are actual in terms of closeness of relationship, less than half (on average 39%) are important (close or very close). To the best of my knowledge, there is no existing research with which to compare this finding, either in real life or online personal networks. I conclude that participants know almost all of their friends on Facebook and they can determine closeness of their relationship with them. This indicates a high level of overlap between participants' personal networks on Facebook and in real life. However, only 40% of relationships are close or very close that means on average only less than half are important. Considering that the average network size for participants is 80, 40% means 32 relationships, which is still many (more than the size of personal networks that many studies have captured in real life).

As summarised in table 7.1, the proportion of ties involved in exchange of resources is relatively smaller than the proportion of relationships that are identified for closeness; on average, 51% of alters have at least one resource, but each alter is most likely to have only one or two resources. On average, 13 percent can provide 1 resource (sd=0.32), 17 percent can provide 2 resources and less than 2 percent can provide 3 resources.

Similarly, less than half (average of 46%) of relationships are identified for emotional interactions. The proportion of relationships that are involved in positive interactions is considerably higher than other relationships; the average increases by the level of interaction from 3 percent for "very unhappy", 5 percent for "unhappy", 10 percent for "neither unhappy nor happy", 19 percent for "happy" and 20 percent for "very happy". So, on average, our participants have positive emotional interaction with almost 39% of their Facebook friends. This is very similar the results for strength of relationship (40 percent were close or very close to ego).

These findings indicate that relationships on Facebook are actual to a large extent (almost all), but around half of them are important. If we consider actual friends as those who have resources

or are involved in emotional interactions, Facebook friends are not actual to a large extent. The definition of actual friends based on exchange of resources or emotional interactions is much more narrow than closeness. Although all are measured subjectively from ego's perception, it would be easier for ego to recall which friend is close and which is not. To identifying whether an alter can provide a resource or emotional interaction, ego requires a higher level of knowledge and engagement. So, alters who can provide resources or are involved in emotional interactions are defined to be important alters (see section 7.3.1). In this way, they are comparable with alters who are close or very close to ego that means, comparing 50% alters who can provide resources with 46% who are involved in emotional interactions and the 40% who are close or very close to ego.

These findings somehow contradict what was previously found in this section: participants' personal network on Facebook considerably overlap with personal networks in real life, but their personal networks in real life moderately overlap with their personal networks on Facebook. The ways that these two types of overlaps are defined and measured can explain this contradiction. The extent to which personal networks in real life overlap with ones on Facebook is measured based on participants' responses to 5 questions; I only focus on 2 questions on close friends. "How many close friends do you have?" and "How many of them are on Facebook?". The extent to which personal networks on Facebook overlap with the ones in real life, however, is measured based on participants' ranking of their relationships based on closeness. Clearly the questions on "close friends" preserve the special meaning of closeness that does not fully correspond with the closeness in ranking of relationships. Perhaps all of the close friends from real life who are on Facebook (the first type of overlap) are ranked as close (the second type of overlap), but there are many other close relationships on Facebook that may not be considered as close friends in real life. In addition to the wording of the questions, the data on the ranked relationships are more detailed and participants rank each friend separately and relative to other friends, while the data on the number of close friends and the proportion who are on Facebook are based on general (aggregated) values. It is suggested that future research consider the special meanings of commonly used words such as "close friend" or "closeness" of relationships when distinguishing between personal networks in real life and on Facebook (Marin and Hampton, 2007). In particular, use of word "close friend" or "friend" in real life can sharply limit the circle of one's relationships to a small number of people and hence result in a considerable gap between personal networks in real life and on Facebook (Helliwell and Huang, 2013).

Table 7.1 Relationships by closeness, being involved in exchange of resources and emotional interactions; N=3123

	min	mean	max	sd
Strength=1	0.003	0.144	0.60	0.112
Strength=2	0.003	0.179	0.47	0.113
Strength=3	0.000	0.215	0.69	0.131
Strength=4	0.000	0.229	0.87	0.207
Strength=5	0.000	0.164	0.98	0.184
Strength=NA	0.000	0.110	0.90	0.204
Resources=1	0.000	0.134	1.00	0.319
Resources=2	0.000	0.162	1.00	0.351
Resources=3	0.000	0.025	0.77	0.126
Resources=4	0.000	0.011	0.20	0.029
Resources=5	0.000	0.017	0.14	0.033
Resources=6	0.000	0.036	0.27	0.054
Resources=7	0.000	0.087	0.39	0.103
Resources=NA	0.000	0.489	1.00	0.419
Emotional=-1	0.000	0.031	0.32	0.080
Emotional=-2	0.000	0.054	0.50	0.118
Emotional=0	0.000	0.096	0.85	0.156
Emotional=1	0.000	0.193	1.00	0.274
Emotional=2	0.000	0.197	1.00	0.293
Emotional=NA	0.000	0.538	1.00	0.376

7.5.2 Multilevel analysis

Analysis explaining the importance of ties is provided in three parts based on three dimensions of importance: strength, exchange of resources and emotional interactions. To answer the question of "Who is important to ego?" I answer three questions of "To whom ego does feel close?", "With whom ego exchanges resources?" and "Who makes ego feel happy or unhappy?" respectively.

To whom does ego feel close?

The dependent variable for this part of the analysis is strength of tie which is measured by closeness of relationship on the scale varying from 1 (very far) to 5 (very close). So, strength of tie and closeness of relationship will be used interchangeably to refer to the dependent variable.

The five models discussed in methods section are developed and results of four models are summarised in table 7.3. The null model is summarised in table 7.2. Shown in this table, the random effect which is the variance of closeness of relationship across the population of 58 personal networks is 0.43. This variance indicates that we expect to explain 0.43 of variation of the dependent variable by taking into account the variation of this variable across personal networks. The fixed effects (intercept) are reported as threshold coefficients with the average of $(-1.90 - 0.87 + 0.43 + 1.60 = -0.74)$ which indicates a mean decrease in closeness of relationship

by 0.74 points on the 5 point scale (1-5).

Table 7.2 Multilevel ordinal logistic regression analysis for strength of tie: Null model.

	Estimate	Std. Error	Pr(> z)
<i>Fixed effects (Threshold coefficients)</i>			
1 2	-1.907	0.106	0.000
2 3	-0.871	0.100	0.000
3 4	0.430	0.099	0.000
4 5	1.604	0.104	0.000
<i>Random effects</i>			
Intercept	0.43		
Log Likelihood	-431.59		
Num. obs.	2780		
Num. personal networks	58		

As shown in table 7.3, kin has a large positive association with closeness of relationship ($\hat{\gamma} = 1.93, S.E. = 0.28$ in model 1). This association is only significant in model1 . The estimate for this association becomes smaller and non-significant in model 1a because a proportion of its explanatory power is covered by it's interactions with measures of social similarity.

Overall, the less the age distance the stronger the relationship, but not among kinship. Age distance has a small negative association ($\hat{\gamma} = -0.31, S.E. = 0.12$ in model4) with closeness of relationship which means, egos feel closer to alters with less age distance. For each ten years of difference in age, the odds ratio of a tie being one level stronger is $exp(-0.31) = 0.73$ which means the probability of a tie being one level stronger declines by 18% for each 10 years age difference. However it's interaction with kin is positive and significant ($\hat{\gamma} = -0.41, S.E. = 0.22$ in model4) which indicates that the negative effect of age distance on closeness of relationship decreases when the relationship is kin. This is consistent with the findings of previous studies that older people have usually many close connections with their children and grandchildren who are younger than themselves (Wellman and Wortley, 1990; Lye, 1996).

Table 7.3 Summary of the multilevel ordinal logistic regression analysis for strength of tie

	Model 1	Model 1a	Model 2	Model 3	Model 3a	Model 4
<i>Fixed effects</i>						
kin	1.93*** (0.28)	0.71 (0.62)	0.59 (0.62)	0.58 (0.62)	0.67 (0.62)	0.86 (0.65)
diff_gender	-0.09 (0.20)	-0.13 (0.24)	-0.13 (0.24)	-0.13 (0.24)	-0.13 (0.24)	-0.19 (0.25)
diff_age	-0.20* (0.10)	-0.32** (0.11)	-0.30** (0.11)	-0.31** (0.12)	-0.32** (0.12)	-0.31** (0.12)
diff_edu	0.58** (0.22)	0.41 (0.25)	0.42+ (0.25)	0.42+ (0.25)	0.43+ (0.26)	0.51+ (0.26)
diff_geo	-0.08*** (0.02)	-0.07** (0.03)	-0.06* (0.03)	-0.06* (0.03)	-0.06* (0.03)	-0.06* (0.03)
degree	-1.01 (2.30)	-1.25 (2.36)	0.07 (2.70)	1.68 (4.88)	14.66 (13.28)	22.52 (14.41)
betweenness	5.33* (2.25)	5.35* (2.22)	5.48* (2.25)	2.06 (4.88)	3.82 (13.48)	15.92 (14.00)
eigen-vector	1.27 (1.08)	1.37 (1.11)	0.74 (1.21)	-0.10 (2.51)	-5.49 (5.75)	-10.41 (6.39)
kin:diff_gender		0.08 (0.46)	0.09 (0.46)	0.06 (0.46)	0.03 (0.46)	0.05 (0.48)
kin:diff_age		0.45* (0.21)	0.47* (0.21)	0.47* (0.21)	0.46* (0.21)	0.41+ (0.22)
kin:diff_edu		0.66 (0.49)	0.68 (0.49)	0.72 (0.49)	0.70 (0.49)	0.61 (0.51)
kin:diff_geo		-0.01 (0.04)	-0.02 (0.04)	-0.02 (0.04)	-0.01 (0.04)	-0.01 (0.04)
size			-0.10* (0.04)	-0.11* (0.05)	-0.11* (0.05)	-0.13+ (0.06)
density			-0.67 (0.43)	-0.73+ (0.44)	-0.76 (0.49)	-1.12+ (0.63)
degree:size				-0.10 (0.55)	-0.68 (0.79)	-0.76 (0.79)
betweenness:size				0.41 (0.53)	0.34 (0.78)	-0.49 (0.77)
eigen-vector:size				0.06 (0.27)	0.30 (0.36)	0.43 (0.35)
degree:density					-5.78 (5.45)	-11.00 (6.84)
betweenness:density					-0.87 (5.01)	-3.78 (5.33)
eigen-vector:density					2.68 (2.93)	5.96+ (3.62)
<i>Random effects</i>						
Intercept	0.816	0.880	0.652	0.657	0.66	1.688
degree						29.173
AIC	1184.27	1185.97	1184.64	1189.90	1194.44	1188.71
Num. obs.	397	397	397	397	397	397
Log Likelihood	-579.14	-575.98	-573.32	-572.95	-572.22	-567.36

Note: Number of personal networks:31
 *** : $p < 0.001$, ** : $p < 0.01$, * : $p < 0.05$, + : $p < 0.1$

The positive association between educational distance and closeness of relationship is weakly significant and indicates that relationships with alters who have different levels of education are likely to be stronger than those who have the same level of education. This finding contradicts what has been found in other studies (see Gilbert and Karahalios (2009)) and can be partially explained considering characteristics of the sample. The composition of our participants based

on education can help in understanding a part of this association which is discussed in section 4.4.1. As shown in tables 4.6 and 4.7, there are two facts contributing to this association: first, on average participants' networks are highly diverse based on education and second, a large proportion of participants have degree of "graduate school", but a very small proportion of their ties have the same level of education. Therefore, participants who have reported their education are very likely to have many alters with a different level of education from themselves and hence it increases the chance of those ties being strong.

Geographical distance has a consistent, although small, negative association with closeness of relationship. This indicates that relationship with alters who live at a distance are less strong than those who live near to ego. This association is negative even when its interaction with kin is included in the model. The interaction is also negative but not significant. This finding should be interpreted with some care. The negative association between geographical distance and closeness of relationship does not mean that geographical distance decreases the closeness of relationship or that such ties have always been weak and have been maintained with the help of online communication technologies. Perhaps both statements are true, a longitudinal study may provide a better understanding of the impact of geographical distance on closeness of relationships.

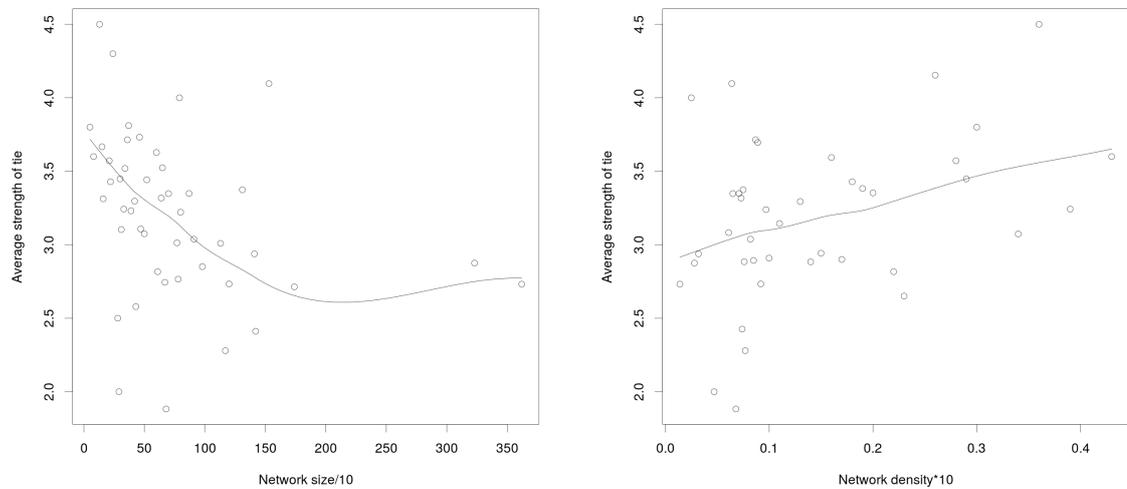
Among the measures of centrality, only the association between betweenness centrality and closeness of relationship ($\hat{\gamma} = 5.33, S.E. = 2.25$) is significant, and only in the three first models. This estimate becomes non-significant as a result of including interaction with network size in model 3. Although it is not significant in the final model, the large positive estimate for betweenness centrality suggests that alters who have a bridging role are more likely to be close to ego than are other alters

Overall, network size ($\hat{\gamma} = -0.13, S.E. = 0.06$) and density ($\hat{\gamma} = -1.12, S.E. = 0.63$) are negatively related to closeness of relationship. The small negative association between network size and closeness of relationship indicates that for each 10 more friends, the odds of a tie to be one level stronger is $\exp(-0.13) = 0.90$, which means the probability of a tie being one level stronger declines by 0.46 for each 10 more friends on Facebook. The weakly significant association between network density and closeness of relationship suggests that ties become weaker in personal networks with a higher level of density. This has been found by Fischer (1982) as, while it seems that relationships within denser networks are stronger, each relationship actually

becomes weaker in a denser network. In other words, the fact that "The whole is greater than the sum of its parts", is actually the function of presence of a few close relationships and not because each relationship becomes stronger.

To better understand the above findings on network size and density, I plotted these measures with the **average** closeness of relationship (average closeness of relationship is taken from each personal network and is plotted against network size and density). The average closeness of relationship for each personal network, represents the "sum of its parts". As shown in figure 7.3(a), average closeness of relationship decreases when network size increases. Note that the curve represents the correlation between the two variables and is calculated based on LOESS (LOcally WEighted Scatter-plot Smoother) methods (Cleveland and Devlin, 1988). This association is consistent with the results of multilevel analysis. However average closeness of relationship increases with network density (till a threshold, see figure 7.3(b)) and this is the opposite of what was found in multilevel analysis (model 2). The fact is, if we consider a personal network, on average closeness of relationship increases when network density increases, and decreases when network size increases. This means that on average, ties are weaker in larger and sparser networks which is commonly accepted.

However, these associations are found when closeness of relationship is aggregated at the level of personal networks and cannot be simply applied to the individual ties within them. If average closeness of relationship increases with network density, it does not indicate that strength of each tie increases with network density. Results of the multilevel analysis weakly suggest the opposite for network density. When network density increases, the closeness of relationship decreases.



(a): Average strength of tie by network size

(b): Average strength of tie by network density

Figure 7.3: Average strength of tie by network size and density

Overall, none of the associations with cross-level interactions are significant except for the interaction between eigenvector centrality and network density which is weakly significant. Although, none of the associations with cross-level interactions are significant, the direction and strength of tie suggest interesting hypotheses for further study. Perhaps, the most notable is the negative interaction between network size and degree centrality as well as the negative interaction of network density with degree and betweenness centrality. These interactions suggest that ties with highly connected alters may be less strong and the strength decreases even more when such ties are located within larger or denser personal networks. For betweenness, the story is different. While alters who are among many other alters are more likely to be close to ego, this likelihood decreases when the network density increases. These are not proved in the present study and are suggested for future research.

Model 4 is same as the previous model (model3a) in terms of the variables included, but in addition to the random intercepts, random slopes are added. This model aims to examine if the associations between independent variables and strength of tie is significantly different among personal networks. For example, if the results of previous models show that degree centrality is negatively associated with strength of tie, is this association uniform to all of the personal networks or is it significantly different between personal networks?

Figure 7.4 plots the relation between degree centrality and strength of tie in each personal network. This plot can be made for any other variable, but degree centrality is chosen, because

it is mostly expected to vary across personal networks due to its dependence on network size and density. Each square represents one personal network and each dot represents a tie within that personal network. The graph clearly shows that the relation between degree centrality and strength of tie varies among personal networks. The correlation is positive for the majority of personal networks, but, there are also some personal networks for which the correlation is negative. Even among those with the same direction, the slope of the correlation line is different from one network to another.

These plot indicate that it is likely that there is slope variation. However, the result of the log-likelihood ratios test is not significant indicating that the association between degree centrality and strength of tie is not significantly different among personal networks. The log likelihood ratio test compares the log-likelihood of model with random slopes (model 4) and without (model 3a) and determines whether the difference is significant by using chi-squared test. The p-value for the likelihood ratio test is larger than 0.10 and hence it does not show any significant difference between the two models. The random slopes have been added for all of the level one variables and the likelihood ratio test was not significant for any of them.

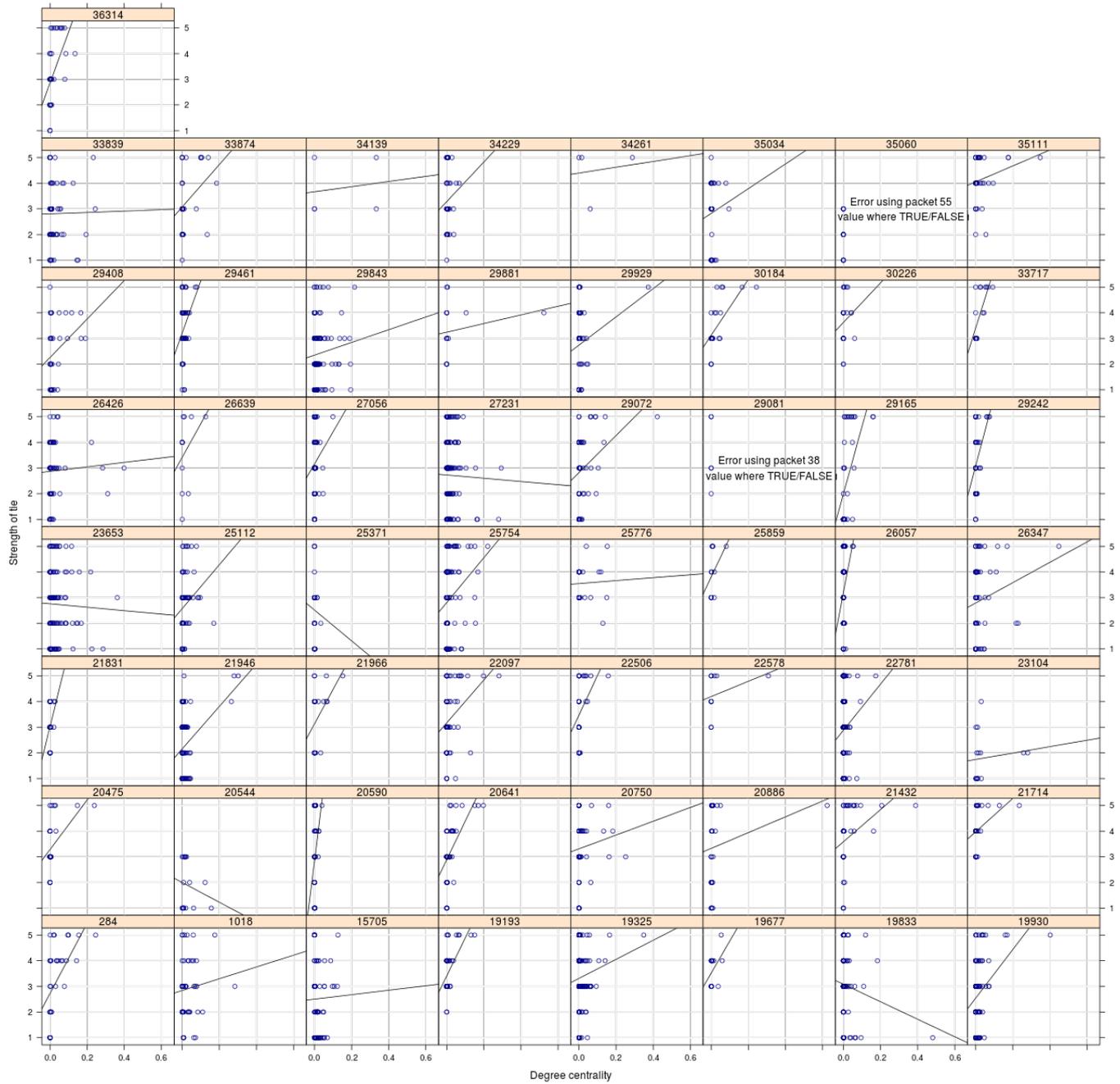


Figure 7.4: Strength of tie by degree centrality in each personal network

With whom does ego exchange resources?

The dependent variable for this part of the analysis is the number of times an alter has been nominated to have skill or resources. Each alter could be nominated up to ten times (for ten resources), but they have actually been nominated for up to a maximum of 7 times. So, the dependent variable is an ordered number from 1 to 7, thus the multilevel models are ordinal logistic and the estimates are interpreted as odds ratios. Those alters who have not been nominated for any resource are excluded from the analysis.

Results of the multilevel analysis are summarised in table 7.4. The following are some of the highlighted findings.

Table 7.4 Summary of the multilevel ordinal logistic regression analysis for exchange of resources

	Model 1	Model 1a	Model 1b	Model 2	Model 3	Model 3a	Model 4
<i>Fixed effects</i>							
kin	2.60*	2.68**	2.73	3.86	8.07 ⁺	8.04	8.05
	(1.03)	(1.01)	(3.87)	(4.08)	(4.90)	(5.05)	(5.05)
diff_gender	-0.65	-0.65	-1.40	-1.49	-1.49	-2.61	-2.61
	(0.85)	(0.83)	(1.44)	(1.48)	(1.63)	(1.85)	(1.85)
diff_age	-0.98*	-0.99*	-1.83 ⁺	-2.25 ⁺	-2.46 ⁺	-2.98*	-2.98*
	(0.41)	(0.40)	(0.98)	(1.22)	(1.31)	(1.45)	(1.45)
diff_edu	1.28 ⁺	1.47 ⁺	1.60	1.48	0.78	0.49	0.49
	(0.76)	(0.79)	(1.13)	(1.12)	(1.21)	(1.27)	(1.27)
diff_geo	-0.18*	-0.18*	-0.18 ⁺	-0.14	-0.08	-0.07	-0.07
	(0.09)	(0.09)	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)
degree	-2.32	-2.60	-2.84	-11.61*	-28.58**	-48.78	-48.77
	(3.84)	(3.78)	(4.33)	(5.52)	(10.42)	(66.04)	(66.45)
betweenness	15.60***	16.01***	15.63**	18.64***	31.99**	100.66 ⁺	100.65 ⁺
	(4.53)	(4.48)	(4.91)	(5.14)	(10.69)	(59.29)	(59.67)
eigen-vector	-3.39	-3.31	-3.10	0.43	12.62 ⁺	10.13	10.13
	(2.51)	(2.45)	(2.78)	(3.20)	(7.12)	(23.97)	(24.08)
strength		-0.18	-0.06	0.54	1.22 ⁺	1.64*	1.64*
		(0.29)	(0.45)	(0.56)	(0.70)	(0.75)	(0.75)
kin:strength			-0.64	-1.28	-2.14*	-2.44*	-2.44*
			(0.81)	(0.82)	(1.02)	(1.05)	(1.05)
kin:diff_gender			1.27	1.59	1.55	2.57	2.57
			(1.91)	(1.95)	(2.05)	(2.27)	(2.27)
kin:diff_age			1.28	1.96	1.78	2.42	2.42
			(1.11)	(1.35)	(1.44)	(1.56)	(1.56)
kin:diff_edu			0.25	0.27	1.19	1.42	1.42
			(1.72)	(1.80)	(1.91)	(2.04)	(2.04)
kin:diff_geo			-0.04	-0.03	-0.20	-0.29	-0.29
			(0.30)	(0.30)	(0.42)	(0.60)	(0.60)
size				0.08	0.47*	0.71*	0.71*
				(0.11)	(0.21)	(0.29)	(0.29)
density				2.41**	4.85**	5.52**	5.52**
				(0.88)	(1.61)	(2.05)	(2.05)
degree:size					-1.07	-0.46	-0.46
					(1.61)	(4.06)	(4.08)
betweenness:size					-2.74	-6.38 ⁺	-6.38 ⁺
					(1.80)	(3.69)	(3.71)
eigen-vector:size					-0.06	-0.32	-0.32
					(0.90)	(1.79)	(1.80)
degree:density						-4.44	-4.45
						(20.31)	(20.40)
betweenness:density						-32.56	-32.56
						(21.90)	(22.02)
eigen-vector:density						12.07	12.07
						(10.13)	(10.14)
<i>Random effects</i>							
Intercept	0.085	7.815e-08	0.257	1.137e-07	2.717e-09	3.256e-07	5.476e-08
degree							3.399e-07
AIC	120.24	121.89	129.18	123.20	122.65	124.65	128.65
Log Likelihood	-48.12	-47.95	-46.59	-41.60	-38.33	-36.32	-36.32
Num. obs.	69	69	69	69	69	69	69

Note: Number of personal networks:31

*** : $p < 0.001$, ** : $p < 0.01$, * : $p < 0.05$, + : $p < 0.1$

Kin has a positive association with the number of resources ($\hat{\gamma} = 2.60, S.E. = 1.03$ in model1) which becomes non-significant in the final model. It indicates that kin are more likely to be nominated to have skills or resources than non-kin.

Among variables of social similarity, only age distance is consistently associated ($\hat{\gamma} = -2.98, S.E. = 1.45$) with the number of exchanged resources even when its interaction with kin has been controlled. Alters are more likely to have skills (known to ego) if they are closer to ego's age.

The positive estimate for educational distance and the negative estimate for geographical distance are only significant in first models and weakly suggest that egos are more likely to know alters who have skills/resources among those who have different level of education or live at a smaller distance.

Among measures of centrality, only the association between betweenness and exchange of resources is significant which indicates that alters who are located within many other alters are more likely to be nominated to have skills/resources. Degree centrality has a negative association with exchange of resources, but it is significant only in two models.

Association between strength of tie and exchange of resources is negative, but non-significant. This association is not stable and changes between models from being negative in the first two models and becomes positive from model 2 when level two variables are added. The estimate for this variable is positive and significant in the full model (model3a).

Among the level one interaction terms, none of estimates are significant. But the estimate for interaction between kin and strength of tie becomes significant in model 3. Comparing the main and interaction effects for kin and strength of tie in the first three models reveals that while the estimate for kin is positive and it is negative for strength of tie the interaction term is negative. This means that while kin are more likely and stronger ties are less likely to be involved in the exchange of resources, stronger ties among kin are less likely to be involved in exchange of resources.

The network level variables are both positively related to exchange of resources. The odds of an alter being nominated to have a resource/skill increases by $\exp(0.71) = 2.03$ (based on model 4) when network size increases by 10. This association is even stronger for network density which

means, an alter is more likely to be nominated to have a resource/skill in denser personal networks.

Overall, the cross level interactions are not significant except for the interaction between network size and betweenness centrality which is weakly significant in model 3 and 4. This negative interaction suggests that network size reduces the effect of betweenness centrality on the number of times an alter has been nominated to have skills/resources. For example, whatever the effect of betweenness centrality on the number of exchanged resources, it will be decreased by $\exp(-6.38) = 0.002$ (from model 3) when network size is increased by 10.

The last two models are almost qualitatively the same. In theory, model 4 is different from model 3a as it aims to control for the random slopes. Similar to the analysis for strength of tie, the random slopes has been added for degree centrality. The result of log-likelihood ratio test does not show any significant difference between model with and without random slopes. I conclude that although it appears that the association between degree centrality and number of potential resources is different between personal networks (see appendix 7.5), results of model 4 show that the difference is not significant.

Who makes ego feel happy or unhappy?

The dependent variable for this part of analysis is the level of positive or negative interactions between ego and alters which is ordinal and scored from -2 to 2. So ordinal logistic multilevel models are used.

Results of the analysis are summarized in table 7.5. The following paragraphs review the most notable findings.

Table 7.5 Summary of the multilevel ordinal logistic regression analysis for emotional interactions

	Model 1	Model 1a	Model 1b	Model 2	Model 3	Model 3a	Model 4
<i>Fixed effects</i>							
kin	1.03*	-0.22	7.15 ⁺	8.28*	7.81*	8.24*	9.71*
	(0.52)	(0.70)	(3.69)	(3.51)	(3.51)	(4.03)	(4.01)
diff_gender	-0.43	-0.01	-0.08	0.11	0.06	0.14	0.01
	(0.43)	(0.52)	(0.71)	(0.71)	(0.70)	(0.73)	(0.76)
diff_age	-0.46 ⁺	-0.06	0.13	0.21	0.21	0.30	0.32
	(0.24)	(0.29)	(0.39)	(0.38)	(0.40)	(0.43)	(0.45)
diff_edu	0.35	0.21	0.39	0.58	0.35	0.30	0.47
	(0.47)	(0.56)	(0.74)	(0.73)	(0.72)	(0.77)	(0.79)
diff_geo	-0.03	-0.06	-0.05	-0.07	-0.04	-0.03	-0.02
	(0.05)	(0.06)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)
degree	-3.12	-7.11	-9.15 ⁺	-11.71*	-28.65**	-73.02	-50.63
	(3.19)	(4.78)	(5.05)	(5.31)	(9.85)	(49.63)	(41.68)
betweenness	5.76 ⁺	6.28	7.83 ⁺	8.48*	21.46*	52.28	44.13
	(3.48)	(4.20)	(4.32)	(4.32)	(8.59)	(39.07)	(46.73)
eigen-vector	1.96	3.80	5.31 ⁺	6.41*	11.12*	30.97	18.51
	(1.64)	(2.55)	(2.78)	(2.75)	(5.43)	(22.96)	(16.78)
strength		1.75***	2.25***	2.19***	2.13***	2.35***	2.66***
		(0.38)	(0.45)	(0.45)	(0.47)	(0.57)	(0.59)
kin:strength			-1.85*	-2.13**	-1.90*	-2.10*	-2.18*
			(0.82)	(0.80)	(0.83)	(0.96)	(0.89)
kin:diff_gender			0.69	0.43	0.81	1.29	1.05
			(1.15)	(1.15)	(1.32)	(1.45)	(1.48)
kin:diff_age			-0.04	-0.08	-0.37	-0.37	-0.86
			(0.60)	(0.58)	(0.63)	(0.70)	(0.78)
kin:diff_edu			-0.08	-0.17	-0.26	-0.39	-0.56
			(1.24)	(1.20)	(1.22)	(1.28)	(1.39)
kin:diff_geo			-0.11	-0.09	-0.12	-0.16	-0.22
			(0.12)	(0.11)	(0.12)	(0.14)	(0.15)
size				0.33*	0.25	0.29	0.18
				(0.14)	(0.17)	(0.22)	(0.30)
density				2.11*	1.92*	2.17	2.32
				(0.97)	(0.93)	(1.34)	(1.83)
degree:size					4.06*	7.04 ⁺	8.97*
					(1.74)	(4.01)	(4.37)
betweenness:size					-1.83	-3.39	-2.78
					(1.42)	(2.44)	(2.82)
eigen-vector:size					-1.18	-2.45	-2.61 ⁺
					(0.76)	(1.72)	(1.57)
degree:density						18.02	2.11
						(18.34)	(14.61)
betweenness:density						-12.33	-8.94
						(18.14)	(21.06)
eigen-vector:density						-8.99	-1.77
						(10.20)	(7.43)
<i>Random effects</i>							
Intercept	0.996	3.207	4.947	2.312	1.559	3.07	11.76
degree							122.77
AIC	258.70	204.22	207.29	204.55	202.73	207.32	207.28
Log Likelihood	-117.35	-89.11	-85.65	-82.27	-78.37	-77.66	-75.64
Num. obs.	107	100	100	100	100	100	100

Note: Number of personal networks:21

*** : $p < 0.001$, ** : $p < 0.01$, * : $p < 0.05$, + : $p < 0.1$

Kin exhibit a positive association with positive emotional interactions; except for one model (model1a) in which the estimate is negative but it is not significant. Although this association changes between models, overall it indicates that kin are significantly more likely to be involved in positive emotional interactions with ego than non-kin.

None of the estimates for social similarity and geographical proximity are significant, which means alters with similar characteristics or close distance are not significantly different from other alters in making ego feel happy or unhappy.

The estimates for measures of centrality are not stable across models and are significant only in models 1b, 2 and 3 before adding the interactions with density.

Strength of tie has a strong significant association with the level of positive interactions, which means that close alters are more likely to make ego happy (and less likely to make unhappy) than others. Adding this variable into model 1a changes the estimate for kin from significantly positive to non-significantly negative. This change indicates that strength of tie reduces the impact of type of tie on emotional interactions. This can be partially explained by the interaction between these two variables of kin and strength of tie (in model1b).

The estimate for the interaction between kin and strength of tie is negative ($\hat{\gamma} = -1.85, S.E. = 0.85$ in model1b). This indicates that kin reduces the impact of strength of tie on the level of positive or negative interaction. Similarly, strength of tie reduces the impact of kin. So, whatever the association between strength of tie and the level of positive or negative interaction, it will be reduced by 1.85 if the tie is kinship. The estimate for the main effect for kin becomes positive and significant again, when we control for the interactions with kin (from model 1a to 1b). The negative interactions reveals the significant positive role of close relationships with non-kin compared with those with kin.

The estimate for network size and density are positive, but become non-significant in the two last models when the interaction terms are added. However, the positive associations weakly suggests that ties may be more positive in larger or denser personal networks.

Among the cross level interactions, only the interaction between degree centrality and network size is significant. This positive interaction means that network size reduces the negative im-

pact of degree centrality on the level of positive interactions, while degree centrality increases the positive impact of network size. This means that whatever the association between degree centrality and the level of positive interaction (which is negative), it will be increased by 4.06 when network size increases by 10. It also shows that while alters with many connections are less likely to make ego feel happy (or more likely to make ego feel unhappy), such alters are less negative in larger networks.

The last two models are almost qualitatively the same. Model 4 aims to explain the variance of the dependent variable based on differences between personal networks by controlling for the random slopes. Figure 7.6 plots the relations between degree centrality and positive or negative interactions for all of the personal networks. The figure clearly shows that there are differences between personal networks. To determine whether the differences are significant, I use the log-likelihood ratio test. The p-value for the test (chi-squared) is larger than 0.1 (0.13) that means there is no significant difference between the model with random slopes and the model without random slopes. In other words, adding random slopes does not improve the model significantly. The random slopes were added for all of the level one variables and none of them have been significant. Degree centrality has been chosen for model 4 based on the theory as it is highly expected to vary between personal networks due to its dependence on network size.

The most notable finding of the analysis for emotional interactions is related to the important role of non-kin strong relationships. It has been found that kin are more likely to make ego feel happy than non-kin, but closeness of relationship is more important than type. Alters with whom ego feel closer are more likely to make ego feel happy than are other alters. However, close relationships with non-kin are more positive than close relationships with kin, which indicates the importance of maintaining close relationships with non-kin members.

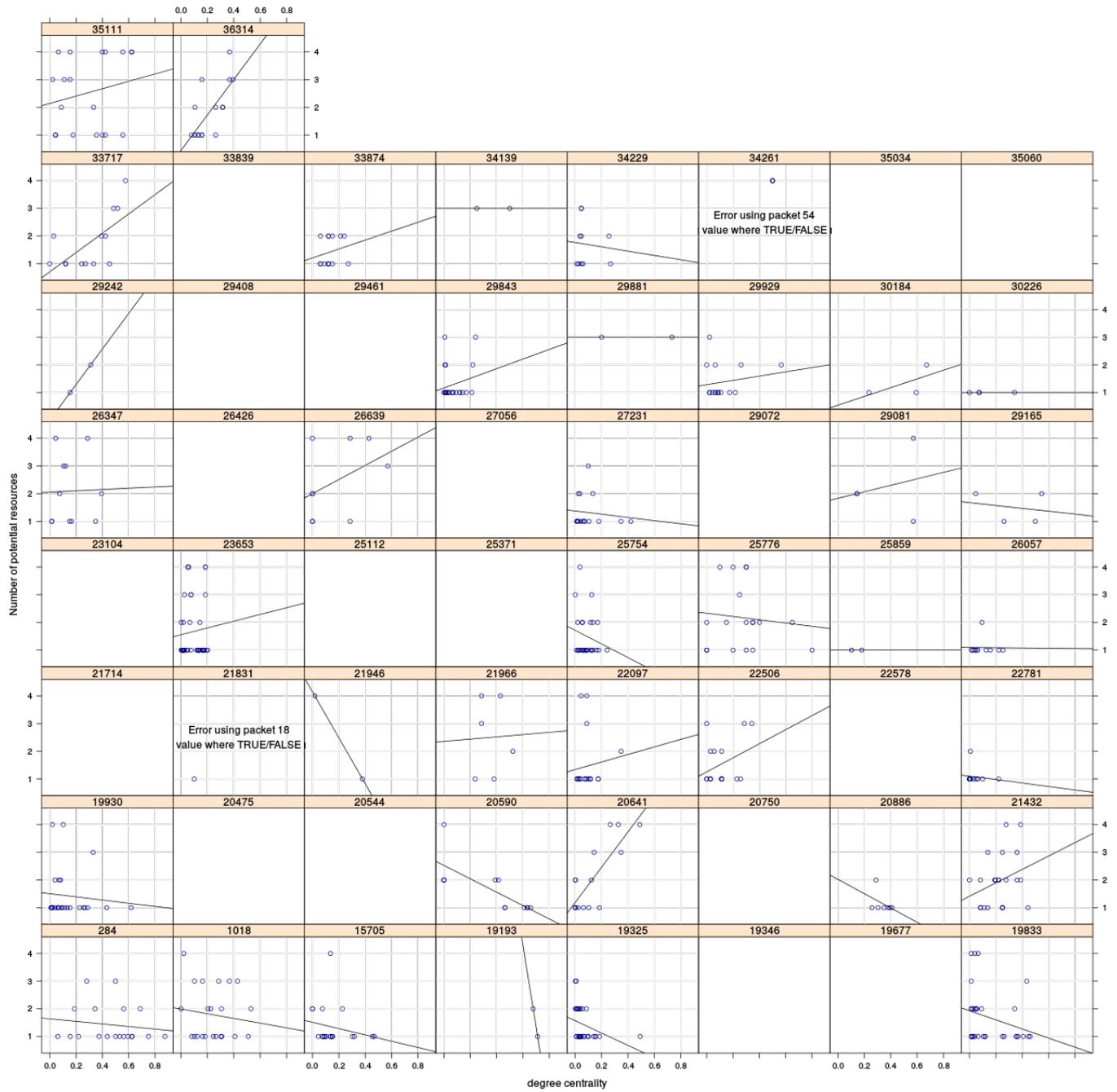


Figure 7.5: Exchange of resources by degree centrality in each personal network

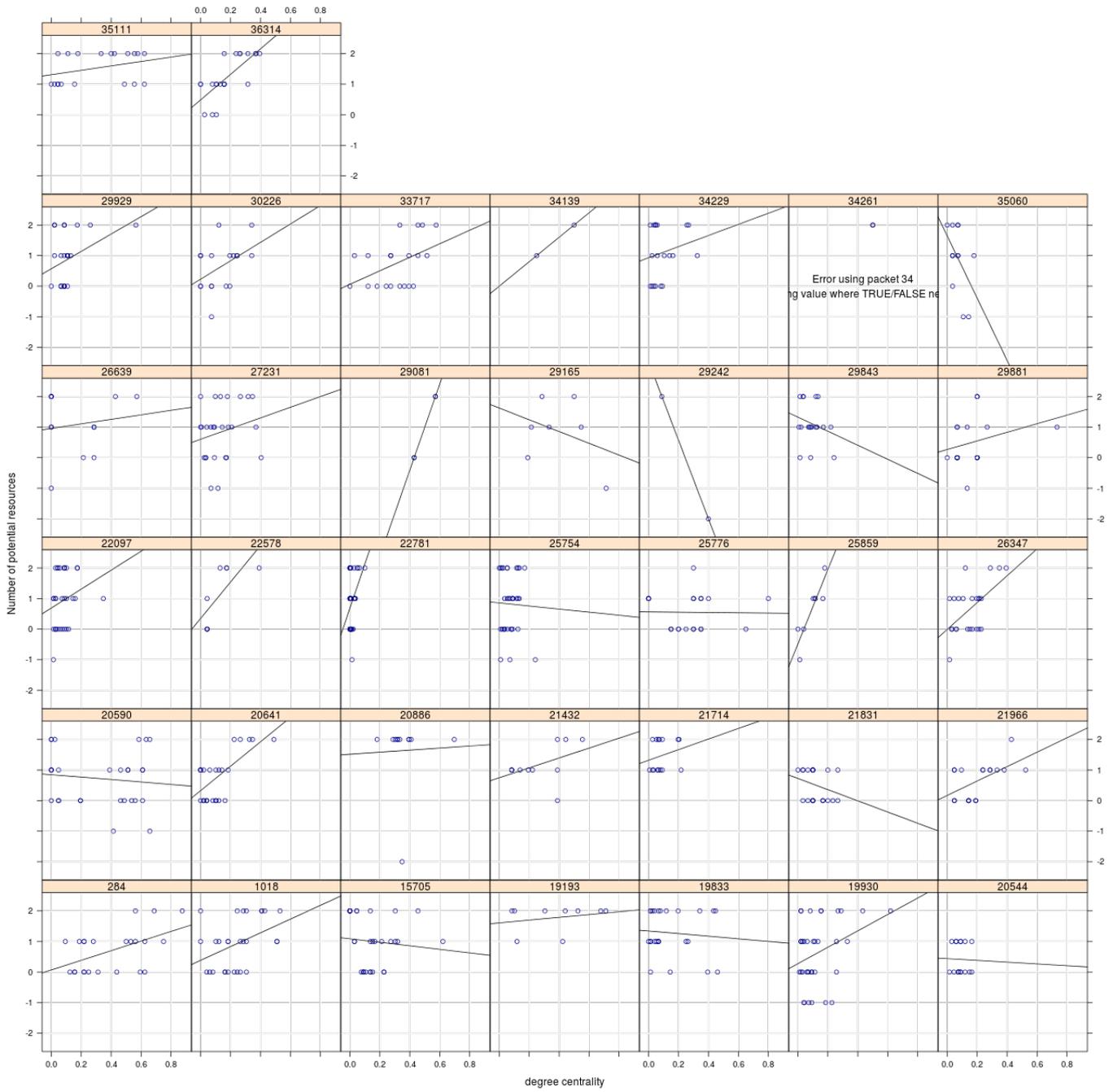


Figure 7.6: Positive and negative emotional interaction by degree centrality in each personal network

7.6 Discussion and conclusion

This chapter has three main findings. First, Facebook networks of participants of this study are to a large extent actual. Second, Facebook relationships that are important in real life, can be characterised by the information collected from Facebook. Third, data on personal networks collected from Facebook can be used for social research with some care. Discussions on these findings are provided in the following paragraphs.

The descriptive analysis revealed that there is a considerable overlap between participants real life with their Facebook networks and vice versa. The majority of participants have reported that almost half or more of their family members or close friends are on Facebook. Participants knew almost all of their Facebook friends in a way that they could identify closeness of relationship with them. However, on average, only 40 to 50 percent of Facebook friends have been important to ego (have been close to ego, have been nominated to have at least one resource or could make ego feel happy or unhappy). It means that while almost all of Facebook friends of our participants are actual, only almost half of them are important.

The patterns of the total number of social contacts, actual and important alters found in the present chapter, can be very close to the patterns of their social networks in real life. A researcher may find similar patterns in individuals personal networks in real life by broadening the boundaries (e.g. knowing someone instead of discussing important matters). By studying online communications, Marlow (2009) found that ego cares about only 13 percent of Facebook relationships and moreover, communicates only with 6 percent of them. Comparing this with the findings of this chapter, the difference can be explained based on how the importance of relationships is defined. Having online communication may not represent overlap with real life communication. People may know many of their Facebook friends or feel close to them, but do not communicate with them on Facebook. There is no straightforward association between the way that people maintain relationships and strength of those relationships (Hogan, 2009).

One of the main findings of this chapter is that compared with characteristics of relationships such as type, social similarity or geographical proximity, structural characteristics of the network can better characterise important relationships. Among the measures of centrality, betweenness better determines the attributes of important alters while eigenvector centrality is the least indicative measure.

However the explanatory power of each measure depends on the dimension of importance. Betweenness centrality is more indicative for exchange of resources than strength of tie and emotional interactions. This can be explained by the fact that alters who have bridging roles are more likely to be involved in exchange of resources while they may not be necessarily close to ego or making ego feel happy or unhappy. Overall, the central alters are important to ego. However, the analysis did not investigate causality. From these analyses, it is not clear why central alters are important to ego; are they central (are located withing many other alters), because they are especially close to ego (e.g. are spouse) or they become important to ego because of their connections with other alters. As stated by (Fischer, 1982), "the answer is both. People who know many of our associates become close to us, as we know about them in groups in addition to via personal relationships. And those people who are close to us, are more likely to get to know other people we know than those who are not close".

In addition to the structural measures for alters, characteristics of network structure (size and density) play an important role in identifying important alters. Ties are found to be stronger in larger or sparser personal networks, but more involved in the exchange of resources or positive emotional interactions. In other words, in smaller or denser networks, ties tend to be weaker, less likely to provide resources and more likely to be negative.

Different sets of measures have been found to best explain different characteristics of important alters. For strength of tie, social similarity provides the most indicative set of measures. Age and geographical distance have negative, but educational distance has positive associations with strength of tie. For the exchange of resources, position of alters in the network structure (centrality) as well as the structural characteristics of network are most indicative. For emotional interactions, strength and type of tie are the most powerful explanatory variables. Social similarity is unrelated and structural characteristics of nodes and networks have a changing and unstable relations. In summary, it can be said that important alters are those that are more similar when it is about closeness of relationship, they are the most central in the network structure when it is about exchange of resources and they are kin or close alter if it is about emotional interactions.

Some of the interesting findings were related to how important kin relationships are in Facebook personal networks. It is found that although always positively related to the three aspects of important alters, kin is more related to the emotional interactions than closeness of relation-

ship or exchange of resources. Kin has been significantly different from non-kin in terms of being important to ego, but the association has lost its significance in later models as a result of including its interaction with other variables. Interactions with kin also provided interesting insights. While less age distance alters were close to ego, kin relationships with more age distance were found to be closer to ego. While being kin or close to ego increased the number of exchanged resources, being close to ego within kinship, decreased it. And more interestingly, While close alters or kin were more likely to make ego feel happy, the likelihood significantly decreased when close alters were ego's kin members. Altogether, these findings indicate the importance of maintaining non-kin social relationships in later life.

Among the socio-demographic attributes, differences in age and education can better explain importance of alters than gender; this finding is consistent with other studies (Marsden, 1988; Smith et al., 2014). Analysis showed that difference in gender does not have a significant association with any aspect of importance of relationships. Geographical proximity, however, had a consistently negative association with dimensions of important alters, even when the interaction with kin was considered. Although the estimate was small, it suggests that geographical proximity still matters; distant friends are less likely to be close, less involved in exchange of resources or emotional interactions.

Finally, this chapter concludes that data on personal networks collected from Facebook can be used for social research with some care. The analysis of associations between personal networks and well-being in previous chapters show that are different results from the findings of previous studies based on personal networks in real life. However this is not because of the way that people conduct their social networks on Facebook, but because they can articulate more than researchers can usually capture from individuals' personal networks in real life. As discussed in Chapter 2 people in modern societies have much larger and more diverse personal networks than are often captured in real life. The definition of relationships on such large and diverse networks are more broad and include circles of relationships from intimate and very close to far acquaintances. Depending on the purpose of study, scholars are recommended to address the question of construct validity of the networks for their research.

The findings of this chapter are based on personal networks of a small number of people aged 50 and over and cannot be generalised to a larger population. This group of people are found to have smaller networks on Facebook compared with other age groups, they are expected to

have much of their online contacts with their family and close friends. In this way, the considerable overlap between Facebook and real life personal networks may be specific to this age group. However, the study creates new insights and suggestions for further research focused on personal networks both online and in real life.

Conclusion

This thesis studied personal networks of older Australians and their associations with subjective well-being (SWB). Data on personal networks are collected from Facebook and combined with the complementary information provided by participants using a purpose-built Facebook application. This chapter has two parts. First, it characterises the online personal networks of the sample of this study. This characterisation provides a detailed view of personal networks in terms of structure (Chapter 3), composition (Chapter 4) and function (Chapters 5 and 6). Second, it reviews the main findings on the associations between the personal networks and SWB. Further, this chapter attempts to place the findings of this research in a wider context by discussing how online social networks can be utilised for social research.

8.1 Personal networks

In general, the personal networks in this study are overall loosely-knit, but locally clustered. As shown in chapter 3, personal networks are on average highly sparse; of each 100 possible relationships among network members, only 15 of them exist. Moreover these relationships are neither evenly nor randomly distributed. Rather, they are highly concentrated within groups; on average, the personal networks have 5 groups (found using a community detection algorithm), each group is densely connected within and sparsely connected to other groups. Each group represents a context (e.g. family) from which its members are derived (Feld, 1981), indicating that the personal networks are constructed based on several contexts. The fact that members of different contexts have different characteristics and perform different roles indicates that the personal networks in this study are structurally diverse.

The personal networks are also compositionally diverse regarding the socio-demographic characteristics of network members (studied in chapter 4). Average diversity is found to be high based on gender, age, education and country of residence, while diversity based on education is the highest. The personal networks of this study are also geographically dispersed, including many

long distance relationships. However, the level of diversity is different for various categories of each characteristic. For example, women have more homogeneous networks mostly composed of women, while men have less homogeneous networks more balanced in the number of men and women. Diversity based on age was higher for older participants and diversity based on education was highest among the most educated participants. While personal networks are in general diverse, they are highly assortative based on socio-demographic characteristics and geographical location (country of residence), indicating the prevalence of connections between alters with similar characteristics.

Although the personal networks are relatively large (compared with the personal networks used in previous studies), they only provide access to a small number of resources; participants can access on average 8.5 resources (out of the 100 possible resources as each participant could identify up to 10 alters for each of the 10 resources). However, the set of resources that alters can provide is diverse and cover almost all types of the resources listed in this research from knowing someone who has university education (most frequent resource) to knowing someone who has a holiday house (very rare). This diversity in the types of available resources is consistent with the personal networks that are found to be structurally and compositionally diverse. Moreover, participants have reported that they can easily ask for almost all of the resources that are potentially available in their network if needed. Participants are also able to provide a similar number of resources that they may receive from their alters.

Further, while there are some examples of negative relationships in the personal networks, they are mostly positive. As described in chapter 6, on average, the number of negative emotional interactions reported by participants is considerably lower than the number of positive interactions (0.32 compared with 5.7). This clearly indicates that participants perceive most of their alters as a source of positive emotional interaction, making them feel happy or very happy.

Further analysis on the characteristics of relationships showed that relationships are "specialised" in terms of providing resources or being involved in emotional interactions. On average, most alters who are identified to have a resource provide only one or two resources, and only a small proportion of alters can provide more than 2. Moreover, different relationships convey different characteristics and are involved in different types and amount of exchanges. Close alters are more likely to be with non-kin and with alters of the same age or different levels of education. Both close alters and kin are involved in providing resources, but kin who have a close relation-

ship with ego are less likely to be involved in providing resources (compared with both kin and close alters). Similarly, kin and close alters have positive emotional interactions with ego, but kin who are close to ego are less likely to have positive emotional interactions with ego.

The personal networks characterised in this thesis resemble the view of the contemporary personal network provided by social networks scholars (Wellman, 2002). For example, Fischer (1982) found that personal networks of northern Californians, are sparse and segmented including many long distance relationships. However, being sparsely-knit is not a universal characteristic of personal networks in all contemporary societies. Fischer and Shavit (1995) compared personal networks in United States with Israel and found that personal networks in these two nations are significantly different in terms of density. Sparsity of personal networks can be explained in two ways. First, network density is related to size (as discussed in chapter 3): generally larger networks are sparser as there are fewer opportunities (or pressure) to know other members in larger networks compared with small ones. Second, the structural characteristics of personal networks are determined by the structured nature of relationships in societies (Feld, 1984). Hence, the extent to which relationships are from diverse contexts and the extent to which members of each context are interconnected - which is itself determined by the social structure such as norms and culture - can explain the extent to which the personal network as a whole is dense. Therefore, personal networks may be sparse even if they are small in size. For example, the personal networks of East Yorkers described in Wellman (1979); Wellman and Hall (1988); Wellman and Wortley (1990) are sparse and composed of several groups even though they included only small number of intimate and close relationships (around 11 relationships). Unfortunately there is no research on Australian population to compare the results of this study with, but I assume that the patterning of the personal networks in this study can be explained based on both network size and presence of multiple contexts in them.

8.2 Personal networks and subjective well-being

The second aim of this study was to examine the associations between personal networks and SWB. Guided by the conceptual model developed in chapter 2, this association is examined based on three aspects of personal networks: homogeneity (Chapter 4), social capital (Chapter 5) and negative interactions (Chapter 6). This section summarises some of the main findings.

Among the structural characteristics, network density and transitivity had the most consistent associations with SWB. It is found that network density is negatively associated with SWB,

while network transitivity is positively associated with SWB (although only with psychological well-being). Although both density and transitivity measure network cohesion, they represent different patterning of relationships among alters, and this can explain their different associations with SWB. It is concluded that while the overall connectedness of personal networks is negatively associated with SWB, alters' tendency for local clustering is positive for SWB. No association was found between SWB and other characteristics of network structure, most notably network size.

The negative association between density and SWB can be explained in two ways. First, there is a trade-off between beneficial and detrimental effects of having a densely-knit networks on well-being (Chapters 2 and 4). In one hand, network density is desirable for well-being as it is structurally suited for the efficient flow of information and enabling collective actions (i.e. in providing support). On the other hand, dense personal networks can limit actions and impose a high level of social control, while sparse networks can provide more opportunities and freedom and access to a more diverse set of resources. The way that each side of trade-off is linked with SWB may be better explained based on other factors that contribute to both network density and well-being. As explained by (Fischer, 1982, P. 149-151), "the classic ideas about network density - that density is related to improved well-being - may be correct, but only for those who lack the resources to manage dispersed networks". He found three different associations between density and psychological mood: a positive association for low-income respondents; a negative association for high-income respondents and a lack of association for all respondents. Data for the present research did not allow for controlling the economic status of participants, but I assume that participants of this study have generally good economic status, given that they have access to the Internet and use online social networks. It is therefore proposed that a potential reason for the negative association between density and SWB is that participants with a better economic status have better SWB and at the same time are able to have a sparser personal network, while participants with lower level of economic status have a lower score of SWB and at the same time are not able to manage a sparse personal network. Future studies are recommended to control for socio-economic characteristics of individuals in examining the links between network density and SWB (more generally network structure and well-being).

Second, the personal networks used in this study are large and segmented. Density may not be a meaningful measure for the cohesion of such networks as it assumes the equal chance of existence for ties between each pairs of alters which is not true due to the structured nature

of relationships in societies (Feld, 1984); some ties are more likely to exist, while the chance of forming some ties is very low. Scholars have pointed out that density is not a precise measure for network cohesion as it greatly varies across networks with different sizes and have suggested average degree (Brooks et al., 2014). The present study did not find any significant association between average degree and SWB. Future research may consider to use (or develop) more accurate and meaningful measures of network cohesion that, for example take into account the connectedness in terms of components rather than the whole network (see Borgatti (2006), Borgatti et al. (2013, P. 150)).

Among the socio-demographic attributes of network members, only diversity based on education was significantly associated with SWB. This positive association may be explained by the effect of education of participants themselves that may contribute to both network diversity and well-being; participants with the highest level of education are found to have the highest level of diversity based on education.

Measures of social capital were found to be only weakly associated with SWB (Chapter 5). Participants with higher amounts of potentially available resources have slightly better psychological well-being. Of the relational measures of social capital (other than transitivity which has been discussed above), only the "average global degree" (indicating bridging social capital) is significantly associated with psychological well-being. This small negative association indicates that the more friends have friends (who are not ego's friends) the worse the psychological well-being of ego is. It suggests that having popular friends may not be desirable for psychological well-being perhaps because alters with many friends would allocate less time and attention to their relationships within ego's personal network (with ego as well as ego's alters).

Studying emotional interactions provided new insights and directions for research in this area. While it is commonly found that it is the detrimental effect of negative interactions that determines well-being, this study found the opposite (Chapter 6). Positive emotional interaction is found to have a positive association with SWB, though the negative effect of negative interactions was found in some (early) models. The negative effects of negative interactions on SWB were found when interactions were considered as dyadic relationships (between ego and her alters). But, taking into account the network structure and the position of alters within this structure eliminated these effects and instead revealed the positive effects of positive interactions on SWB. It is proposed that to better understand the effect of positive and negative interactions on well-

being, future research should consider the interconnections among alters and the corresponding measures in their analytical models.

Of the personal characteristics of ego, it is consistently found in different chapters of this study that age and having a spouse are positively associated with SWB. This is consistent with findings of other studies that older people often reported to have a better SWB compared with their younger counterparts (Jivraj et al., 2014). Similarly, the positive association between having spouse and SWB in later life is consistent with the findings of many other studies (e.g. Lawton et al. (1984); Manzoli et al. (2007)).

In sum, the findings of associations between personal networks and SWB somewhat contradict what has been found in previous studies. In particular, it is found that network size is unrelated to SWB, density is negatively associated with SWB, and measures of homogeneity and social capital exhibit either a lack of or a negative association with SWB. Further, a strong detrimental effect of negative interactions on SWB, that has been commonly found in previous research, is not confirmed in this study. Although this can partly be attributed to the fact that the sample of this study is relatively small and non-representative for the target population (i.e. resulting in a low variance of the dependent variables), this study provides some intriguing insights into the associations between personal networks and well-being as well as possibilities for future research. The contradictory findings can be better understood by considering the differences between this study and the previous studies, as explained in the following paragraphs.

One of the important differences between this study and previous studies in this area is related to the fact that data on personal networks used in this study are collected from Facebook, while the previous studies on health and well-being are based on personal networks in real life. So, the extent to which Facebook personal networks are different from personal networks in real life may explain the differences between findings of this study and the previous studies. This is examined by answering two questions: Are the findings of this study different from previous studies because Facebook personal networks are different from personal networks in real life? Or, do Facebook personal networks just reflect personal networks in real life but, personal networks in real life are constructed by previous studies differently? In particular, previous studies have often limited personal networks to a small number of core network members.

These questions are examined in chapter 7 by ascertaining the extent to which personal networks

on Facebook represent personal networks in real life. It is found that participants' personal networks on Facebook considerably overlap with their personal networks in real life. Although participants have family members and close friends who are not on Facebook (indicating a partial overlap), almost all of their relationships on Facebook are "actual" and many of them are "important". On average, participants had almost half or more of their family members or close friends on Facebook. Only a small proportion of participants had friends on Facebook whom they have never met. Of the relationships on Facebook, on average almost all (89%) are identified for closeness of relationships that means participants know almost all of their Facebook friends to the extent that they can recall how close is their relationship. However, only around half of the relationships are "important" in real life; on average around 39% of the relationships are "close" or "very close"; 51% can provide at least one resource and 46% are involved in emotional interactions. These findings indicate that Facebook personal networks are "actual" to a large extent, but only a part of them are "important" in real life. I conclude that the differences between findings of this study and the previous studies are not because Facebook personal networks are significantly different from personal networks in real life. Rather, it is proposed that the reason why the present study finds different associations between networks and SWB is because previous studies have limited personal networks to only the "important" relationships. In support of this contention, it is found that limiting personal networks to include only the important relationships produced a positive association between density and SWB (Chapter 6); it was the effect of including not-important (not-close) relationships in personal networks that resulted in the negative associations between density and SWB.

Perhaps the underlying difference between personal networks used in this study and personal networks in the previous studies is in their sizes. It may be true that the use of communication technologies have expanded individuals' social networks, but there is strong evidence that having large networks is not specific to the recent growth in use of these technologies. It is rather an inherent part of an individual's social life in a contemporary society. Dunbar has found that people can maintain an average number of 150 social relationships during their life (Dunbar, 1992); these 150 are the people that one knows and keeps in contact with. Scholars have pointed out that the size of personal networks in modern societies is considerably higher than this (Wellman, 2011; McCarty et al., 2001); Bernard et al. (2001) found an average of 290 for American personal networks, while some researchers have estimated the size of personal networks at between 1700 and 5500 (Killworth et al., 1990). Certainly the size of personal networks depend on the techniques used (e.g. asking people via survey or using contact diaries) and the definition of

relationships (e.g. whether someone knows someone or whether they communicate regularly). But it is clear that personal networks in contemporary societies are much larger than the few core network members (often fewer than 10) that have been the main focus of many previous studies, especially in studying health and well-being.

The fact that people can have considerably larger networks on Facebook is most likely to just reflect the fact that people actually have those large networks in real life. Facebook may make it affordable to keep those many social contacts. It is acknowledged that Facebook encourages expanding personal networks by suggesting new friends or reducing some of the social barriers by providing ways to know people without being known. But as older people including the sample of this study are among the least active users of Facebook, it is very likely that their Facebook friends are based on some kind of relationship in real life. So, if this study did not find any significant association between network size and SWB, this suggests that network size may not be a relevant measure after all. It can be argued that this finding is because Facebook personal networks include many acquaintances (weak ties). But, this study did not find any significant association between network size and SWB, even when the network was limited to the "close" and "very close" friends (Chapter 6). The fact is that the network size that is found to have a positive effect on well-being (Burt, 1987), does not actually measure the network size. It is rather a distinction between being socially isolated and having some friends. In this way, having no social relationship is greatly different from having one friend. Similarly, having one friend may be very different from having two or more friends. However, as found in this study when personal networks are large, size may not be related with well-being; having 80 friends may not be qualitatively different from having 120 or 200 friends. Meanwhile, we should note that network size may be indirectly related to SWB as it is somewhat related to all other characteristics of personal networks (see section 3.4.3), diversity of attributes of network members as well as the resources accessible through them.

This thesis started with the ageing of Australian population, the related challenges in particular health and well-being and its determinants in particular social relationships. This thesis demonstrated that there is no simple and straightforward link between social relationships and well-being. It might be easy to conclude that the lack of relationships or social support has detrimental effects on well-being, but this thesis shows that individuals' social environment is much more complex than the mere existence of relationships or social support. The findings of this study improves our understanding of this complexity and provided a basis for further research

in this area. In this way, rather than providing policy recommendations this thesis gives some suggestions that can further improve this field of research which may in turn improve policy recommendations.

First of all, as discussed in many sections of this thesis, research on social networks in later life is very limited in Australia. Despite the lot of emphases from both academic and the public on the importance of studying social relationships of older people and their associations with health and well-being, the amount of Australian research on these topics is very small. There is no data derived from a representative sample that can provide a basic view of Australians' personal networks. There is a need for further research on different aspects of personal networks of older Australians. People aged 50 years old and over form a unique age group for the study on social networks. On the one hand, many people have established their relationships, many have partners and children and many have been settled in their residential area and have established relationships with neighbours. But, on the other hand some of the most important life events such as retirement or bereavement that have major effects on social relationships, are most common among this age group. Therefore personal networks of people in this group can be used to study not only this specific age group, but also more general issues such as social integration (e.g. through studying the inter-generational relationships). Facebook personal networks are well-suited for such studies as they depict the persistent social relationships as well as the new ones; relationships on Facebook are as markers of one's "walks of life". For older adults who have passed different stages in their lives, many relationships are already established and are often depicted in their Facebook personal networks.

Second, studies on health and well-being need to consider the formal use of social network analysis rather than the loose use of concepts and terms borrowed from this approach. This provides a solid ground for the research in this area and hence reduces the likelihood of misusing or misinterpreting the concepts and measures, over-estimating the power of social relationships and moreover, result in more comparative findings.

Third, future studies involved in collecting data on social networks are recommended to utilise Online Social Networks. As discussed in this thesis, challenges in collecting data on social networks are central issues hindering further development in this area of research. This thesis explained these challenges in the context of personal networks, demonstrated new methods as well as the innovative tool developed for the purpose of this study. It is shown that how social

researchers can effectively utilise Online Social Networks, considering the methodological issues and ethical concerns in this regards. Future research may use the methods and tools developed in this study (which is aimed to be published as open source software soon) in different areas, customise or advance it for the purpose of their study or develop similar or advanced methods and tools.

Fourth, further rigorous research is needed on the validity of data from Online Social Networks for social research. This study provided a basis for such validity checking and employed it for the purpose of this study. The findings - that the Facebook personal networks considerably overlap with personal networks in real life- may not be generalised to the wider population. Further studies are needed based on more representative samples. Future research may focus only on this topic (studying for example how personal networks on Facebook overlap with real life networks) by employing data on personal networks from both sides. Scholars have developed tools facilitating personal networks collection in real life (e.g. EgoNet or EgoWeb). It will be very helpful to use them to collect the maximal personal networks in real life and the corresponding Facebook personal networks (i.e. using the methods used in this study) that can reveal the overlaps to the extent that is possible by practical research. Until we have some robust findings on this topic, researchers may develop ways to check the validity of data from online social networks for the purpose of their research.

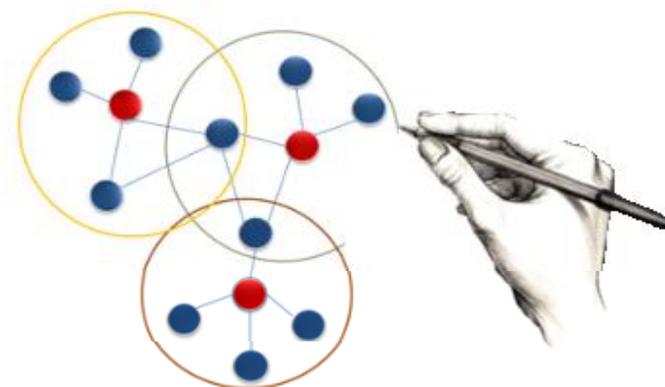
Finally, research on social networks is located at the nexus of some important areas of research (i.e. health and well-being) and the advancements in communication technologies. This nexus provides a unique opportunity for scholars to study aspects of social life that were very difficult to do in the past. Although we have experienced many advancements in health and well-being and the overall life expectancy is increased, with the growing population maintaining the healthy life is still an important issue. The advancements in communication technologies that greatly foster the connectivity of the population can have both positive and negative consequences. While there are still some debates and concerns in utilising social media for social research, this thesis proposes that the use of social network approach and the rich data from online social networks can provide new answers to the old questions on health and well-being.

Appendix A

Australian Seniors' Online Networks (AuSON): data collection

AuSON

Australian Seniors' Online Networks



Mahin Raissi (PhD candidate)
Robert Ackland (chair of panel)
Heather Booth (supervisor)
ADSRI, Australian National University

Nov. 2012

AuSON - collecting information about Australian Seniors' Online Networks

- This tutorial briefly shows you each of the stages of using AuSON
- AuSON is a Facebook application developed by researchers at the Australian National University, for the purpose of studying the social networks and well-being of Australian Seniors.
- Tutorial written by: Mahin Raissi
- AuSON designed and built by: Mahin Raissi, Lin Chen, Mahmoud Sadeghi and Robert Ackland

Some points about using AuSON

- If you are 50+ and you are eligible to vote in Australia, we expect it will take you about one hour to complete AuSON (depending on how many FB friends you have).
- ✓ Otherwise, it will be very short as you won't need to do all of the activities (note: on completion you will have an opportunity to invite your Facebook friends to participate).
- ✓ Please note that it is important that you complete all stages.
- ✓ If you find you are spending too much time on the Steps where you need to move photos into boxes (Steps 1-6) just do as much as you can, and please then move to Step 7.
- ✓ NOTE that AuSON only works with recent versions of Firefox, Internet Explorer and Google Chrome. It does not work with the iPad or smart phones.

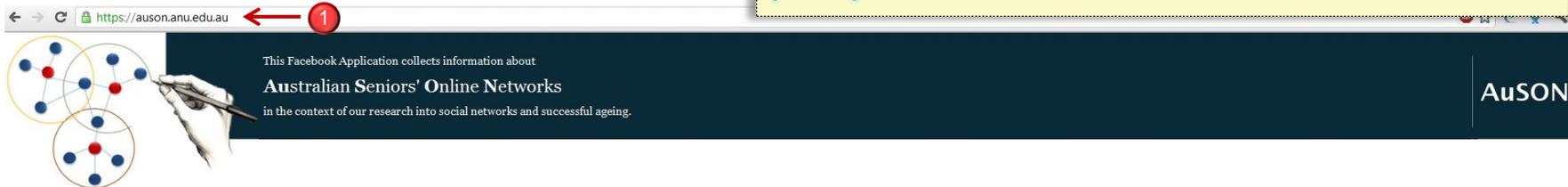
Welcome to AuSON

How do I participate in this research?

Instructions:

- 1- enter the URL in the address bar
- 2- read the information page
- 3- click on the “I want to participate” button

4- NOTE that AuSON only works with recent versions of Firefox, Internet Explorer and Google Chrome. It does not work with the iPad or smart phones.



Welcome to AuSON - Collecting information about **Australian Seniors' Online Networks**.

AuSON is a Facebook application developed by researchers at the Australian National University, for the purpose of studying the social networks and well-being of Australian Seniors. For this research project we are defining Australian Seniors as those who are 50+ years old and eligible to vote in Australia.

Information for participants

If you are not an Australian Senior, but you have friends on Facebook who are, we would still like you to participate in our research project! It will be very quick for you to participate, as you will not need to complete all of the activities.

Participation in this research involves the following five actions:



It is fun to do!

* Supported web browsers: Firefox, Google Chrome, IE(enable compatible mode on address bar)

I want to participate Cancel

4

4

Please wait ...

← → ↻ <https://auson.anu.edu.au/php/View/fb-fetch.php>

This Facebook Application collects information about
Australian Seniors' Online Networks
in the context of our research into social networks and successful ageing.

AuSON

Please wait while your network is collected and clustered. Based on your network size, it may take some minutes.
It will automatically redirect to the next page ...

View your own network and continue ...

Great! Your profile and social network structure have now been collected by AuSON.

1 → [View your own network now](#)

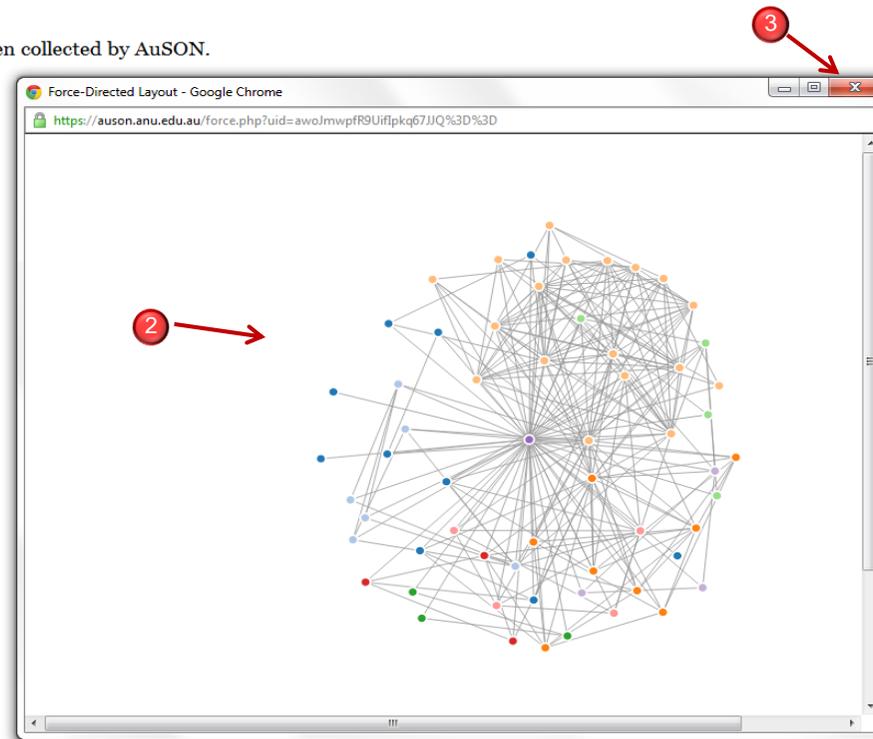
Please tell us more about yourself.

4 → 1. Are you eligible to vote in Australia?

Yes
 No

2. What is your year of birth?

5 → [Continue](#)



Instructions:

1,2,3 – View a map of your own social network

4- Let us know if you are Australian Senior by answering two simple questions

5- Continue your participation

6- If you are NOT Australian Senior, go to page 15 (you will be asked to invite your Facebook friends to participate in this research)

Step 1: Group your Facebook friends

- Instructions:**
- 1- Edit group's information
 - 2- Add a new group
 - 3- Remove a group
 - 4- Remove a friend from a group
 - 5- Add a friend to a group

AuSON
Australian Seniors' Online Networks

Step One **1** **3** Group your Facebook friends

Please arrange your friends into groups in a way that is meaningful for you.

AuSON has automatically grouped your friends based on whether they are friends with one another on Facebook.

Why are some friends not in groups?

How do I remove or add someone from a group?

But what if someone belongs to more than one group?

Please note: no need to group all friends; just as many as possible to save your time for the other steps.

Friends who are categorized

Friends who are NOT categorized yet

Group2
High School
MasSc
Reading

Add Group

Next Step

Step 2: Add your social contacts who are not in Facebook

Instructions: him or her.

1- Double click to add a new social contact **3- Edit an added contact by double clicking on his or her photo.**

2- Enter the following information for the new contact: name, sex, age, groups that she or he may belong to and people who know **4- Answer five questions about your Facebook and non-Facebook friends.**

The screenshot shows the Facebook 'Add new Offline Contact' dialog box. Red circles with numbers 1 through 4 are placed over specific elements:

- 1:** Points to the 'Contact Name' input field containing 'Armin'.
- 2:** Points to the 'Sex' dropdown menu set to 'male'.
- 3:** Points to the 'Age' input field containing '34'.
- 4:** Points to the 'Family' group button in the group selection section.

The dialog box includes the following sections:

- Contact Information:** Contact Name (Armin), Sex (male), Age (34).
- Group Selection:** A list of groups including CBSU, CITZ, CuEC, Family (highlighted), High School, IsTal, MasSc, Online, Reading, and Uncategorized.
- Friends Selection:** A grid of profile pictures with the instruction: 'From all of people who are listed below, please select up to 10 persons who know this person.' One person, 'Mohammad Akbar', is highlighted.
- Questions:** A list of questions about family members and close friends, with radio button options.

Step four: what can you and your friends provide?

Instructions:

- 1- select if you have this resource
- 2- drag a photo and drop it into a box

Step Four

Do any of your social contacts have these skills or resources? What about yourself?

Here we have a list of 10 skills and resources. Please group your social contacts (Facebook and non-Facebook) according to the skills and resources they have. For each skill or resource you can select up to 10 persons.

To add a person to a box (a resource or skill) simply drag his or her photo and drop into the box. To remove a person from a box (e.g. if you added someone by mistake), drag his or her photo and drop into the area below the box. You can also move a person from one box to another one.

Note: one person can be in more than one box.

Groups

- CBSU
- CITZ
- CuEC
- Family
- High School
- IsTal
- MasSc
- Online
- Reading
- Uncategorized

To your knowledge, do any of your friends ... ?

1- ... know about financial matters.

I know this myself

2- ... have good computer skills.

I have this skill myself

3- ... know about law (e.g. relating to your landlord, your employer or government regulations).

I know this myself

4- ... could help your family or yourself to get a job (including part time, casual or voluntary jobs).

I can do this myself

5- ... know a lot about health.

I have this knowledge myself

6- ... have the capacity to help when moving house.

I have this skill myself

[Previous Step](#) [Next Step](#)

Step five: from whom can you easily ask for help?

Instructions:

- 1- your selected friends in step 4 will be displayed in this step
- 2- remove a photo from a box
- 3- move a photos between boxes

Step Five

- Groups**
- CBSU
 - CITZ
 - CuEC
 - Family
 - High School
 - IsTal
 - MasSc
 - Online
 - Reading
 - Uncategorized

From whom can you easily ask for help? To whom can you easily give help?

Here you can see the previous list of skills and resources. But now we would like to know which of these people you feel you can easily receive each skill or resource from. In the case where you have this skill or resource yourself, who can you easily provide this skill or resource to?

We are already showing all of your friends who you indicated in Step 4 have this skill or resource. But you can add or remove friends from these boxes by dragging the photos. You can put the same friend in both boxes for a given skill or resource.

Note: one person can be in more than one box.

1- Give advice about financial matters.

I can ask advice from ... I can give advice to ...

2- Give advice or help using computer or internet.

I can ask advice from ... I can give advice to ...

3- Give advice on matters of law (e.g. in relation to your landlord, your employer or government regulations).

I can ask advice from ... I can give advice to ...

4- Could help your family or yourself to get a job (including part time, casual or voluntary jobs).

I can ask for help from ... I can give help to ...

5- Give advice, information or reference about health problems.

I can ask advice from ... I can give advice to ...

6- Help when moving house.

I can ask for help from ... I can give help to ...

Previous Step

Next Step

Step six: who makes you feel happy or unhappy?

Instructions:
1- Drag a photo and drop it into a box

Step Six

- Groups
 - CBSU
 - CITZ
 - CuEC
 - Family
- High School
- IsTal
- MaaSc
- Online
- Reading
- Uncategorized

Who makes you feel happy or unhappy?

Different people affect our mood in different ways. Please place each of your social contacts (as many as you can) into one of the boxes below according to how happy or unhappy they make you feel.

Each person can be placed in one box only.

You can move a person from a box to another box. To remove a person from a box, drag his or her photo into the region below the box.

Very happy	Happy	Neither unhappy nor happy	Unhappy	Very unhappy

Previous Step

1

Next Step

Step seven: about you

Step Seven: About you

1. What is your postcode?

2615

2. Where were you born?

- Australia
- Other English-speaking country
- Other Non-English-speaking country
- Not sure

3. What is your current work status? (select all that apply)

- In full-time paid work
- In part-time paid work
- Completely retired (not working at all)
- Partially retired
- Self-employed
- Disabled/sick
- Doing unpaid work
- Homemaker
- Studying
- Unemployed
- Other

3.a At what age do you expect to completely retire?

4. Have you looked for any paid work in the last 12 months?

- Yes
- No

5. In the last 12 months, did you do any unpaid voluntary work with an organisation or charity?

- Yes
- No

6. How many people live in your household (including you)?

3

7. How often do household members...?

- I live alone

	Always	Often	Sometimes	Seldom	Never
Make you feel cared for	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Express interest in how you are doing	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Step eight: use of Facebook

Step Eight: Use of Facebook

1. How often, do you visit Facebook?

- More than once a day
- Daily or almost daily
- Once or twice a week
- Once or twice a month
- Less than once a month

2. When you use Facebook, how long on average do you spend?

- Less than 10 minutes
- Between 10 and 30 minutes
- Between 30 minutes and 1 hour
- Between 1 and 2 hours
- More than 2 hours

3. How do you use Facebook? (select all that apply)

- To communicate with family members.
- To communicate with friends.
- To reunite with old friends.
- To make new friends.
- To share/obtain information.
- To share/be up to date with the news.
- To keep up with current events and announcements.
- For business purposes (e.g. advertisement)
- For entertainment (e.g. watching videos or playing online games)

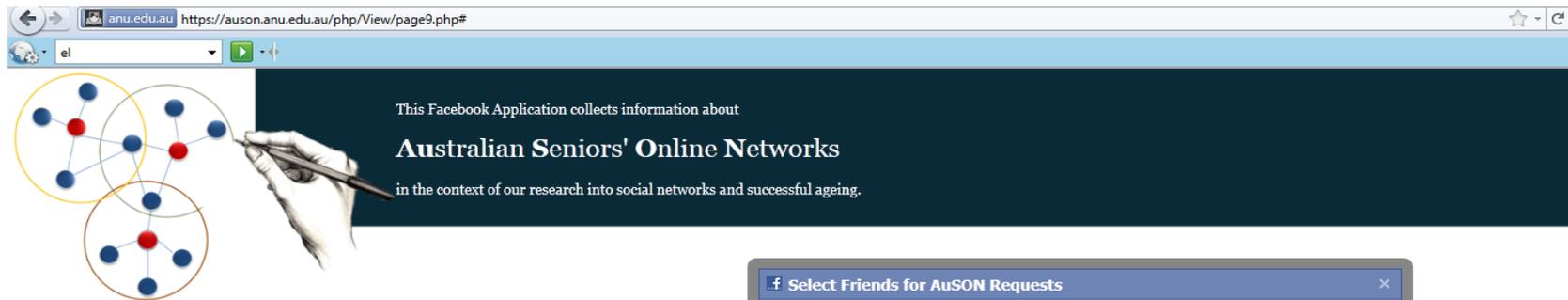
Other

4. In each of following statements, which option best describes your situation? Since I am using Facebook ...

	Decreased a lot	Somewhat decreased	Remained the same	Somewhat increased	Increased a lot	Not applicable
my contact with my family has ...	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
my contact with my friends has ...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>
my contact with people who share my hobbies/ recreational activities has ...	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
my contact with people who share my religion has ...	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
my contact with people in my profession/occupation has ...	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input checked="" type="radio"/>	<input type="radio"/>	<input type="radio"/>

Thank you!

Invite your Facebook friends to join this research



Instructions:

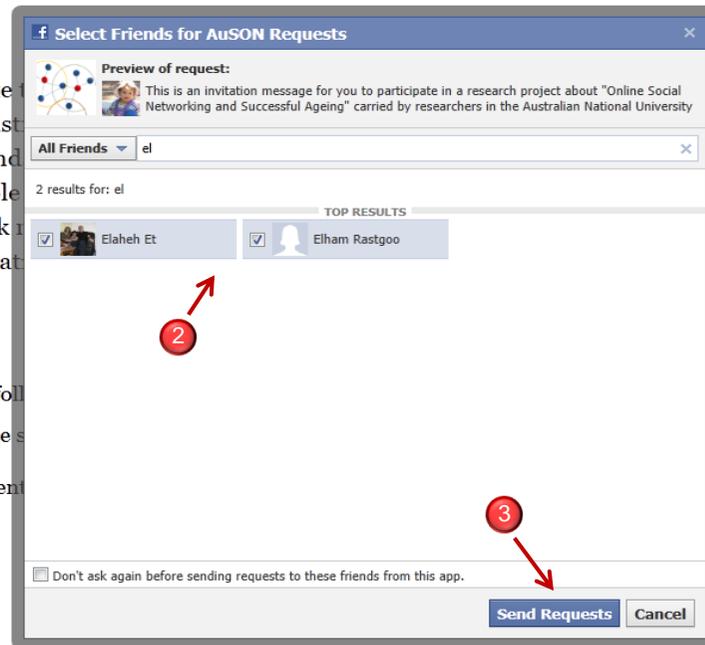
- 1- click on the "invite your friends" button
- 2- choose friends that you like to invite
- 3- click on the "Send Request" button

We really appreciate your help to better represent Australian seniors on your Facebook friends list. Then you will be able to receive automatic Facebook notifications and a preview of the invitation message.

Invite your friends

1

We will be running a follow-up study, please select your friends to invite. Hereby I give consent



2

3

study to invite some of your friends. You will see a list of friends in that

Thank you!

You can access AuSON by: <http://auson.anu.edu.au/>

For further information see: <http://auson.anu.edu.au/information>

Please visit our page on Facebook: <http://www.facebook.com/pages/AuSON-Australian-Seniors-Online-Networks/187164254753920>

This research is funded under an ARC Linkage Project “The role of online social networks in successful ageing: benefiting from ‘who you know’ at older ages”, with National Seniors Australia as Industry Partner

mahin.raissi@anu.edu.au

The invitation letter and information that are provided to the participants of this study.



ONLINE SOCIAL NETWORKS AND WELLBEING OF OLDER AUSTRALIANS

April 2012

Dear Respondent,

National Seniors Australia (NSA) is collaborating with the Australian Demographic and Social Research Institute (ADRSI) and NEC Australia in a study of social activity and wellbeing of older Australians.

We invite you to participate in our study by providing us access to your online activities on Facebook.com and completing the online survey questionnaire. This will take about **40 minutes to complete the questionnaire** and your data will be **confidential**.

Your participation will help us to understand the role of Online Social Networking in the wellbeing of older Australians. This information will be used to inform Government regarding policies which could potentially assist in enhancing wellbeing for older Australians.

ADRSI is part of the Australian National University and carries out research on demographic and social issues in the Australian community.

Attached you will find an information sheet giving answers to some of the questions you may have about the study. If you have any further queries, please do not hesitate to contact Associate Professor Heather Booth on 02 6125 4062, or Associate Professor Robert Ackland on 02 6125 0312. We thank you in advance for your participation.

Yours sincerely,

A handwritten signature in black ink that reads "Heather Booth".

Heather Booth

Associate Professor

Australian Demographic and Social Research

Institute, Australian National University

INFORMATION FOR PARTICIPANTS**ONLINE SOCIAL NETWORKING AND WELLBEING OF OLDER AUSTRALIANS**

Below you will find answers to some of the questions you may have about this study. You will also find contact details in case you have further queries.

Who is conducting this study and who has provided the funding?

This is a part of Social Network and Ageing Project (SNAP) as a PhD thesis. SNAP is being conducted by National Seniors Australia (NSA) in collaboration with social researchers from the Australian National University (ANU). The SNAP leader is Associate Professor Heather Booth, Australian Demographic and Social Research Institute (ADSRI), ANU. The study is supported by the Australian Research Council, through grant number LP0990974 (2009), by NSA and by NEC Australia.

Who will be invited to participate in the study?

We are inviting all Australian Seniors (50+) who use Facebook.com to participate in this study.

What is the study about?

The study aims to understand impacts of using online social networking websites (e.g. Facebook.com) on the wellbeing of older Australians. The study also examines the relationship between online and real life social networking for old people. As the result of this research we can create a better insight about impacts of using online social networking web sites on seniors' well-being. Findings can be used to inform policy makers to improve seniors' usage of internet and social networking facilities with the aim of promoting their well-being. So your participation in this study will be valuable for older people, Australians and broadly the world.

Which information will be collected in this study?

By participating in this study, you are giving us permission to collect data about some parts of your online activities on Facebook.com. This data will include: your profile information that is visible by public (e.g Sex, Age, home town, current city and work and education experience), list of your friends and your relationship like family member or friend (as you have defined in your profile) and other activities such as comments, likes and posting messages. These data will be collected periodically over one year, started from when you participate in our study. We also will collect other data that you will provide through online survey that is more complementary information about your social connections, your well-being and your attitudes toward using

Facebook and its impacts on your life. Survey data will be collected only two times during the study.

Will anyone else know what I have answered?

The responses to the questionnaire and your Facebook data will be entirely **confidential**.

Your Facebook ID (as well as your friends' ID) will be replaced by a new random ID immediately after reading programmatically. We only save the new ID and will use that in our analysis and reports. So you are not identifiable even by the researcher. No any identifiable pieces of your information will be shared to third party or showed or described in documents. All data will be used to find patterns and general rules and in this way, data will be analysed in aggregate level and your data will not be analysed or discussed individually.

All these data will be stored on local computers at ANU. All computers will be password protected, and access to the data will be password-protected only accessible to research team.

The information collected through the survey and Facebook.com will be analysed only by authorised ANU researchers who are involved in this study.

We abide by the Australian Government Privacy Act regulations (which can be found at your local library or online: <http://www.privacy.gov.au/>) and also Facebook.com Policies and Terms of Services (which can be found online: <http://www.facebook.com/legal/terms> and <http://developers.facebook.com/policy>).

Do I have to participate in this study?

Participation in this study is completely voluntary. If you wish to participate, simply click the provided URL and then you can join the study by approving our Facebook application. After approving the application, we will be able to fill out the survey. More detailed information will be provided in each step.

How can I withdraw from participation?

Participation in this study is completely voluntary and you can withdraw from participation in any time by removing the application and we will remove your data from our database as you wish.

Further Information

We will be happy to answer any questions you may have about the questionnaire or about the study in general. Please address your queries to:

Ms. Mahin Raissi, PhD student in Australian Demographic & Social Research Institute, ANU College of Arts and Social Sciences
Tel: +612 612 55655
Email: mahin.raissi@anu.edu.au

Dr. Robert Ackland, Associate professor, Australian Demographic & Social Research Institute, ANU College of Arts and Social Sciences
Tel: +61 2 6125 0312
Email: robert.ackland@anu.edu.au

Dr Heather Booth, Associate professor, and SNAP project leader, Australian Demographic & Social Research Institute, ANU College of Arts and Social Sciences
Tel: +61 2 6125 4062
Email: heather.booth@anu.edu.au

What if I have concerns or complaints?

The ethical aspects of this study have been approved by the Australian National University Human Ethics Committee. If you have any concerns about the way the study is conducted, or about your rights as a study participant, you may contact the ANU Human Ethics Committee at: ANU Human Ethics Committee, Research Office, Innovations Building No 124, ANU, Canberra, ACT 0200. Tel: 02 6125 3427. Email: human.ethics.officer@anu.edu.au

Thank you for considering this study

If you wish to take part, please click on the bellow URL:

<http://auson.anu.edu.au>

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