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Happy To See You?

How social networks and negative ties affect subjective wellbeing

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1 Introduction

In 2022 happiness stalled at an all-time low, according to a global survey (Ray, 2023). Since the global COVID-19 pandemic, the survey showed a drop in positive emotions and experiences indicating a lower happiness. The global pandemic that started in 2019 led to a lot of social distancing and lockdowns. This in turn was detrimental for feelings of loneliness and depression (Palgi et al., 2020). By being secluded from the outside world and one's personal network, social isolation took its toll on many people. These events have strongly renewed perspectives on loneliness and happiness, especially in terms of personal social networks. The availability of one's social network can be influential for their feelings of happiness, or subjective wellbeing. This study therefore analyses the influence of one's network size and negative ties on their subjective wellbeing and compares these effects between young adults and old adults from the San Francisco Bay area.

Happiness in academic research is often called subjective wellbeing, and is not simply an emotional state, but rather a multidimensional concept. The people that we know can play a large role in our subjective wellbeing, and as up to a third of the elderly is lonely (World Health Organisation, 2021), the question arises whether social support networks influence the young and the old in similar ways. Existing research indicates that a larger network is associated with a higher subjective wellbeing (Burt, 1987; Small, 2013). However, some also indicate that properties of the relationships in a network are more indicative of wellbeing outcomes (Perry & Pescosolido, 2010). The influence of negative network ties has recently gotten some attention (Offer, 2020), but has not been studied extensively. It is therefore important to expand the existing academic interest in the effects of negative ties and social support networks on subjective wellbeing.

The aim of this thesis is exactly that: to find out how social support networks of young and old adults influence their subjective wellbeing and what the role of negative ties in these networks might be. In order to study this, data from the University of California Berkeley Social Networks Study (Fisher, 2019a) is used to investigate the relationship between social network size, negative ties, age and subjective wellbeing. In doing so, other variables are taken into account such as gender and educational level. If a social network has the ability to affect one's subjective wellbeing in a positive way, can it also do this in a negative way?

The existing views and studies on the topics are assessed in chapter 2, leading to three hypotheses. Chapter 3 consists of the methodological explanation of the data, variable operationalizations and analysis. The results of the analysis are discussed in chapter 3. Finally, the findings are discussed in chapter 4, which also includes a discussion of the limitations of the study and suggestions for future research.

2 Theoretical framework

2.1 Subjective wellbeing

Subjective wellbeing is a concept that is used as a way to understand a person's quality of life (Andrews & Robinson, 1991). Different terms are often used interchangeably to study different concepts that are similar to each other, like happiness or life satisfaction. Academic interest in wellbeing has been categorized in two streams, namely *emotional wellbeing* and *eudemonic wellbeing* (Magyar & Keyes, 2019). While the two are separate concepts, they do have a degree of overlap (King & Hicks, 2007). Research into eudemonic wellbeing, which is also called *psychological wellbeing*, investigates how a person functions in their life. It includes aspects of life such as social integration, personal growth, and autonomy (Magyar & Keyes, 2019). Research into emotional wellbeing, also called hedonic or *subjective wellbeing*, investigates how a person feels. It measures the perception of one's life (Magyar & Keyes, 2019) which is often subdivided into three components: positive affect, negative affect and life satisfaction (Diener, 1984; Andrews & Robinson, 1991; Diener, Lucas & Scollon, 2006; Diener & Ryan, 2009). Since this thesis focusses on the mental health aspect of wellbeing, the concept of subjective wellbeing is used as a variable that is measured through observations the various components. Different methods for the measurement of subjective wellbeing are discussed at the end of this section.

The affect system is argued to be a system that is in place in organisms to stimulate actions of approach and withdrawal (Watson et al., 1999; Fredrickson, 2001). The personal experiences that follow from an interaction or event can stimulate someone to either approach or continue these actions, or to avoid similar outcomes by withdrawing from similar interactions or events (Cacioppo, Gardner & Berntson, 1999). The affect system is seen as a biologically evolved system that increases chances of survival (Watson et al., 1999). In humans, survival chances may be increased by stimulating behavior such as cooperation or sexual interaction with other humans and finding food and water. Experiences that follow from such events are called *positive affect*. At the same time, survival chances may be decreased by being hungry, having conflicts with others, or the absence of shelter, which are associated with *negative affect*.

Positive affect refers to the experiences of positive emotions, physical sensations or moods that are consciously accessible (Fredrickson, 2001). It includes reactions to favorable experiences in a range of positive emotional states, such as joy, pride, enthusiasm, hope and excitement (Carver & Scheier, 1990; Stiglitz, Sen & Fitoussi, 2009). Positive affect is an important part of overall wellbeing, as it can lead to positive personal outcomes such as a higher self-esteem (Hewitt, 2017), prevention of depressive feelings (Fredrickson, 2003) and physical health benefits like higher resistance to illness (Naragon-Gainey & Watson, 2019). The presence of positive affect is a sign that appropriate resources for survival are in place, in other words when a person can flourish. The trait of positive affect in a person therefore has a positive influence on their subjective wellbeing, since it indicates that good things are happening to the individual.

Negative affect are the emotions, physical sensations or moods that follow from interactions and events that lead to an undesirable outcome, such as pain or punishment (Naragon-Gainey & Watson, 2019). Examples of negative affect are the physical sensation of pain or hunger, and the feeling of fear or anxiety. If the presence of positive affect is associated with a higher subjective wellbeing, the presence of negative affect must be associated with a lower subjective wellbeing. Although this seems logical, it is not universally agreed upon.

Negative affect is a part of the affect system, but while seemingly the opposite of positive affect, this might not be the case. It has been argued that the affect system does not exist as a linear concept, but that it is on a circumflex plane (Russell & Barrett, 1999; Watson et al., 1999; Barrett, 2017). Therefore, there is discussion on whether the presence of negative affect has a negative influence on subjective wellbeing (Magyar & Keyes, 2019; Kasdan, 2015; Barrett, 2017). For example, earlier studies have indicated that the experience of negative affect can improve regulation of emotion (Kashdan, Barrett & McKnight, 2015), while others associate negative affect with the occurrence of negative events and thus a lower wellbeing (Carver & Scheier, 1990; Veenhoven, 2008). Since positive and negative affect are not directly correlated with each other, some experiences can have both positive and negative affect as a result. In subjective wellbeing research it is still accepted that negative affect influences subjective wellbeing in a negative way (Veenhoven, 2008; Diener & Ryan, 2009; Magyar & Keyes, 2019). The ratio between positive and negative affect is then an important indicator for subjective wellbeing.

The final component of subjective wellbeing, according to the emotional wellbeing stream, is life satisfaction. Where the affect system is the emotional component of wellbeing, life satisfaction is the cognitive component (Andrews & Robins, 1991; Veenhoven, 2008; Kainulainen, Saari & Veenhoven, 2018). It is a cognitive component because a person considers the difference between their lived life and their ideal life (Kainulainen, Saari & Veenhoven, 2018). However, Veenhoven (2008) states that life satisfaction is also in part influenced by the way someone feels at the moment of considering their life satisfaction. It must therefore not be seen as purely cognitive, but in part also emotional (also see Andrews & Robins, 1991). The distinction of life satisfaction as the cognitive component of subjective wellbeing is still a widely accepted view (Diener, 1984; Andrews & Robins, 1991; Veenhoven, 2008; Magyar & Keyes, 2019), but should be looked at with a degree of nuance.

The relationship between subjective wellbeing and age has not been uniformly proven. While physical wellbeing decreases with age – loss of muscular and skeletal mass due to aging is called sarcopenia (Delmonico & Beck, 2016) – subjective wellbeing does not correlate naturally with age. Some research has indicated that subjective wellbeing is stable over age, and only changes at old ages over 80 years old (Diener & Suh, 1997; Hansen & Slagsvold, 2012). While Diener & Suh (1997) argued that only the composition of subjective wellbeing changes, but not the outcome of subjective wellbeing, Hansen & Slagsvold (2012) argue that subjective wellbeing increases at very old age. More recent research (López Ulloa, Møller & Sousa-Poza, 2013; Blanchflower, 2021) indicates that the relationship between age and subjective wellbeing is U-shaped. This means that there is no difference between young and old people, but that there is a dip in subjective wellbeing in middle age.

While there is debate on whether subjective wellbeing changes with age, there are also similarities in the literature that suggest a consensus among the cited studies: that subjective wellbeing is similar among young and old adults until 80 years. Similarly, the importance of networks for one's subjective wellbeing also decreases after the age of 80 (Litwin & Stoeckel, 2013). This thesis aims expand the knowledge on age groups that do not seem to differ in subjective wellbeing by researching young adults of 21-30 years old and old adults of 50-70 years old. The very old are not taken into equation, nor are those in mid-life. The aim of this thesis is therefore to answer the research question:

> ***To what degree do differences in social support networks between young and old adults influence their subjective wellbeing?***

2.1.1 Measurement of subjective wellbeing

Subjective wellbeing has been measured in many different ways. There does not seem to be a standard that is widely used, although many applications of subjective wellbeing measures adhere to similar principles. One of the first measures of subjective wellbeing was done by Cantril (1965), by using an eleven-step ladder which he called the self-anchoring scale. Respondents were asked to respond by pointing at a number between zero and ten when asked questions about their perceptions, values and goals. Zero indicated a value like low, bad or not at all, and ten indicating a value such as high, good or completely (Cantril, 1965). Scales with similar order are still regularly used to measure subjective wellbeing (Andrews & Robins, 1991; Magyar & Keyes, 2019). When looking at components of subjective wellbeing, scales with multiple items show a higher reliability and validity compared to single-item measures (Diener, 1984; Andrews & Robins, 1991), although the attention span of respondents must be considered.

Questions regarding the affect system are focused on feelings that a person has had in the recent past (Magyar & Keyes, 2019). These questions are aimed at feelings in the past few weeks in order to question experienced feelings rather than a general idea (Diener et al., 2010) and are often multiple questions with scale answers. The component of life satisfaction is questioned with more general questions about one’s life, such as one’s satisfaction with life and the distance of their current life situation to an ideal life (Diener et al., 1985).

2.2 Aging and networks

As people transition through different life stages, their social networks change. One's social network size increases from adolescence into young adulthood, but in old adulthood network size decreases or stagnates (Bruine de Bruin, Parker & Strough, 2020; Fung et al., 2001; Weiss et al., 2022; Wrzus et al., 2013). In this thesis young adults are defined as people aged 21-30 years old and old adults are defined as 50-70 years old, although these age ranges may differ in cited studies. Younger adults typically have larger social networks that are still developing due to factors that increase the possibilities of meeting new people. They include, but are not limited to, finishing their education, career development, and settling down with a partner (Weiss et al, 2022). Research also suggests that the difference in online social networking might influence the difference in network sizes between young and old adults (Chang et al., 2015; Ping Yu, Ellison & Lampe, 2018).

Older adults often see their social network size decrease due to life course transitions. This reduction can be attributed to factors including retirement, children moving out, divorce and deaths in the network (Weiss et al., 2022). The quality of the social relations of older adults becomes increasingly more important as the quantity shrinks. While the overall size of the network of older adults decreases, the amount of close social ties does not always change (Fung et al., 2001; Bruine de Bruin, Parker & Strough, 2020). These close social ties can contribute to the wellbeing of older adults, as research indicates that the presence of close friends is especially important for old adults when it comes to their perception of life quality (Rafnsson, Shankar & Steptoe, 2015; Beller & Wagner, 2018; Ali et al., 2023). Based on these theoretical insights, I hypothesize that

H1: Young adults have a larger social network than old adults.

One of the risks of the smaller network sizes of older adults is the higher likelihood of social isolation and loneliness (Barjaková et al., 2023; Böger & Huxhold, 2018). Social isolation and loneliness are topics that are important to understand and mitigate, since they have negative effects on the wellbeing of individuals, both mental and physical (Machielse, 2006; World Health Organisation, 2021). Similarly, increases in network size and frequency of contact have a positive effect on the subjective wellbeing (Baxter et al., 1998; Cornwell & Laumann, 2015; Rafnsson, Shankar & Steptoe, 2015). Social interactions can thus influence the affect system as well as the overall life satisfaction. The connection between social support networks and subjective wellbeing will be further discussed in the next section.

2.3 Social support networks

Social support is the help that one gets from the social ties that are in their network. Different types of social support are identified in the literature. While some definitions are open to discussion, there is a general consensus on the main types of social support, including emotional support, informational support, and tangible support (Barrera & Anlay, 1983; Uchino, 2004).

Emotional support encompasses interactions where individuals can discuss intimate matters, such as personal problems they may be experiencing in their lives (Berkman et al., 2000). Informational support refers to the exchange of information, such as advice seeking interactions and exchanging information that can help a person solve specific problems (Weiss, 1974; Schaefer, Coyne & Lazarus, 1981). Tangible support indicates a form of help in which time or resources are offered up to help someone. Tangible support is sometimes also called instrumental support, examples of which are caring for a sick friend or family member, loaning money, or doing chores for someone (Weiss, 1974; Schaefer, Coyne & Lazarus, 1981).

The mobilization of these resources is determined by accessibility to a social network (Burt, 1987; Lin, 2001; Cohen, 2004; Pena-López & Sánchez-Santos, 2017). A larger network increases the possibility and probability of utilizing the network resources necessary for improving subjective wellbeing. A study by Small (2013) shows that the strength of ties in the network are not necessarily important when resources are to be accessed, the availability of the resources were found to be more important. Therefore, the network size becomes an important factor when utilizing one's social network for support.

According to early network research by Burt (1987), subjective wellbeing is influenced by network size rather than the number of close ties. However, more recent studies suggest a contrary perspective, emphasizing that the nuances within a network have greater impact on personal outcomes than the broad concept of network size. For example, the type of information that is discussed within topic-specific networks (Perry & Pescosolido, 2010) or the geographical location of ties (Moore et al., 2018) has been found to be better predictors of personal outcomes than network size alone. Nevertheless, based on the existing literature the second hypothesis is:

H2: A larger network is associated with a higher subjective wellbeing.

2.3.1 Negative ties

Social network support has been studied thoroughly by investigating the advantages of being connected, but only more recently the negative side of social ties has gotten attention (Uchino, 2004; Labianca & Brass, 2006; Offer, 2021). Social network research into negative ties is important because the effect of being connected to a negative tie can influence the effect of social support on wellbeing outcomes (Uchino, 2004; Brooks & Dunkel Schetter, 2011; Offer, 2020). Social negativity is defined as connections who are a source of conflict, insensitivity and interference (Brooks & Dunkel Schetter, 2011). Research by Offer (2020) has shown that being connected to a negative tie can have a similar effect to not being connected: it can cause loneliness and stress. Loneliness and stress are examples of negative affect and are therefore associated with a lower subjective wellbeing.

Research in psychology has shown that negative events may have a greater cognitive effect compared to positive events (Taylor, 1991), which begs the question if this might also be true for negative and positive ties in a network. Having a social support network can be a buffer for experiences of negative ties (Unicho, 2004; Brooks & Dunkel Schetter, 2011; Offer, 2020). This means that the effect of negative ties on wellbeing outcomes is moderated by the support network. However, little research has been done on the opposite moderating effect, leading to the final hypothesis:

H3: The number of negative ties in the network negatively moderates the relationship between social support and subjective wellbeing.

The effect of negative ties on the subjective wellbeing may be partly within the influence of the ego who experiences the effect: networks change, and ties can be dropped. According to Fisher and Offer (2020), those who are seen as negative ties are the most likely to be dropped by an ego. However, negative ties can also become neutral or positive ties, for example when they begin to offer positive support to the ego (Kyemereh & Schafer, 2024). The way a person deals with the negative ties in a network can thus be within one's own reach.

However, negative ties that are also relatives are unlikely to be removed from a social network (Fisher & Offer, 2020). The fact that ties are family appears to be more important than a negative sentiment that comes with that tie. Negative ties are as often as not relatives (Kyemereh & Schafer, 2024), indicating that about half of the negative ties one has in their network are unlikely to be dropped at all. The effect of these negative family ties can therefore only be diminished when turned into positive or neutral ties.

3 Methods

3.1 Research design and sample

This study uses data from the first wave of the University of California Berkley Social Networks Study (UCNets). The UCNets is a panel study which contains three waves: from 2015, 2017 and 2018. This thesis uses the data from the first wave. Data was collected in six different counties of the San Francisco Bay Area in the United States. Furthermore, sampling was focused on two age groups that are most likely to experience life transformations. These groups are young adults, from 21 to 30 years old and old adults from 50 to 70 years old (Fisher, 2019a). For the interviews only English and Spanish speaking people were considered to partake in the survey. Protocols around ethics were directed by Dr. L.E. Lawton, although specifics are not available in the documentation (Lawton, 2022).

The survey uses a stratified sample design. Three strata were defined based on geographics, the strata being city, inner suburban and outer suburban. The city centers of the San Francisco Bay Area, San Francisco, Oakland and San Jose are denominated as city. Suburban areas within 25 miles of these city centers are denominated as inner suburban, and outer suburban areas are those further than 25 miles from these city centers (Fisher, 2019a).

120 census tracts from the 2010 United States Census were chosen randomly in the three geographical strata. In each tract, around 100 addresses were selected, proportional to the population of the tract. From these addresses a random selection of 30 addresses was used for the sample. After the survey weighting was used in order to be able to generalize the sample to the San Francisco Bay Area's English-speaking population (Fisher, 2019a).

Two main sampling methods were used for the UCNets: address-based sampling (ABS), as described above, and sampling through online advertisements on Facebook. ABS was used as the main sampling method, using address lists from the United States Postal Service that were obtained through a third party. Letters were mailed to approximately 50.000 potential participants with an invitation to partake in the survey. Not all of those who received the letters were eligible to partake in the survey. The corrected response rate for eligible recipients of the mailings was 7.72%. For the sake of contrast, the 2021 General Social Survey in the United States yielded a response rate between 12.6 and 14.2% (Davern et al., 2021). The total valid response of the first wave of the UCNets ABS was N = 834 (Fisher, 2019a).

The ABS method failed to reach a sufficient number of respondents in the age group of 21-30 years old. To reach these younger respondents, online advertisements were used via Facebook. The advertisements were seen by about 420.000 people, of whom 3.207 clicked the advertisement. 878 people started the enrollment, 433 started the survey and 290 people completed the survey. The response rate of the online advertisements is not calculable, since it is unknown how many of those who saw the advertisement were eligible to partake in the survey: they were sampled with non-random criteria (Fisher, 2019a). Finally, 35 respondents were reached through referrals from participants who partook through ABS or online sampling.

The first wave of UCNets' surveys was conducted in 2015-2016 and has a total valid response of N = 1159. The sample consists of 485 respondents aged 21-30 years old and 674 respondents aged 50-70 years old. From the age group 21-30 years old 78% took the web survey, in contrast to the age group of 50-70 years old where 26% took the web survey (Fisher, 2019a). The rate of completion of the participants that started the survey was highest amongst those reached through ABS at 94% and lowest amongst participants reached through Facebook advertisements at 67% (Fisher, 2019a).

3.2 Instruments

Two instruments were used in the data collection of UCNets: a screener and the main survey. In the ABS method the screener was taken by calling a free phone number. The caller was then asked whether there were persons in their household in the relevant age groups. If more than one person in the household was qualified for the survey, one of them was randomly picked by a program. If only one person qualified, that person was picked. The screener then asked the selected person for general information and contact information. The selected person was also asked if they would be willing to take the survey online. The selected person was also asked which day and time might be convenient to be interviewed face-to-face. People who were reached through online advertisements took the same screener on their device (Fisher, 2019a).

Surveys were either taken face-to-face (FTF) or via web surveys, for the ABS sampling 25 % of respondents were directed to the web survey. The respondents who were reached through online advertisements all took the web survey. The survey took around one hour to complete, and an incentive of $25 was given to respondents of the first wave. The second and third waves were accompanied with higher monetary incentives of respectively $35 and $50. The main survey asked for demographic information, followed by sections about the network of the participant. Other questions concerned life events, physical and mental health, and internet use. The interviewer also noted down ratings about the respondent on behavior, appearance, and interview settings (Fisher, 2019a).

3.3 Analytical design

A statistical analysis will be performed using the statistical software SPSS. The hypotheses will be tested by executing a hierarchical multiple linear regression analysis. The stepwise model specification is used to check the influence of the independent variables on the dependent variables by entering variables in the model one by one. The data will be inspected by performing a linear regression analysis with the forward method, which forms a model in which the variables that explain the most variance are added to the model first, followed by those that explain increasingly less variance. Based on these inspections and the theory, the order of model building for the stepwise method is determined.

The first hypothesis will be tested by comparing the age groups of young adults and old adults on their network sizes. To determine if there is indeed a difference in network size between the age groups, an independent sample T-test will be performed. The second and third hypotheses are tested by inspecting the regression models.

The hierarchical regression analysis will be executed using the stepwise method. In the first model only the dependent variable of subjective wellbeing and the independent variable of network size are added. In the second model the control variables gender, education and age are added. In the third model the variables of negative ties and age group are added. The fourth and final model is completed by adding the interaction terms for network size with negative ties and residual age with age group.

Assumption checks will be done for the regression, such as a multicollinearity check and a check for homoscedasticity, these are described in Appendix 2.

3.4 Measurements and operationalization of concepts

A hierarchical multiple regression analysis will be executed to test the hypotheses. The variables that will be used to test the hypotheses are described in this section. Two datasets of the UCNETS will be used: the data on the ego-level and the data on the alter-level. The relevant syntax for transformations, inspections of the variables and analyses can be found in Appendix 3. The survey distinguishes two age groups that will be used, namely younger adults and older adults. Respondents aged 21-30 years old are coded as 0 and respondents aged 50-70 years old are coded as 1. No recoding was needed to use the age variables.

3.4.1 Social network size

Multiple questions regarding the personal networks are present in the dataset. Name generator questions were asked to the respondents about emotional support, advice seeking, practical support, health support and social activities. The respondents are *egos* and the network members, who are named by respondents are called *alters* (Borgatti, Everett & Johnson, 2018, pp. 28). However, estimating the network sizes will not be done by adding up the number of names named for these questions, since there might be duplicates in the different answer categories. Data about the alters is stored in a separate dataset (36975-0001, hereafter 'alters dataset'). In the alters dataset corrections were made for duplicates and missing data, it is therefore more trustworthy and chosen to be used for estimating the network size of respondents (Fisher, 2019b, p. 60).

The alters data contains the unique identifiers of the respondents, as well as unique identifiers for each alter. An aggregation was made of the unique identifiers of all alters per respondent. The sum of alters per respondent was put into a new variable which represents the network size. This variable has a minimum score of 1 and a maximum score of 45, showing that the largest network that was named by a respondent consists of 45 alters. All respondents named at least one alter in their network.

Finally, the variable is centered by subtracting the mean from each value. This is necessary for it to be viable for use in an interaction term, so a possible moderation can be analyzed.

3.4.2 Subjective wellbeing

The survey includes a Kessler Psychological Distress Scale (Kessler et al., 2002), two items from the PTST-Checklist for Civilians, or PLC-C for short (Weathers et al., 1994) and two items about positive feelings. Respondents were asked how often in the past 30 days they felt certain ways. Kessler's scale consists of six items that assess psychological distress by asking how often in the past 30 days respondents had felt *nervous; hopeless; restless or fidgety; so depressed that nothing* *could cheer you up; that everything was an effort; worthless.* These items represent negative affect. The items from the PLC-C asked how often respondents had felt *irritable or had an angry outburst* and how often they were *bothered by repeated, disturbing memories, thoughts, or images of a stressful experience from the past?* These items also represent negative affect. The items about positive feelings asked how often in the past 30 days the respondents had felt *hopeful about the future* and *that you enjoyed life*, they represent positive affect.

For eight of the ten questions, namely the Kessler scale items and the PLC-C items, a higher score indicates a higher degree of psychological distress. The two questions about positive feelings are formulated in a way where a higher score indicates a higher degree of positive feelings. The answer categories of the two deviant items are therefore mirrored. An explanatory factor analysis was used to check for unidimensionality, with list-wise deletion of missing values to correlate the same respondents' answers with each other. Ideally only one item would have an eigenvalue higher than one. The results of the factor analysis show two values higher than one, namely 1.124 and 4.706. Since one of the exceeding values is nearly one, unidimensionality among the items is assumed and one factor is extracted to represent subjective wellbeing.

The Cronbach's alpha of the scale variable is 0.866. Deleting any of the items would decrease the Cronbach's alpha. An extra item about self-reported happiness was assessed to represent life satisfaction, but this item did not address long-term life satisfaction since it asked about the previous seven days. Adding this item to the scale also did not increase the trustworthiness, it was therefore not included.

Correlations between the items of the scale are all significant at $p = 0.001$ and reach from $r = 0.129$ to $r = 0.669$, with most correlations being higher than $r = 0.380$. The scale variable was then created by computing the mean of the ten items. The new variable ranges between 1.3 and 5, with an average score of 3.98 and a standard deviation of 0.63. The variable has no missing values.

3.4.3 Control variables: age, gender, and education

Each respondent was asked their date of birth, and the date of the interview was noted down as well. From these data a new variable was created that shows the exact age of the respondent at the time of the interview in years with decimals. This variable will be used as a control variable. The gender of the respondents was asked and coded as 1 = male and 2 = female. In order to use gender as a control variable, it was recoded into a dummy variable where 0 = male and 1 = female.

The level of education of the respondents is a variable with ten answer categories, of which one is 'other'. The answers to 'other' are hidden in the dataset, making the 32 answers to this question unusable for statistical analysis. They will therefore be coded as missing values. The other nine categories are combined to form a final 3 categories: lower than bachelor's degree, bachelor's degree and higher than bachelor's degree, respectively coded as 0, 1 and 2.

3.4.4 Negative ties and interaction terms

Negative ties were measured in the survey by asking the respondents if there were people in their network who they consider demanding or difficult. There was space for six such alters to be named. The variable that counts these demanding alters therefore has a reach from zero to six. The variable on negative ties will be used as a continuous variable.

In order to use the variable in an interaction term, it needs to be centered. This is done by subtracting the mean from all values. The interaction term is calculated by multiplying the centered variables for network size and negative ties. Another interaction term was created for age and age group by multiplying the residual age of respondents with their dummy code for age group.

4 Results

4.1 Univariate descriptive statistics

The univariate statistics of the variables are shown in Table 1, where they are distinguished per age group. The average network size of young adults between 21-30 is 18.52, nearly two alters larger than the average of old adults, which is 16.89. The largest networks of young and old adults consist of 41 and 45 alters respectively, while the minimum for both age groups is one alter.

The scale variable for subjective wellbeing has a reach from 1.30 to 5.00 when looking at both age groups. The average on subjective wellbeing is higher for old adults, contrary to expectations. The significance of this difference will be discussed in further chapters. Subjective wellbeing shows a distribution skewed to the right: on average, respondents show few signs of psychological distress, which indicates a high subjective wellbeing.

The average age among the young adults is 26.15 years old. Among old adults the average age is 61.37 years old. Most respondents are between 50 and 70 years old, namely 58.2%. The distribution of gender among both age groups is relatively equal, with over 60% females in both age groups. In total 65.9% of the sample is female.

The distribution of educational level approaches a normal distribution among young people, with 53.6% of them having reached a bachelor's degree and the rest of the respondents almost equally distributed between lower than a bachelor's degree and higher than a bachelor's degree. Educational level among old adults is more evenly distributed, as shown in Table 1.

Table 1: Descriptive statistics of the variables

Variable	**Mean (*SD*)[a]**		**Minimum**		**Maximum**		**Non-response %**	
Age group cohort	**21-30**	**50-70**	**21-30**	**50-70**	**21-30**	**50-70**	**21-30**	**50-70**
Network size	18.52 (*7.18*)	16.89 (*7.26*)	1	1	41	45	0.2%	0.3%
Subjective wellbeing	3.75 (*0.64*)	4.15 (*0.57*)	1.30	1.70	4.90	5.00	0.0%	0.0%
Age	26.15 (*2.71*)	61.37 (*5.96*)	21.00	50.00	31.00	70.92	0.0%	0.0%
Negative ties	1.47 (*1.40*)	1.23 (*1.26*)	0	0	6	6	0.0%	0.0%
Gender	31.3% 68.7%	36.1% Male 63.9% Female					0.0%	0.0%
Education	23.3% 53.6% 21.6%	28.8% Lower than bachelor's degree 33.1% Bachelor's degree 33.5% Higher than bachelor's degree					1.4%	4.6%

[a] For categorical variables the distribution in percentages is shown

4.2 Multivariate linear regression analysis

A hierarchical multivariate regression analysis was performed where four models were built using the stepwise extension of the model specification, with which one can add variables at will in the next model. The model building is shown in Table 2. The final model, containing all variables, has the best model fit with an adjusted R^2 that indicates 16.6% of the variance in subjective wellbeing is explained by the independent variables in model 4. The standard error of the estimate shows that the perceived values for the dependent variable come closer to the predicted variable when more independent variables are added to the model.

Table 2: Summary of the modelbuilding with the explanatory power of the models, with subjective wellbeing as the dependent variable

Model	R^2	Adjusted R^2	Standard Error of the Estimate
1: Network size	0.6%	0.5%	0.627
2: Network size, gender, education, age	13.8%	13.5%	0.584
3: Network size, gender, education, age, negative ties, age group	15.8%	15.3%	0.578
4: Network size, gender, education, age, negative ties, age group, interaction network size ∗ negative ties, interaction residual age ∗ age group	16.6%	16.0%	0.576

H1: Young adults have a larger social network than old adults.

To test the first hypothesis, an independent samples T-test was done to compare the means of the network size of young and old adults. The test uses the null hypothesis that there is no difference between the age groups, the alternative hypothesis states that there is indeed a difference between the age groups when it comes to their network size. The mean network size of the age group 21 – 30 years old is 18.52 (SE = 7.18, N = 484) and the mean of the age group 50 – 70 years old is 16.89 (SE = 7.26, N = 672). This indicates that there is a difference in network sizes between the age groups, with young adults having larger networks.

In order to find out if the difference is significant, the T-test must be executed and interpreted. The results of the equality of variance test show that the variances of the two groups should be assumed to be equal, with $F = 0.019$ and $p = 0.890$. The T-test with equal variances assumed results in the test values of $t = 3.782$ and $p < 0.001$. The null hypothesis of this test is therefore rejected, showing a significant difference in network sizes. The average network sizes of young and old adults therefore differ from each other at a 95% confidence level. Support for the first hypothesis is found.

H2: A larger network is associated with a higher subjective wellbeing.

To test the second hypothesis, numerous regression models were assessed. Four final regression models were built with the stepwise method, the results of which are displayed in Table 3. The first model only includes the dependent variable of subjective wellbeing with network size. The second model also includes the control variables gender, education and age in years. The third model includes the variables for negative ties and age group, and in the fourth model the interaction terms are added

Based on the second model, the coefficient of network size of b = 0.010, which is significant at $p < 0.001$, indicates that there is a positive and significant effect of network size on subjective wellbeing among both age groups when controlling for gender, education and age. A 30-year-old male with no bachelor's degree or higher and no social network, has an average subjective wellbeing of $3.361 + 30 * 0.012 = 3.721$, with every social network tie that is added to his network the subjective wellbeing increases with b = 0.010 ($p < 0.001$). If this 30-year-old male would have the maximum network of 41 alters his subjective wellbeing would be around 10% higher compared to having the smallest network of 1 alter.

In models 3 and 4 the effect of network size on subjective wellbeing remains positive and significant when adding variables of negative ties, age group and the interactions. These findings show support for the second hypothesis: a larger network is indeed associated with a higher subjective wellbeing.

Table 3: Coefficients of the model estimations with subjective wellbeing as dependent variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
	b (SE)	***b (SE)***	***b (SE)***	***b (SE)***
Constant	3.981*** (0.019)	3.361*** (0.083)	3.324*** (0.117)	3.648*** (0.269)
Network size	0.007** (0.003)	0.010*** (0.002)	0.013*** (0.003)	0.012*** (0.003)
Gender		-0.020 (0.037)	-0.008 (0.037)	-0.006 (0.037)
Education		0.070** (0.024)	0.060* (0.024)	0.066** (0.024)
Age in years		0.012*** (0.001)	0.014*** (0.004)	0.001 (0.010)
Negative ties			-0.068*** (0.014)	-0.083*** (0.015)
Age group			-0.087 (0.131)	0.361 (0.358)
Interaction network size ∗ negative ties				0.005** (0.002)
Interaction residual age ∗ age group				0.014 (0.011)

* significant at $p < 0.05$, ** significant at $p < 0.01$, *** significant at $p < 0.001$

H3: The number of negative ties in the network negatively moderates the relationship between social support and subjective wellbeing.

The variables for negative ties and age group are added in model 3 and in model 4 the interaction terms are added. The direct effect of each extra negative tie in model 3 of b = -0.068 ($p < 0.001$) shows a negative effect of negative ties on the subjective wellbeing. While the effect of people in a network is still positive, this shows that were a person to become a negative tie, the decrease in subjective wellbeing is larger than the decrease would be when simply dropping the tie, which would be b = -0.013. Negative ties thus have a strong negative effect on subjective wellbeing compared to the positive effect of network size. For reference's sake, the person in the group of young adults with the largest network named 41 alters, making the positive effect of their network size on their subjective wellbeing $41 * 0.013 = 0.533$. If that person named the maximum of six negative ties the effect of negative ties on their subjective wellbeing would be $6 * -0.068 = -5.932$. Negative ties are thus a significant predictor of the subjective wellbeing.

The interaction variable as shown in model 4 in Table 3 shows a similar tendency. It is significant with b = 0.005 ($p < 0.01$). According to this final model, adding a new negative tie to one's network would alter the subjective wellbeing with (0.012 - 0.083 + 0.005) -0.066. A new negative thus as a negative effect on subjective wellbeing. If a negative tie is already in the network, their effect on the subjective wellbeing is (-0.083 + 0.005) -0.078. Because the coefficient of the interaction term has a smaller positive effect than the negative coefficient of negative ties is, these coefficients show support for the third hypothesis.

When considering changing or dropping negative ties for the sake of subjective wellbeing, changing a negative tie to a positive or neutral one is more beneficial for the subjective wellbeing than dropping the tie altogether. Dropping the tie would expel the negative effect but would also diminish the effect of the extra tie in the network, while changing the negative tie to a positive or neutral tie would expel the negative effect while keeping the positive effect of having the extra tie in the network. The effort it may take to transform the negative tie into a positive has not been taken into account in this equation.

Finally, it is important to look at the different effects between the age groups. The interaction term between residual age and age group tells something about this. This term shows the difference between young adults, which are the reference group, and the old adults. The positive coefficient of b = 0.014 ($p > 0.05$) suggests that the positive effect of age in this sample is even higher among the group of old adults compared to the group of young adults. However, since this effect is not significant interpretation and generalization of this results should be done with caution.

5. Discussion and conclusions

This thesis has sought to answer the question: '*To what degree do differences in social supports networks between young and old adults influence their subjective wellbeing?'* A quantitative research design with a hierarchical linear regression analysis was used to study network data.

The results from the network data show that the networks of young adults are significantly larger than those of old adults. These findings are in line with the literature that suggests that life transitions increase network sizes of young adults and decrease network sizes for old adults (Weiss et al., 2022). Although the difference is significant, the network sizes differ 1.63 person, where average networks are larger than 16 people. While the results support the hypothesis about network size differences, the difference is smaller than expected. Still, young adults have significantly larger social networks than old adults.

The association between network size and subjective wellbeing is found to be positive. This shows that people with larger social networks have a higher subjective wellbeing. The causality of this association has not been proven in this research, and both directions are quite possible. One could argue that a larger network makes a person happier, but it could also be the case that those who are happier have an easier time making and maintaining friendships. Future research could research the causal direction between these variables. What should be taken away from this research is that those with a larger network also have a higher subjective wellbeing. For old adults, the effect of network size on subjective wellbeing is even larger than for young adults, indicating that one's social network becomes increasingly more important for subjective wellbeing at older age.

While the association between a large network and high subjective wellbeing may be established, the effects of the negative ties of a network have received less attention in existing research. The analyses in this thesis indicate that the negative ties someone has may have a larger influence on their subjective wellbeing than their overall network size. This shows that, although a network can be supportive, negative ties may have a larger or longer lasting impact on subjective wellbeing than positive or neutral ties. This is in line with earlier findings in different research fields that indicated that negative events have a longer lasting cognitive impact than positive events (Taylor, 1991). The impact of negative ties in a network is thus an interesting finding that might be deployed to increase subjective wellbeing.

Furthermore, the results from this analysis indicate that keeping a negative tie in the network is more demanding on the subjective wellbeing than dropping that tie. However, transforming a negative tie into a positive or neutral tie would yield the best results for one's subjective wellbeing, not taking into account the effort such a transformation would cost. While psychological research has focused on the impact of negative events (e.g. Kensinger, 2009), social network research may find interesting results when further studying the differences of positive and negative ties on the subjective wellbeing.

Future research may focus on the gap between positive and negative network influences and aim to learn from it for the sake of happiness and network mechanisms. The richness of the UCNets data leaves much room for further analysis of network processes. Life satisfaction, an aspect of subjective wellbeing, is unfortunately not available in this dataset. Future research may therefore also aim to indicate the validity of the subjective wellbeing measures compared to the theoretically founded measures. Finally, longitudinal facets of the data can be used to assess the causality between network measures and subjective wellbeing.

The results of this research have shown that the differences in support network sizes of young and old adults influence their subjective wellbeing, showing that young adults have larger networks, that a larger network size is associated with a higher subjective wellbeing and the importance of support networks for old adults. What is perhaps most interesting is that this research shows how negative ties in a social support network can have detrimental effects on subjective wellbeing: negative ties can have a larger negative effect on subjective wellbeing than the positive effect that the accessible network can have. This thesis has shown how networks can positively and negatively influence one's subjective wellbeing and can be used as a stepping stone in utilizing networks in order to optimize subjective wellbeing.

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Appendix 1: Operationalizations of the variables

In this appendix the variables that are used in the analysis are described. Most data that is used is from the first wave dataset which contains the answers of each respondent, called 36975-0005. However, this dataset does not contain identifying information for alters. Information about alters was put into a separate dataset, called 36975-0001. This dataset, the ‘alters dataset’, was used for calculating the network size, as described below. The other variables are from the first wave dataset (36975-0005).

Social network size

Respondents were asked seven name-generating questions containing different themes. The questions are:

Who do you typically do [social activities] with?

Who do you confide in about [personal matters]?

Whose advise do you or would you seek out?

Please give us the names of people who have [given you any practical help] in the last few months?

Who would [you ask for help if you were seriously injured or sick and needed some help]?

Who are the people that you help out practically, or with advice, or in other kinds of ways at least occasionally?

Who are the people that you sometimes find demanding or difficult?

Respondents could name up to six people for each category, with the exception of the question about social activities, for which up to nine people could be named. The sum of people for each question is taken up in the general first wave dataset, these variables have the code for the question followed with _count, (eg. b9a_count). However, since the same name could be named for different questions, there can be overlap in the name generating answers. The sum of these questions will therefore not be used to prevent duplicates.

For all the names that the respondent has given questions were asked about demographics of the **alters** as well as some biographical and geographical information in relation to the respondent. For a complete overview of the questions that were asked about the **alters**, see sections C and D of the Documentation (UCNets Documentation, 2019).

All information about the **alters** was saved in a separate dataset. This dataset was used to calculate the network size. All **alters** were given a unique identifier, matched with the unique identifier of their respective respondents. The unique identifier of the **alters** is called ID_W1_W2_W3 and the unique identifier of the respondents is called PRIM_KEY. An aggregation was made of these identifiers per respondent, resulting in a variable that contains the number of alters per respondent. This newly calculated variable is called ALTERS_COUNT, and was matched to the first wave dataset by matching the PRIM_KEY variable.

Subjective wellbeing

The variable of subjective wellbeing was calculated by using the Kessler's schale that was implemented in the survey by questions H.16.a to H.16.j. Then ten questions that comprise the scale are about how the respondent had been feeling during the previous 30 days. The questions are:

H.16.a. About how often during the past 30 days did you feel nervous?
H.16.b During the past 30 days, about how often did you feel hopeless?
H.16.c During the past 30 days, about how often did you feel hopeful about the future?
H.16.d During the past 30 days, about how often did you feel restless or fidgety?
H.16.e During the past 30 days, about how often did you feel irritable or have angry outburst?
H.16.f During the past 30 days, about how often did you feel so depressed that nothing could cheer you up?
H.16.g During the past 30 days, about how often did you feel that you enjoyed life?
H.16.h During the past 30 days, about how often did you feel that everything was an effort?
H.16.i During the past 30 days, about how often did you feel worthless?
H.16.j During the past 30 days, about how often have you been bothered by repeated, disturbing memories, thoughts, or images of a stressful experience form the past?

Respondents could answer the question with *1. All of the time; 2. Most of the time; 3. Some of the time; 4. A little of the time; 5. None of the time*.

The ten items were tested for internal scale validity, using the Cronbach's Alpha as a marker. The initial Cronbach's Alpha of the scale was 0.662. After mirroring items H.16.c and H.16.g, the Cronbach's Alpha was 0.866. Removing any of the items would negatively impact the Cronbach's Alpha.

The ten scale items were then computed into a new variable by computing the mean of the ten items. The new variable is named K10_wellb and has a reach between 1.3 and 5, with an average score of 3.98 and a standard deviation of 0.63.

Age

Multiple age variables are available, I have made the decision to use the age variable that uses age in years with two decimals as a control variable in order to get the most accurate results. The variable for age is called AGE_EX and does not need transformations.

Gender

The gender variable is called GENDER and has the values 1 = male and 2 = female. In order to use gender as a dummy variable it has been recoded to 0 = male and 1 = female.

Education

Respondents were asked *'What is the highest year or degree of schooling that you have completed?'*. The answer categories were *1. Less than 9th grade; 2. 9th grade to 12th grade, but did not graduate high school; 3. High school graduate; 4. GED or equivalent; 5. Some college; 6. Associate degree; 7. Bachelor's degree; 8. Master's degree; 9. Higher professional degree (like MD, JD, or PhD); 10. Other.*

For the tenth category of 'other,' the respondents were asked to explain or elaborate on their answer. The answers to this open question are hidden in the dataset. Therefore, the 32 answers to 'other' are coded as missing values.

The nine other categories are recoded into three new categories, where 0 = lower than bachelor's degree; 1 = bachelor's degree; 2 = higher than bachelor's degree.

Negative ties

The variable for negative ties is a name generating question that asks '*Who are the people that you sometimes find demanding or difficult?'*. Respondents could give up to six names in the answer to this question. If someone did not give up any names their answer was put into the variable B9A_NAS6. If names were given, the number of names was put into the variable B9_COUNT.

The original variable was centered for it to be useable in the interaction term of the regression. The mean value was subtracted from all values of the variable, creating the new variable Cent_Negative_Ties. The interaction term was then created by multiplying the centered variables for network size and negative ties, resulting in the interaction variable called AlterscountxNegties.

Appendix 2: Assumption checks for the regression analysis

Linearity

The residual plot in figure 1 shows a random cloud of points around the zero-line, which indicates that there is a linear relationship.

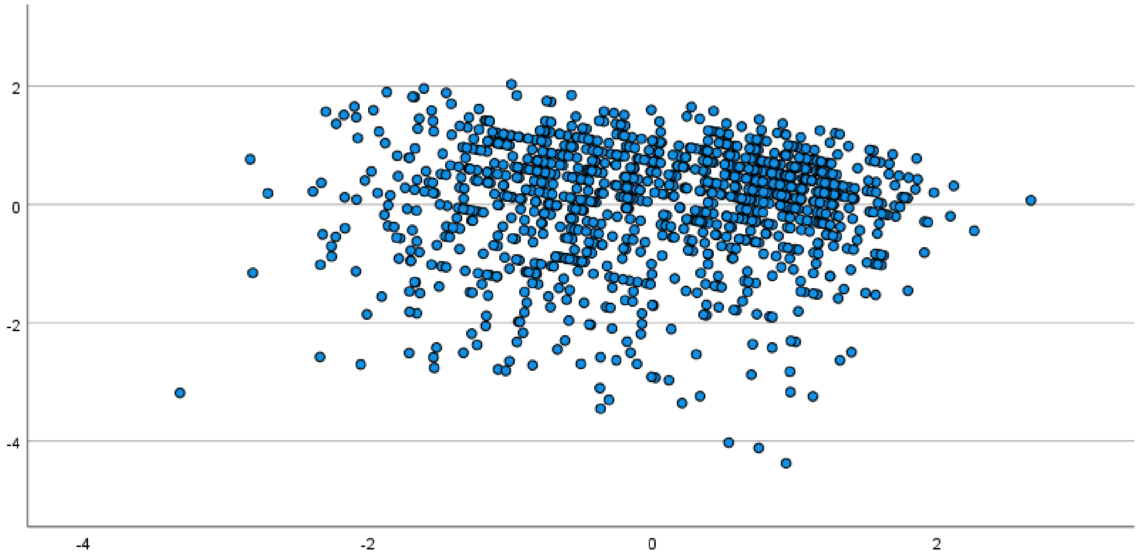

Figure 1: Scatterplot of the standardized residuals on the y-axis and the standardized predicted values on the x-axis, with subjective wellbeing as the dependent variable

Random sample

The sample was taken from the San Francisco Bay Area. People were randomly selected from U.S. Postal Service data. The online sampling cannot be said to be completely random, since only those who were on Facebook could enter the survey. This must be considered when interpreting the results of the regression analysis.

Normality

The assumption of normality is checked by assessing the P-P plot, which is shown in figure 2, and the histogram of the standardized residuals displayed in figure 3. These plots show a distribution that is slightly left-skewed, indicating that people are on average happier. The dependent variable is not completely normally distributed.

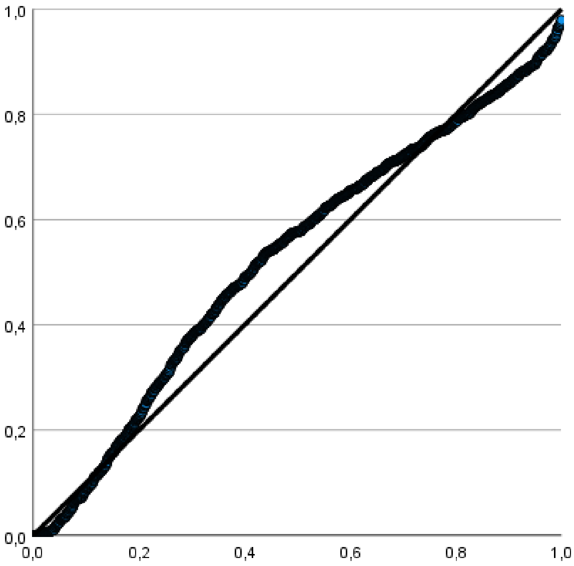

Figure 2: P-P plot of the standardized residuals with subjective wellbeing as the dependent variable

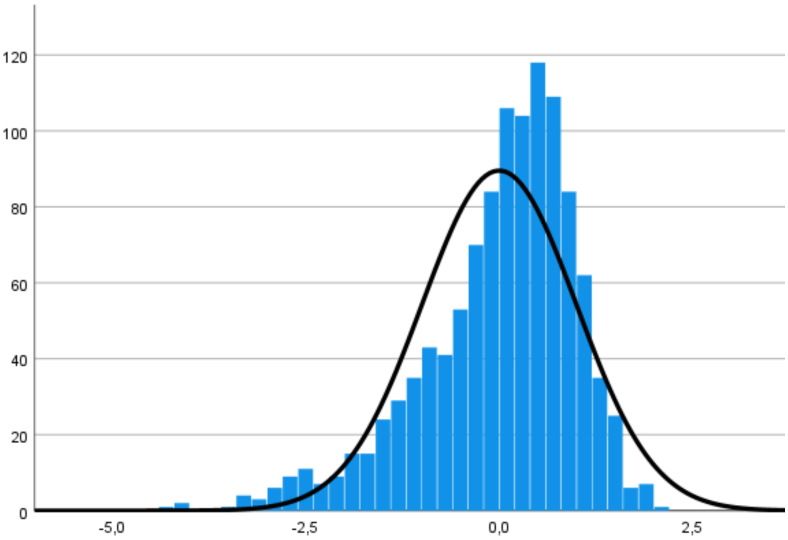

Figure 3: Histogram of the standardized residuals with subjective wellbeing as the dependent variable

Homoscedasticity

The scatterplot in figure 1 shows a random spread of points. There is no cohesion between the standardized residuals and the dependent variable, which is in line with the assumption of homoscedasticity.

Multicollinearity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,981	,019		212,508	,000					
	Cent_Alters_Count	,007	,003	,080	2,680	,007	,080	,080	,080	1,000	1,000
2	(Constant)	3,982	,018		215,733	,000					
	Cent_Alters_Count	,011	,003	,125	4,106	<,001	,080	,122	,121	,937	1,067
	Cent_Negative_Ties	-,085	,014	-,179	-5,887	<,001	-,148	-,174	-,173	,937	1,067
3	(Constant)	3,965	,019		210,371	,000					
	Cent_Alters_Count	,010	,003	,115	3,796	<,001	,080	,113	,111	,931	1,074
	Cent_Negative_Ties	-,105	,015	-,222	-6,868	<,001	-,148	-,201	-,201	,819	1,221
	AlterscountxNegties	,007	,002	,119	3,750	<,001	,054	,112	,110	,848	1,180
4	(Constant)	3,329	,117		28,535	<,001					
	Cent_Alters_Count	,012	,003	,138	4,727	<,001	,080	,140	,130	,878	1,139
	Cent_Negative_Ties	-,083	,015	-,175	-5,714	<,001	-,148	-,169	-,157	,798	1,253
	AlterscountxNegties	,005	,002	,087	2,920	,004	,054	,087	,080	,841	1,189
	exact age in years with decimals	,014	,004	,395	3,810	<,001	,341	,114	,104	,070	14,301
	Level of education	,058	,023	,070	2,475	,013	,127	,074	,068	,948	1,055
	gender	-,005	,037	-,004	-,143	,886	-,024	-,004	-,004	,979	1,022
	agegroup, numeric, 0 - younger group, 1 - older group	-,083	,131	-,066	-,637	,524	,321	-,019	-,017	,071	14,154

a. Dependent Variable: K10_wellb

Figure 4: Regression coefficients and VIF-scores

The VIF scores are shown in figure are all lower than 1, except for those on age group and age in years. There is high multicollinearity between these variables, but this was expected since both regard age. There is no abnormal multicollinearity among the variables.

Appendix 3: SPSS syntax

```
*Dataset = 36975-0001.
***NETWORK VARIABLE.
*Syntax for counting the number of ties for each ego variable.
*PRIM_KEY is the unique identifier for alters, ID_W1_W2_W3 is the unique identifier of alter.
DATASET ACTIVATE DataSet1.
AGGREGATE
  /OUTFILE=* MODE=ADDVARIABLES OVERWRITEVARS=YES
  /BREAK=PRIM_KEY
  /ALTERS_COUNT=NU(ID_W1_W2_W3).

*Removing cases so only PRIME_KEY remains with ALTER_COUNT.
* Identify Duplicate Cases.
SORT CASES BY PRIM_KEY(A).
MATCH FILES
  /FILE=*
  /BY PRIM_KEY
  /FIRST=PrimaryFirst
  /LAST=PrimaryLast.
DO IF (PrimaryFirst).
COMPUTE  MatchSequence=1-PrimaryLast.
ELSE.
COMPUTE  MatchSequence=MatchSequence+1.
END IF.
LEAVE  MatchSequence.
FORMATS  MatchSequence (f7).
COMPUTE  InDupGrp=MatchSequence>0.
SORT CASES InDupGrp(D).
MATCH FILES
  /FILE=*
  /DROP=PrimaryFirst InDupGrp MatchSequence.
VARIABLE LABELS  PrimaryLast 'Indicator of each last matching case as Primary'.
VALUE LABELS  PrimaryLast 0 'Duplicate Case' 1 'Primary Case'.
VARIABLE LEVEL  PrimaryLast (ORDINAL).
FREQUENCIES VARIABLES=PrimaryLast.
```

```
EXECUTE.

USE ALL.
COMPUTE filter_$=(PrimaryLast = 1).
VARIABLE LABELS filter_$ 'PrimaryLast = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.



FILTER OFF.
USE ALL.
SELECT IF (PrimaryLast = 1).
EXECUTE.
*___________________________________________________________.

*Dataset = 36975-0005.
*Syntax for merging the ego (36975-005) and edited alter (36975-0001) data.
DATASET ACTIVATE DataSet1.
GET FILE='X:\My '+
    'Documents\Master\scrips\ICPSR_36975\DS0001\36975-001-
Data_ALTERS_SELECTED_COUNTED.sav'.
DATASET NAME DataSet2.
DATASET ACTIVATE DataSet1.
SORT CASES BY PRIM_KEY.
DATASET ACTIVATE DataSet2.
SORT CASES BY PRIM_KEY.
DATASET ACTIVATE DataSet1.
MATCH FILES /FILE=*
  /FILE='DataSet2'
  /BY PRIM_KEY.
EXECUTE.

*Saved as new dataset called "UCNETS_Selected_Data_Boels"
```

```
*_____________________________________________________________.
***NETWORK SIZE VARIABLE.
*Centering the network size variabe by subtracting the mean.
DESCRIPTIVES VARIABLES=ALTERS_COUNT
  /STATISTICS=MEAN STDDEV MIN MAX.

COMPUTE Cent_Alters_Count=ALTERS_COUNT - 17.571799.
EXECUTE.

***WELBEING VARIABLE.
*Reliability test of the scale items.
DATASET ACTIVATE DataSet1.
RELIABILITY
  /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL MEANS VARIANCE CORR.

FACTOR
  /VARIABLES H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J
  /MISSING LISTWISE
  /ANALYSIS H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J
  /PRINT INITIAL EXTRACTION
  /PLOT EIGEN
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PC
  /ROTATION NOROTATE
  /METHOD=CORRELATION.


*Recoding to mirror two items of the Kessler scale.
DATASET ACTIVATE DataSet1.
RECODE H16C H16G (1=5) (2=4) (3=3) (4=2) (5=1).
```

```
EXECUTE.

*Reliability test of the scale items after transformation.
DATASET ACTIVATE DataSet1.
RELIABILITY
  /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL MEANS VARIANCE CORR.

CORRELATIONS
  /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J
  /PRINT=TWOTAIL NOSIG FULL
  /MISSING=PAIRWISE.

    *Adding H10 'how many days have you felt happy'.
    RELIABILITY
      /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J H10
      /SCALE('ALL VARIABLES') ALL
      /MODEL=ALPHA.

    RELIABILITY
      /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J H10
      /SCALE('ALL VARIABLES') ALL
      /MODEL=ALPHA
      /STATISTICS=CORR COV
      /SUMMARY=TOTAL MEANS VARIANCE CORR.

    *Transform H10 so it has a max score of 5.
    COMPUTE H10new5=H10 / 7 * 5.
    EXECUTE.

    RELIABILITY
      /VARIABLES=H16A H16B H16C H16D H16E H16F H16G H16H H16I H16J H10new5
```

```
    /SCALE('ALL VARIABLES') ALL
    /MODEL=ALPHA
    /STATISTICS=CORR COV
    /SUMMARY=TOTAL MEANS VARIANCE CORR.
```

*CONCLUSION: CA is highest with H10 omitted. When H10 is transformed the CA is bareley effected by omitting the variable.

```
*Computing the scale items in a new variable.
COMPUTE K10_wellb=MEAN (H16A, H16B, H16C, H16D, H16E, H16F, H16G, H16H, H16I,
H16J).
EXECUTE.

DESCRIPTIVES VARIABLES=K10_wellb
  /STATISTICS=MEAN STDDEV MIN MAX.

***NEGATIVE TIES VARIABLE.
*Centering the variable.
DESCRIPTIVES VARIABLES=B9A_COUNT
  /STATISTICS=MEAN STDDEV MIN MAX.

COMPUTE Cent_Negative_Ties=B9A_COUNT - 1.329594.
EXECUTE.

*Interaction term.
COMPUTE AlterscountxNegties=Cent_Alters_Count * Cent_Negative_Ties.
EXECUTE.

***EDUCATION VARIABLE.
*Recoding education variable.
RECODE K1 (10=SYSMIS) (1=0) (2=0) (3=0) (4=0) (5=0) (6=0) (7=1) (8=2) (9=2) INTO
Education.
VARIABLE LABELS  Education 'Level of education'.
EXECUTE.
```

```
***GENDER VARIABLE.
RECODE GENDER (1=0) (2=1).
EXECUTE.

*__SPLIT FILE.
SORT CASES  BY AGEGROUP.
SPLIT FILE LAYERED BY AGEGROUP.

 *Computing residual ages for both age groups.
IF  (AGEGROUP = 0) ResidAgeYoung=AGE_EX - 26.1483.
EXECUTE.

IF  (AGEGROUP = 1) ResidAgeOld=AGE_EX - 61.3701.
EXECUTE.



*Combining both residual age variables into one.
COMPUTE ResidAge=$SYSMIS.
EXECUTE.

IF MISSING(ResidAge) Residage=ResidAgeYoung.

IF MISSING(ResidAge) Residage=ResidAgeOld.
EXECUTE.

*Computing an interaction variable for residual age.
COMPUTE Int_ResidAgexAGEGROUP=ResidAge * AGEGROUP.
EXECUTE.

 *____________________________________________________________.
***UNIVARIATE STATISTICS.
*Descriptives for continuous variables.
  DESCRIPTIVES VARIABLES=ALTERS_COUNT K10_wellb AGE_EX B9A_COUNT
  /STATISTICS=MEAN STDDEV MIN MAX.
```

```
*Descriptives for categorical variables.
FREQUENCIES VARIABLES=AGEGROUP GENDER Education
  /ORDER=ANALYSIS.

SPLIT FILE OFF.

*______________________________________________________________.
*T-Test to compare network size means of the age groups.
T-TEST GROUPS=AGEGROUP(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=ALTERS_COUNT
  /ES DISPLAY(TRUE)
  /CRITERIA=CI(.95).

*T-test wellbeing age groups.
T-TEST GROUPS=AGEGROUP(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=K10_wellb
  /ES DISPLAY(TRUE)
  /CRITERIA=CI(.95).

T-TEST GROUPS=GENDER(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=K10_wellb
  /ES DISPLAY(TRUE)
  /CRITERIA=CI(.95).

*Trying the regression analysis.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=ENTER Cent_Alters_Count
```

```
  /METHOD=ENTER AGEGROUP
  /METHOD=ENTER AGE_EX Education GENDER Cent_Negative_Ties
  /METHOD=ENTER AlterscountxNegties.

*Other version of regression.
DATASET ACTIVATE DataSet1.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=ENTER ALTERS_COUNT
  /METHOD=ENTER AlterscountxNegties
  /METHOD=ENTER AGEGROUP AGE_EX GENDER.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=FORWARD ALTERS_COUNT Cent_Negative_Ties AlterscountxNegties
AGEGROUP AGE_EX GENDER.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=BACKWARD ALTERS_COUNT Cent_Negative_Ties AlterscountxNegties
AGEGROUP AGE_EX GENDER.

*Direct effect of negative ties on wellbeing.
```

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=BACKWARD Cent_Negative_Ties.

*Recoding the centered variable for negative ties so that they are categorical.
*0=low (0,1,2) 1=medium (3,4) 2=high (5,6).
*This did not work so will not be used.
RECODE Cent_Negative_Ties (Lowest thru 0.68=0) (1.60 thru 2.7=1) (3.60 thru Highest=2)
INTO
    Cent_Negties_buckets.
VARIABLE LABELS  Cent_Negties_buckets 'Negative ties categorized '.
EXECUTE.

*Final regression model.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT K10_wellb
  /METHOD=ENTER Cent_Alters_Count
  /METHOD=ENTER GENDER Education AGE_EX
  /METHOD=ENTER Cent_Negative_Ties AGEGROUP
  /METHOD=ENTER AlterscountxNegties Int_ResidAgexAGEGROUP
  /PARTIALPLOT ALL
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS HISTOGRAM(ZRESID) NORMPROB(ZRESID).
```