THE RELATIONSHIP BETWEEN ONLINE SOCIAL SUPPORT AND PSYCHOLOGICAL WELLBEING: A RANDOM SURVEY IN MALDIVES AND NEW ZEALAND

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ABSTRACT

Background

Previous research has repeatedly established that 'in-person' (offline) social support, both perceived and actual, is associated with psychological wellbeing. However, the growing literature on the relationship between social support acquired from social networking sites (SNSs) and psychological wellbeing is less clear. Some studies have reported a positive association between online perceived social support and psychological wellbeing, but these studies were based predominantly on convenience samples of college students primarily from the United States and Asia.

Objectives

The objectives of the current study were, using randomly a selected community sample from two diverse cultures and a small convenience clinical sample to:

1) contribute to the growing literature on the association between SNS use and psychological wellbeing;
2) study how SNS usage is associated with people's online perceived social support while controlling for key factors including online self-disclosure, age, gender, personality traits, country of residence, and urban versus rural living;
3) examine relationships between online perceived social support and psychological wellbeing and to compare the strength of the statistical association of this relationship to traditional 'in-person' or offline perceived social support;
4) examine the moderating effects of key demographic and personality variables in the relationships between time spent on SNSs, online social support, offline social support, online self-disclosure and psychological wellbeing.
5) address some of the methodological limitations in the emerging literature on the use of SNS, online social support, and psychological wellbeing; and to
6) contribute to cross-cultural psychological research by comparing the effects of online and offline perceived social support on psychological wellbeing in two diverse national ethnic groupings.

Methods

Using a quantitative cross-sectional survey of randomly selected community samples from New Zealand, (N = 385) and Maldives, (N = 411), this study evaluated the association between online perceived social support and psychological wellbeing, using carefully selected best measures available at the time. The study hypotheses were also tested on a third sample, a small convenience clinical sample from New Zealand, (N = 78) for comparison with the general population groups.

Results

The multivariable regression analyses show that time spent on online SNSs, particularly engaging in online self-disclosure, was positively related to online perceived social support in both New Zealand and Maldives random community samples. Although time spent on SNSs was positively associated with online perceived social support in the New Zealand clinical sample after controlling for demographic and personality variables, online self-disclosure was not significantly associated with online perceived social support in this group. Time spent on SNSs was not significantly associated with psychological wellbeing in any of the sample groups. Also, higher levels of perceived social support from online interaction were not associated with better psychological wellbeing in any of the three sample groups. In contrast to perceived online social support, perceived social support from offline social networks was positively associated with psychological wellbeing in both New Zealand and Maldives random community samples. In the clinical sample, unlike in the general population samples, the results showed only a marginally significant positive association between offline perceived social support and psychological wellbeing.

Conclusions

This study's finding that traditional offline social support is significantly associated with better psychological wellbeing aligns with the robust general literature that has shown social support to be a strong predictor of psychological wellbeing. The additional new finding from this work suggests that online perceived social support is not as beneficial as offline perceived social support in its association with psychological wellbeing. These results confirm the importance of real-life social support derived from offline social networks in psychological wellbeing. The role of social support derived online did not add measurably to psychological wellbeing levels but neither did it detract from that link. A range of factors are identified for future cross-sectional research to further explore the relationship between SNS use and psychological wellbeing. Future research could benefit from well-designed measures of online social support using longitudinal study designs to address causal relationships between online social support and psychological wellbeing.

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LIST OF ABBREVIATIONS

BDI-II	Beck Depression Inventory-2
BFI-10	Big Five Inventory-10 item
CES	Cyberbullying Experience Questionnaire
CES-D	Center for Epidemiological Studies Depression Scale
CES-DC	Center for Epidemiological Studies Depression Scale for Children
CTI	Cognitive Triad Inventory
DASS-21	Depression Anxiety Stress Scales -21-items
DE	Dynamic Equilibrium
DSM-5	Diagnostic and Statistical Manual of Mental Disorders
EFA	Exploratory Factor Analyses
ESC	Emotional Support Scale
FMSS	Facebook Measure of Social Support
GMPSS	Global Measure of Perceived Stress Scale
IRT	Item Response Theory
ISCS	Internet Social Capital Scales
ISEL	Interpersonal Supportive Evaluation List
ISSB	Inventory of Socially Supportive Behaviors
MDD	Major Depressive Disorder
MHC-SF	Mental Health Continuum-Short Form
MSPSS	Multidimensional Scale of Perceived Social Support
oMSPSS	Online Multidimensional Scale of Perceived Social Support
oRDS	Online Revised Disclosure Scale
OSS	Online Social Support scale
PHQ-9	Patient Health Questionnaire-9
PRQ-2000	Personal Resource Questionnaire
PSS	Perceived Social Support
PSSS	Perceived Scale of Social Support
SEM	Structural Equation Modelling
SNS	Social Networking Sites
SPANE	Scale of Positive and Negative Experience
SSQ	Social Support Questionnaire

SWB	Subjective Wellbeing
SWBI	Sense of Wellbeing Inventory
SWLS	Satisfaction With Life Scale
UOW	University of Otago, Wellington
WHOQOL-BRIEF	The World Health Organization Quality of Life - Brief measure

PREFACE

Living in New Zealand, I am thousands of miles away from my home country, the Republic of Maldives, where my family and friends are. For the past five years, the use of online communication tools to stay connected with my family and friends has been an integral part of my life. When my academic interest in social support began, my thoughts went to the role of online communication in social connectedness and the implications for its increasing usage. Additionally, my life experiences in both Maldives and New Zealand encouraged me to consider the importance of cross-cultural similarities and differences in human behaviour.

For many, innovative social networking applications have become part of their lives as an easy way to keep in touch with family and friends. Over the last decade, the use of online social networking sites (SNSs) has expanded dramatically. A recent report forecast that in 2019, there would be around 2.77 billion social media users around the globe (Clement, 2018). SNSs offer a virtual environment with opportunities to connect with others, gain information and read news, without geographical or time constraints. More people of all ages are using social networking sites such as Facebook, Instagram, YouTube, Twitter, and Snapchat on a daily basis (Smith & Anderson, 2018). This behaviour may have major implications for psychological wellbeing. Therefore, understanding the relationship between SNS use and a user's psychological wellbeing is important. While the positive association between face-to-face social support and psychological wellbeing is now well-established, the benefits of social connections and support received through SNS are unclear. The purpose of this research project is to contribute to an emerging literature about online social support and psychological wellbeing. In this study, I chose to address some gaps in this literature as described below.

Chapter One provides the context for subsequent reviews and discussions on online social support and wellbeing by providing an overview and definition of the key constructs. These include SNS, online social support, in-person social support, and psychological wellbeing. The chapter explores the literature on the conceptualisation of these constructs and the various theoretical frameworks used by researchers to understand them. As will become clear, an important issue in the extant online social support research published so far is that many researchers have not clearly defined online social support (Meng et al., 2017). Without precision, theoretical and pragmatic connections between social support and SNS usage cannot be validly investigated. In addition, there is also a lack of coherence in theories regarding relationships between online social support and SNS (Meng et al., 2017).

Chapter Two explores the relationship between online social support and wellbeing through a narrative review of the literature. This chapter aims to determine what is already known about the relationship between the use of SNS and online perceived social support as well as the relationship between online perceived social support and psychological wellbeing of SNS users (i.e., use of SNS leads to online perceived social support which in turn leads to an increase in psychological wellbeing). In this chapter, I attempt to synthesise the current research evidence and identify gaps, in order to inform the study hypotheses for this research project. The Chapter concludes with the study aims and research hypotheses for the present study.

Chapter Three describes the study methodology, including survey development, sampling methods, description of the selected survey measures, data cleaning processes, and analytical strategies employed in the research. Following this, the detailed procedures used for collecting data from the three samples (New Zealand and Maldives random community samples, and the New Zealand convenience clinical sample) are described. This chapter also presents basic descriptive statistics pertaining to the samples' sociodemographic characteristics. Importantly, this chapter also examined the measurement invariance of the four key variables, online PSS, offline PSS, online self-disclosure, and psychological wellbeing for both the New Zealand and Maldives community samples.

Chapter Four provides preliminary results for the study variables. This includes the distribution of data for each variable and presentation of bivariate relationships between variables for each of the three sub-samples separately and answers the first research question.

Chapter Five provides results relating to the first study hypothesis and research question two. These results are based on the combined random samples from New Zealand and Maldives.

Chapter Six provides results for the research question three and the results investigating study hypotheses two and three for the combined random samples from Maldives and New Zealand.

Chapter Seven presents the results for all three study hypotheses, but for each of the three sub-samples separately. The purpose of this chapter is to analyse cross-cultural similarities and differences with respect to the study hypotheses. The chapter also explores the differences in the relationship between online perceived social support and psychological wellbeing between the general population samples and a clinical sample.

Chapter Eight discusses the overall results and positions the findings within relevant theoretical frameworks and other empirical research. The limitations of the current research and suggestions for future studies are also included. Finally, the significance and implications of the project are discussed.

The Appendices include the documents which relate to the sample survey, ethics approval, and the instrument used in the current study. Statistical tables related to variables measured and the regression analyses are also provided.

CHAPTER 1: SOCIAL SUPPORT AND PSYCHOLOGICAL WELLBEING

In this chapter, in-person social support, hereafter called '*offline social support'* and social support acquired from online social networking sites (SNSs) such as Facebook and Twitter, hereafter referred to as '*online social support'* are examined as constructs. Offline social support involves activities including people meeting face-to-face, talking on the telephone, writing to each other including personal one on one emails, participating in sports together, going to movies, having meals or going to social events together. Defining offline social support was particularly important in distinguishing it from social support acquired from online social networking sites (SNSs). Following the review of offline and online social support, this chapter examines the construct '*psychological wellbeing'*, which is the key outcome variable of this study.

What is Social Support?

The nature and effects of offline social support have been a topic of psychological research interest for almost four decades (Berkman & Syme, 1979; Dunkel-Schetter & Brooks, 2009; S. Henderson, 1984; Kawachi & Berkman, 2001; I. G. Sarason & Sarason, 2009; Thoits, 1995). In general, social support has been defined as a set of behaviours involving human interaction through which individuals express, receive, and perceive emotional support, instrumental aid, and information. There is considerable evidence that social support plays a major part in maintaining one's mental wellbeing (Brissette et al., 2002; Chu et al., 2010; S. Cobb, 1976; S. Cohen & Wills, 1985; House et al., 1988a; H.-H. Wang et al., 2003).

Conceptualisation of Social Support

There is a general consensus in the literature that social support is a complex and multidimensional construct. Vaux more than three decades ago wrote that "no single and simple definition of social support is adequate because social support is a metaconstruct: a higher-order theoretical construct comprised of several legitimate and distinguishable theoretical constructs" (Vaux, 1985, p. 28). This seems to be the case still with multiple definitions of social support (Ditzen & Heinrichs, 2014). Efforts to better define social support have led to the development of several typologies of social support as described in the following section.

Types of Social Support

There are several classification structures developed for distinguishing between different types of support. Some divided support into *instrumental* and *affective* support (Catherine & Barbara, 2008; Dunkel-Schetter & Bennett, 1990; House et al., 1988b; Streeter & Franklin, 1992). Instrumental support (also referred to as tangible support), is defined as the provision of practical help, tangible goods or services (e.g., helping with transportation, household chores, physical assistance or lending money) when necessary (House et al., 1988b; Wills & Shinar, 2000). Affective support includes emotional support, offering empathy, and encouragement (Catherine & Barbara, 2008). These distinctions provide an important framework for classifying different types of support. Some authors such as Gottlieb (1978) have provided alternative distinctions which offer more detailed conceptualisations of the different types of support.

Over 40 years ago, Gottlieb (1978) gave a comprehensive description of categories of supportive behaviours which fall under both the instrumental and affective support types. These include emotionally supportive actions, resolving problems, indirect personal influence, and physical action. Each category contains several further subtypes of supportive behaviours. For example, in the category of problem-solving behaviours he included giving advice, and guidance, modelling appropriate behaviours and direct practical assistance.

Another important classification of social support was developed by two well-known Canadian researchers, Barrera and Ainlay (1983). They proposed six categories of social support based on a review of literature showing the types of social support commonly cited in the research studies reviewed. Their categories are:

1. *Material aid*: giving tangible materials in the form of money and other physical objects;
2. *Behavioural assistance*: sharing of chores or tasks through physically supportive actions
3. *Intimate interaction*: emotional support such as listening, caring, expressing appreciation and understanding;

4. *Guidance:* advice, information, or instruction offered;
5. *Feedback:* giving helpful feedback about the individual's behaviour, thoughts, and feelings;
6. *Positive social interaction*: engaging in social interactions for fun and relaxation.

Both Gottlieb (1978) and Barrera and Ainlay (1983) social support typologies are generally similar and they are useful in understanding the kinds of behaviours that are associated with each type of support. Furthermore, some argue that identifying different types of social support facilitates matching the support with a person's needs (Cutrona & Russell, 1990).

Over the last four decades, there seems to have been no further conceptualisations of types of social support to challenge those identified by these early researchers. Although these distinctions are important, there are also meaningful connections and overlaps between social support types. However, distinctions among the social support types may also help researchers make decisions around areas of focus in their work and the selection of associated measures.

Sources of Social Support

Social support can be derived from different sources. The three most common sources of support identified by researchers include support from a significant other, from family members, and from friends (Zimet et al., 1998). Other sources of support come from co-workers, classmates, and community groups (Heaney & Israel, 2008). A number of studies have examined the comparative effect of social support from different sources on wellbeing and stress. For example, support from family has been identified as crucial for wellbeing in elderly samples (H. Li et al., 2014). Support from family and friends was found to be equally important for adults in a meta-analysis of studies conducted in Turkey which examined the relationship between wellbeing and social support (Yalçın, 2015). In another large meta-analytic review, support from teachers and school personnel was found to be more important for adolescents (Chu et al., 2010) than support from family and friends. On the other hand, in a recent study, Alsubaie and colleagues found that support from friends was more important than support from family in a sample of undergraduate students (Alsubaie et al., 2019). These findings confirm that support from family and friends is important for adults. For young people such as adolescents, support from teachers and school appears to be more important, perhaps because school is a huge part of adolescents' lives.

Other Key Dimensions of Social Support

Empirical research and theoretical formulations have mainly focused on three different dimensions of social support: *social embeddedness*, *perceived social support*, and *enacted social support* as described by Manuel Barrera (Barrera, 1986).

Social embeddedness refers to the relationships people have with significant others in their social network. It is the quality and quantity of interpersonal ties between people and reflected in social relationships (e.g., marital status). Social connections are also said to be important for one's sense of belonging to one's community (Gottlieb, 1983; McMillan & Chavis, 1986; S. B. Sarason, 1974; Snowden, 2001), and have been shown to predict health and life expectancy (Berkman & Syme, 1979). Measures that conceptualise social support as social embeddedness for the most part centre around a person's social network. That is, they recognise the direct and indirect connections between individuals and their family, friends, and peers. These connections are seen as the foundations against which support is enacted and perceived. Therefore, social embeddedness has been associated with both enacted and perceived support (Barrera, 1986; Hayton et al., 2012).

Perceived social support refers to people's own evaluation of the availability and adequacy of support given to them and/or their global satisfaction with this (S. Henderson, 1981; I. G. Sarason et al., 1990). This concept fits with cognitive models of managing stress in that an individual's values and beliefs about both their stressful life events, and the resources available to them, are important for coping (Folkman et al., 1986). There are two commonly measured dimensions of perceived social support. They are perceived availability and perceived adequacy of supportive ties (Barrera et al., 1981; S. Cohen & Hoberman, 1983; S. Henderson et al., 1980; I. G. Sarason et al., 1983). Some argued that perceived social support remains relatively stable over several years (I. G. Sarason et al., 1986), and which has therefore been interpreted as part of the self-concept, i.e., as a personality trait (I. G. Sarason et al., 1990). Benefits of perceived support may be experienced even in the absence of any actual support being provided

(S. Cohen, 1988). Moreover, many studies have shown that perceived social support has a stronger relationship with measures of psychological distress, and wellbeing than enacted social support (Barrera, 1986; Gjesfjeld et al., 2010; Procidano & Heller, 1983; I. G. Sarason et al., 1987).

Enacted social support assesses the specific supportive behaviours that are provided to recipients by their support networks. The term ‘enacted support’ has been used interchangeably with received or actual social support. This type of support practices can include such activities as listening, communicating concern, loaning cash or arrangements, assisting with a task, offering guidance, and showing affection.

Although received support is a more accurate measure of supportive behaviours received from individuals’ social networks as noted, researchers have argued that received support predicts outcomes less consistently than perceived support (Barrera, 1986; Dunkel-Schetter & Bennett, 1990; Lakey & Drew, 1997; Lakey & Orehek, 2011). Some have provided potential explanations for these seemingly counterintuitive findings. First, receiving support may undermine the recipient’s self-worth which may then have a negative impact on the person’s wellbeing even if attenuated by support (Bolger & Amarel, 2007). Second, individuals may receive more support in response to stressors experienced, but these stressors could still lead to poor wellbeing (Barrera, 1986; Seidman et al., 2006). Third, some argue that support received might not meet the needs of the recipient where they are not matched with the needs of the recipient (Scholz et al., 2012).

While it is important to distinguish between social support concepts, understanding the connections between them is also important. Some argue that social connections contribute to an individual’s perception that he or she can rely on others for emotional or tangible support (Kaul & Lakey, 2003). This perception of having support may be related to an individual’s decision to seek actual support. Despite the important interconnections between social support concepts and dimensions, concerns remain about the frequent observation that enacted support is only weakly associated with perceived support. For example, Haber and colleagues (2007) found an average correlation of $r = .35$, $p < .001$ between received and perceived social support in a meta-analytic review of 23 studies (Haber et al., 2007). They noted that this effect size is inconsistent with received social support being the primary variable contributing to perceived social support. Recent research also reported that the association between received and perceived social support was weak (emotional: $r = .26$, tangible: $r = .23$) in a convenience sample of adults from the United States (Melrose et al., 2015). Similarly, Eagle and colleagues (2019) found an overall weak association ($r = .14$ and $r =.18$) between received social support and perceived social support in a sample of clergy (Eagle et al., 2019).

Section Summary

It is clear that social support is a complex construct. Many researchers tend to combine dimensions and types of social support (Chronister et al., 2006). Reviews of the literature indicate that social support is an umbrella term that can include the subjective evaluation and actuality that one is cared for, has assistance from other people, and that one is part of a supportive network. Supportive resources can be provided through either emotional support, informational support, or tangible support, and these can be received from different sources.

An ongoing debate in the literature has concerned the question of which type of support is more important in the life of the recipient. What has clearly emerged from the existing literature on traditional social support is the distinction between enacted and perceived support. Several studies show that perceived support is only modestly correlated with measures of enacted support (Eagle et al., 2019; Haber et al., 2007; Melrose et al., 2015). Furthermore, there is strong evidence to support a positive relationship between perceived support and positive mental health outcomes (Barrera, 1986; Lakey et al., 2010). On the other hand, the association between enacted support and mental health outcomes is inconsistent (Dunkel-Schetter & Bennett, 1990; Kessler et al., 1992; Wethington & Kessler, 1986).

This chapter highlights the importance of clearly defining social support for research purposes, particularly differentiating between perceived social support and enacted social support. Overall, perceived social support has been found to be more significant than enacted social support with regard to wellbeing outcomes.

Online Social Networking and Online Social Support

Social Networking Sites (SNSs) – Some Emerging Research Trends

Social networking sites (SNSs) have been in existence since 1997 (Boyd & Ellison, 2007). Since that time, SNSs have gone through tremendous advancements in terms of their features and applications. Today SNS use has become one of the most popular activities on the internet. There are currently 2.77 billion social network users worldwide (Clement, 2018). According to their original work on online social network sites, Boyd and Ellison (2007) defined SNS as:

> Web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system (p. 211).

In addition to active, real-time communication between users, SNSs likewise give an opportunity to people to make online content, post photos, and video clips, share music, and make and maintain friendships (Barsky & Purdon, 2006). Furthermore, SNSs offer the opportunity to communicate, either in one-on-one, in closed groups or in the wider public space. Figure 1 shows the most popular SNS sites based on monthly active users worldwide as per recent statistics (Clement, 2019a).

Some argue that social networking is essentially a "way of being and relating to others" (Kuss & Griffiths, 2017, p. 5). Today's younger generations, particularly teenagers, have grown up in a world that relies on technology as an essential part of their lives and this may have several implications as discussed next.

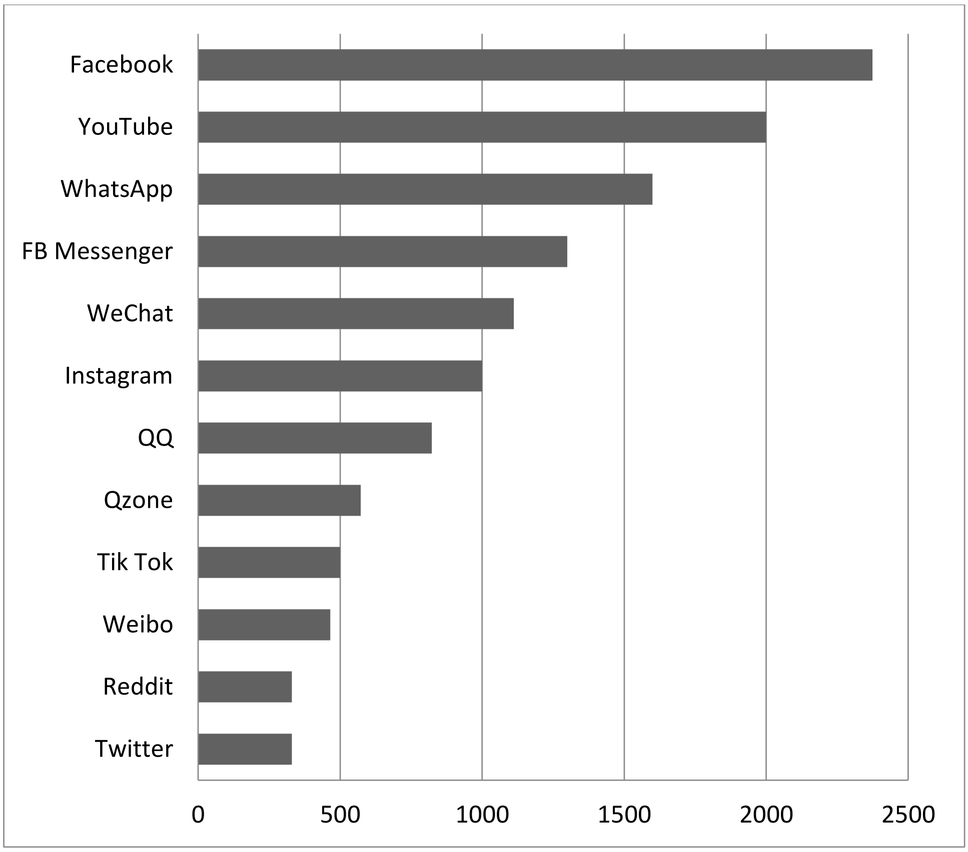

Figure 1. Most popular social networks worldwide as of July 2019, ranked by number of active monthly users (in millions)

Reasons for SNS use. A frequent question people ask is "why do people use SNSs?" Recent studies on SNS research have focused on understanding the motivations for SNS use. According to Raacke and Bonds-Raacke (2008), who surveyed 116 college students in the United States who were ethnically diverse, the most common reason for students using SNSs were to maintain relationships with old friends (91.1%) followed by posting/looking at pictures (57.4%). Other reported uses included 'to learn about events' (33.7%), 'to post social functions' (21.8%), 'to feel connected' (19.8%), 'to share information about yourself', (13.9%), and 'make new friends' (54.5%). Almost one-tenth of the students used SNSs for academic purposes, and eight percent indicated using SNSs for dating purposes. Another study examined the reason for SNS use in a sample of 1200 SNS users from Norway with mean ages of 16, 17, 22, and 29 years for four popular SNSs (Brandtzaeg & Heim, 2009). This study found that the most important reason was to get in contact with new people (31%). The second most valued was to keep in touch with their friends (21%), whereas the third was general socialising (14%) (Brandtzæg & Heim, 2009).

SNS use and psychological wellbeing. The literature is characterised by mixed results regarding the benefits of SNS use. Although a recent meta-analysis consisting of 67 studies found a small negative association between time spent on SNSs and psychological wellbeing (Huang, 2017), other reviews of the literature and large scales studies suggest that the nature of this relationship is still unclear. Consistent with Huang (2017) conclusion, a recent study of a large national sample of New Zealand adults indicated that levels of social media use had a weak positive association with psychological distress (Stronge et al., 2019). In a review of studies that measured social media use and depression, 16% of studies found a positive association, 6% found a negative association, and 13% failed to find a reliable association. The rest of the studies suggested a more complex relationship between SNS use and depression involving other factors that may mediate or moderate this relationship (Baker & Algorta, 2016). Another literature review conducted by Seabrook and colleagues in 2016 reported that positive interaction on Facebook led to lower levels of depression and anxiety, whereas negative interaction was associated with higher levels of depression and anxiety (Seabrook et al., 2016) for a third of the studies, whereas the rest found no association. A recent large study examining almost 500,000 adolescents in the United States, reported that time spent on social media has a weak but positive association with depressive symptoms and suicide-related outcomes (Twenge et al., 2017). The authors concluded that screen time should be considered an important risk factor for depression and suicide. Some argue that factors such as negative social comparison may have an impact on a person's wellbeing. Based on a study of 240 SNS users in the United States, Panger (2014) reported that unfavourable social comparisons were related to poor wellbeing. This study also found that negative self-comparison was more common on Facebook than Twitter and therefore users of the former were more vulnerable to poor wellbeing (Panger, 2014). These findings suggest that negative outcomes of SNS may depend on the quality of interactions rather than frequency of SNS use.

SNS use and online victimisation. Although research suggests that SNS use can be beneficial for maintaining social relations, this may also carry risks. Researchers have begun to examine the risks of online victimisation as a result of increased SNS use. Keipi and colleagues in 2017 found a positive link between strong identification with online communities and experiences of both hate victimisation and harassment in a representative sample of 15-30 year olds from four Western countries (N = 2,557) (Keipi et al., 2017). This finding contrasts with earlier work where strong ties online have been found to safeguard against experiences of victimisation (Yun-Kyoung Cho & Yoo, 2017; Desmet et al., 2014), which is consistent with studies finding offline support and strong ties both being linked to lessened victimisation online (Yun-Kyoung Cho & Yoo, 2017). Based on a large survey of social media use from the Pew Centre in the United States, Lenhard (2015) reported that the use of different SNSs has diversified, with young adults using multiple SNS applications compared to older cohorts (Lenhard, 2015). This may increase the risk of online victimisation. Individuals' online social interaction and risk of victimisation may differ according to the features of the SNS used. For example, Facebook community pages that allow anonymous posting enable users to discuss taboo topics and explore stigma-related identities giving rise to new opportunities and risks (Bazarova et al., 2015).

SNS use and online addiction. There is a growing evidence base to suggest that excessive SNS use may lead to symptoms traditionally associated with addiction (Andreassen, 2015; Kuss & Griffiths, 2017). Symptoms described include mood alteration, tolerance, withdrawal, relapse, and salience. For certain people, SNS use may turn into the absolute most significant action that they participate in, leading to a preoccupation with SNS use accompanied by negative psychological outcomes (Kuss & Griffiths, 2017). Some researchers argue that it is important to distinguish between excessive social networking behaviour versus SNS addiction, with the latter being associated with negative consequences. Excessive users remain in control and appreciate other activities (Andreassen, 2015). Online addiction has not been included in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric, 2013) as a formal diagnosis. The DSM-5 is a taxonomic and diagnostic tool for psychiatric disorders published by the American Psychiatric Association. It also lists symptoms for an "internet gaming disorder" in its chapter on conditions for further study and recommends that "excessive use of social media on the internet" receive similar operationalisation and validity research.

Social benefits of SNSs. With the popularity of SNS use, a growing body of research has examined the role of online communication for exchanging social support. Based on a review of 88 journal studies, Meng and colleagues (2017) reported, in general, there was a positive relationship between SNS use and online social support. This review highlighted that most of the studies focused on Facebook, thus limiting the generalisation of the findings to other SNS sites. Many SNSs, may help connect people to friends, family, colleagues, strangers, and role models and can help users to maintain and make new friendships, express thoughts and feelings, and express identity. Some argue that the primary social functions that SNSs perform may augment the benefits of engaging in face-to-face interaction by extending the reach and accessibility of social networks (Boyd & Ellison, 2007; Ellison & Boyd, 2013). Support for the beneficial effect of online social support in increasing offline social support was reported in a recent study of 573 university students in Hong Kong by Zhang (2017). She concluded that online enacted social support was positively related to offline perceived social support.

Taken together, this section has shown that SNS use can involve a broad range of usage motivations and needs for usage, ranging from social connection, information searching, and gaming to romantic pursuits. This review of the SNS literature also highlights the deep penetration of its use in many aspects of the everyday life of users, and the benefits and negative consequences this may have on psychological wellbeing and mental health.

What is Online Social Support?

Although the role of online social support in health has been studied ever since the internet enabled people to communicate virtually, research into the provision of online social support in the context of SNS only began in the last decade (Ellison et al., 2007). The current study also focuses solely on online social support from SNSs. In the next section, we focus on understanding online social support by providing a conceptual framework for this.

Conceptualising Online Social Support

To date, only a few researchers have attempted to conceptualise online social support based on existing theoretical models of social support. This section will discuss the overlap between conceptualisations of offline and online social support and the unique aspects of online social support.

A primary difference between online social support and offline social support is the context. Unlike offline social support, online social support exchange depends on the virtual world. Some argue that similar to offline social support, online social support includes various supportive behaviours that are exchanged between network members (Trepte et al., 2014). If the only major difference between online social support and offline social support is in the setting, it can be argued that the conceptual frameworks pertaining to offline social support can help us conceptualise online social support. As such, the three concepts of *social embeddedness, perceived social support,* and *enacted social support* proposed by Barrera (1986) would also apply to online social support.

Aspects of social embeddedness such as quality and quantity of social connections can be applied to the online context where, for example, "weak" online ties could manifest in having many Facebook friends but not interacting frequently with them. On the other hand, having "strong" online ties could be seen in having frequent and meaningful interactions with Facebook contacts. Support for this idea was found in a study by Grieve and colleagues who reported that the quality and quantity of Facebook connectedness was positively associated with life satisfaction and lower depression and anxiety in a sample of college students (Grieve et al., 2013). Similarly, Burke and Lento (2010) explored relationships among SNS use, social capital, and psychological wellbeing among 1193 SNS users from different countries. Their findings showed that the number of SNS friends (quantity) and amount of directed communication (quality) was positively associated with social capital and negatively associated with loneliness (Burke et al., 2010). Another study of 1910 Facebook users also reported a positive association between strong Facebook friendship ties and 'composed' communication and psychological wellbeing compared to weak ties or "one-click" communications (Burke & Kraut, 2016).

Parallel with the offline context, online *perceived* social support can be conceptualised as a person's own evaluation of the availability and adequacy of support received from online contacts. Perceived online social support may be more appropriate to measure than *enacted* support, given that some types of support available in the offline context such as showing physical affection (Barrera, 1986) may not be possible in the online context. However, in the online context, enacted support takes the form of the actual amount of verbal communication (both public and private messaging) and non-verbal communication (e.g., sharing pictures, videos, giving “likes” to messages), and can include offering information, giving advice, and receiving money from online contacts when in need (Trepte et al., 2014). Not all of these are possible offline.

Types of Online Social Support

Again, very little research has explored the different types of online social support available. Those who have explored this area have drawn on notions of offline social support and social capital to define online social support. For example, Trepte and colleagues (2014) argued that online social support is probably an extension of offline social support. Trepte and colleagues (2014) conducted a longitudinal study comparing ‘online perceived informational support’ and ‘online perceived emotional support’ in predicting life satisfaction. Life satisfaction (Diener, 1984) is considered one dimension of psychological wellbeing (see the section on psychological wellbeing). Based on their findings, they concluded that online social support was generally more informational support (e.g., birthday wishes, information on relevant topics) and less emotional or tangible support, and therefore has less positive effect on life satisfaction compared to offline social support (Trepte et al., 2014).

Although Trepte and colleagues (2014) argued that online social support is mostly informational support, a closer look at the different types of online social support reveals overlap with more aspects of support described by Barrera and Ainlay (1983). Online social support may not be in the form of behavioural assistance or material aid but it can be in the form of emotional support, or guidance (i.e., advice, information, instructions) or feedback, or positive interactions. Unique types of online social support can include supportive responses through SNS features such as ‘likes’, ‘retweets’, and ‘sharing’. A ‘like’ is an action that can be made by an SNS user on SNSs by clicking a button as a quick way to show approval. Re-tweeting or sharing is when someone re-shares a post or news shared by one of his or her online contacts or followers with either some or all of one’s online contacts.

There may be other specific aspects of online social support that are different from offline social support which are important to acknowledge when understanding the role of online social support. C.-P. Lin and Bhattacherjee proposed a cognitive model of online social support (C.-P. Lin & Bhattacherjee, 2009). They argued that technology-efficacy, that is an individual's belief in his/her ability to use technology and their perception of how beneficial they find online social support, is important in acquiring online social support. These authors concluded that technology-efficacy leads to an increase in SNS use which increases their level of online social support. They also argued that both the sense of technology-efficacy and the amount of time spent communicating online influences support outcomes (C.-P. Lin and Bhattacherjee, 2009). Another unique feature of online social support is the ability to connect with networks or seek emotional or informational support without revealing one's identity (e.g., seeking support from online health related support groups). Unlike in offline social interaction, there may be a valid form of online behaviour which does not require self-disclosure by the recipient (i.e., "lurking"), without divulging personal details in a way not possible in the offline context (Malik & Coulson, 2011). It is not yet known to what extent online self-disclosure and reciprocity of social interaction are necessary for an individual to receive support online. By contrast, the importance of reciprocity in offline social support exchange has been studied by researchers with the general finding that social support is beneficial to wellbeing when there is a balance between giving and receiving social support (Aktas & Sertel-Berk, 2015; Antonucci & Jackson, 1990; Lu, 1997; Wahrendorf et al., 2010).

In summary, there seems to be no consensus regarding the conceptualisation of online social support. However, similar to offline social support, online social support can be conceptualised based on strength of social ties, subjective evaluation of support available, or objective amount of different types of support available. Online social support includes less physical and material aid compared to offline social support. Other unique aspects of online social support include the influence of technology-efficacy and the possibility of receiving support while maintaining anonymity.

Correlates of Social Support

Social capital

Social capital is a closely related term that is often cited in social support literature. Similar to social support, social capital has been described as a construct that is multifaceted and challenging to conceptualise (Falzer, 2007). Although social support and social capital share some common elements, theoretically they are two distinct ideas. Ichiro Kawachi, a well-known social capital researcher, defined it as the quality of resources in a community (Kawachi & Berkman, 2001). Saegert and Carpiano (2017) concluded that social support and social capital are distinct but related concepts that are important for both individual and collective wellbeing. They argued that while social support can be integrated into theories and conceptual models of social capital, social capital helps us understand the broader range of structural elements that make up social relationships of which social support is simply one element. A frequently cited social capital model closely related to social support was put forth by Robert Putnam (Putnam, 1996). He defined social capital as "features of social life – networks, norms, and trust that enable participants to act together more effectively to pursue shared objectives" (Putnam, 1996, p. 3). Putnam later identified two forms of social capital: *bridging* and *bonding* social capital (Putnam, 2000). Bridging social capital is made up of weak ties created through a heterogeneous network that may bring in novel information. Bonding social capital represents strong ties that arrive from close relationships within family and close friends or other close networks. Some argue that bridging social capital is the same as informational support because both are based on weak ties, whereas bonding social capital can be conceptualised as more similar to emotional social support (Trepte et al., 2014). One study found statistical evidence to support Trepte and colleagues' argument with positive correlations between bonding social capital measures and a measure of perceived emotional support (Appel et al., 2014).

A number of studies have explored the relationship between social capital and wellbeing. De Silva and colleagues conducted a systematic review of twenty-one studies which explored the relationship between social capital and mental health (De Silva et al., 2005). Their results revealed that 'cognitive social capital' or respondents' appraisals of their social environment and the strength of social connections were consistently related to mental health. On the other hand, studies on the relationship between structural aspects of social capital and mental health produced mixed results (De Silva et al., 2005). Another consistently reported finding reported in social capital literature is the positive association between bonding social capital and wellbeing. On the other hand, results regarding the relationship between bridging social capital and wellbeing have been inconsistent (Appel et al., 2014; McPherson et al., 2014; Trepte et al., 2014). Bonding social capital is more closely related to social support than bridging social capital as per their definitions. Therefore, positive relations between bonding social capital and wellbeing are to be expected.

Given the expanding significance of social connections shaped through online networks, studies have also differentiated between online and offline forms of social capital (e.g., Ellison et al., 2007; Williams, 2006). Some argue that SNS use facilitates bridging social capital and, to a lesser extent, bonding social capital (Ellison et al., 2007, Trepte et al., 2014). Steinfield and colleagues (2008) examined the impact of relationships between the use of Facebook and bridging social capital, through a longitudinal analysis in a randomly selected sample of university students. Their research showed that the intensity of Facebook use was related to increases in bridging social capital or widening of social networks. This was particularly true for those who had low self-esteem (Steinfield et al., 2008). Although Steinfield and colleagues' (2008) study did not measure bonding social capital, it is likely that SNS use may facilitate an increase in bonding social capital in association with increases in social network size.

Personality

Individual characteristics such as personality factors have been linked to social support. The Big Five personality traits described in Costa and McCrae's (Costa & McCrae, 1992) as the Five Factor Model (FFM) represent a taxonomy of five broad personality dimensions. The five dimensions are: extroversion, neuroticism, conscientiousness, agreeableness, and openness to experience. Table 1 provides a description of each trait which emerged reliably over decades of factor analytic research (Ashton & Lee, 2001; McCrae & Costa, 1997). In this section, we review the literature on personality and social support.

Table 1. *Description of the Five-Factor Personality Traits*

Personality Factors	Description
Extroversion	The level of sociability that projects one's positive emotions, surgency, and the tendency to seek stimulation and the company of others.
Neuroticism	The level of unpleasant emotions experienced such as anger, anxiety, depression, or vulnerability; sometimes called emotional instability.
Conscientiousness	The level of self-discipline, organisation, work ethic, and planning. It is related to the way in which people manage their impulses.
Open to Experience	The level of creativity and curiosity. Individuals who are open to experience tend to appreciate art, are adventurous, and are willing to try new things.
Agreeableness	The level of kindness, trust, and sympathy towards others. Agreeable individuals value getting along with others and are sympathetic towards others.

Of the five factors, research has consistently shown that extroversion and neuroticism influence individuals' perceived social support in the offline context (Asendorpf & Van Aken, 2003; Bolger & Eckenrode, 1991; Chay, 1993; Halamandaris & Power, 1997; Swickert et al., 2010). It is not surprising that these traits show a strong relationship with social support given they influence support-seeking behaviour and how people perceive the usefulness of support they get (I. G. Sarason et al., 1986). Furthermore, it is thought that extroversion and neuroticism play a particularly important role in human social abilities (Digman, 1990; Goldberg, 1990; John, 1990): extroversion typically correlates with the psychological characteristics that make a person sociable and outgoing (Digman, 1990), while those who score high on neuroticism tend to have a reduced level of sociability (Furukawa et al., 1998; Russell et al., 1997). Some argue that when participants are asked to report their perception of the social support available to them, extroverts, as compared with introverts, are more likely to perceive greater levels of social support (Swickert, 2009).

Neuroticism is associated with avoidance coping (i.e., efforts to avoid dealing with stressors) and has also been negatively associated with the seeking of social support. Indeed, people with high neuroticism scores, compared to those with lower scores in this dimension, may actually withdraw from others during times of stress (Davidson et al., 2016; Lee-Baggley et al., 2005; McCrae & Costa, 1986). The role of neuroticism has been of particular interest for researchers looking at the relationship between social support and psychological wellbeing (S. Henderson, 1981). Henderson and colleagues (1981) hypothesised a ‘plaintive set’, which may make many psychiatric patients (likely to be high in neurosis) prone to describing their social support as inadequate (S. Henderson, 1981).

In fewer studies, researchers have explored the relationships between perceived social support and agreeableness, conscientiousness, and openness. Research shows that individuals who score high on agreeableness, compared to those lower on the dimension, tend to perceive greater levels of support available to them (Asendorpf & Van Aken, 2003; Branje et al., 2005; Finch & Graziano, 2001; Swickert et al., 2010). In spite of the fact that individuals who score high on conscientiousness are considered competent and they may basically not require as much support from others, research has found evidence that individuals who are high in conscientiousness report greater levels of satisfaction with support providers (Asendorpf & Van Aken, 2003; Swickert et al., 2010). Few studies have looked at the relationship between openness and social support, and those that have tend to be inconsistent (Swickert, 2009).

With the rise in SNS use, some researchers have examined the role of personality characteristics in relation to online social support and wellbeing (Hu et al., 2017). Evidence for two opposing views – that is the ‘rich get richer’ and the ‘social compensation’ hypotheses – have been found in studies looking at individual differences in online social networking.

According to the “rich get richer” hypothesis, people who are already able to form offline social networks and are extroverted are also more likely to benefit from online social networking (Amichai-Hamburger & Vinitzky, 2010; Gosling et al., 2011; J. H. Lin et al., 2011; Pfeil, Zaphiris, et al., 2009; P. Sheldon, 2008; Swickert et al., 2002; Wilson et al., 2009). Amichai-Hamburger and Vinitzky (2010) found that college students who were more extroverted had more Facebook friends than individuals who were less extroverted. Lin and colleagues reported that college students who were more extroverted were able to acquire more online social capital compared to those who were less extroverted (Lin et al., 2011). A study using data collected from the New Zealand Attitudes and Values Study (N = 6,428) also found that those who were more extroverted showed a high level of 'felt belongingness' or social capital regardless of whether they had a Facebook profile or not compared to those who were less extroverted (Stronge et al., 2015).

Studies that support the second, opposing "social compensation" hypothesis posit that internet mediated social interaction may be used to compensate for poor social interaction offline (e.g., Hu et al., 2017; Valkenburg et al., 2005; Zywica & Danowski, 2008). Studies that support this hypothesis conclude that shy individuals prefer communication that does not require face-to-face contact. These studies also report that shy individuals are less apprehensive about online communication than those who are more social (Pierce, 2009; Saunders & Chester, 2008). Campbell and colleagues (2006) combined online and offline surveys of undergraduate students who were regular internet users, and concluded that for the "socially fearful", the internet offers a low risk approach to socialising and a preliminary form of rehearsing for future face-to-face encounters. They also reported that there may be the risk of social isolation and loneliness associated with internet use for socially fearful students. A study of university students by Zywica and Danowski (2008) showed support for both the social compensation hypothesis and the rich-get-richer hypothesis. Outgoing individuals were found to be more prevalent in both online and offline networks. Introverts who were less prevalent in offline networks were found to endeavor for and be more well-known on social networks (Zywica & Danowski, 2008). Indian and Grieve (2014) examined the difference between online and offline social support in predicting subjective wellbeing in a sample of university students scoring high or low on a social anxiety measure. They found that online social interaction was more strongly related to the well-being of socially anxious individuals when compared to their offline social support (Indian & Grieve, 2014). In the "high socially anxious" group, online social connectedness was negatively related to depression and anxiety and positively related to subjective wellbeing (Indian & Grieve, 2014). On the other hand, Strong and colleagues' large study examining New Zealand community participants found that introverted people reported less 'felt belongingness' if they had a Facebook profile relative to introverted people who did not have a Facebook profile (Stronge et al., 2015).

Although there may be the risk of social isolation with high SNS use, online social support could be beneficial for reducing distress associated with psychological problems and increasing social bonding in at least college students although these studies were only correlational (A. J. Campbell et al., 2006; Grieve et al., 2013; Indian & Grieve, 2014). Further research is required to explore the links between personality factors such as neuroticism and social support in the context of online social networks ideally using longitudinal approaches.

Taken together, the review of literature on personality and social support suggests the importance of personality traits in an individual which may result in a particular cognitive structuring of his or her immediate network environment. While studies have shown a consistent link between social support and wellbeing, individuals who are anxious or have high levels of neurotic personality traits may experience difficulty connecting with other people effectively and obtaining necessary social support from their networks. Studies that support this assumption have found that individuals high in extroversion, high in agreeableness, and low in neuroticism report higher levels of perceived social support (Asendorpf & Van Aken, 2003; Bolger & Eckenrode, 1991; Cukrowicz et al., 2008; Finch & Graziano, 2001; Swickert et al., 2002). Therefore, when studying the relationship between particular dimensions of social support (perceived social support) and wellbeing, it may be important to control for personality factors.

Self-disclosure

Self-disclosure is described broadly as a process of communicating information about oneself to another (Kokkonen & Ignatius, 2007) but there is no consensus on a common definition of self-disclosure. Some define self-disclosure as all forms of verbal and non-verbal communication that reveal any information about an individual (D. A. Taylor & Altman, 1987; Wheeless & Grotz, 1976). Others refer to self-disclosure as generally intentional communication which provides insights into personal thoughts and feelings (Derlega & Berg, 1987).

One of the best-known theories of self-disclosure, developed by D. A. Taylor and Altman (1987), is called the social penetration theory. According to this theory, there are two dimensions to self-disclosure: breadth and depth. The breadth dimension concerns the various topics discussed between individuals and is largely made up of superficial information about ourselves that people commonly share with a number of different people. The depth of disclosure is the degree to which very personal or intimate information is shared with others and this usually occurs later on in friendships or only with close contacts (D. A. Taylor & Altman, 1987). According to Taylor and Altman, self-disclosure facilitates the development of social relationships through systematic exchange of personal information (D. A. Taylor & Altman, 1987). Therefore, it can be considered that self-disclosure is an integral part of social support through its role in helping to develop strong ties between individuals or groups. Research findings support this argument in the offline context. In one example, a longitudinal study found positive associations between self-disclosure and relationship quality as measured by satisfaction, love, and commitment, thus suggesting that self-disclosure is an important relational behaviour that influences intimacy and relationship continuation (Sprecher & Hendrick, 2004).

Research evidence generally supports a positive link between self-disclosure and psychological wellbeing and also between self-disclosure and coping with trauma (Helgeson & Lopez, 2010; Hook & Andrews, 2005). A positive relationship between self-disclosure and post-traumatic growth (PTG) has also been found (Tedeschi & Calhoun, 2004). PTG is the experience of positive changes that occur as an outcome of coping with adversity and is associated with improved wellbeing (Tedeschi & Calhoun, 2004). Perhaps these findings could also extend to the context of self-disclosure on SNS. Researchers have examined social support, psychological wellbeing, and differences in personality, gender, age, and culture in relation to online self-disclosure levels and have reported variable results. The research literature on online self-disclosure is discussed in the following section.

Online self-disclosure and online social support. A number of studies have explored the role of self-disclosure in online communication (Nguyen et al., 2012). Similar to the research on offline self-disclosure, researchers have focused on various aspects of self-disclosure such as content, predictors, and functions, as well as consequences of online communication (Trepte & Reinecke, 2013). However, studies looking more specifically at the role of online self-disclosure in online social support are scarce. Some studies have looked at the link between self-disclosure through SNSs and social capital, a related concept of social support as discussed earlier. For instance, Ellison and colleagues (2007) in their cross-sectional study of 286 undergraduate students found that self-disclosure measured as an aspect of their intensity of Facebook use was positively related to establishing and maintaining social capital (Ellison et al., 2007). In Liu and Brown's (2014) cross-sectional study, young adults' self-disclosure on SNSs was significantly related to bridging social capital and forming close relationships through reciprocity (D. Liu & Brown, 2014). Liu and Brown did not differentiate between online and offline social capital in their study. Jeong and colleagues (2014) examined both online and offline self-disclosure and social capital (bridging and bonding) in a large random community from South Korea. They found a cross-sectional positive association between online self-disclosure and online social capital (Jeong et al., 2014). Interestingly, they found that online self-disclosure was associated with only online social capital (bridging and bonding), while offline self-disclosure affected only offline social capital (bridging and bonding). This is an important finding which suggests that online and offline relationships appear to function independently, and that the benefits of online disclosure may not transfer to offline networks.

Trepte and Reinecke (2013) found that willingness to self-disclose and frequency of SNS use are mutually reinforcing over time. Trepte and Reinecke (2013) conducted a longitudinal study of SNS use, online self-disclosure and online bonding social capital using SNS users in Germany. Data was collected at two intervals, six months apart. Their results showed that SNS use over time led to an increase in online-self-disclosure and this relationship was reinforced by an increase in participants' online bonding social capital (Trepte et al., 2013; Trepte & Reinecke, 2013). Then Utz (2015) studied the relationship between self-disclosure on SNS and social connection in 151 German college students. The author found that self-disclosure, particularly in more intimate private conversations was associated with an increase in feelings of connectedness for the revealer. Taken together, these findings suggest that self-disclosure on SNSs can be beneficial for maintaining old and establishing new relationships.

Lee and colleagues' (2013) cross-sectional study is one of few explorations of the relationship between online self-disclosure and online social support in a college student sample of 265 from South Korea. They found that online self-disclosure was positively associated with online social support (K.-T. Lee et al., 2013). This suggests that online self-disclosure may facilitate social relationships online. However, these results need to be interpreted with caution given that the study used a convenience sample of college students.

Online self-disclosure and psychological wellbeing. Despite growing interest in online self-disclosure, research examining the relationship between online self-disclosure and psychological wellbeing appears to be limited. For instance, Lee and colleagues (2011) examined the association between amount of online self-disclosure and subjective wellbeing in a large sample of university students from South Korea. They found that amount of self-disclosure (measured by depth) on SNS was positively related to subjective wellbeing (G. Lee et al., 2011). Although the authors did not ask who participants disclosed most to (e.g., people they knew offline or those who are intimate contacts), they argued that SNS, users interact mostly with their existing real-world contacts. Similar findings were reported by Jeong and colleagues (2014) in a cross-sectional study using a large random community sample in South Korea (Jeong et al., 2014). Some researchers argue that online self-disclosure does not directly affect psychological wellbeing. For instance, Kim and Lee (2011) found a positive indirect association between online-self disclosure and wellbeing mediated by perceived social support in their study of US college students (J. Kim & Lee, 2011). Similar results were reported by Lee and colleagues (2013) in their study of university students in South Korea (K.-T. Lee et al., 2013).

Online self-disclosure and personality. Hollenbaugh and Ferris (2014) studied the relationship between personality and various dimensions of online self-disclosure via Facebook only. They found that neuroticism was negatively related to *breadth* of self-disclosure, while openness was positively related to *breadth* of self-disclosure. Extroversion was positively related to *depth* of self-disclosure while none of the other personality traits showed a significant relationship with depth. No traits were related to *amount* of disclosure. Similar to Hollenbaugh and Ferris, Seidman (2013) also found that extroversion was positively related to *depth* of disclosure but not *breadth* of self-disclosure. On the other hand, conscientiousness was negatively related to *depth* of disclosure while agreeableness was positively related to *amount* of disclosure. Openness was not related to any type of self-disclosure. In contrast, Amichai-Hamburger and Vinitzky (2010) found that although extroversion was positively related to number of friends on Facebook, it was negatively related to online self-disclosure. They also found that those individuals who scored higher on the trait of conscientiousness shared less personal information than individuals who scored lower. In contrast to Hollenbaugh and Ferris's findings, Seidman (2013) found that neuroticism was positively related to both breadth and depth of self-disclosure. Interestingly, Amichai-Hamburger and Vinitzky found a U-shaped correlation between neurotic personality traits and the amount of self-disclosure. That is, the result indicates that people with low or high levels of neuroticism tended to share more information than people with moderate levels of neuroticism. This may indicate that one behaviour may stem from different motivations. It is evident from the few studies reviewed here that the relationship between personality factors and self-disclosure online is still unclear. The strongest finding appears to be the positive association between extroversion and depth. Inconsistent findings may have resulted from the different measures used in these studies. All the studies were cross-sectional and used convenience samples.

Online self-disclosure and gender. A few studies report gender differences in online self-disclosure. Sheldon (2013) found that women disclosed more to both close face-to-face friends and close Facebook friends than men, in a sample of university students in the United States. On the other hand, men had more intimate discussions with their recently added Facebook friends than women (P. Sheldon, 2013). In a large scale study carried out in Russia, similar results were found (Kisilevich et al., 2011). They also found that overall, women revealed more online than men, but men revealed more on certain topics than women. Similarly, Y.-C. Wang et al. (2016) concluded that women disclosed more online than men based on their examination of 2000 Facebook status updates of people in the United States. By contrast, Hollenbaugh and Ferris (2014) in their study of Facebook users found no significant association between gender and online self-disclosure. In Hollenbaugh and Ferris's study, the sample was predominantly women (77.1%). Therefore, results from these studies suggest that there may be differences in online self-disclosure behaviour between men and women in which overall, women tend to disclose more online, but men may disclose more than women on certain topics. However, this needs further investigation. Except for Wang and colleagues' (2016) study, all others were based on self-report measures.

Online self-disclosure and age. A small number of studies have examined age difference in online self-disclosure and the results are mixed. Kisilevich and colleagues (2011) reported that younger adults disclosed more personal details online than their older counterparts (Kisilevich et al., 2011). In contrast, Wang and colleagues (2016) reported that older people disclosed more than younger people on Facebook (Y.-C. Wang et al., 2016). Finally, Hollenbaugh and Ferris (2014) found no significant association between age and online self-disclosure. Therefore, these studies provide inconclusive findings regarding age and online self-disclosure.

Online self-disclosure and culture. Some cross-cultural differences in self-disclosure on SNSs have been observed. For instance, Almakrami (2015) compared online self-disclosure between participants from Saudi Arabia and Australia. They reported that compared to Australians, Saudi Arabians disclosed more on Facebook. In both countries, self-disclosure was positively related to initiating and maintaining relationships. Almakrami concluded that Australians were more concerned about their privacy than Saudi Arabians. Almakrami argued that because Saudi Arabia has tighter social restrictions surrounding the development of social non-familial relationships, people may perceive Facebook as a platform that is free of such restrictions and disclose more (Almakrami, 2015). Zhao and colleagues (2012) compared online self-disclosure of adults from the United States and China (Zhao et al., 2012). Their results showed that, for online disclosure, there was no significant difference between the United States and Chinese respondents, whereas, for face-to-face disclosure, the Americans disclosed significantly more than the Chinese. Furthermore, there was no difference between Americans and Chinese with regard to whom they disclosed to. Both groups reported that they would disclose to close relationship connections more than co-workers or strangers (Zhao et al., 2012). Combined, these findings suggest that there may be cross-cultural differences in the amount of self-disclosure on SNS while the association between self-disclosure and social relationships may be similar across cultures.

In summary, online self-disclosure is an area of interest for researchers particularly in relation to its impact on social support and wellbeing. There is some evidence to suggest that online self-disclosure is an important component of relationship development by promoting trust, commitment, and intimacy between online communicators (Hollenbaugh & Ferris, 2014; N. Park et al., 2011). Mixed findings exist regarding the relationship between gender differences, age, and personality with online self-disclosure. Hence, exploring these demographic factors in relation to online self-disclosure as well as controlling for them will be of value in understanding the developing investigation into online use, individual traits, and wellbeing.

Demographic factors related to social support

Gender. Extensive research has focused on the importance of gender in the relationship between offline social support and wellbeing. Gender differences in social support have been linked to several factors including differences in socialisation (with male socialisation de-emphasising the expression of feelings and focusing more on autonomy), self-reliance, and independence. Female socialisation emphasises verbal expressiveness and focuses on warmth and intimacy (Matud et al., 2003; Olson & Shultz, 1994). The general finding has been that women are more likely than men to seek and provide social support (Coventry et al., 2004; S. E. Taylor et al., 2000; Vaux, 1985). A closer review of the literature, however, shows a more complex picture. For instance, an adult cohort study found that females have more close relationships than males, although males have larger social networks (Fuhrer et al., 1999). In addition, women are considered social support providers more often than men are, particularly in times of stress (Neff & Karney, 2005). Moreover, women generally report seeking and receiving higher levels of emotional support than men do (Burda et al., 1984). Based on their study of gender and personality differences in social support, Reevy and Maslach (2001) argued that it is not the biological sex, but gender related characteristics that predict social support. They found that feminine characteristics were more associated with seeking and receiving emotional support than masculine characteristics. On the other hand, masculine characteristics were associated with receiving greater tangible support (Reevy & Maslach, 2001).

Research on gender differences in relation to online social support from SNS use is limited. Using an experimental design, Teoh and colleagues (2015) examined gender differences in online perceived social support in a sample of 133 college students in Singapore. They found that women reported that online perceived support provided by friends was more beneficial than social support from strangers. On the other hand, social support provided by friends and strangers did not differ in the benefits reported by men (Teoh et al., 2015). Based on their findings, they also concluded that women found online social support more beneficial than men. Luarn and colleagues (2015) also reported that women received online social support more than men. This study evaluated online posts by 145 Facebook users and their association with friendship strength measured by a self-report scale (Luarn et al., 2015). Based on these studies and literature on offline social support, gender differences may be present in online social support, with women reporting a greater level of online social support than men. Furthermore, it is also likely that gender may moderate the associations between the intensity of SNS use, online PSS, and psychological wellbeing.

Age. Studies of both young and older adults suggest that offline social support from family and friends may vary in its impact on psychological wellbeing over time. An earlier review by Alan Vaux (1985) concluded that in general young adults have larger support networks and report greater perception of support from friends compared to adolescents or the older generation but family support is more important during adolescence (Vaux, 1985). Furthermore, Vaux concluded that the association between social support and wellbeing did not vary with age. In contrast, later studies have reported more complex association between age, social support, and wellbeing. Van Baarsen (2002) studied the impact of social support on adjusting to loneliness following the loss of a life partner in later life in a longitudinal study. His study found that partner loss was associated with decreased perception of social support, and this did not change despite having close friends especially soon after their loss (van Baarsen, 2002). Conversely, and consistent with Vaux (1985), Seidlecki and colleagues (2014) reported no difference in the relationship between social support and wellbeing across age although the social network and enacted support decreased with age. Segrin (2006) found that regardless of age, all participants benefited from perceived family support through reducing symptoms of depression, this relationship was stronger for younger than older people. Overall, it appears that whilst everyone benefits from social support regardless of age in terms of wellbeing, the structure of social support changes as people get older with fewer close contacts. Van Baarsen's (2002) study findings suggest that there may be other factors, such as loneliness after partner loss and self-esteem which may affect support seeking behaviour or perceived social support levels.

Researchers have found that overall, SNS use is higher among younger than older age groups. Smith and Anderson (2018) found that some 88% of 19-29 year olds indicated that they use some form of social media, this rate falling to 64% among those aged 50 to 64 year and to 37% among Americans 65 and older (Smith & Anderson, 2018). Furthermore, presence across different social media platforms and interactions among larger online social networks is higher among younger teenagers compared to older teenagers (Pfeil, Arjan, et al., 2009). Despite these findings, older generations are increasingly using SNSs to exchange information and emotional support (Smith, & Anderson, 2018). Despite a higher use of social media among teenagers, a recent meta-analysis reported that the effect sizes between the intensity of SNS use and social support were stronger among older students (D. Liu et al., 2018). One of the weaknesses of this meta-analysis was the lack of older age groups in the 31 studies analysed. Most samples were college students. Only two studies used middle school students. Although researchers have investigated age differences in SNS activities, further research is needed to examine the age differences in the relationship between SNS, online social support and psychological outcomes.

Region. An important predictor of social support and its related psychological outcomes is community type, especially the difference between rural and urban communities. Generally, studies have reported that, compared to rural dwellers, urban dwellers had higher levels of depression, which has been associated with lower social support in both western and non-western countries (J.-M. Kim et al., 2004; Romans et al., 2011; Tobiasz-Adamczyk & Zawisza, 2017). No studies have yet examined whether there are differences in online social support between urban and rural communities.

Culture. Numerous studies with multicultural samples have demonstrated the benefits of both offline perceived and received support from close people (Hombrados-Mendieta et al., 2013; H. S. Kim et al., 2008; Morling et al., 2003). Studies have demonstrated that there may be cultural differences in how people seek and receive social support from their social networks. A review of literature on social support and culture presented evidence that Asians and Asian Americans are more hesitant to explicitly ask for support from close others than are ‘European’ Americans (H. S. Kim et al., 2008). H. S. Kim and colleagues (2008) proposed that this distinction in support seeking may be due to Asians having more concerns about the expected consequences of support seeking, such as disrupting group harmony or receiving criticism from others compared to ‘European’ Americans (H. S. Kim et al., 2008). In addition, J. Kim and colleagues (2008) found that ‘European’ Americans benefited from talking about the stressor explicitly while Asians benefited more from being with others without disclosing their stress.

Whilst research evidence exists for the positive association between offline social support and psychological wellbeing across different cultures, less is known about the cross-cultural differences in the association between online social support and psychological wellbeing. The cultural norms and expectations in offline social support provision may be translated to communication patterns in online platforms and guide users' online support (D. Liu et al., 2018). The majority of the studies looking at the relationship between SNS use behavior and online social support have been undertaken in some areas of Asia along with the United States and Europe. No studies have been published looking at the Middle East, East Asia, Africa, South America, or Australasia/Pasifika to date.

Section Summary

In summary, the studies exploring the relationship between demographic factors and online social support seem to be limited. Based on the literature on offline social support, it can be postulated that gender differences may be present in online social support, with women reporting a greater level of online social support than men. Although researchers have studied age differences in SNS activities, little research has focused on age differences in the relationship between online social support and psychological outcomes. Overall, it appears that whilst offline social support is beneficial for psychological wellbeing, regardless of age, the structure of social support changes as people get older with a smaller number of close contacts. This may well be true in the online context as well. Generally, studies have reported that, compared to rural dwellers, urban dwellers had higher levels of depression, which has been associated with lower offline social support in both western and non-western countries. No studies have yet examined whether there are differences in online social support between urban and rural communities. Whilst research provides evidence for cross-cultural differences in providing and obtaining offline social support, less is known about online social support.

Psychological well-being

The literature on psychological wellbeing is substantial, having stemmed from the growing field of positive psychology. Psychological research on wellbeing has been influenced by two philosophical views, namely the hedonic and eudaimonic approaches. The hedonic approach is based on the notion that increased positive feelings and decreased negative affect lead to happiness. Hedonic concepts are based on the concept of subjective wellbeing (SWB), a term commonly used to denote the 'happy or good life' (Diener, 1984; L. Henderson & Knight, 2012) The eudaimonic approach emphasises positive functioning and often requires engaging in effortful activity (Deci & Ryan, 2008; Ryan & Deci, 2001; Ryff, 1989).

Theories of well-being

In order to understand the conceptualisations of well-being, a brief overview of the different models of well-being are explored below.

Subjective wellbeing. The theory of subjective wellbeing (SWB) is based upon the hedonic approach which emphasises positive affect. Early work by A. Campbell (1976) contends that wellbeing dwells within the person, and thus does not incorporate reference to objective substances of life, such as health, income, social relations, or functioning (A. Campbell, 1976). Support for this was reported in the early influential work by Bradburn (1969) who found SWB to be a function of the independent dimensions of general positive and negative affect. Building on this work, (Diener, 1984, 2000, 2008) defined SWB as an individual's affective and cognitive evaluation of his/her life or overall life satisfaction (Diener, 2008). However, whether as claimed by Diener and colleagues, SWB represents a dominantly cognitive evaluation, is a subject of debate. In contrast, a substantial body of research showed evidence of the essence of SWB being affect (Blore et al., 2011; Longo, 2015; Tomyn & Cummins, 2011).

Set-point theory of wellbeing. Some argue that wellbeing is generally a stable condition which is more strongly influenced by enduring personality dispositions. These theorists propose that most individuals adjust to nearly any life event and the level of happiness fluctuates around a biologically determined set point that rarely changes (Costa & McCrae, 1980). In suggesting a SWB personality theory, Costa and McCrae (1980) drew on the set-point theory. They demonstrated that individuals have differing SWB baselines or set-points owing in part to variations in personality traits of extroversion and neuroticism. They reported extroverts rated higher on SWB than introverts and relatively neurotic people rated lower than emotionally stable individuals. Another prominent theory in this field, developed by Headey and Wearing (1989), is the dynamic equilibrium (DE) theory of subjective wellbeing. According to this theory, each person has a "normal" or balanced pattern of life events and a “normal” or balanced level of SWB, both of which are predictable on the basis of stable personal characteristics such as personality traits. Provided the normal pattern of events is maintained, no change in SWB occurs. Only deviations from normal events change the normal level of SWB. The change is usually temporary, however, because stable personality traits play a key equilibrating function, and therefore a person is likely to revert to his or her normal levels over time. Some argue that people with high levels of neuroticism tend to use less effective emotional regulation strategies than those who have lower levels of neuroticism (Bolger & Zuckerman, 1995).

Despite empirical evidence to support the set-point theory of wellbeing (Lykken & Tellegen, 1996), conflicting evidence has been found in recent years. In their literature review, Diener et al. (2006) concluded that people have diverse set points which are at least partially heritable. After reviewing longitudinal and cross-sectional research, they also suggested that the happiness set-point can change and that people may differ in circumstances in the rate and magnitude of adaptation they display to changes (Diener et al., 2006). Wildeman and colleagues (2014) studied how being in jail impacts the level of happiness of a person, both while in prison and after being released. They found that being in prison has adverse effects on one’s baseline wellbeing, compared to when not in prison (Wildeman et al., 2014). Similarly, others have also concluded that events such as divorce, death of a spouse, unemployment, and disability are associated with lasting changes in SWB (Lucas, 2007).

Optimal experience model of wellbeing. One of the early models of wellbeing that is based on the eudaimonic approach was proposed by Mihalyi Csikszentmihalyi called the theory of optimal experience (Csikszentmihalyi, 1990). The theory of optimal experience draws upon theories of humanistic psychology. For instance, akin to Abraham Maslow's well-known model of self-actualisation and "hierarchy of needs", Csikszentmihalyi argued that achieving a positive state of flow entails engaging in activities that challenge one's skills while simultaneously providing a sense of mastery and competence (Rothunde & Csikszentmihalyi, 2006). Consistent with this, others have also found that having goals and attaining them are reliable correlates of wellbeing (Emmons, 1986). Seligman reiterates this in his book "Flourish: A visionary new understanding of happiness and wellbeing" (Seligman, 2011).

Psychological wellbeing model. Ryff (1989) argued that key aspects of psychological wellbeing were neglected in earlier models of SWB. She subsequently developed a more comprehensive model of psychological wellbeing derived from developmental and humanistic psychology which includes six related yet distinct components. This well-being model is based on the premise that people are striving to function fully and realise their distinctive skills. Ryff's six dimensions of psychological wellbeing incorporate positive assessment of oneself and one's past (self-acceptance), a sense of continued development and advancement as a person (environmental mastery), the conviction that one's life is deliberate and important (purpose in life), quality relations with others (positive relations with others), the capacity to oversee one's life and encompassing world effectively (personal growth), and a sense of self-determination (autonomy) (Ryff, 1989; Ryff & Singer, 1995). Despite widespread interest in Ryff's PWB model, the validity of the six dimensions has been questioned. That is, studies have failed to consistently replicate the six factor structure (Abbott et al., 2006; F. Chen et al., 2013).

Self-determination theory. Another prominent eudaimonic model of psychological wellbeing is the self-determination theory proposed by Ryan and colleagues (2008). The self-determination theory postulates the existence of three inherent fundamental needs, which are universal (Ryan et al., 2008). They are: Autonomy – the ability to self-regulate behaviour and the capacity to act as an agent of one's own life; Competence – the requirement to feel assured in doing what one is doing; and Relatedness – the need to have close and safe human connections, whilst still respecting autonomy and facilitating competence. According to the self-determination theory, when these needs are satisfied, motivation and wellbeing are enhanced, and when they are limited, there is a negative impact on our ability to function well. Evidence to support this theory has been reported by others (Bartholomew et al., 2011; Bernard et al., 2014; Milyavskaya & Koestner, 2011).

Mixed models of psychological wellbeing. Some wellbeing researchers have proposed models that combine both hedonic and eudaimonic components of wellbeing. For instance, Seligman (2002) proposed an Authentic Happiness model of wellbeing which highlights three pathways conducive to happiness: pleasure, engagement, and meaning. Pleasurable experience highlights the positive emotions and thus reflects hedonistic orientation. Engagement reflects eudaimonic orientations as it is characterised by an individual's capacity to thrive, love for learning and bravery. The third pathway, meaning, is strongly associated with the eudaimonic perspective (Steger, 2012). The meaning pathway includes using one's strengths in the service of positive institutions. More recently Seligman has revised his original authentic happiness model and proposed the model of PERMA (Seligman, 2011). The PERMA is the acronym for the five – according to Seligman – important building blocks of wellbeing and happiness which are positive emotion, engagement, relations, meaning, and achievement. The PERMA model includes two additional elements to the original authentic happiness model. These are 'Relationships' and 'Accomplishment'. The relationships pathway reflects a eudaimonic philosophy by suggesting that happiness can be attained by promoting the happiness of others (Brülde & Bykvist, 2010). The final pathway, accomplishment, is achieved by applying one's skills and efforts toward a specific and fixed goal. It has been proposed that achieving, learning, and pursuing mastery at both an individual and group level can be distinct pathways to attaining happiness, which also reflects a eudaimonic orientation (Diener, 2008).

A second model of wellbeing which combined hedonic and eudaimonic perspectives was proposed by Corey Keyes (Keyes, 2006; Keyes et al., 2002). Keyes proposed the term ‘flourishing’ to refer to a state where people experience positive emotions, and positive social and psychological functioning, most of the time. Flourishing is contrasted with languishing, a state of stagnation and emptiness denoted by markers of psychopathology and the absence of positive mental health. Keyes' mental health model also takes into account mental illness symptoms or psychopathology on a separate but related continuum. Specifically, flourishing not only includes positive evidence of healthy functioning (e.g., feeling good and functioning well) but also denotes an absence of psychopathology. Keyes' broad measure of flourishing incorporates psychological wellbeing, SWB, and social well-being (that is, how well a person is functioning in their social life) which considers the quality of one’s relationships with other people, the neighbourhood, and the community (Keyes, 2007; Keyes & Shapiro, 2004). Social wellbeing complements eudaimonic aspects of wellbeing that emphasise functioning well in one’s private life, such as PWB.

Alternative conceptualisations of wellbeing. Other approaches to wellbeing that are not fully encompassed by hedonic or eudaimonic traditions have been proposed by some. For instance, Diener and Ryan (2009) proposed a psychological framework of wellbeing theories which distinguishes six categories: telic theories, top-down versus bottom-up theories, cognitive theories, evolutionary theories, theories of temperament and personality, and relative standard theories. The framework describes the different models of wellbeing under each category (see article for details). Another ‘hybrid’ model that combines research and theories from varying paradigms is called the sustainable happiness model (Lyubomirsky et al., 2005). This model proposes that multiple factors account for wellbeing including genetics, circumstances, and personal choice. Evidence to support this model has been found in a longitudinal study (Lyubomirsky et al., 2011). In general, there seems to be a lack of research evidence to support such combined models of wellbeing.

Demographic factors also show some differential effects on wellbeing levels. Mixed findings have been reported on gender differences in psychological wellbeing across broad and large sample studies (Batz & Tay, 2018). Many large surveys showed little evidence of gender differences (Batz-Barbarich et al., 2018; Helliwell, 2003; Khumalo et al., 2012; Zuckerman et al., 2017). Some showed higher scores for men (Pinquart & Sörensen, 2001), while others showed higher scores for women on some sub-scales such as those assessing social functioning (Ryff & Singer, 1998) and life satisfaction (Tay et al., 2014).

The association between age and mental wellbeing is also complex. Large surveys using single-item measures of wellbeing (e.g., overall rating of life satisfaction) usually find a U-shaped relationship with age: younger and older people tend to have higher well-being scores than the middle aged, although there may be a decline in wellbeing among the very old (Blanchflower & Oswald, 2008; Clark & Oswald, 1994). Middle-aged adults also have the highest prevalence of common mental disorders (Singleton et al., 2001). Blanchflower and Oswald (2008) have shown that the U-shaped relationship holds across different cohorts and in many nations.

The studies suggest a significant correlation between well-being and urban/rural living, education, income, paid employment, and marriage (Diener et al., 1995; Diener & Ryan, 2009; Veenhoven, 2008). Urban/rural differences in psychological wellbeing depend on several factors such as level of social integration, physical and mental health, and socioeconomic status (Amato & Zuo, 1992). The studies illustrate that adults between 45 and 54 years, adults with higher education (16 or more years) and married adults are more likely to flourish compared to females, younger adults, less educated, and unmarried adults (Keyes, 2002; Keyes & Simoes, 2012).

Personality traits are shown to be an important predictor for flourishing. Numerous studies have shown a strong predictive value of personality traits related to subjective and psychological well-being (Deneve & Cooper, 1998; Kotov et al., 2010; Steel et al., 2008). In particular, low neuroticism, high extroversion, and high conscientiousness are suggested to be positively related to subjective and psychological wellbeing (Keyes et al., 2002). Steel, Schmidt, and Schulz (2008) argued in a meta-analysis that personality traits have a much greater influence on the level of mental health of a person than was previously assumed. The analysis shows that extroversion is accountable for approximately 19% of variance in positive affect, and neuroticism is accountable for 29% of variance for negative affect. These findings confirm the importance of personality traits on psychological wellbeing (Steel et al., 2008).

Section Summary

From this brief review of key theories and models of well-being, it is clear that psychological well-being is a complex multifaceted construct. There is considerable conceptual overlap between the various models of well-being. What is apparent from the literature is that well-being includes both hedonic and eudaimonic aspects of well-being. Both hedonic and eudaimonic theories of wellbeing reflect specific, distinguishable types of happiness; however, each perspective considered limited aspects of psychological well-being (Carlisle et al., 2009). Hedonic well-being, with its focus on feelings, neglects functioning, in addition to neglecting important sources of wellbeing. Eudaimonic theories stress meaning and functioning at the expense of more immediate emotional states and gratifications. Thus, neither hedonia nor eudaimonia alone constitute a complete understanding of wellbeing; both perspectives are vital to happiness (K. M. Sheldon & Lyubomirsky, 2006).

Based on the different theoretical models, wellbeing may be conceptualised in terms of people's emotional responses (positive and negative feelings) and their cognitive or evaluative responses or satisfaction with life (Diener, 1984). It also includes concepts such as autonomy or self-determination, interest and engagement, positive relationships, self-acceptance, optimism, mastery, control, and a sense of meaning or purpose in life (Deci & Ryan, 2008; Diener et al., 2006; Ryff, 1989). Furthermore, the evidence on the importance of social connections to wellbeing suggests that measures of well-being should include aspects of social well-being such as satisfaction with social relations (Helliwell & Putnam, 2004; Keyes, 2007). Therefore, it is recommended that multiple aspects be considered when examining and assessing wellbeing (Diener et al., 2006; L. Henderson & Knight, 2012; Huta & Ryan, 2010). This may be achieved by incorporating the integrative frameworks developed by Seligman (2002) and Keyes (2007).

Theories Linking Offline Social Support with Psychological Wellbeing

The following section begins with a brief review of research and theory regarding offline social support and wellbeing.

Relationship Between Social Support and Psychological Wellbeing

There are two dominant models that address the link between social support and wellbeing proposed by Cohen and Wills (1985): the main effects model and the stress-buffering model.

Main effects model

The "main effects model" or the "direct model" implies that social support has a positive effect on health and operates at all times, irrespective of the individual's life situation and independent of their exposure to stress (Berkman & Syme, 1979; House et al., 1988b). In this model, social support can prevent the occurrence of the stress that may otherwise negatively affect health. Social support is regarded as a basic human need, and therefore people will feel better psychologically when that need is met (House et al., 1988) and people with high social support will have better mental health than those with low social support (Lakey & Orehek, 2011).

Several studies have provided support for the main effects model over the last four decades (Beeble et al., 2009; Burton et al., 2004; Lakey & Cronin, 2008; Stroebe et al., 2005; Wade & Kendler, 2000). The evidence that social support is beneficial (main effects) for psychological wellbeing and that poor social support is associated with (or leads to ill health) is considerable. The majority of the studies are from Western countries. A relevant New Zealand large longitudinal study also provides support for the positive association between social connectedness and mental health (Saeri et al., 2017). The available evidence shows that the provision of social support and good social relations constitute a resource for health and can make an important contribution to health and wellbeing (S. Cohen, 1988; Kawachi & Berkman, 2001; Schwarzer & Leppin, 1991; Wilkinson & Marmot, 2003). On the other hand, a lack of social support may lead to an increased risk of physical and psychological illness (House et al., 1988b) and mortality (Berkman & Syme, 1979; Blazer, 1982). Berkman and Syme's (1979) classic study of almost 4000 residents of Alameda County in the USA, for example, revealed that people with the lowest levels of support contacts, at the time the study commenced, had age-adjusted mortality rates two to four or five times higher than those reporting many social contacts after nine or more years of follow-up (Berkman & Syme, 1979). Recent reviews of literature have also generally found a positive relationship between social support and mental health (Harandi et al., 2017; Siedlecki et al., 2014). Overall, therefore, there is strong evidence from studies linking social support and wellbeing suggesting a direct relationship exists between these irrespective of life stressors. Of note again, research studies report that perceived social support is more consistently associated with psychological wellbeing compared to enacted support in this literature (Beeble et al., 2009; Chu et al., 2010; Gariépy et al., 2016; Haber et al., 2007; Lakey & Cronin, 2008; Nurullah, 2012; Stice et al., 2011; Uchino, 2009; Yalçın, 2015).

Stress-buffering model

In the stress-buffering model, social support protects (or "buffers") people from the negative effects of stressful life events (e.g., loss of loved ones, trauma, and violence) (Beeble et al., 2009; Mezuk et al., 2010; Thoits, 1986). According to this model, the availability of social support moderates the negative effects elicited by stress by enhancing an individual's coping abilities through perceived social support. A key distinction from the main effects model is that in the stress-buffering model, in the absence of stress, social support is not predictive of mental health (S. Cohen & Wills, 1985).

Recent researchers argue that one of the most serious problems with the stress-buffering model is the inconsistent research support for it compared to that regarding the main effects model (Lakey & Cronin, 2008). Based on Lakey and Cronin's (2008) review, Lakey and Orehek (2011) argued that most of the known research links between perceived support and mental health reflect main effects rather than stress-buffering effects. Unlike the proposed stress-buffering effects between perceived social support and mental health, research evidence suggests that perceived social support has a direct link to mental health and this relationship is highly replicable (Lakey & Orehek, 2011). In fact, several studies have found no link between enacted support and mental health or have found that receiving enacted support is associated with worse mental health (Bolger & Amarel, 2007; Finch et al., 1999; Lakey et al., 2010).

Chapter Summary

It is clear that social support is a complex construct. Many researchers tend to combine dimensions and types of social support (Chronister et al., 2006). Reviews of the literature indicate that social support is an umbrella term that can include the subjective evaluation and actuality that one is loved and cared for, has help from other people, and that one is part of a supportive network. Supportive resources can be provided through either emotional support, informational support, or tangible support, and these can be received from different sources.

An on-going debate in the literature has concerned the question of which type of support is more important in the life of the recipient. What has clearly emerged from the existing literature on traditional social support is the distinction between enacted and perceived support. Several studies show that perceived support is only modestly correlated with measures of enacted support (Haber et al., 2007; Melrose et al., 2015) (Eagle et al., 2019). Furthermore, there is strong evidence to support a positive relationship between perceived support and positive mental health outcomes (Barrera, 1986; Lakey et al., 2010). On the other hand, the association between enacted support and mental health outcomes is inconsistent (Dunkel-Schetter & Bennett, 1990; Kessler et al., 1992; Wethington & Kessler, 1986). This review highlights the importance of clearly defining social support for research purposes. Overall, perceived social support has been found to be more significant than enacted social support with regard to wellbeing outcomes.

Although an overwhelming amount of research on offline social support has emerged over several decades, research interest in online social support began only in the last decade. With the increasing use of SNSs, the way people interact has changed dramatically. The review of SNS literature also highlights the deep penetration of its use in many aspects of the everyday life of users with possible benefits and negative consequences to wellbeing and mental health. One of the areas of focus in SNS literature has been the social benefits of SNS use, e.g., obtaining social support and whether this support has similar benefits as offline social support.

There seems to be no consensus regarding the conceptualisation of online social support. However, similar to offline social support, online social support can be conceptualised based on strength of social ties, subjective evaluation of support available, or objective amount of different types of support available. Online social support includes less physical and material aid compared to offline social support. Other unique aspects of online social support include the influence of technology-efficacy and the possibility of receiving support while maintaining anonymity.

There is a growing interest in examining the relationship between online social support and psychological wellbeing. Feelings of wellbeing are fundamental to the overall health of an individual, enabling them to successfully overcome difficulties and achieve what they want out of life. Through the brief review of key theories and models of wellbeing in this chapter, it is clear that psychological wellbeing is a complex multifaceted construct. There is considerable conceptual overlap between the various models of well-being. What is apparent from the literature is that well-being includes both hedonic and eudaimonic aspects.

In the next chapter, a narrative review of literature on the association between online social support and psychological wellbeing is presented. Based on the evaluations of the study concepts in this chapter and the literature review presented in the next chapter, a conceptual model of the study with hypotheses is presented in the next chapter.

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CHAPTER 2: NARRATIVE REVIEW OF THE LITERATURE ON THE RELATIONSHIP BETWEEN ONLINE SOCIAL SUPPORT, OFFLINE SOCIAL SUPPORT, AND PSYCHOLOGICAL WELLBEING

Chapter One reviewed the key concepts studied in the current project including associations between offline social support and psychological wellbeing. This chapter provides a more in-depth literature review on the relationship between online social support and wellbeing. The chapter concludes by introducing a conceptual model for the current project and the associated hypotheses to be tested. The model and hypotheses were developed on the basis of the literature presented in both the previous chapter and the literature reviewed in this chapter.

Relationship Between Online Social Support and Psychological Wellbeing

A recent systematic review evaluated 22 articles published between 2003 and 2016 on the impact of SNS use and psychological wellbeing (Erfani et al., 2018). This review found that 16 studies demonstrated positive effects of SNS use on users' psychological wellbeing. Of these 16 studies, only four examined the association between online social support and psychological wellbeing. These studies will be reviewed later in this chapter. Another recent systematic review by Gilmour and colleagues examined the effects of Facebook-based social support on health (Gilmour et al., 2019). Based on the review of 27 studies, they concluded that Facebook-based social support was related to improved general physical and mental health. Both these reviews have limitations. Erfani and colleagues focused on general SNS use and psychological wellbeing. As a result, they missed several studies that specifically focused on the effects of online social support on psychological wellbeing (Erfani et al., 2018). Gilmour and colleagues' review was limited to online support from Facebook only. People acquire online social support from other SNSs in addition to Facebook. To address these limitations, a comprehensive review of literature on online social support (acquired from any SNS) and psychological wellbeing was conducted in this study and the results are discussed below.

The review of primary research studies included all quantitative studies investigating the association between any type of online social support and mental health in the last 15 years (2004 – 2019). The search strategy was last updated on 31 May 2019. Studies examining general SNS use rather than specific online social support as a predictor variable were excluded. Two main search methods were used to identify papers to include in this review: electronic searching and hand searching of specific journals or articles and other publications. In addition to searching for published studies, efforts were also made to search the grey literature on the topic. The grey literature search comprised a web-based search to obtain unpublished sources using Google search. The criteria used to search the grey literature were the same as those used in the electronic searches. The electronic search was conducted using the online databases,-Psyc INFO, Web of Science, PubMed, and Google Scholar. The following search terms or phrases were used in most of the databases;

1. *"Social support" OR "Perceived support" OR "Online Support" OR "Social capital" AND*
2. *"Online social network" OR "SNS" OR "Facebook" OR "Social media" AND*
3. *"Life satisfaction" OR "Mental health" OR "Mental disorders" OR "Wellbeing" OR "Quality of life" OR "depression" OR "Anxiety" OR "Stress"*

Thirty-two articles were included in the final review for this study. Some of these studies were published after the survey design and data collection stages of the current thesis project. The data obtained from these studies focused on the design of the studies, the samples, the measures used, and how online social support was measured and the relevant findings. These results are presented in Table 2.

Results

Of the 32 studies reviewed, 24 reported positive relationships specifically between online social support measures and wellbeing and/or negative associations between online social support measures and negative psychological factors. Eight out of the 25 studies did not find any significant associations. Out of the 24 studies with significant findings, 15 studies were carried out with non-random college student samples. Two studies used convenience samples of SNS users. One study compared a clinical sample with a community sample while another combined a community and college sample. Only one study used a random community sample. These studies are discussed in detail below.

Positive associations between online social support and psychological wellbeing. Of the 24 studies (which produced significant findings) 15 found positive relationships between online social support and psychological wellbeing or life satisfaction. Kim and Lee (2011) examined the pathways between number of Facebook friends, self-representation, online PSS, and subjective wellbeing in a sample of 391 undergraduate students in the United States. J. Kim and Lee (2011) adapted the 40-item Interpersonal Support Evaluation List (S. Cohen & Hoberman, 1983) to measure online PSS. Subjective wellbeing was measured using the four-item Subjective Happiness Scale (Lyubomirsky & Lepper, 1999). They found a positive association between online PSS and subjective wellbeing. They also found that the number of Facebook friends was positively associated with subjective wellbeing (although the relationship was not as strong as the former) (J. Kim & Lee, 2011). Manago and colleagues examined the association between Facebook use, online PSS, and wellbeing in a sample of 88 university students from the United States. Online PSS was measured using the adapted 40-item Interpersonal Support Evaluation List (S. Cohen & Hoberman, 1983). Wellbeing was measured by adapting the Student's Life Satisfaction Scale (Huebner, 1991). In addition, different characteristics of the Facebook network were measured. They found that online PSS was positively associated with wellbeing (bivariate correlation). Manago and colleagues did not explore this relationship further by controlling for other variables although they did find that Facebook network size and communicating with people they know in offline contexts was positively associated with online PSS after controlling for other factors (Manago et al., 2012).

Oh et al. (2014) examined the association between SNS use and psychological wellbeing in 339 undergraduate students from the United States. Oh and colleagues also adapted the 40-item Interpersonal Support Evaluation List (S. Cohen & Hoberman, 1983) to measure online PSS (companionship, appraisal support, and esteem support). They adopted four items from the Satisfaction with Life Scale (Diener et al., 1985) to measure subjective wellbeing. They found a positive direct relationship between subjective wellbeing. In addition, they found an indirect positive association between appraisal support and esteem support and subjective wellbeing via sense of community. C.-Y. Liu and Yu (2013) compared the relationship between online PSS and offline PSS and the association of these with psychological wellbeing among 330 Taiwanese college students. Online PSS and offline PSS were measured by adapting the

Interpersonal Support Evaluation List (S. Cohen & Hoberman, 1983). Wellbeing was measured using Ryff's scales of psychological wellbeing (Ryff & Keyes, 1995). They found that online PSS was positively related with psychological wellbeing ($\beta = .09$, $p < .05$), although this relationship was weaker than the association between in-person social support and wellbeing ($\beta = .59$, $p < .001$) (C.-Y. Liu & Yu, 2013). Zhang (2017) conducted a cross-sectional study comparing the association between enacted online social support from Facebook and life satisfaction versus perceived social support (non-specified) and life satisfaction in a sample of 560 university students in Hong Kong. Enacted social support on Facebook was measured using four items developed by Li and colleagues (X. Li et al., 2015). Perceived social support was measured using five items from the Medical Outcome Study Social Support Survey (Sherbourne & Stewart, 1991). Depression was measured with the Patient Health Questionnaire (PHQ-9: Kroenke et al., 2001). Wellbeing was measured using the five-item Satisfaction with Life Scale (Diener et al., 1985). Their study found that enacted social support on Facebook was positively related to satisfaction with life but was not significantly associated with depressive symptoms. Compared to the relationship between online enacted social support and life satisfaction ($\beta = .12$, $p < .01$), the relationship between perceived social support and life satisfaction was much stronger ($\beta = .25$, $p < .001$). Although Zhang called the predictor variable 'enacted online social support', the author's description of the measure suggests that this was assessing perceived availability of social support.

Nabi and colleagues (2013) used an online survey to examine effects of the number of Facebook friends and perceived social support on psychological wellbeing in a sample of undergraduate students from the United States. Perceived social support was measured using the 12-item Multidimensional Scale of Perceived Social Support (Zimet et al., 1988). Nabi and colleagues did not specify whether perceived social support was obtained from online or offline contacts. Wellbeing was measured using the five-item Satisfaction with Life Scale (Diener et al., 1985). They found that the number of Facebook friends was positively associated with subjective wellbeing (a direct link). In addition, they found that the number of Facebook friends was indirectly positively associated with subjective wellbeing via perceived social support. The effect of perceived social support on subjective wellbeing was stronger than the effect of the number of Facebook friends (Nabi et al., 2013). Jang and colleagues (2016) examined the relationship between several factors including self-esteem, Facebook use, Facebook social comparison, perceived social support, and mental health in a sample of 358 university students in South Korea. Perceived social support was measured using four items from the Multidimensional Scale of Perceived Social Support (Zimet et al., 1998). Similar to Nabi and colleagues (2013), Jang and colleagues also did not specify whether perceived social support was obtained from online or offline contacts. Mental health was measured with five items from the RAND Mental Health Inventory (Stewart et al., 2012). They found that although Facebook use was not directly associated with mental health, intensity of Facebook use was associated with perceived social support which in turn was positively associated with mental health.

Two studies found evidence to support a positive association between online social support and wellbeing in specific groups. In a sample of Chinese adults with HIV/AIDS who used an online SNS platform developed and used specifically in China, Han and colleagues (2018) first explored the relationship between online enacted (receiving and giving) social support and online PSS. They also examined the effects of online PSS and offline PSS on subjective wellbeing (Han et al., 2018). Online enacted social support was measured using 9 items developed by Li and colleagues (X. Li et al., 2015). Online PSS was measured by adapting the 12-item Multidimensional Scale of Perceived Social Support. Offline PSS was measured by the original Multidimensional Scale of Perceived Social Support (MSPSS: Zimet et al., 1998). Subjective wellbeing was measured using the five-item Satisfaction with Life Scale (Diener et al., 1985). Their results showed that both online received and giving social support were positively associated with online PSS. As expected, online PSS and offline PSS were positively related (r =.274, p < .001). They also found that both online PSS and offline PSS were positively associated with subjective wellbeing. Interestingly, they found that the association between online PSS and subjective wellbeing was slightly stronger (β = .27, p < .001) than association between offline PSS and subjective wellbeing (β = .25, p < .001). Chan (2018) examined the relationship between SNS communication quality, friendship satisfaction, social support, and subjective wellbeing in a random community sample of 925 people aged from 18 to over 70 years in Hong Kong. Social support was measured from items adapted from the MOS Social Support Survey (Sherbourne & Stewart, 1991). Subjective wellbeing was measured using the five-item Satisfaction with Life Scale (Diener et al., 1985). Chan found that the number of Facebook friends but not the number of ‘WhatsApp Groups’ was positively associated with social support for the 18-34 and the 35-55 year old groups but not the 55-70+ year old group. He also found that number of Facebook friends was positively associated with subjective wellbeing for the 18-34 year old group but not the 35-54 or 55-77+ year old groups. On the other hand, the ‘WhatsApp groups’ were associated with subjective wellbeing for the 35-55 year old group but not others (Chan, 2018). This inconsistent finding may have occurred due to the difference between functions of the two applications. WhatsApp is an instant messaging application unlike Facebook which is an SNS platform that has many more functions to connect people. Both friendship satisfaction and social support were positively associated with subjective wellbeing for all three age groups. Chan did not specify whether friendship satisfaction and social support were for online or offline contexts. Chan’s study indicates that perceived social support (general) is beneficial for all ages but number of Facebook friends emerged as an important factor for the younger group only. Indian and Grieve (2014) examined the relationship between offline PSS, online PSS, and subjective wellbeing in a sample of 299 Facebook users divided into high and low anxiety groups. Online PSS was measured using the adapted Interpersonal Support Evaluation List (S. Cohen & Hoberman, 1983). Offline PSS was measured using the original Interpersonal Support Evaluation List. Subjective wellbeing was measured using the five-item Satisfaction with Life Scale (Diener et al., 1985). They found that online PSS was associated with higher levels of well-being for people with high levels of social anxiety. In the high anxiety group, offline social support was not significantly associated with psychological wellbeing when controlled for online support in a hierarchical regression analysis. On the other hand, in the low social anxiety group, offline social support was related to wellbeing but not online social support.

Three studies reported positive associations between different factors of online social support and wellbeing. Grieve and colleagues (2013) examined the association between online or Facebook social connectedness and wellbeing in a sample of 344 university students and community members in Australia. Offline social connectedness was measured using the original 20-item Revised Social Connectedness Scale (R. M. Lee et al., 2001). Facebook social connectedness was measured by adapting the Revised Social Connectedness Scale. The Satisfaction with Life Scale (Diener et al., 1985) was used to assess subjective wellbeing. Depression and anxiety were measured using two seven-item subscales from the Depression Anxiety Stress Scales (Lovibond & Lovibond, 1995). Using bivariate statistics, Grieve and colleagues found that online social connectedness was positively associated with subjective wellbeing. Burke and Kraut (2016) surveyed 1910 Facebook users to measure how friendship tie strength on Facebook was associated with measures of wellbeing (Burke & Kraut, 2016). The online friendship tie strength was measured using a self-report measure which asked participants to pick Facebook friends they discuss important issues and enjoy socialising with, and then rate how close they feel to them. Therefore, online friendship tie strength as measured by Burke and Kraut can be considered an index of social support. Subjective wellbeing measures used were the Satisfaction with Life Scale (Diener et al., 1985), the CES-D depression scale (Radloff, 1977), the UCLA Loneliness Scale (Russell, 1996), and the Positive and Negative Affective Scales (Watson et al., 1988). The results suggested that receiving communication from strong ties is associated with improvements in wellbeing while receiving communication from weak ties is not. Furthermore, their study found that targeted communication from strong ties was associated with increases in wellbeing. On the other hand, receiving brief responses such as a “like” or “poke” or reading posts of others or viewing others’ photos was not. The study concluded that online interactions influence wellbeing, particularly when this involves personalised and effortful communication from close friends (Burke & Kraut, 2016). Hu and colleagues (2017) explored the effects of Facebooking on individuals’ social relationships and psychological wellbeing in a sample of 405 university students from the United States. Two scales were created by adapting existing scales to measure Facebook or offline social relationship satisfaction. Perceived social support (non-specified) was measured using 16 items from the Interpersonal Supportive Evaluation List (S. Cohen & Wills, 1985). Subjective wellbeing was measured using the Satisfaction with Life Scale (Diener et al., 1985). They found that intensity of Facebook use was positively related to online social relationship satisfaction and perceived social support while negatively related to offline social relationship satisfaction. Online social relationship satisfaction was positively linked to psychological wellbeing (a direct link). The study also found that Facebook use was indirectly linked to wellbeing through online social relationship satisfaction, perceived social support, and offline social relationship satisfaction. This suggests that intensity of Facebook use may be both good and bad for wellbeing.

Study using random samples. One cross-sectional study used random samples. Jeong and colleagues studied a randomly selected community sample of adults in South Korea (Jeong et al., 2014). Their study found that "online bonding capital" and "online bridging social capital" predicted greater "online wellbeing" but not "offline wellbeing", while "offline wellbeing" was predicted only by "offline bonding social capital". Online wellbeing was considered different from general offline wellbeing but details regarding these were not provided by the authors.

Negative associations between online social support and negative psychological factors. Of the 24 studies (which produced significant findings) 9 found negative relationships between online social support and negative psychological variables. Nick and colleagues (2018) compared the effects of online social support and offline social support on psychological wellbeing using a combined sample of US college students and community participants. Nick and colleagues developed their own 48-item measure of online social support. In-person social support was measured using the Perceived Social Support Scale (Procidano & Heller, 1983). Some of the key outcome measures used were the Cyberbullying Experiences Survey (Doane et al., 2013), the Rosenberg Self-Esteem Scale (Rosenberg, 1965), the Cognitive Triad Inventory (Beckham et al., 1986), the Beck Depression Inventory-II (Beck et al., 1996), and the Life Experiences Survey (I. G. Sarason et al., 1978). They found that both online social support and offline PSS were negatively associated with depressive symptoms after controlling for stressful life events. Nick and colleagues interpreted this as supporting the main hypothesis over the stress-buffering hypothesis. That is, there was no significant interaction between stressful life events and online social support in predicting depressive symptoms. They also found that online social support was positively associated with self-esteem and negatively associated with depressive thoughts. Although the results (direction of relationships) for online and in-person support were similar, the effect of in-person social support on depressive symptoms was stronger (β = -.39, p < .001) compared to the effect of online social support on depression (β = -.12, p < .05). Another interesting finding was that offline PSS offset the negative effects of cyberbullying. There was no significant interaction effect between online social support and cyberbullying, suggesting that online social support did not diminish the negative effects of online peer victimisation (Nick et al., 2018). Similarly, Cole and colleagues (2017) reported that perceived availability of social support and enacted support online were associated with lower levels of depression-related thoughts and feelings and also minimisation of the adverse effects of peer victimisation in a large sample of college students. In this study, Cole developed a 16-item measure of online and offline enacted social support and also developed a 16-item measure of online and in-person victimisation. Perceived social support from (the sources were not specified) was measured using the Perceived Social Support Scale (Procidano & Heller, 1983). Cole used a single latent Depressive Thoughts and Feelings Factor (DTF) which was derived from the Dysfunctional Attitudes Scale (Weissman, 1980), the Beck Depression Inventory-II (Beck et al., 1996), and the Rosenberg Self-Esteem Scale (Rosenberg, 1965). Although Cole and colleagues measured actual support from online contacts rather than online PSS, the results supported both main effect and stress-buffering models. That is online enacted social support was negatively associated with DTF (main effect) irrespective of the level of online victimisation. In addition, online social support significantly reduced the strength (stress-buffering) of the relationship between online victimisation and the DTF factor. Their results also showed that both online and in-person support had similar association with depression-related thoughts and feelings, but the association between in-person social support and depressive thoughts was stronger than those between depressive thoughts and online social support (Cole et al., 2017). Park and colleagues (2016) compared the effects of online PSS and enacted social support on depression in a sample of undergraduate students from the United States. Online PSS was measured by adapting the 12-item abbreviated version of the Social Provision Scale (Cutrona & Russell, 1990). Actual social support was measured by an index derived from evaluating their comments in response to comments made by friends. Participants' depressive symptoms were assessed by the 12-item depression subscale of the ruminative response scale (Nolen-Hoeksema & Morrow, 1991). They found that online PSS was negatively associated with depressive symptoms. Furthermore, they found that the participants perceived their network to be less supportive than it was in reality (J. Park et al., 2016).

Grieve and colleagues’ (2013) study findings indicated that Facebook social connectedness was negatively related to measures of both anxiety and depression. In addition, two studies reported that online PSS was negatively associated with loneliness (Wright, 2012) and perceived stress (Wright et al., 2013) in college students (Wright, 2012; Wright et al., 2013). Online PSS was negatively related to depressive symptoms in a study of high school children in Belgium (Frison & Eggermont, 2015). In the same group, further analyses showed that in girls, both active private and public Facebook use predicted online PSS, which in turn predicted lower levels of depressed mood. On the other hand, in boys, active public Facebook use also predicted greater online PSS, but online PSS did not significantly predict depressed mood (Frison & Eggermont, 2016). In another study of 292 university students from South Korea, it was reported that online PSS was negatively associated with loneliness (Seo et al., 2016). The findings described above suggest that social support from SNSs could not only be beneficial for general wellbeing, but may also help reduce common mental health problems or negative experiences such as anxiety, depression, loneliness, and online victimisation in some groups.

No relationship between online social support and psychological wellbeing. Of the 32 studies, eight studies (of which two studies were longitudinal studies) found no relationship between online PSS and psychological wellbeing.

Cross-sectional studies. Seven cross-sectional studies found no relationships between online social support and wellbeing. In 2017, Chen and Li studied a sample of undergraduate students in the United States and the psychological effects of their Facebook use (H.-T. Chen & Li, 2017). They reported that ‘received’ online social support did not significantly relate to stress or life satisfaction. In addition, they found that provision of online social support was associated with reduced life satisfaction, but this was the opposite for those who had low self-esteem. Kim (2014) studied a large sample (N = 629) of undergraduate students from the United States. The study detected no significant relationship between social support acquired from Facebook use and subjective wellbeing. Their study concluded that although intensity of Facebook use was positively related to online received social support, there was no significant association between online received support and life satisfaction (H. Kim, 2014). Similarly, McCloskey and colleagues (2015) explored the relationship between online social support and wellbeing using a newly developed measure of social support from Facebook use (FMSS) (McCloskey et al., 2015). Their study also used a large convenience sample of undergraduate students (N = 633). Using bivariate correlational analyses, their study found that generally the FMSS subscales were positively associated with offline social support measures. However, the FMSS or online PSS did not show a significant positive association with quality of life measures. Unexpectedly, the emotional support factor of the FMSS was associated with higher depressive symptoms and lower psychological wellbeing subscale of the quality of life measure. In a study of a LGBT youth sample in the United States, Ybarra and colleagues (2015) found that online PSS was not a significant protective factor against cyberbullying and online sexual harassment. On the other hand, in-person social support was associated with reduced odds of bully victimisation (both online and in-person) and sexual harassment (in-person) (Ybarra et al., 2015). McConnell and colleagues also studied a sample of LGBTQ youth and their FB use (McConnell et al., 2017). They reported that Facebook social integration, non-specified PSS, and seeking online support did not predict psychological distress, and that offering online social support to online friends predicted higher levels of psychological distress.

Study using a random sample. Lima and colleagues (2017) conducted a study with an adult community sample in Portugal (Lima et al., 2017). They found that Facebook friendship was not a significant predictor of bonding social support or health. Facebook friendships had a negative relationship with bonding social support and had a negative indirect effect on health.

Longitudinal studies. Trepte and colleagues (2014) studied the relationship between online and offline PSS in a longitudinal study of 327 SNS users in Germany. Participants were selected via two popular SNS sites (Facebook and StudiVZ). Data was collected across four waves, six months apart. Using structural equation modelling, the authors tested the relationship between online PSS and satisfaction with life. Their study found although there was an increase in satisfaction with online PSS over the course of two years, there was no significant relationship between online social support and life satisfaction. On the other hand, they found a significant positive relationship between offline PSS and life satisfaction.

Similarly, Utz and Breuer (2017) examined the relationship between online PSS, stress, and life satisfaction in a large longitudinal study of 3,367 respondents who were representative of Dutch internet users. Utz and Breuer collected data at six intervals at an average of six months apart. They measured online PSS using a modified

UCLA Social Support Inventory. Stress was measured using four items and life satisfaction was measured using one item with a 7-point Likert scale which asked participants, “how satisfied are you with your life as a whole?” Their study found that although asking for advice on SNSs was positively associated with online social support, there was no significant association between online social support and life satisfaction over time. Contrary to previous findings by others (e.g., Indian & Grieve, 2014; Nabi et al., 2013; Wright et al., 2013), Utz and Breuer found a significant positive association between online social support and stress (Utz & Breuer, 2017). This might reflect people who have high levels of stress asking for more advice online which increases their online support level. However, the online support did not have a significant positive effect on psychological wellbeing. This study has several strengths, including longitudinal design. However, the findings need to be interpreted with some caution in that they used a single item to assess wellbeing, suggesting this measure is of questionable validity.

Summary

The review of literature indicates that the direction of the relationship between online social support and psychological wellbeing may vary depending on a number of factors, including the quality of online interactions (Frison & Eggermont, 2016), satisfaction with social support (Wright et al., 2013) as well as age (Chan, 2018), gender (Frison & Eggermont, 2016), and the level of existing offline social engagement (C.-Y Liu, 2013). Although disclosure on SNSs was generally associated with increased online PSS (Jeong et al., 2014; G. Lee et al., 2011), disclosing intimate feelings and thoughts has also been found to have a negative association with online PSS and on mental health (Zhang, 2017). Private communication appears to be of greater benefit to online PSS and mental health, particularly for adolescent girls, as opposed to public posting and interaction (Frison & Eggermont, 2016). ‘Honesty’ in online interactions (J. Kim & Lee, 2011) and ‘strong ties’ with friends on Facebook (H. Kim, 2014) were also predictive of increased online social support, indicating that quality of interactions and relationships are important to improve perceptions of support. Overall, only a small number of studies have controlled for these confounding variables. There is also a lack of consistency in the online PSS measures used and in the outcome variables and measures used, which makes it difficult to generalise the findings across studies. However, what has emerged from this preliminary work is a general tendency for online perceived social support to have a positive influence on psychological wellbeing mainly for special groups such as college students (e.g., Nabi et al., 2013; Liu & Yu, 2013; Manago & Greenfield, 2012; Oh et al., 2014; Zhang, 2017; Han et al. 2018; Nick et al, 2018) and to help decrease anxiety and depression levels for some (Indian & Grieve, 2014; Grieve et al., 2013). On the other hand, online enacted social support was less consistently related to psychological wellbeing (Kim, 2014; Utz and Breuer, 2017).

Taken together this review of studies indicate that online social support may be somewhat beneficial for specific groups, particularly college students. This is understandable given that college students are frequently living away from home and therefore more likely to rely on SNS for support and social connections. However, given that it is not only college students who are spending more time on SNSs and receiving social support online, it could be expected that there will be a positive relationship between online PSS and psychological wellbeing in the general population. However, some studies have failed to replicate these positive findings, raising the possibility that online social support may not be beneficial for even all college students.

This review of the literature on online social support and wellbeing reveals common limitations across the studies reviewed. What is intriguing is the somewhat inconsistent findings on the association between online social support and wellbeing. The methodological shortcomings (e.g., over-reliance on college students, use of convenience samples, social support measurement issues), in the literature may help explain these inconsistencies. Only a few studies drew community samples or special populations including specific SNS users (e.g., visually impaired, LGBTQ, high anxiety groups). There is also a lack of diversity in age ranges of the sample with only two studies reporting the mean age of participants being over 30 years old. A further limitation is that the majority have focused on a single social network site, despite different sites providing opportunities for different kinds of social interaction (e.g., Indian & Grieve, 2014; Longman, et al., 2009). Additionally, some studies have measured online social support and offline support in such different ways that comparison between them is not possible (e.g., Trepte et al., 2014). Although Trepte and colleagues measured perceived social support, their measure may not have been valid given that they adapted a bonding social capital scale which was focused on only perceived emotional support from generic online contacts. McCloskey and colleagues (2015) used a measure specifically developed to measure online PSS; the support was measured from Facebook interactions only. In addition, the validity and reliability of McCloskey's measure may be problematic given the scale generally asked for very specific supportive behaviours on Facebook that may have not fully covered the perceived social support dimensions.

Aims and Objectives of the Study

In light of the findings from this review, the aim of this project is to simultaneously evaluate relevant psychological and demographic factors in relation to SNS behaviour. More specifically, it aims to explore how SNS use influences people's perceived online social support with a specific focus on culture, age, gender, personality traits, and demographic location. This approach could help explain the inconsistencies found in published research on SNS and social support. Another gap in online social networking, social support, and wellbeing literature arises from the use of fairly narrow convenience sampled demographic groups, such as teenagers and college students. Randomly recruited population-based data is necessary to accurately characterise the extent of the SNS/social support/wellbeing associations in ways which are generalisable to the wider population.

Conceptual Model for the Study

The conceptual model is the basis for the analysis of the data (Figure 2). Given the likely variability in the amount of time people spent on SNSs, it is important to consider this factor in any model that proposes to explore the experience of online PSS.

Wellbeing is the dependent or outcome variable, and online PSS and offline PSS are the main independent factors or predictor variables hypothesised to influence wellbeing. The focus is on **perceived** social support rather than enacted support. This focus is justified by the finding that perceived social support is consistently associated with better psychological well-being, while enacted receiving social support seems to generate mixed results (Beeble et al., 2009; Chu et al., 2010; Haber et al., 2007; Lakey

& Cronin, 2008; Nurullah, 2012; Stice et al., 2011; Uchino, 2009; Yalçın, 2015). Both online PSS and offline PSS were conceived as having a potential positive effect on wellbeing given findings observed in the literature discussed in this chapter. Online self-disclosure is explored as an additional element positively linked to wellbeing, based on the assumption that online self-disclosure is a prerequisite for exchanging social support.

The conceptual model for the project is based upon the “main effect” theory of social support and health outcomes because of the strong evidence for it. In the main effect model, the direct association between online PSS and offline PSS and mental health is tested. In addition, the study explores the potential covariates including personality traits, age, gender, region, and country. These factors may have different effects on the associations between the independent and dependent variables.

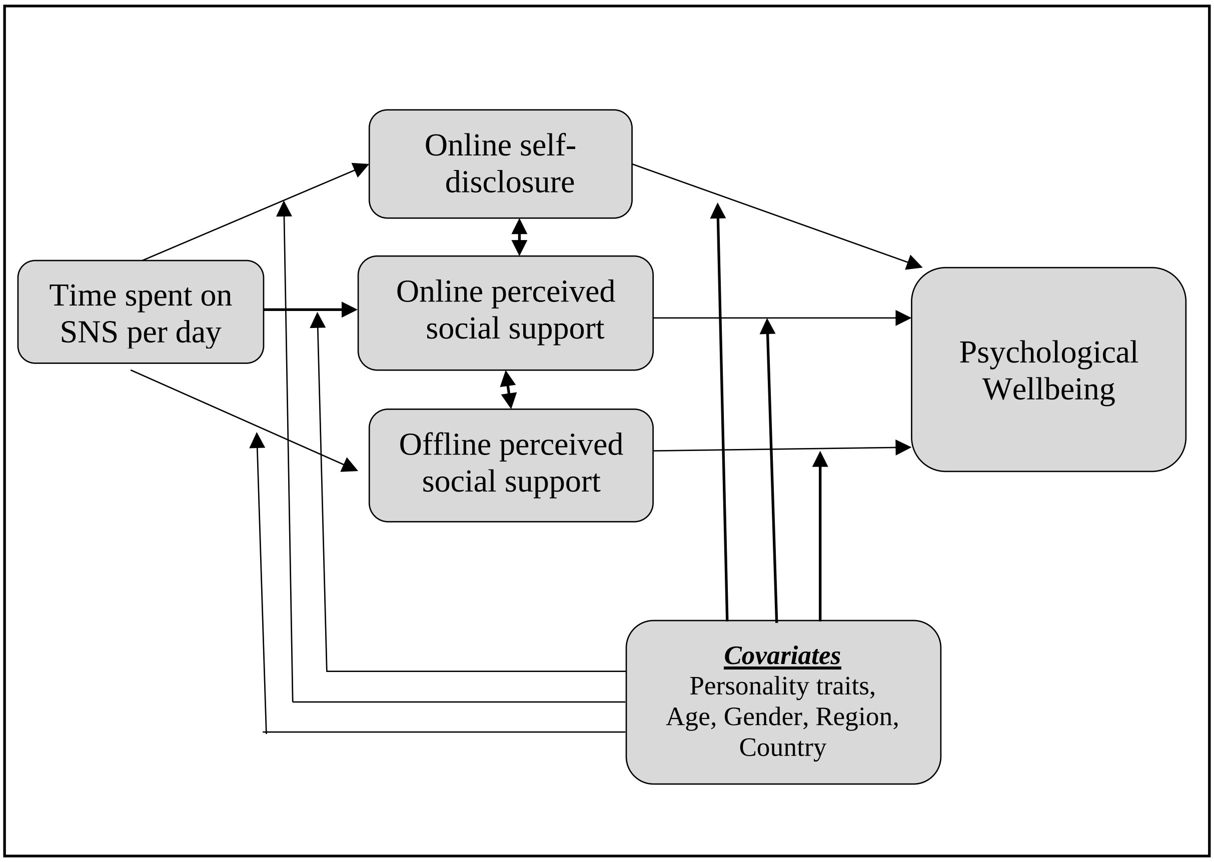

Figure 2. Conceptual model showing the main hypotheses and relationship between other study variables and wellbeing

Research Questions and Hypotheses

On the basis of the conceptual model of the current study, two research questions and three specific hypotheses were explored in accordance with the objectives of the study and informed by the literature:

R1: Is there an association between amount of time spent on SNSs per day and psychological wellbeing?
H1: There is a positive relationship between the amount of time spent on SNSs per day and online perceived social support
R2: Do demographic and personality variables moderate the relationship between amount of time spent on SNSs per day and online perceived social support, offline perceived social support, and online self-disclosure?
H2: Online perceived social support is positively related to wellbeing

H3: Offline perceived social support is positively related to wellbeing
R3: Is the association between predictor variables (online perceived social support, offline perceived social support, and online self-disclosure) and psychological wellbeing moderated by demographic and personality variables?

Table 2. Summary of Studies Included in the Present Systematic Review in Chronological Order (N = 32)

Reference	Country	Sample, Sampling	Study design and Analysis	Measures	Key Findings
Smedema and McKenzie (2010)	United States	*N* = 175 Diagnosed with visual impairment. Recruited online through consumer organisations for blind or visually impaired. Female = 50.9% Mean age = 26.7	Cross-sectional survey SNS Type: Mixed Regression	Outcome Measure: SWBI – 36 items – consists of 5 subscales – physical wellbeing, psychological wellbeing, family and social wellbeing, financial wellbeing and medical care. Social Support Measure: PRQ-2000 measures PSS (unspecified) 15 positively worded items Controls: None	Engaging in online chat/instant messaging was positively associated with perceived social support. Engaging in online chat/instant messaging was positively associated with both physical and psychological well-being. Note: PSS was not used as a predictor of wellbeing
J. Kim and Lee (2011)	United States	N = 391 Undergraduate students Female = 71.9%	Cross sectional Online survey sent via email SNS type: Facebook only SEM	Outcome variable: Five items Subjective Happiness Scale SS Measure: Online PSS was measured using modified ISEL- seven items. Controls: None	Number of friends on Facebook predicted wellbeing. However, number of friends was found to have a curvilinear relationship with PSS. Online PSS was explored as a mediator between honest self-presentation on Facebook and wellbeing. Honest self-presentation on Facebook predicted greater

					levels of online PSS, which predicted greater wellbeing
Manago et al. (2012)	United States	*N* = 88 Undergrad students with any SNS account Female = 67 Age range – 18-28 years	Cross-section Online survey SNS Type: Any Regression and correlation	Outcome Measure: Modified scale to measure global life satisfaction SS Measure: Modified ISEL for perceived support Quality of online friendships Online network size Controls: Self-esteem	Online network size and maintained connections online predicted online PSS and life satisfaction positively. There was a positive correlation between online PSS and life satisfaction (Pearson correlation).
Wright (2012)	United States	*N* = 283 College students Female, 62% Mean age, 19.92, SD = 1.95	Cross-section Online survey Convenience sample SNS Type: Facebook Multiple regression	Outcome Measure: Perceived stress measured by GMPSS SS Measure: Perceived emotional support measured by ESC -20 items (none-specific) Controls: None	Emotional support predicted lower levels of perceived stress for Facebook partners
C.-Y. Liu and Yu (2013)	Taiwan	*N* = 330 Taiwanese college students who use FB Convenience sample Male = 37%	Cross-sectional survey SNS type: Facebook only	Outcome measure: Psychological wellbeing measured using Ryff's psychological wellbeing scale	Facebook use predicted greater level of online PSS, which predicted greater wellbeing.

			SEM	SS Measure: Online PSS measured using Modified ISEL for FB – 40 items (Online PSS). Original ISEL (Offline PSS) Controls: None	The relationship between online PSS and wellbeing was also mediated by offline PSS. The direct relationship between offline PSS and wellbeing was over and above the relationship between online PSS and wellbeing.
Grieve et al. (2013)	Australia	*N* = 274 University student s plus general community members aged 18 and above Females, 232	Cross-sectional Online survey disseminated via emails and FB SNS type: Facebook Correlational	Outcome Measure: SWB measured using SWLS Depression/Anxiety measured using DASS-21 SS Measure: Offline social connectedness measured using modified Social Connectedness Scale –Revised -20 items FB social connectedness measured using modified Social Connectedness Scale –Revised -20 items Controls: None	Mean offline social connectedness higher than mean Facebook social connectedness Facebook social connectedness was positively related to SWB and negatively related with anxiety and depression.

Nabi et al. (2013)	United States	*N* = 401 Undergrad students 95% reported having FB Females = 78% Ave age = 19.9 years	Cross-section Online survey SNS Type: Facebook SEM	Outcome Measure: SRRS - Perceived Stress SWLS - SWB SS Measure: MSPSS -12 items (not specified) SNS interpersonal network size Number of FB friends Controls: Gender, stress level	PSS mediated the relationship between Facebook friends and PWB. That is, increase in Facebook friends increased perceptions of social support, which then reduce stress. Number of Facebook friends directly predicted wellbeing PSS was directly associated with wellbeing. PSS also showed an indirect effect on wellbeing and physical illness by reducing perceived stress.
Wright et al. (2013)	United States	*N* = 361 College students Female, 54% Mean age, 20.26, SD = 2.72	Cross-section Online survey Convenience sample SNS Type: Facebook SEM	Outcome Measure: Depression measured by CES-D SS Measure: Online social support size and satisfaction with online social support using adapted SSQ Offline social support size and satisfaction with online social support using original SSQ Controls: None	Communication competence was found to positively predict Facebook and offline social support network and satisfaction with social support which in turn predicted lower levels of depression. Relationship between offline social support and depression was stronger compared to online social support
K.-T. Lee et al. (2013)	South Korea	*N* = 265	Cross-sectional survey	Outcome Measure:	Loneliness negatively predicated wellbeing and positively predicted

		University students, FB users Female, 53% Mean age = 26.84, SD = 7.70	SNS Type: Facebook SEM	wellbeing measured with three items from previous related research SS Measure: Social support items were worded to measure online PSS from SNS Other Loneliness measured by Russell's UCLA Loneliness Scale Self-disclosure measured with depth of disclosure subscale Controls: None	self-disclosure (direct effects). Self-disclosure was positively associated with SNS based social support which in turn was positively associated with psychological wellbeing.
H. Kim (2014)	United States	N = 626 Undergraduates (USA) 62% women	Cross-sectional Anonymous online survey SNS type: Facebook only Regression analyses	Outcome variable: SWB measured with SWLS SS Measure: Enacted support from Facebook using modified ISSB Scale – 11 items Enacted support from other means using modified ISSB Scale – 11 items Controls: None	Facebook use was positively related to Facebook social support. Females have higher social support (other) than males. Social support from Facebook did not predict life satisfaction. Social support from other means significantly predicted life satisfaction

Trepte et al. (2014)	Germany	SNS users (*Mage* = 25.65, *SD* = 6.38) Online recruitment via SNS Female = 195	Longitudinal online survey -4 Waves (2009 - 2011) Online survey disseminated via Facebook and StudiVZ SNS type: General Repeated measures ANOVA SEM	Outcome measure: SWB measured using SWLS SS Measure: Adapted Bonding Social Capital Scale from the ISCS scale – (to measure PSS from SNS) UCLA short form (Received offline SS) UCLA – 4 items (Satisfaction with the offline support received) Controls: None	Informational online support exceeded offline support over the course of 2 years. Emotional offline support exceeded emotional online support over the course of 2 years. Instrumental offline support exceeded instrumental online support over the course of 2 years. Offline social support was a significant longitudinal predictor of satisfaction with social support Online social support predicted satisfaction with social support longitudinally Offline social support was related to life satisfaction but not online social support Note: Relationship between social support and life satisfaction was tested cross-sectionally within waves.
Jeong et al. (2014)	South Korea	Random community sample N = 1200 Adult SNS users randomly selected	Cross-sectional survey SNS Type: Any SEM	Outcome Measure: SWLS to measure online wellbeing and offline wellbeing separately SS Measure: Online Bridging Social Capital	Online social capital (bonding and bridging) predicted greater online psychological wellbeing but not offline psychological wellbeing, while offline wellbeing was

		from a list of local population Male = 51.7%		Offline Bridging Social Capital Online Bonding Social Capital Offline Bonding Social Capital Controls: None	influenced only by offline bonding social capital.
Ybarra et al. (2015)	United States	*N* = 5,542 LGBT youth - randomly recruited from the Harris Poll Online opt in panel (n = 2989 respondents) Aged 13-18 years Cisgender female = 51% Cisgender male = 41% Gender minority, transgender, gender nonconforming or another gender identity = 8%	Cross-section Online survey SNS Type: Any Hierarchical regression	Outcome Measure: Online peer-victimisation Sexual victimization Depression – CES-D SS Measure: MSPSS – Modified Friend subscale for Online context –Four items) MSPSS – Original Friend subscale – Four items Controls: Sexual identity Gender	Online social support significantly predicted higher level of online generalised sexual victimisation. In person SS significantly predicted lower levels of online and offline bullying and marginally predicted lower levels of offline sexual victimisation.
Oh et al. (2014)	United States	*N* = 339 Undergraduate students and their friends Women 51.2%	Cross-sectional SNS type: Any SEM	WB Measure: SWLS – four items adapted SS Measure: Adapted 9 items from ISEL – (perceived appraisal support,	Companionship was directly associated with life satisfaction Appraisal support and esteem support were indirectly related to SWB via sense of community.

		Snowball sampling techniques		companionship, esteem support) to measure online PSS Sense of community – three items from Sheldon and Gunz (2009) measure (does not specify whether this is offline or online)	
Indian and Grieve (2014)	Not specified	*N* = 299 Facebook users Female, 86% Mean age = 28.35, SD = 10.88	Cross-sectional Online survey Convenience sample SNS Type: Facebook Hierarchical multiple regression	Outcome Measure: SWB measured by SWLS SS Measure: Facebook social support measured by adapted ISEL appraisal subscale Offline PSS measured using original ISEL appraisal subscale Controls: Gender	In the low anxiety group, Facebook social support was not a significant predictor of SWB whereas offline PSS was. In the high anxiety group, offline PSS was a significant predictor of SWB, however, the addition of Facebook social support made this relationship non-significant. Facebook social support predicted SWB in this group.
Frison and Eggermont (2015)	Belgium	*N* = 910 High school in Belgium 51.9% girls Mean age 15.44	Cross-sectional using a survey questionnaire Randomly selected high schools.	Outcome Measure: Depressed mood measured by CES-DC -20 items SS Measure: Online PSS – measured from modified MSPSS - 4 items (Friend subscale) Other	Daily stress significantly predicted increase SS seeking through Facebook which in turn predicted high online PSS. High online PSS predicted lower levels of depression.

			SNS Type: Facebook SEM	Daily Stress Controls: Gender	
McCloskey et al. (2015)	United States	*N* = 633 Undergrad students from a Midwestern University Convenience sample Female = 70.1% Caucasian = 64.8%	Cross-sectional online survey Recruited via flyers places around the campus. SNS Type: Facebook EFA and correlation	Outcome variable: PHQ9 (depression) WHOQOL-BRIEF to measure quality of life (QOL) SS Measure: FMSS (self-developed) – Offline PSS was measured by MSPSS-12 items Received SS was measured by ISSB Controls: None	FMSS yielded four factors FMSS demonstrated convergent validity with traditional measures of social support FMSS- perceived support was not significantly related to either depression nor QOL. FMSS emotional support was positively related to depression and negatively related to the psychological wellbeing domain. FMSS negative support subscale was negatively related with depression and also with the psychological wellbeing, social relations, and environmental wellbeing domains of WHOQOL.
Frison and Eggermont (2016)	Belgium	*N* = 910 High school in Belgium	Cross-section using a survey questionnaire	Outcome Measure: Depressed mood measured by CES-DC -20 items	In girls, both active private and public Facebook use predicted

		51.9% girls Mean age 15.44	Randomly selected high schools. SNS Type : Facebook SEM	SS Measure: Online PSS – measured from modified MSPSS - 4 items (family subscale) Controls: Gender	online PSS, which in turn predicted lower levels of depressed mood. In boys, active public use significantly predicted greater online PSS, but SS did not significantly predict depressed mood. While active public Facebook use predicted online PSS, it was also related to increased depressed mood in boys
Burke and Kraut (2016)	Any	*N* = 1193 Adult English-speakers who use SNS Female = 40.5%	Longitudinal – 3 wave between June and August 2011. Online survey Recruited via FB and email invitations SNS Type: Facebook Multilevel regression	Outcome Measure: SWB measured using SWLS SS Measure: Average tie strength on FB based on one item for 8 friends Controls: Gender, age, activity level of FB, friend count, major life events	Receiving communication from strong ties on Facebook was associated with improvements in wellbeing while receiving communication from weak ties was not. Receiving wall posts or comments was marginally associated with increase in wellbeing, while receiving one-click communication (e.g., ‘likes’ or passive communication was not.
Jang et al. (2016)	South Korea	*N* = 358 College students	Cross-sectional Online survey	Outcome Measure: Mental Health Inventory	Facebook use predicted higher levels of PSS.

		Female, 70.0%	Convenience sample SNS Type: Facebook SEM	SS Measure: MSPSS – Original Friend subscale – Four items SS Measure: MSPSS -12 items Controls: None	PSS significantly predicted higher levels of mental health.
J. Park et al. (2016)	United States	Study 1, Undergraduate students *N* = 61 Female, 61% Mean age = 19.95, SD = 1.13 Study 2, *N* = 42	Cross-sectional survey Convenience sample SNS Type: Facebook Study 1 & 2: Hierarchical logistical regression using generalised linear mixed models	Study 1: Outcome Measure: Depression measured by BDI-II SS Measure: Enacted FB support- self-developed Online PSS measured using modified Social Provisions Scale -12 items Controls: FB positive and negative self-disclosure Study 2: Outcome Measure: Depression measured by BDI-II SS Measure: Enacted FB support Online PSS measured using modified SPS -12 items	Participants with higher depressive symptoms drew more enacted Facebook support when negative feelings were disclosed on Facebook, whereas those who did not disclose did not receive Facebook support. Online PSS was negatively associated with depressive symptoms. Study 2: Participants with MDD received more support from Facebook when negative feelings were disclosed on Facebook, whereas those who did not disclose did not receive support. This

		Diagnosed with MDD and 21 control participants Female, 86% Mean age = 29.95, SD = 7.40		Offline SS measured by self-developed measure Controls: FB positive and negative self-disclosure	association was not found for those participants without MDD. Online PSS was negatively associated with depressive symptoms and this relationship was stronger for participants with MDD.
Seo et al. (2016)	South Korea	*N* = 285 University Students Mean age = 21.81, SD = 2.19	Cross-sectional online survey SNS Type: Facebook SEM	Outcome Measure: Loneliness using Revised UCLA Loneliness Scale SS Measure: FB network size and quality Online PSS measured using few offline PSS scales Other Loneliness measured by Russell's UCLA Loneliness Scale Self-disclosure was measured by depth of disclosure subscale Controls: Interpersonal awareness	Overall, number of interactions was positively associated with online PSS. On the other hand, average comment time was negatively associated with online PSS. Online PSS in turn reduced loneliness levels. This result was found to be greater in those with greater interpersonal awareness
Hu et al. (2017)	United States	N = 405 College students Female 71%	Cross-sectional Survey posted online for students	Outcome variable: SWB measured with SWLS SS Measure:	Intensity of Facebook use had a direct positive effect on online social relationship satisfaction and perceived social support and a negative direct effect on offline social relationship satisfaction.

			SNS type: Facebook only SEM	Satisfaction with Facebook social relationships measured by adapting existing scale. Satisfaction with offline social relationships measured by adapting existing scale. Perceived SS – not specified Controls: Personality – Big Five Inventory	Online social relationship satisfaction was positively related to offline social relationship satisfaction and SWB. Satisfaction with offline social relationships was positively linked to perceived social support and negatively associated with social interaction anxiety Satisfaction with online social relationship did not have an indirect effect on SWB. Overall, offline social relationships and perceived social support had stronger positive effects on SWB compared to satisfaction with online social relations.
Utz and Breuer (2017)	Netherlands	*N* = 1330 Dutch adult internet users Wave 1, N = 3,367 Wave 2, N = 2,678 Wave 3, N = 2,272 Wave 4, N = 1,953 Wave 5, N = 1,627 Wave 6, N = 1,330	Longitudinal study Online surveys Time interval between each interval was 6 months SNS Type: Any	Outcome Measure: Stress – 4 items from Perceived Stress Life Satisfaction – 1 item from Manchester Short Assessment of Quality of Life Scale SS Measure: Online PSS was measured using the Modified UCLA social support inventory	There were no longitudinal relationships between online social support and life satisfaction or stress. It also did not mediate the paths from asking for advice on SNS to the well-being indicators. Online social support was not predictive of either life satisfaction or stress. Online social support also did not mediate the paths from

		Female 56.69% - final wave Age, 18 and above	Cross-lagged SEM	Controls: None	asking for advice on SNSs to the well-being indicators The means of online social support, stress, and life satisfaction were quite stable across all waves for SNS users and non-users.
Cole et al. (2017)	United States	*N* = 231 Undergraduate students Females, 177 Mean age = 19.28 (SD 1.15)	Cross-sectional online survey SNS Type: Facebook Least squares regression and SEM	Outcome Measure: Depressive thoughts using CTI – 36 item scale BDI-II DAS -40 Cyberbullying experience Questionnaire (CES) -42-items SS Measure: Perceived Social Support (PSS) – 20 item friend subscale was used. Social Network Scales – newly developed to measure 1) satisfaction with received and giving SS, and 2) ways that people buy, victimise or ostracise one another, both in person and online. Controls: Offline social support	Online PSS and offline PSS both predicted lower levels of depressive thoughts and feelings, but effect of in-person support was stronger than the effect of online support. Online support significantly reduced the strength of relation between victimisation and negative depressive thoughts and feelings (buffering effect).

Zhang (2017)	Hong Kong	*N* = 573 College students N = 573 Female 59.7% Aged bet 18-25 years 97.7% were FB users	Cross-sectional survey Stratified sampling method SNS Type: Facebook Hierarchical regression	Outcome Measure: Depressive symptoms – PHQ-9 SWLS SS Measure: Enacted social support on Facebook – self-developed four items Perceived Support (generic) using modified Medical Outcome Study social support scale -19 items Controls: Gender, year in school, major, residence, time spent on Facebook, and Facebook network size	Both enacted Facebook social support and generic PSS were positively associated with satisfaction with life, but the generic PSS had a stronger effect on wellbeing than enacted Facebook support. Only generic PSS significantly predicted lower levels of depression but not Facebook enacted social support
Lima et al. (2017)	Portugal	Study 1: *N* = 350 Community sample Female, 44% Mean age = 46.4, SD = 17.1	Cross-sectional Online survey SNS Type: Facebook Study 1: SEM and mediated regression Study 2: SEM	Study 1: Outcome Measure: Mental health – five items from SF-36 SWB – 2 items from SWLS SS Measure: Online friends network Offline friends network Bonding SS (generic) Bridging SS (generic) Controls: Age, gender, SES, education, living alone	Study 1: Facebook friendship was not a significant predictor of bonding SS or health.

		Study2: *N* = 803 Community sample Female, 50% Mean age = 44.1, SD = 15.6		Study 2: Outcome Measure: As study 1, plus self-esteem SS Measure: Online friends network Offline friends network Bonding SS (generic) Bridging SS (generic) Controls: None	Study 2: Facebook friendships had a negative relationship with bonding SS and had a negative indirect effect on health.
H.-T. Chen and Li (2017)	United States	*N* = 382 Undergraduate students Female. 52% Mean age= 20.17, SD=1.85	Cross-sectional online survey SNS Type: Facebook Moderated regression	Outcome Measure: Stress was measured using the Perceived Stress Scale SWB was measured using SWLS SS Measure: Received SS on Facebook was measuring using adapted ISSB Provided social support on Facebook was measured using adapted ISSB Controls: Self-esteem Provided support (Model 1) and received support (Model 2)	Receiving social support on Facebook was not significantly associated with stress or life satisfaction. Providing social support was associated with increased stress and reduced life satisfaction, with self-esteem moderating the relationship between providing social support and life satisfaction. Low self-esteem predicted greater life satisfaction for greater social support providing behaviours, whereas high self-esteem did not.

McConnell et al. (2017)	United States	*N* = 175 LGBTQ young adults Mean age = 24.02, SD 1.65	Cross-sectional online survey SNS Type: Facebook Multiple regression	Outcome Measure: Psychological distress was measured using Brief Symptom Inventory SS Measure: Facebook social integration Online support behaviour was measured using giving and receiving social support dimensions PSS (not specified) was measured using MSPSS Controls: Age, gender, ethnicity	Facebook social integration, non-specified PSS, and seeking online support did not predict psychological distress, though offering online social support predicted higher levels of psychological distress.
Han et al. (2018)	China	*N* = 432 Weibo users who have a diagnosis of HIV 95.8% male 79.6% completed college or had higher level of education 74.5% employed 71.3% used Weibo for more than 2 years 81.5% check more than 7 times a week	Cross-sectional online survey Recruited from Weibo SNS Type: Weibo Hierarchical regression	Outcome Measure: SWLS SS Measure: Enacted receiving support – 4 items that indicated the frequency of receiving social support on Weibo in the past 6 months. Enacted giving support – 5 items that indicated the frequency of giving SS on Weibo Perceived offline SS – MSPSS Perceived online SS – modified significant other and friends subscales	Receiving and giving social support on Weibo significantly predicted higher levels of online PSS. Online PSS significantly predicted higher levels of SWB whereas, frequency of Weibo use predicted wellbeing negatively. Offline PSS also significantly predicted higher levels of SWB. The strength of the relationship between online PSS and SWB was stronger than the relationship between offline PSS and SWB.

				of MSPPS to measure close and non-close friends. Controls: Age, employment, education, income, years of using Weibo, Frequency of Weibo use.	
Nick et al. (2018)	United States	*N* = 1090 (*n* = 98, sample 1; *n* = 306, sample 2, *n* = 686, sample 3) Sample 1 – College students Female, 77.6% Mean age 19.21, SD 1.08 Sample 2 – Community participants Female, 46.4% Mean age, 31.98, SD, 5.18 Sample 3 – Community participants mean age 29.43, SD 5.94, 50.1% female	Cross-section Online survey Convenience samples SNS Type: Any EFA, IRT, and SEM, hierarchical regression	Outcome Measure: Online victimisation using cyberbullying experiences survey Positive and negative life events using Life Experiences Survey Self-esteem using the Rosenberg Self-esteem Scale Positive and negative cognitions using Cognitive Triad Inventory Depression using DBI-II SS Measure: OSS – new measure of online PSS SS Measure: MSPSS -12 items Controls: None	Similar to in-person social support, online social support offsets the adverse effect of negative life events on self-esteem and depression-related outcome Online social support counteracts the effects of online victimization in much the same way that in-person friends do. The only substantive difference between the online and in-person results was that the main effects of offline PSS were stronger than the main effects of online PSS.

Chan (2018)	Hong Kong	*N* = 925, Random sample selected using landline directories Female, 52% Age = 18 and above	Cross-sectional survey SNS Type: Facebook Hierarchical regression	Outcome Measure: SWB measured using SWLS Positive and negative emotions measured using SPANE SS Measure: Online enacted support measuring using MOS Social Support Survey Controls: Age, gender, education, income, religion, marital status, and children	Online social support was positively related to psychological wellbeing only in the 35 to 54 years old group but did not predict positive or negative emotions. Facebook-based communication and Facebook friends predicted greater psychological wellbeing in the 18- to 34- years old group, and Facebook-based communication also predicted greater negative emotions in the 18- to 34-year old group.

CHAPTER 3: METHOD

This chapter describes the methods used in the project and includes descriptions of:

1. The study setting,
2. The participant selection process followed by descriptive statistics for each sample group,
3. Description of the measures used in the project, with a rationale for their selection,
4. The study design,
5. Procedure and field activities,
6. The data cleaning process, and
7. The data analyses protocol undertaken in this project.

Study Setting

This study was conducted in Maldives and New Zealand as shown in Figure 3. There were several reasons for choosing Maldives and New Zealand as the study sites. These include: (a) the primary investigator's familiarity with both contexts, including psychological research experience in both countries; (b) support from the University of Otago and from Maldivian local residents in carrying out fieldwork; (c) most literature on online social networking behavior, social support, and psychological wellbeing has not focused on cross-cultural differences; and (d) investigate the universality and applicability of social support and psychological wellbeing factors across cultures.

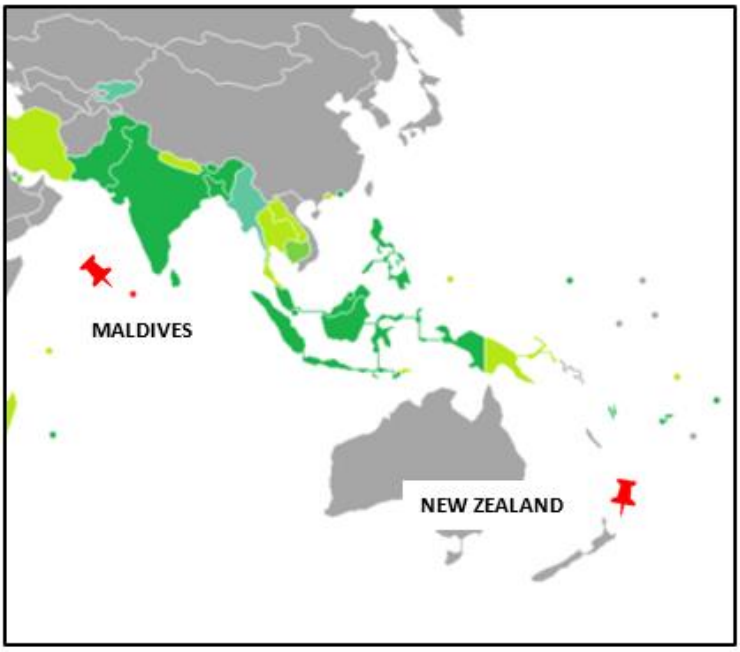

Figure 3. Map of Maldives and New Zealand's locations on the globe

New Zealand (NZ)

Participants were selected from the capital city Wellington and two rural areas (one each from the North and South Islands of the country). Wellington was chosen as an urban setting given that it is a large city. The two rural areas were selected randomly from 10 postcode boundaries (www.nzpost.co.nz) for sampling. Further details regarding the sampling process are provided later in this chapter.

New Zealand is a developed country, located in the southwestern Pacific Ocean. The country comprises two main islands; the North Island and the South Island. According to the last census conducted in 2013, the population totalled 4,677,400 people. The English language is spoken by 98% of the population although English, Māori, and sign language are all official languages of the country. In the 2013 census, 74.0% of New Zealand residents identified as European, 14.9% as Māori, 11.8% as Asian, and 7.4% as Pacific people. In the 2013 Census, 55.0% of the population identified with one or more religions, including 49.0 % identifying as Christians. A total of 41.9 % indicated that they had no religion. The Māori based Ringataū and Rātana religions (1.4%) also identified as Christians. Other significant minority religions include Hinduism (2.3%), Buddhism (1.5%) and Islam (1.2%). The average life expectancy for females is 83.19 years and for males is 79.48 years (www.stats.govt.nz).

In contrast to Maldives, New Zealand is a high-income economy with a real Gross Domestic Product (GDP) of US$ 205 billion in 2017 (World Bank, 2018). In New Zealand, 94% of the population uses the internet and more than half the population uses Facebook (www.internetworldstats.com).

In the 2012/13 New Zealand Health Survey, one in six New Zealand adults (16%) had been diagnosed with a common mental disorder at some time in their lives. The suicide rate has recently been estimated at 12.40 per 100,000 per annum (WHO, 2017).

Maldives

Participants were selected from the capital city Male' and seven islands from both north and south atolls. Participant recruitment processes are described later in this chapter. Maldives is a developing country, located in South Asia and contains 20 administrative atolls consisting of 1,192 islands of which only 188 are inhabited. Maldives is dispersed over a distance of 90,000 square kilometres with less than 0.5% of this having land region. The country stretches 820 km across the equator and the country's width widest point is 130 km.

According to the latest census conducted in 2014, the population of the country is 402,071 of which Maldivians represent 84%, with 16% being immigrants. The majority of immigrants are from South Asian countries arriving primarily for employment. Of the total population, approximately one third live in Male', making it one of the most densely populated cities in the world. Approximately 40% of the Maldivian population is under the age of 25. Maldivians are a homogeneous population speaking one language (Dhivehi) and by law they are all Sunni Muslims. Life expectancy for females is 79.99 years and for males is 77.2 years (WHO, 2017).

With a real GDP of US$ 4.6 billion in 2017 (World Bank, 2018), the Maldivian economy has shown steady growth over the previous decade. The economy depends heavily on tourism, which is the primary economic industry of the country. Fishing is the Maldives's second largest industry. The country lacks land-based natural and mineral resources making all economic development highly dependent on imports. Consistent economic growth has led to the graduation of Maldives from the least developing country to an upper middle-income country (Ministry of Foreign Affairs, 2011, Maldives).

As a country with limited natural resources, Maldives has prioritised telecommunications as a critical strategy for developing skills, increasing productivity, and promoting the nation's export and business interests in the global market. As a result, Maldivians rank among the highest internet users in South Asia (Internet World Stats, 2019). As of June 2017, 81.9% of the population used the internet, with more than 90% being Facebook users (Internet World Stats, 2019). Maldives is one of the world's most geographically dispersed countries, making social media a powerful tool for the communication and dissemination of information and news.

There is a paucity of recent research on mental health in the Maldives. This is the case with regard to both addressing the mental wellbeing and the prevalence of mental disorders in the country. In 2003, the Maldivian Ministry of Health conducted a nation-wide survey to assess the magnitude of mental and neurological disorders. The survey revealed that the lifetime prevalence of some form of mental health condition was 29.10% with almost 5% experiencing anxiety and depression and nearly 4% reporting somatic symptoms, while the prevalence of psychoses was at 1%. Furthermore, compared to men, twice as many women were found to suffer from depression, anxiety and somatic symptoms (Niyaz & Naz, 2003). The suicide rate has been estimated at 10.83 per 100,000 per annum (WHO, 2017).

Participant Recruitment and Sampling Procedure

The study comprised three groups; two general population samples randomly selected from New Zealand and Maldives, and one convenience sample drawn from New Zealand (clinical sample).

Procedure for Selecting Participants

In this section, the different procedures utilised for selecting the three subsamples are discussed.

Selection of the New Zealand random community sample. Using stratified random sampling, 1062 NZ community residents were selected from the New Zealand electoral rolls obtained by a formal request from the New Zealand Electoral Commission. The sample for this study was selected from three different regions across New Zealand. In order to compare urban and rural dwellers, approximately equal numbers of people from both areas were selected. Using the post-code boundary map published by New Zealand Post (www.nzpost.co.nz), which differentiates urban and rural regions (see Figure 4), two post-code areas (3 and 10) were randomly selected (from the North and South Islands). From these two areas, rural postcodes were determined. Subsequently, the total number of people in these postcode areas was identified from electoral rolls for sampling. Wellington city (area 5) was selected as the urban region.

The sampling technique used in this study was stratified random sampling. Stratified sampling involves dividing the population into groups (strata), and then selecting random samples from each of the strata. When sub-populations within an overall population vary in terms of number, it is considered advantageous to sample each subsample or stratum independently for better representation of the whole population (Hibberts et al., 2012).

To conduct stratified random sampling, first, within each stratum (from each selected area of the map), the total population was obtained from the electoral roll. Then the number desired to be sampled from each stratum was determined. This gave the sampling fraction (i.e., number desired / total available). Based on the power estimates, the desired number of respondents was approximately 400 and the total number of people living in the areas selected for sampling was 182,437. Therefore, the sample fraction was calculated to be .002. A uniform random number between zero and one was subsequently calculated (SPSS, IBM Corp. Released 2013) for each person listed on the electoral roll who satisfied the region criteria. Then if an individual’s random number was between zero and the sampling fraction (e.g., between 0 and .002), that individual was selected. Each stratum was oversampled to allow for nonresponses. Table 3 shows the breakdown of the sample selected.

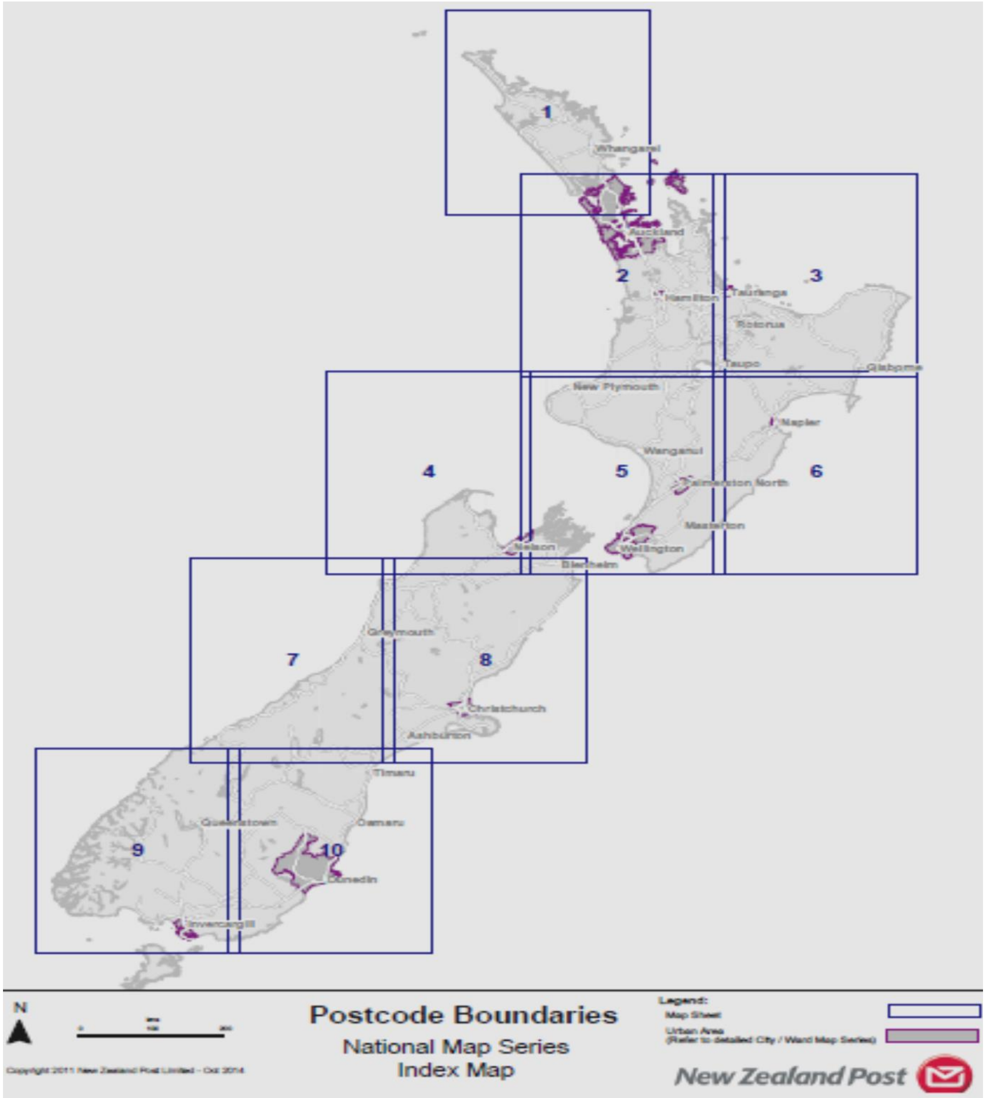

Figure 4. Map of New Zealand showing postcode boundaries

Table 3. *Total Number of Voters and Total Number Selected for Sampling from the Capital and Two Rural Areas for the New Zealand Community Sample*

Sampled areas	Total no. of voters	Sampled number
Wellington	135413	547
Rural North	24891	264
Rural South	22133	251

Selection of the New Zealand clinical sample. The clinical group approached in this study was a convenience sample (*N* = 181) of New Zealanders who had either completed or were completing treatment for anxiety and depression at the time of recruitment. This group was recruited from the patient database of one of the thesis supervisors, Professor Sarah Romans' private psychiatry practice in Wellington. Only her past and current patients who had said 'yes' or 'maybe' to a previously asked routine question regarding whether they would be interested in taking part in health-related research were approached.

Selection of the Maldives random community sample. The Maldives random sample was a community-resident group, aged 18 years or above, who were living in the capital city Male' or outer islands. This age cut-off was selected because the electoral rolls were used as the sampling frame (i.e., eligible voters are aged 18 years or older).

A total of 1,053 participants were drawn by random sampling using the Maldives Electoral roll published in 2013. Maldives Electoral rolls were formally requested from the Maldives Election Commission. First, five islands (across the north, central and south regions) along with the capital city were selected by the researcher. There are no formal urban/rural boundaries defined in Maldives. For the purpose of this study, participants from the capital city were considered urban residents while participants from the outer islands were considered rural residents, given the major differences in population density and services across these groupings. The reason for selecting the five islands (shown in Figure 5) was the ease of accessibility and availability of local volunteer research assistants in these islands. The sampling technique used for selecting the Maldives community sample was the same as the procedure described above for the New Zealand random community sample selection. There were two reasons for selecting a stratified approach: firstly, it was economical and time saving; and secondly, stratified sampling ensured equal chance of selection of participants from north, south, and central regions of the population. To conduct each stratified random sample, first, within each stratum, the total population was determined from the Maldives electoral roll. Then the optimal number desired to be sampled from each stratum was determined. This gave the sampling fraction (number desired/total available). Based on the power estimates, the desired number of respondents was approximately 400 and the total number of people living in the areas selected for sampling was 64,132. Therefore, the sample fraction was calculated to be .006. Then, a uniform random number between zero and one was calculated (SPSS, IBM Corp. Released 2013) for each person listed on the electoral roll who satisfied the region criteria. That is, if an individual's random number was between zero and the sampling fraction (e.g., between 0 and .006), that individual was sampled. Table 4 shows the breakdown of the sample selected.

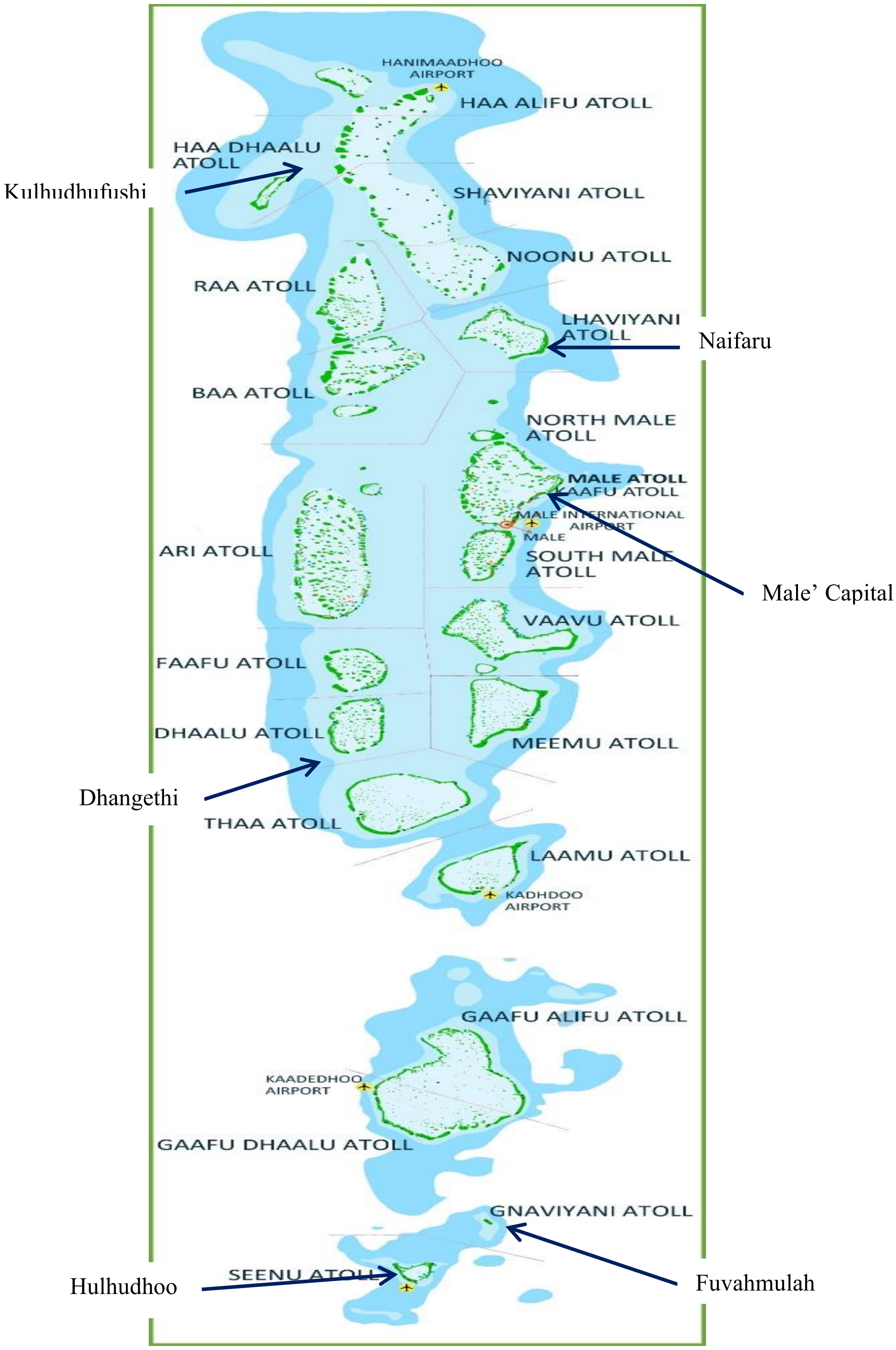

Figure 5. Sampled regions and islands in the Maldives

Table 4. *Total Number of Voters and Total Number Sampled from the Capital and the Islands for Maldives Community Sample*

Sampled areas	Total no. of voters	Sampled number
Male'	43256	553
Kulhudhufushi	6012	102
Dhangethi	633	112
Naifaru	3585	101
Fuvahmulah	7950	100
Hulhudhoo	2696	94

Response Rate

Table 5 shows the total number of participants invited and the total number of participants who responded. Both New Zealand and the Maldives had approximately similar response rates (36.3% and 39% respectively). The New Zealand Clinical group had a slightly higher response rate (43.1%) compared to the New Zealand community sample group.

Table 5. *Total Number of Responders and Response Rates for the Three Subsamples*

Sample groups	Total sampled	Total responded	Response rate (%)
NZ random community sample	1062	385	36.3
Maldives random community sample	1053	411	39.0
NZ Clinical	181	78	43.1

Ethical Considerations

Ethical approval to conduct the research was obtained from the University of Otago Human Ethics Committee and the Maldives Ministry of Health Ethics Committee, both responsible for reviewing and approving research applications involving humans. Informed consent, privacy, and confidentiality were addressed by following protocols set by the Committees. Information about the study and privacy was outlined in an information sheet (see Appendix A-1). Written informed consent was obtained from participants. Confidentiality and privacy were addressed by ensuring that personal details from electoral rolls and the patient register were used for sampling purposes only and only at the data entry stage to ensure that no identifiable information was used in data analyses. To deal with any distress provoked when completing the psychometric measures, a note was added in the information sheet directing the person to contact a health professional if the survey raised any concerns. The note also gave details of the academic supervisors (a consultant psychiatrist and a clinical psychologist) for this study as alternative first contacts.

Sample Size and Power Estimates

Power estimates were determined for the two random samples. It was hoped to recruit 400 participants from both New Zealand and the Maldives general populations as this would satisfy the power estimates which are discussed below.

There were a number of analyses proposed in this study, all of which have particular requirements for sample size. The primary statistical analyses planned in this project were multivariable regressions examining the effect of online perceived social support, offline perceived social support, online self-disclosure, personality, age, gender, region, and country on wellbeing. A further aim was to conduct within group analyses and to allow multiple independent variables in the regression analyses. At least 300 subjects per country were required to ensure that the study had sufficient power to find meaningful or statistically significant effects.

Wellbeing was a continuous variable measured using the Mental Health Continuum-Short Form (MHC-SF) (Keyes et al., 2008). The range of the MHC-CF scale is expected to be from 14 to 84. Based on the data in (Keyes et al., 2008), the standard deviation (SD) of the measure of wellbeing used was approximately 1.0. Therefore, for the regression of wellbeing on online/offline social support, the sample size required to give 80% power to detect a correlation of 0.20 or higher that is statistically significant at the 0.05 level is 200 subjects per group (Faul et al., 2009).

Assuming effect size = 0.5 and power = 0.8, the sample size for group comparisons recommended by Aday and Cornelius (2006) is 65 per group. Therefore, in order to conduct subgroup analyses and to allow multiple independent variables in the regression analyses, 300 subjects per group were needed to ensure sufficient power to find meaningful effects at statistically significant levels.

Participant Characteristics

Demographic information gathered included age, gender, and region of residence for all sub-groups. Marital status and education level were collected for the two New Zealand sub-samples only (the New Zealand survey instrument was modified to include marital status and education level after data collection in Maldives was completed) for the use of post-thesis publications focusing on New Zealand specific samples. The demographic characteristics of the three samples are reviewed below and presented in Table 6.

Data Distributions

The distribution of the data for all demographic variables was inspected visually to examine for normality and locate outliers. This overview informed decisions around whether to use parametric or non-parametric statistics. The data distributions are shown graphically for all variables in Appendices B–D.

Demographics

The total participant group included 385 New Zealand community residents (143 men, 240 women), 411 Maldivian community residents (170 men, 241 women), and 78 in the New Zealand clinical group (31 men, 47 women). Relationship status and educational level were not asked in the survey questionnaire for the Maldivian random community sample because the decision to include them in the New Zealand survey questionnaire was made after the data collection was completed in Maldives. The three sub-groups did not differ with regard to gender. However, they did differ in terms of age.

Age. Age was not normally distributed for the Maldives community sample, while the distribution of age in the New Zealand community sample and the New Zealand clinical sample did appear to be normal (for details see Appendix B). Therefore, non-parametric statistics were used to describe the data for age. For the New Zealand community sample, the interquartile range was between 38.50 and 59.50 years, with a full range of 22 years. For the Maldives community sample, the interquartile range was between 24 and 42 years, with a full range of 18 years. For the New Zealand Clinical group, the interquartile range was between 29 and 48 years, with a full range of 19 years. Age bands are presented for the three sub-groups in Table 6. The New Zealand community sample (*Mdn* = 51.00 years) as a whole was older and differed significantly from the median age of the Maldivian community group (*Mdn* = 30.50 years), Mann-Whitney test, U = 35150.00, p < .001. The median age for the New Zealand community sample (*Mdn* = 51.00 years) differed significantly from the median age of the New Zealand Clinical sample (*Mdn* = 38.50 years), U = 9291.50, p < .001. The median age for the Maldives community sample (*Mdn* = 30.50 years) differed significantly from the median age of the New Zealand Clinical sample (*Mdn* = 38.50 years), U = 11467.00, p < .001.

Gender. The actual numbers and percentages of male and female participants across the two groups are presented in Table 6. Chi-squared tests were used to determine whether there were any significant differences in the male to female ratios across the sub-samples. There was no significant association between gender and whether participants were in the New Zealand community, or Maldives community or New Zealand Clinical sub-samples (χ^2 (3) = 1.734, p = .639). See Appendix C for within-group gender percentages.

Relationship status. Marital status was recorded only for the New Zealand community and the New Zealand Clinical samples. The raw numbers and percentages of the different marital status groupings that the participants belonged to are presented in Table 6. The majority of the participants in the New Zealand community sample were married/cohabiting/partnered (79.5%), while the rest were either single (13%) or divorced/separated (5.9%) or widowed (1.6%). Similarly, the majority of the New Zealand Clinical participants were married/cohabiting/partnered (60.6%) while the rest were either single (31%) or divorced/separated (7%) or widowed (1.4%).

Ethnicity. Ethnic groups were recorded only for the New Zealand community sample and the New Zealand Clinical sample and are presented in Table 6. Participants were able to nominate more than one ethnic group from the eight options used in the New Zealand Census guidelines (New Zealand European; Maori; Samoan; Cook Island

Māori; Tongan; Niuean; Indian; and Other). Very few nominated more than one ethnic group or identified as Indians, hence they were grouped into the category ‘other’. Samoan, Cook Island Māori, Tongan, and Niuean were grouped as Pasifika. The raw numbers and percentages of the different ethnic groups that the participants identified with are presented in Table 6. The majority of the participants were New Zealand Europeans in both the New Zealand community and New Zealand clinical samples (81% and 75.3%). Ethnicity for Maldivians was not asked because they are generally understood to be a homogeneous ethnic group.

Education level. Education level was recorded for only the New Zealand community sample and the New Zealand Clinical sample. The raw numbers and percentages of the different education levels that the participants reported are presented in Table 6. A little over half of the participants in the New Zealand community sample had completed tertiary education qualifications (56%) while the rest had either completed a Vocational or Trade Certificate (13.6%) or NCEA levels (16.8%) or some High Schooling (13.6%). On the other hand, the majority of the New Zealand Clinical sample had tertiary education (80.3%) while the rest had either a Vocational or Trade Certificate (7%) or NCEA levels (9.9%) or some High Schooling (2.8%).

Region. The raw numbers and percentages of urban and rural participants across the New Zealand community sample and the Maldivian community sample groups are presented in Table 6. The New Zealand Clinical sample was all urban residents. Chi-squared tests were used to determine whether there were any significant differences in the urban to rural ratios across the New Zealand and Maldives community subsamples. There was a significant association between region and whether the participants were in the New Zealand community sample or the Maldives community sample (χ^2 (1) = 6.869, p = .009). That is, there were significantly more urban residents (50.5%) and significantly fewer rural residents (49.5%) in the New Zealand community sample than the Maldives community sample (41.29% versus 58.8% respectively). See Appendix D for within-group regional differences for each country.

Table 6. *Demographic Characteristics of Participants by Sample Groups (New Zealand Community Sample, n = 385; and Maldives Community Sample, n = 411; New Zealand Clinical Sample, n =78)*

Characteristic	New Zealand Community *n* (%)	Maldives Community *n* (%)	New Zealand Clinical *n* (%)
Age (band)			
17-30	54 (14.2)	202 (50)	23 (30.3)
31-40	54 (14.2)	95 (23.5)	22 (28.9)
41-50	81 (21.4)	57 (14.1)	14 (18.4)
51-60	104 (27.4)	29 (7.2)	10 (13.2)
≥ 61	86 (22.7)	21 (5.2)	7 (9.2)
Gender			
Male	143 (37.3)	170 (41.4)	31 (39.7)
Female	240 (62.7)	241 (58.6)	47 (60.3)
Marital Status			
Married/Cohabiting/Partnered	299 (79.5)		43 (60.6)
Single	49 (13.0)		22 (31.0)
Divorced/Separated	22 (5.9)		5 (7.0)
Widowed	6 (1.6)		1 (1.4)
Ethnic group			
New Zealand European	306 (81.0)		58 (75.3)
Māori	35 (9.3)		2 (2.6)
Pasifika	1 (0.3)		1 (1.3)
Chinese	22 (5.9)		
Maldivian		411 (100)	
Other	29 (7.7)		16 (20.8)
Educational Level			
Some High School	52 (13.6)		2 (2.8)
NCEA Levels	63 (16.8)		7 (9.9)
Vocational or Trade Cert	51 (13.6)		5 (7.0)
University	210 (56.0)		57 (80.3)
Region			
Urban	191 (50.5)	169 (41.2)	76 (100)
Rural	187 (49.5)	241 (58.8)	

Note: Data on educational level and marital status were not collected for the Maldives random community sample; Missing values are presented later in Table 8

Section Summary

Comparison between demographic data from the two robust samples (New Zealand and Maldives community samples) showed some similarities and differences. The New Zealand community sample was significantly older than the Maldivian community sample. There was no significant association between gender and whether participants were in the New Zealand community or Maldives community sample. There were significantly more urban residents and significantly fewer rural residents in the New Zealand community sample than the Maldives community sample.

Survey Instrument

A structured multi-sectional survey questionnaire in English (for New Zealand, see Appendix A-1) and Dhivehi (for Maldives, see Appendix A-5) was used to measure the chosen study variables. The key variables were psychological wellbeing, online and offline perceived social support, online self-disclosure, and personality. After drafting the questionnaire, it was trial tested prior to the main data collection (described later in the Chapter).

Measures

Although self-report measures are widely used in social science research, the reliance on self-reported data alone can lead to collecting intentionally or unintentionally distorted information as a result of social desirability and other biases (Schrammel et al., 2009). However, given the limited resources available for this project and time constraints, only self-report measures were used to assess participants' wellbeing, online PSS, offline PSS, online self-disclosure, and personality traits. Measures were chosen with reference to the following criteria:

1) Psychometric properties including reliability and validity.
2) The utility of the measure (completion time, prior use in studies with samples comparable to the target population of this study, and ease of scoring).
3) The frequency of use in relevant previous research, especially with similar samples.
4) The availability of measures from their authors.

Online Perceived Social Support Measure

The selection of an online PSS measure was limited by the lack of published validated scales measuring social support from all types of SNS. However, several studies have adapted offline social support measures to use in the online context (McCloskey et al., 2015). A review of available online social support measures in 2016 is underway (Ali, Bell, & Romans, in preparation). The PhD candidate chose to adapt the Multidimensional Scale of Perceived Social Support (MSPSS) originally developed by Zimet et al. (1998) for use in the offline context. This is referred to as the Online

Multidimensional Scale of Perceived Social Support (oMSPSS) hereafter. The oMSPSS aims to measures respondents' perceptions of online social support received from significant others, family, and friends. An alternative measure of online social support was considered. This was a recently developed measure called the Facebook-based Measure of Social Support (FMSS), which measures online perceived social support from any kind of SNS. This measure was adapted with permission from the measurement developers, McCloskey et al. (2015). The original FMSS had demonstrated adequate internal reliability and a factor (negative social support) correlated in the expected manner with depression and quality of life measures in the original study by McCloskey and colleagues (2015). Data were collected but not analysed in the current study due to preliminary analysis of the reliability of the measure producing unfavourable results (New Zealand Random sample, $\alpha = .64$; Maldives Random sample, $\alpha = .59$; and New Zealand Clinical sample, $\alpha = .63$).

Online multidimensional scale of perceived social support (oMSPSS). The oMSPSS uses Likert scales and consists of 12 Likert-type items. Participants rate their agreement with each item on a 7-point scale ranging from 1 (very strongly disagree) to 7 (very strongly agree). The items from the original scale were adapted by phrasing them in terms of perceived online social support. For example, the original item 1 "there is a special person(s) who is around when I am in need" was changed to "there is a special person(s) in my online social network who is around when I am in need" (see Appendix 1-A, items 9-20).

Rationale for the selection of the oMSPSS. Based on our review of available online PSS measures (both adapted and original), it was decided that the oMSPSS was sufficient for this study. The original MSPSS was easy to adapt to the online context while still maintaining the original wording of the items. At least 4 studies have adapted the original MSPSS to measure online PSS previously (Y-K. Cho & Yoo, 2016; Frison & Eggermont, 2015; Nabi et al., 2013; Ybarra et al., 2015). The adapted MSPSS has shown good internal consistency when adapted to the online context, ($\alpha = .96$, Obst et al., 2010; $\alpha = .95$, Cho & Yoo, 2016). The overall internal consistency for the oMSPSS in this study was excellent across all three sub-samples (see Table 7). The mean score for the oMSPSS obtained from this study was 46.49 (16.84). To date, there have been few applications of the full MSPSS in the online context. However, studies using the adapted subscales of the oMSPSS have reported positive relationships between these and measures of life satisfaction, and negative relationships with measures of perceived stress (Nabi et al., 2013). These findings are consistent with the oMSPSS having construct validity.

Administration and scoring of the oMSPSS. Similar to the original MSPSS, the oMSPSS is a self-report measure. The instructions specifically mention that the statements needed to be responded to be based on participants' interaction with people within the SNS context only. The scoring was simple with no reversed items. Total social support was assessed by averaging all 12 items. There are no set cut-off scores available for the oMSPSS. However, higher scores on oMSPSS indicate higher levels of perceived online social support. Higher scores have been correlated positively with personal relationships in a study on social support formation (Obst & Stafurik, 2010).

Offline Perceived Social Support Measure

The current project also sought to measure perceived social support from offline social networks and to compare this with online perceived social support. Based on the review of available measures of offline perceived social support, the original MSPSS developed by Zimet and colleagues (1988) was selected (see Appendix 1-A, items 52-63).

Multidimensional scale of perceived social support (MSPSS). As noted above under online social support assessment, the MSPSS consists of 12 items. Participants indicate their agreement with each item on a 7-point scale ranging from 1 (very strongly disagree) to 7 (very strongly agree). Example items include "There is a special person(s) who is around when I am in need" and "I get the emotional help and support I need from my family".

Rationale for selection of the MSPSS. The MSPSS is a widely used measure which has good internal and test-retest reliabilities and moderate construct validity (Zimet et al., 1988). The psychometric properties of the MSPSS have been validated in several population groups across different cultures and races (e.g., Canty-Mitchell & Zimet, 2000; Chou, 2000; C. L. Cobb & Xie, 2015; Ekback et al., 2013; Kazarian & McCabe, 1991; Ng et al., 2010; Tonsing et al., 2012; Zimet et al., 1990). The internal consistencies obtained in this study for the scale were excellent across the four sub-samples (see Table 7). In addition, it made sense to use this measure for offline social support assessment, given it provided the basis for our online social support assessment, enabling comparisons to be made easily across online and offline contexts.

The mean score for the MSPSS obtained from this study was 66.74 (14.38). Prior studies by the scale's authors measuring social support in the offline context have suggested that scores higher than 61 on the MSPSS denote "high" social support, while scores between 36 and 60 denote "moderate" social support, and scores less than 35 denote "low" social support (Zimet et al., 1998). Of the total sample, as seen in the frequency tables (see Appendix E), approximately 71.3% had scores at or above 61 (high) while approximately 21.7% had scores between 36 to 60 (moderate), and 4.7% had scores at or below 35 (low).

Administration and scoring of the MSPSS. The MSPSS is self-reported and written in simple language. For this study, instructions for the MSPSS specifically expressed that respondents were to complete the items in relation to their offline social relationships. In addition to an overall scale score, the MSPSS also provides total scores for three sub-scales, that is, support from (a) significant other(s), (b) family, and (c) friends. In this study, only the total scale score was used in the analyses. To calculate the total score, you simply add the total number of responses to all 12 items. There is no reverse coding. Higher total scores indicate greater perceived offline social support.

Self-Disclosure Measure

There is no consensus with regard to the most valid measurement of self-disclosure. Nguyen and colleagues (2012) in a review article reported that there was a lack of consistency in how self-disclosure was measured across studies. In line with this, identifying a self-report measure of online disclosure was challenging, as no two studies have used the same measure. In the current project, a measure was adapted from Hollenbourg and Ferris' (2014) Revised Self-Disclosure Scale (RDS) and is referred to as the Online Self-Disclosure Scale (oSDS) (see Appendix 1-A, items 35-51).

Online self-disclosure scale (oSDS). The oSDS consists of 17 items which measure the amount, depth, and breadth of self-disclosure. The amount is measured by seven items, depth is measured by five items, and breadth is measured by five items. Hollenbourg and Ferris (2014) adapted their scale from the original Revised Self-disclosure Scale (RDS) by Wheeless (1978). Unlike Wheeless' measure, Hollenbourg and Ferris' scale added new items to measure breadth of disclosure. 'Breadth' is considered a central dimension of self-disclosure according to research and theory.

The scale asks participants to indicate how much they agree on a scale from 1 ("strongly agree") to 5 ("strongly disagree") with each statement about self-disclosure behaviour. Hollenbourg and Ferris (2014) were specifically interested in online self-disclosure within the Facebook context. Hence, for the current project, the scale was revised to fit the general SNS context. For example, the item "My Facebook posts range over a wide variety of topics" was changed to "My SNS posts range over a wide variety of topics".

Rationale for the selection of the oSDS. The original RDS by Wheeless (1978) contained 31 items measuring five dimensions of self-disclosure (intended disclosure, amount, positive-negative, depth, and honesty). As noted, breadth, a core dimension of the self-disclosure construct was not included. Amount, depth, and breadth of information people share with others are key dimensions of the construct (Altman and Taylor, 1973; West and Turner, 2007). The modified RDS by Hollenbourg and Ferris was chosen because it was short, yet covered all three of these key dimensions of self-disclosure, indicating strong content validity (Hollenbaugh & Ferris, 2014). Additionally, it had already been used in the online context and showed acceptable internal consistency for its three subscales (amount, α = .71, depth, α = .79, breadth, α = .76). Although Hollenbough and Ferris did not analyse the total score, others have reported acceptable internal consistency (α = .78) (Myers & Johnson, 2004). The overall internal consistency for the 17 items used in their study was similar to previous studies and is excellent across the three sub-samples (see Table 7). The mean score for the oSDS obtained from the current study was 39.49 (9.66). Cut-off scores for the oSDS have not been determined by the authors of the Scale. Others using the oSDS to measure online self-disclosure have reported that high scores on the oSDS suggested that participants disclosed more about themselves on SNSs (Hollenbaugh & Ferris, 2014). The mean oSDS for participants of the current study is quite similar to what other studies have reported (e.g., Hollenbough and Ferris, 2014).

Administration and scoring of the oSDS. The oSDS is an easy to read, self-report measure. At the start of the oSDS items, specific instructions asked the respondent to rate each item based on how he/she communicated on SNSs. In addition, the instructions included a definition of 'disclosure'. A total score is obtained by adding the responses given for each item.

Personality

Several commonly used measures of personality tests assessing the Big Five traits (see Chapter Two) were reviewed including the NEO Five-Factor Inventory, the Big Five Inventory-44, The Eysenck Personality Questionnaire, and The Minnesota Multiphasic Personality Inventory (MMPI). The Big Five Inventory -10 (BFI-10) developed by Rammstedt and John (2007) was chosen for this project (see Appendix 1-A, items 78-87). The BFI-10 was adapted from the long form, Big Five Inventory-44.

The big five inventory -10 (BFI-10). The BFI-10 is an abbreviated version of the well-established BFI (John, 1990). The BFI-10 was developed through a robust adaptation process (for details, see Rammstedt & John, 2007). The BFI-10 assesses the Big Five personality traits (i.e., Extroversion, Neuroticism, Conscientiousness, Openness, and Agreeableness): see Table 1, for a description of each trait. In the BFI-10, each dimension of the Big Five is measured with two items: one coded in the positive and one in the negative direction of the scale. The items are answered on a five-point Likert-type scale ranging from 1 ("strongly agree") to 5 ("strongly disagree"). For example, extroversion is assessed by the two items "I see myself as someone who . . ." (1) ". . . is reserved" and (2) ". . . is outgoing, sociable."

Rationale for the selection of the BFI-10. The BFI-10 was chosen because it is short, simply worded and quick to administer. It has been validated both in the United States and Germany and has shown adequate psychometric properties (Rammstedt & John, 2007). Although the BFI-10 scale includes less than 25% of the full BFI-44 items, it predicted almost 70% of the variance of the full scale. Rammstedt and John (2007) did not report the internal consistency for each of the sub-scales, but the test-retest reliabilities were acceptable, with all reliability coefficients r = 0.68 or above (Extroversion, r =.83; Agreeableness, r =.68; Conscientiousness, r = .77; Neuroticism, r = .74; and Openness, r = .72). This suggests that the BFI-10 scales achieved respectable levels of stability over 6 – 8 weeks in both cultures, supporting some cross-cultural appropriateness. An assessment of the measure's construct validity using factor analysis found the expected five-factor structure in each of Rammstedt and John's two samples. Convergent validity with NEO-PI-R was found to be substantial (r = .67), with the highest correlations being for extroversion, neuroticism, and conscientiousness. Discriminant validity was excellent (mean inter-correlations ranged from .08 to.13) in both samples.

For the current study, the sub-scales of extroversion, conscientiousness, and neuroticism displayed Cronbach's alpha coefficients between .50 and .59 for the New Zealand community sample, between .35 and .49 for the Maldives community sample, and between .58 and .70 for the New Zealand Clinical sample (see Table 7). Though in the moderate range, these coefficients were deemed acceptable for research studies provided the results are treated with caution (Tabachnick, 2007). Unfortunately, in the current study, the internal consistencies could not be obtained for agreeableness and openness due to violations of reliability assumptions. Rammstedt and John (2007) also reported that agreeableness and openness subscales were less representative of the BFI-44 scales compared to extroversion, conscientiousness, and neuroticism. Hence, it was decided that in this study, only the latter three trait subscales would be used in the analyses. The mean scores for these three factors obtained from the current project were 7.1 (2.00), 8.2 (1.67), and 5.2 (1.90) respectively. A prior study using the BFI-10 on a general population sample reported similar means as this study for extroversion, conscientiousness, and neuroticism (Rammstedt & John, 2007).

Administration and scoring of the BFI-10. The BFI-10 contains 10 items which participants respond to by choosing from a 5-point Likert scale. The scale is made up of 5 factors (two items per dimension); higher scores on each scale indicate higher levels of that particular trait. Scale scores are computed by recoding the negatively coded items and averaging both items assessing one dimension. Each of the personality factors has a minimum possible score of 2 and a maximum possible score of 10. If one item response was missing, sub-scale scores were not computed for the corresponding sub-scale that includes the missing item. In the current study, the mean score of the overall extroversion subscale was M = 7.16, SD = 2.00. The mean score of the overall conscientiousness subscale was M = 8.20, SD = 1.67. The mean score of the overall neuroticism subscale was M = 5.15, SD = 1.90.

Wellbeing

A literature search for wellbeing tools yielded more than a hundred measures of wellbeing. A handful were population-based self-report measures of psychological wellbeing based on Diener's (2009) multidimensional model. The most common measures of SWB are self-reports. Often measures of wellbeing used single-item questionnaires which have obvious advantages in terms of their brevity. They are usually considered valid if they converge with other measures of SWB (Diener, 2009). However, Diener (2009) argues that single-item scales are less reliable than multi-item scales as their internal consistency cannot be estimated. In addition, they cannot cover all aspects of SWB, but rely on the participant's integration of many areas of wellbeing in arriving at their single response. They do not offer a comprehensive view of a person's subjective wellbeing. Hence, only multi-item measures were considered in this section.

Based on the review of the conceptual frameworks of psychological wellbeing discussed in Chapter 2, the Mental Health Continuum-Short Form (MHC-SF) (Keyes et al., 2008) was selected for this study. The Mental Health Continuum Short Form (MHC-SF) (Keyes, 2009) shows promise in that it covers the key domains of wellbeing: affective and cognitive evaluation of life, psychological attributes, and positive functioning. It has shown excellent psychometric properties and is easy to administer. Another benefit of the MHC-SF is that it has external validity.

Mental health continuum – short form (MHC-SF). The MHC-SF consists of 14 items measuring wellbeing on a 6-point Likert scale ranging from 'never' to 'everyday'. Example items include 'During the past month, how often did you feel… 1) happy; 2) satisfied with life; 3) that your life has a sense of direction or meaning to it' (see Appendix 1-A, items 64-77).

Rationale for the selection of the MHC-SF. The MHC-SF was chosen because it was short, yet as mentioned above it covers the key domains of wellbeing, namely affective and cognitive evaluation of life, psychological attributes, and positive functioning. The MHC-SF has demonstrated excellent internal validity in studies using both adolescents and adults in many different countries (Keyes, 2006; Keyes et al., 2008; Lamers et al., 2011; Westerhof & Keyes, 2010). The estimates of 4-week test-retest reliability coefficient for the long form scales range from .57 for the general psychological wellbeing domain, .64 for the overall emotional wellbeing domain, to .71 for the overall social wellbeing domain (Robitschek & Keyes, 2009). The test-retest reliability of the MHC-SF over three successive 3-month periods averaged .68 and the 9-month test-retest was .65 (Lamers et al., 2011). The three factor structure of the long and short forms of the MHC – emotional, psychological, and social wellbeing – has been confirmed in nationally representative samples of American adults (Gallagher et al., 2009), college students (Robitschek & Keyes, 2009), and in a nationally representative sample of adolescents between the ages of 12 and 18 (Keyes, 2006) as well as in South Africa (Keyes et al., 2008) and the Netherlands (Lamers et al., 2011). This suggests the scale has cross-cultural generalisability. The internal consistencies obtained in this study for the scale across the three sub-samples were also excellent. The mean value obtained from our study for the MHC-SF was 58.40 (15.04) (Table 7). The mean score obtained in this study was slightly higher than those reported in previous research from two different countries (Keyes et al., 2008; Lamers et al., 2011).

Administration and scoring of the MHC-SF. The MHC-SF is an easy to read self-report measure. The instructions specifically asked the respondents to rate the items based on how they have been feeling during the past month. In addition to giving the option of obtaining a total score for the scale, scores can be obtained for three subscales (H. S. Kim et al., 2008). In this study, only the total score was used in the analyses. Total scores from the MHC-SF can range from 14 to 84, with higher cumulative scores representing higher levels of psychological wellbeing.

Table 7. *Means, Variances, and Reliability Coefficients for Continuous Variables Separately for the Three Sub-samples*

			New Zealand Community Sample				Maldives Community Sample				New Zealand Clinical Sample			
Variable	Min	Max	*n*	*Mean*	*SD*	*α*	*n*	*Mean*	*SD*	*α*	*n*	*Mean*	*SD*	*α*
oMSPSS	12	84	215	43.7	16.3	.94	283	48.6	17.0	.92	48	47.1	14.1	.92
MSPSS	12	84	381	69.5	13.5	.96	406	64.1	14.5	.92	69	67.3	13.3	.93
oSDS	17	85	216	35.0	9.1	.87	282	42.9	8.6	.75	46	37.0	8.9	.85
BFI-10														
Extroversion	2	10	379	6.3	2.0	.59	405	7.9	1.7	.38	69	5.7	2.3	.67
Conscientiousness	2	10	379	8.3	1.6	.50	405	8.1	1.7	.49	69	6.8	2.0	.58
Neuroticism	2	10	379	5.4	1.9	.52	405	4.9	1.8	.35	69	7.7	1.9	.70
MHC-SF	14	84	379	62.7	13.2	0.92	406	57.1	15.9	.90	69	51.5	13.9	.90

Note: MHC-SF = Mental Health Continuum-Short Form, oMSPSS = Online Multidimensional Scale of Perceived Social Support, MSPSS = Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory; Missing values are presented in Table 8.

Study Design

Design Considerations

The current study was a cross-sectional survey of two random samples selected from New Zealand and Maldives. This design was chosen for the following reasons: (i) it was relatively inexpensive and quick to implement given the time and logistical constraints; (ii) it facilitated the collection of data on many factors at the same time; (iii) the use of random samples provided the opportunity to generalise to the target populations we were interested in; and (iv) the survey permitted a contemporary snapshot of current variables and their interactions with each other. The data collection process will be outlined later in the chapter. Figure 6 shows the procedure for data collection for this project.

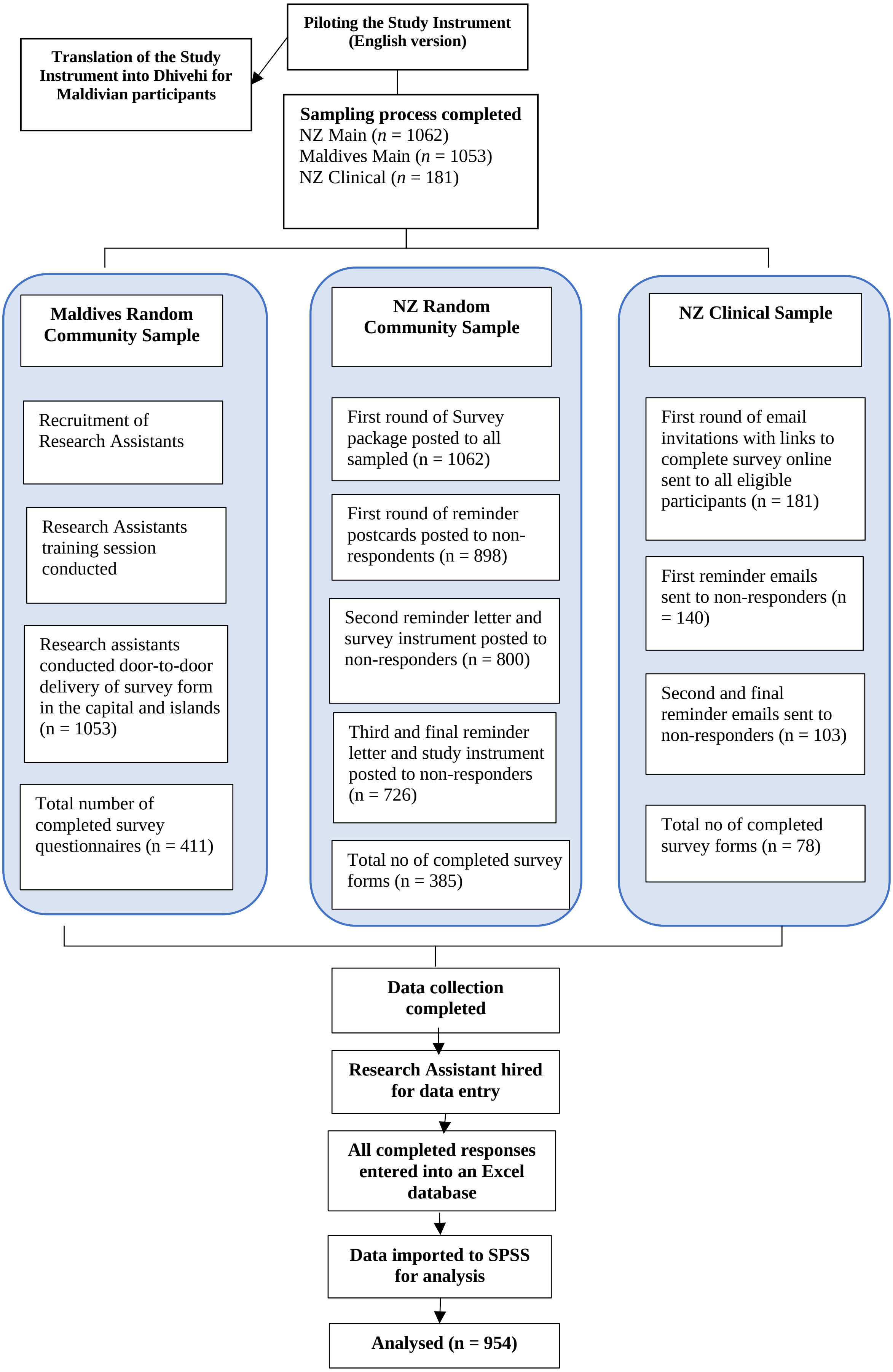

Figure 6. The flow of participants and their data through each stage of the research project

Piloting the Study Instrument

The draft study questionnaire which included tools previously developed by other authors was initially discussed with members of the research team (supervisors) and other researchers from the School of Medicine, University of Otago Wellington (UOW). These researchers had experience in survey instrument design and in conducting research with Māori and non-New Zealand participants.

After initial revisions to the instrument's layout, wording, and sequencing based on the guidelines proposed by Dillman (2007) on questionnaire design, the revised instrument was piloted with a small group somewhat similar to the selected population to ensure that the questions were interpreted by the respondents as intended. During this stage, the data collection process was also tested to identify problems and ways to maximise the completion rates. Pilot testing was carried out to evaluate the study instrument based on the criteria described by van Teijlingen and Hundley (2002):

1. To test the utility and face validity of the study instrument.
2. To ensure the questions were understandable to respondents as well to the investigator.
3. To establish whether the data collection techniques were effective.
4. To identify logistical problems which may occur when using the proposed methods.
5. To assess the probable cost and duration of the main survey and its various stages.

To assess the survey questionnaire using these criteria, a convenience sample of 20 (staff from the Department of Psychological Medicine, UOW, and personal contacts) were approached. The survey instrument was completed either online or on paper. They were asked to comment either verbally or in writing on the ease of completion and the length of time required to complete the questionnaire, and to identify items which were confusing or hard to understand. Eleven people responded to the request to participate in the piloting feedback process. Those who did not respond were not contacted again. Of these 11 responders, two completed paper-based versions of the questionnaire and 9 completed it online. Their feedback was discussed with the research project supervisors and agreed changes were made to the composite study survey.

Adjustments after the pilot study

The main adjustments in the survey questionnaire were as follows:

1. The comprehensibility of some items that were not answered. For this reason, difficult or negatively worded or double-barrelled questions were simplified.
2. Questionnaire design and layout with particular focus on question order and visual design.
3. It became clear that additional information such as the function of SNS use, and measurement of social support exclusively from online social networks, were required to address the key research questions. Consequently, more questions to measure the function of specific SNS use and an additional measure of online social support (in addition to the oMSPSS described earlier) were added.

Translation of the Study Instrument to Dhivehi

After the pilot study, the revised English survey questionnaire was translated into Dhivehi for the Maldives samples. The translation process was completed using the conceptual translation method used in the Euro-Reves Protocol (Robine & Jagger, 2003). This method involved relying on detailed explanations of the terms used in each question as well as the fundamental concepts that the question was intended to measure. This approach differs from the forward-backward technique in the ‘backward’ step. That is a checker determines whether each question has been correctly translated so that the desired ideas have effectively been captured instead of translating the question back to the original language. Translations were completed by three people, including the primary investigator, who all speak Dhivehi as their first language, and who also have an understanding of the psychological concepts used in the questionnaire. The full translated questionnaire was then checked by the primary investigator for consistency in the descriptions of concepts. The final translated questionnaire was then given to a professional translator for grammatical and phrase checks.

Procedure and Field Activity

New Zealand random community sample. Participants were posted a survey pack which contained the participant information sheet, consent form, the paper-based questionnaire with return postage-paid envelope. Information on accessing the online version of the same questionnaire (via Qualtrics, a survey program) was also provided with the paper-based version of the questionnaire for those who opted to complete the online questionnaire (see the top of the survey questionnaire, Appendix A). Qualtrics is a simple to use web-based survey tool (www.qualtrics.com) used by researchers and supported by the University of Otago. Follow-up reminders were sent to non-responders in three waves. Non-responders were identified by cross-checking the returned questionnaires which had come in either by post or completed online against the full list of participants. The first reminder was a postcard sent two weeks after the initial posting. After three weeks, a full follow-up questionnaire set was sent to non-responders and two weeks later a third full questionnaire set was sent to the non-responders. Participants were offered a chance to enter a draw to win a Tablet or a $400 gift card as an incentive for taking part in the research.

Maldives random community sample. Data collection in the Maldives took place between December 2015 and June 2016. Given that Maldives does not have an efficient local postal service, the Maldives data collection protocol was changed from a postal method (which was initially proposed for both Maldives and New Zealand) to a face-to-face approach and distribution of the questionnaire using trained research assistants.

Selected participants were approached face-to-face by the primary investigator and volunteer research assistants (RAs). The RAs from the capital city Male' were recruited through a secondary school which provided contact details of students who had completed their final year of high school. The RAs were given one day of focused training about the research study and how to collect data reliably. The RAs were assigned to different districts and given a list of names and addresses of participants for their specified districts. The RAs were told to first introduce themselves, explain why they were approaching that participant and to give a brief description of the survey; if the person approached agreed to participate, RAs were asked to hand them the information sheet and survey instrument and request completion of the questionnaire while they waited. On a weekly basis, the primary investigator met with the RAs and reviewed the status of data collection (e.g., the number of completed questionnaires, incorrect addresses, refusals and reasons for refusal if given etc.). The primary investigator also reviewed the completed questionnaires by checking for ambiguity, inconsistency or missing data.

The recruited RAs were volunteers from the five islands where random samples were taken. The island-based RAs were oriented individually via phone and further instructions on data collection were emailed to them. Survey questionnaires along with sample lists with their addresses were sent directly to the island-based RAs by ferries. Participants who were not available for survey participation at the time of the first visit were visited at least once more (except in Male' city because of time and budget constraints for travel). If after the second attempt, the participants could not be contacted at the address, this was recorded as an ineligible case (i.e., assumed to not reside at that address) and another person was selected from the sampling frame of the same Atoll. RAs were requested to check-in daily either by phone or email with the primary researcher. Completed questionnaires were packed and ferried back to the primary investigator. Participants were offered a chance to enter a draw to win a Tablet or a $400 gift card as an incentive for taking part in the research.

New Zealand clinical sample. For the clinical sample, an online survey only was used. Participants were invited to take part in the study via email. Email addresses of all eligible candidates were accessed from the patient register. An automated email was generated using Qualtrics software and sent to participants to complete the online version of the survey instrument. A first reminder was sent after two weeks to those who had not responded to the first invitation. A second reminder was sent again after a further week to those who still had not completed the questionnaire.

Data Entry, Cleaning, and Management

Data Entry

After collecting the data, the responses from the 953 completed questionnaires were entered into an Excel spreadsheet by an experienced research assistant who was fluent in both Dhivehi and English. Before commencing data entry work, some study-specific training was given to the research assistant. To ensure that the survey responses were entered accurately, 10% of the first 50 entries were checked randomly against the original questionnaires for the accuracy of the data by the primary researcher. In addition, 25% of the completed questionnaires were double entered to reduce data entry error.

Answers to survey questions were kept confidential and were only viewed by the PhD candidate and the research assistant. After completion of data entry, the data needed to be cleaned and the mistakes rectified to make the dataset ready for statistical analysis.

Data Cleaning

Data cleaning identified inconsistencies in responses and missing responses in the data using SPSS. To perform checks, descriptive statistical methods such as frequency, mean, standard deviation, range, maximum and minimum values were used. The following activities were performed during data cleaning:

Range checks. Range checks were undertaken as a first step of data cleaning for all variables. Descriptive statistics were used to locate and correct outliers. For example, for each question, the minimum and maximum values were examined to see whether they fell within each question's expected range (e.g., gender must be either male or female, valid values for all questions with Likert scales must be within the expected range). For variables without specific values, such as age, checking was undertaken to see whether values were at least logically acceptable and consistent with other related data.

Consistency checks. A large proportion of the data cleaning time involved checking the consistency between variables. In particular, a specific consistency check was performed on SNS use as instructed in the questionnaire. For instance, if a respondent said he/she did not use SNSs, then all the questions on SNS use and online social support and online self-disclosure questions had to be skipped and not included in the analyses. Only four respondents had not skipped the questions on SNS use after saying they did not use SNS. If a responder said he/she did not use SNS, but completed the next follow-up question which asks how much time they spent, and if they said, ‘more than 10 minutes’ and had completed the online SS and self-disclosure questions, then the question on SNS use was changed to a ‘yes’. However, if the respondent said he/she used SNSs but ‘spent less than 10 minutes’, then the responses on online SS and self-disclosure were deleted from the analysis.

A consistent strategy was necessary to deal with errors. If an inconsistency was obviously the result of a mistake made by the researcher/research assistant, then these mistakes were first corrected by going back to the original questionnaires. With some missing data, it was possible to infer responses for missing items using the information from other related variables. For example, if the response to the question ‘your gender’ was missing, demographic information from electoral rolls was checked and the correct response was entered. If it was not possible, the incorrect data was recorded as a “missing” value. In the event that many inconsistencies were observed in the information for a particular respondent or the questionnaire comprised many missing values, that individual was excluded from further analysis and was added to the non-respondent list. Only two questionnaires had to be excluded from the analysis for this reason.

Missing data. Table 8 shows the missing values for the key variables. The online PSS and online self-disclosure had much higher missing values because participants who used SNS for 10 minutes or less were asked to skip the items that measured these two scales. For the oMSPSS, MSPSS, oSDS, and MHC-SF scales, the number of missing items for each person who reported using SNS for 10 minutes or more was calculated in SPSS. If 25% or more of the items were missing for anyone, then that individual’s score was not used in the analyses. The MHC-SF has 14 items, hence 25% = 3.5, therefore, if a participant had more than three items missing their score was omitted. If three or fewer items were missing, a formula was used to produce a corrected total score. For example, for someone with 12 MHC-SF items known, the score = 14 x MEAN (12 known items). The same formula was used to obtain mean total scores for the oMSPSS, MSPSS, and oSDS scales. For the extroversion, neuroticism, and conscientiousness scales of the BFI-10, if one of the items was missing for a subscale, the individual’s score for that subscale was not used in the analyses (there were only two items in each of these scales).

For multivariable analyses (see Chapters 5, 6, and 7), which includes online PSS scores, only those participants who had known values for all variables (predictors and outcome) were included in the analyses. The sample size (n) for each analysis is given in the results chapters.

Table 8. *Percentage of Missing Values for Each Variable for Those Who Spent More Than 10 Minutes a Day on SNS by the Three Sub-groups.*

Variables	NZ Main (*N* = 385)		Maldives Main (*N* = 411)		NZ Clinical (N =78)	
	missing	% missing	missing	% missing	missing	% missing
Online PSS*	385-215= 170	44.2%	411-283 = 128	31.1%	78 -48 =30	38.5%
Offline PSS	385-381=4	1%	411-406 = 5	1.2%	78 - 69 = 9	11.5%
Online self-disclosure*	385- 216 = 169	43.9%	411 -282 =129	31.4%	78 -46 =32	41%
Wellbeing	385-379=6	1.6%	411- 406 = 5	1.2%	78 -69 = 9	11.5%
Extroversion	385-379 = 6	1.6%	411 - 405= 6	1.5%	78 -69 = 9	11.5%
Neuroticism	385-379 = 6	1.6%	411 - 405 = 6	1.5%	78 -69 = 9	11.5%
Conscientiousness	385-379 = 6	1.6%	411 - 405 =6	1.5%	78 -69 = 9	11.5%
Age	385-379 = 6	1.6%	411- 404 =7	1.7%	78 -76 = 2	2.5%
Gender	385-383 = 2	0.6%	411- 411=0	0%	78 -78 = 0	0%
Region	385-378 = 7	1.8%	411- 410 =1	0.2%	78 -78 = 0	0%

Note.* Online PSS and online self-disclosure scores are obtained only for those who said they used SNSs. Actual missing values are similar to offline PSS values

Data Analysis Protocol

Statistical analyses in this thesis are based on the conceptual framework described in Chapter Two. A variety of statistical analyses were used as summarised below.

Descriptive Statistics

Analyses started with descriptive statistics or univariate analyses to summarise the data, and also to understand the distribution, central tendency and dispersion of the study variables. For the main continuous variables (MHC-SF, oMSPSS, MSPSS, oSDS, Extroversion, Conscientiousness, and Neuroticism), histograms were produced to check (a) the shape and distribution of the data, (b) implausible values, (c) gaps in values, and (d) extreme values. In addition, means and standard deviations, or where relevant median and interquartile ranges were used for the presentation of the data. Categorical variables were presented using numbers and percentages of groups. The results of the univariate analyses are presented in the results chapters.

An Estimation Approach to Measurement Invariance

In order to compare mean differences and to conduct regression analyses for the key variables (online PSS, offline PSS, online self-disclosure, and psychological wellbeing) across New Zealanders and Maldivians from the general population samples, measurement invariance (MI) was examined using an estimation approach. Measurement invariance or lack of equivalence refers to “lack of bias” (Meredith & Millsap, 1992, p. 209), and tests whether “measurements yield measures of the same attributes” (Horn & McArdle, 1992, p. 117). It has been recognized as a crucial step for group comparison studies as it demonstrates whether different group members interpret the questionnaire items in the same way with similar response anchors (e.g., Milfont & Fischer, 2010; Vandenberg & Lance, 2000). Moreover, it allows researchers to compare different groups in a meaningful way with respect to their means and correlations between their variables (Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). In our recent attempt to establish MI, UOW biostatistician, Dr Willink (see his report attached in Appendix O) demonstrated that estimating measurement **variance** (MV) is more appropriate than testing measurement **invariance** (MI), in this case. He noted that “error can never be exactly equal to zero; and when this premise holds, the concept of approximating the true value is more logically satisfactory than the concept of testing the hypothesis of strict MI” (Willink, p 2). Dr Willink gives a number of reasons for focusing on MV rather than MI. Most importantly, he argues that MI testing (goodness-of-fit testing) is not generally appropriate as MI cannot be strictly achieved in research involving samples that would be expected to differ (e.g., because of cultural differences). In this way, Dr Willink argues that it is not possible for a questionnaire to be ‘strictly invariant’. Hence the estimation approach makes the idea of ‘fitness-for-purpose’ more appropriate. That is, if the questionnaire is used in populations that differ greatly, then a small amount of MV will not matter. Therefore, when the focus is on estimation, not testing, there is no need for the conventional analysis of MI using hierarchical tests of configural invariance, metric invariance, scalar invariance, and residual invariance. Criticisms of such statistical tests and empirically derived cut-off values have been made on several grounds (Nye & Drasgow, 2011). In addition, Dr Willink argues that “in the general field of statistical analysis, there is an ongoing shift from the concept of ‘hypothesis tests’ to the concept of estimation using confidence intervals” (p. 3). In addition, the estimation process allows the researcher to focus on the validity of the conclusions and, if needed, make adjustments to the scores and restate the conclusions.

Based on the above arguments, the approach taken in this study was to accept that there must be some MV, to estimate its size, and then to examine whether the results, i.e., comparisons between groups in relation to the study variables, changed the conclusions. Adopting the estimation approach means that traditional methods of MI such as the ‘alignment method’ may also lose some relevance. (see Dr Willink’s report for detailed explanation).

For the purpose of MV analysis, the set of items measuring a variable (e.g., online PSS) in the survey form was called the ‘questionnaire or Q’ and was administered to participants in samples drawn from two populations, A (New Zealand community sample) and B (Maldives community sample), in order to measure the magnitude of four ‘personal properties’ or variables (i.e., online PSS, offline PSS, online self-disclosure, and psychological wellbeing) symbolised by θ. The questionnaire addresses these properties simultaneously, with any particular property θ

being measured using *m* questions (items), each of which has a numerical response on a Likert scale (e.g. 1, 2, ..., 7). For each participant, the *m* responses for the questions are summed to give the score on that property for that participant. This score is an estimate of the underlying unknown *true value* or *true level* of that property for that participant. The scores and responses differ from the true magnitudes by amounts known as *error*, with error being positive or negative, as above.

If, for any property, X_i represents the score for participant ***i*** in population A and X_j represents the score for participant j in population B, then the analysis of MV can be based around the following equations. The quantities D_i and D_j represent deviations from the population means and represent E_i and E_j measurement error.

$$X_i = \alpha_{\mathbf{A}} + \beta_{\mathrm{A}} D_i + E_i$$

$$X_j = \alpha_{\mathbf{B}} + \beta_{\mathbf{B}} D_j + E_j$$

The alpha and beta quantities are unknown parameters that have to be estimated, and the amount of MV is reflected in the difference between the estimates of $\alpha_{\mathbf{A}}$ and $\alpha_{\mathbf{B}}$, and the difference between β_{A} and β_{B}.

Comparison of group means of four main multi-item variables

Before comparing the mean levels of the four variables (online PSS, offline PSS, online self-disclosure, and psychological wellbeing) between the New Zealand and Maldives random community groups, MV was estimated. If MI were to exist with regard to testing of means, then $\alpha_A = \alpha_B$. Therefore, to estimate the size of the corresponding component of MV, we seek to estimate the difference $\alpha_B - \alpha_A$ using the sample data. The results are presented in Chapter 4.

Comparing populations in relation to associations between variables: Hypotheses 1-3).

The associations between key variables used in hypotheses testing was indicated by regression coefficients that represent slopes. Therefore, they do not depend on intercepts which means that there is no requirement for the questionnaire to have equal variance. So the estimation of the relevant MV centres on the differences between β_{A}

and β_B. Furthermore, the effect of residual variance is only to weaken the ability of the questionnaire to detect true differences. Therefore, the MV that might arise from a false difference in the residual variances could not alter original conclusions that the hypotheses are true. The analysis is therefore based around the covariance matrices of the responses to the questions, which contains all the information available about β_A and β_B and all the information available about correlations between the responses to these questions. The MV estimation and further analysis of associations for the New Zealand and Maldives community samples are presented in Chapter 7.

Bivariate Analysis

Bivariate analyses of two variables were used for the purpose of determining the empirical relationship between them. These included a Chi-square test of independence for categorical variables and one-way analysis of variance (ANOVA) for the continuous independent variables.

Multivariable Analysis

In order to determine the association between the predictors and outcome variable of the study, adjusting for a range of covariates, multivariable regression analyses were performed. This allowed for the determination of the relative contributions of different independent variables to the outcome measure (level of psychological wellbeing).

Moderation analyses were conducted using Model 1 of the PROCESS macro for SPSS (Hayes, 2017) to investigate the moderating effects of demographic and personality variables in the relationship between online PSS/offline PSS and psychological wellbeing. The two moderators (gender, country) were dummy coded prior to analysis.

Robustness of the Data and Analyses

The following section summarises the strategies and tasks carried out to ensure that the research method and data analysis were robust, particularly for the two community samples:

1. Random samples were selected using electoral rolls as a sampling frame to minimise bias.
2. The original MSPSS was used to measure offline PSS which is a well-validated measure.
3. The adapted MSPSS used to assess the online social support showed high internal consistency for all three sample groups (see Table 7) and allowed appropriate comparison with the offline social support measure.
4. The online self-disclosure measure adapted for this study had not been validated in other populations but showed high internal consistency in our analysis (see Table 7).
5. A wellbeing measure was used that had been validated in other populations and showed excellent internal consistency in both previous studies and the current study.
6. To measure personality the original BFI-10 was used. This has been validated in the past with adequate results (Rammstedt, 2007; Rammstedt & John, 2007). Our analysis showed that three factors (Extroversion, Neuroticism, and Conscientiousness) had 'adequate' internal consistency. The remaining two factors (Openness and Agreeableness), were not used in the analysis as their internal consistency was unable to be established. Rammstedt and John's (2007) based on their validation study concluded that the former three factors showed more promising psychometric results than the latter.
7. As detailed earlier, a very low percentage of observations were removed due to missing data.
8. The probability distribution for all variables was examined in the two random samples to ensure appropriate statistical tests were used.
9. Regression analyses using overall social support scores as independent variables, and wellbeing as the dependent variable produced consistent results across both random sub-samples.

CHAPTER 4: RESULTS 1 - PRELIMINARY ANALYSIS

Prior to conducting inferential statistics, preliminary analyses for the study's primary variables were obtained for the combined random sample for the purpose of testing hypotheses one to three reported in Chapters five and six. In addition, preliminary analyses including between group differences in variables measured is reported in this chapter: (Group 1 = New Zealand random community sample; Group 2 = Maldivian random community sample; Group 3 = New Zealand convenience clinical sample). Demographic characteristics of the three sub-samples were outlined in Chapter 3, under the demographics section and in Table 6.

Preliminary Results For the Combined Random Sample

Amount of Time Spent on SNSs Per Day in Percentages

Figure 7 shows the number of people (in percentages) in the combined random sample who are in different categories of time spent on SNS per day including those who spent 10 minutes or less on SNSs per day (N = 782). This shows that 38.24% of the participants spent 10 minutes or less time per day on SNSs. Almost half of the participants spent between 10 minutes to two hours per day on SNSs. Overall, approximately 15% of the combined random sample spent two or more hours per day on SNSs.

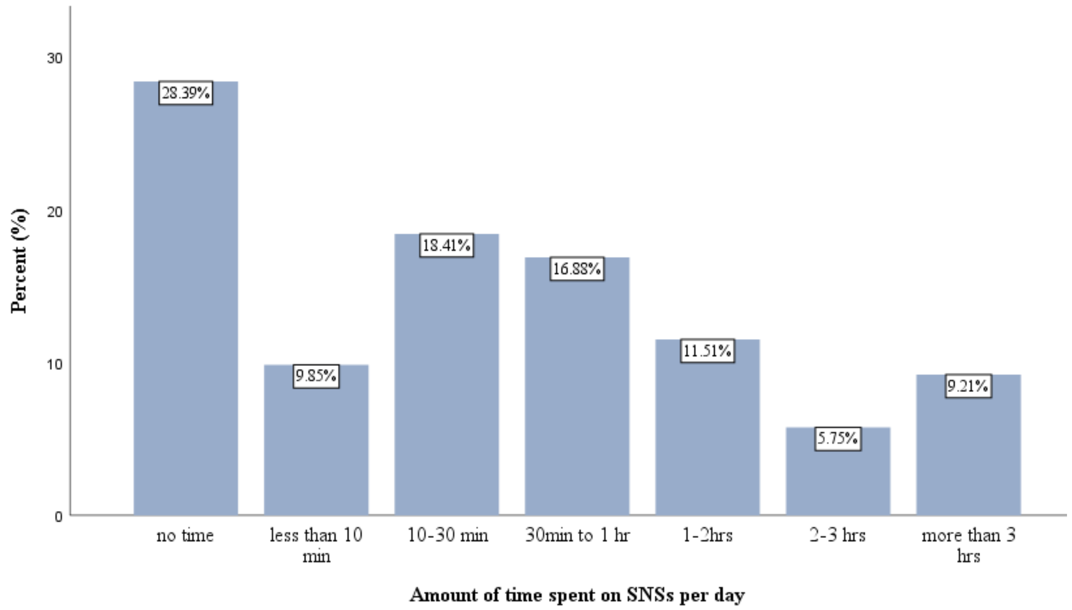

Figure 7. Self-reported amount of time spent on SNSs per day for the combined New Zealand and Maldives random community sample (*N* = 782).

Descriptive Statistics for the Key Measures

In this section, the results are computed for the combined sample who used SNSs for 10 minutes or more per day. The means, standard deviations, and ranges for key variables (online PSS, offline PSS, online self-disclosure, extroversion, conscientiousness, neuroticism, and psychological wellbeing) are displayed in Table 9. All the measures produced approximately similar means and standard deviations as previous researchers have (see Chapter 3 on measures for details). Normality tests and visual inspection of distributions were undertaken for the variables, online PSS, online self-disclosure, and psychological wellbeing (key outcome variables tested as per the conceptual model depicted in Figure 2, and they are reported in the relevant sections below. All variables demonstrated approximately normal univariate distributions, with skews within the acceptable range of ±2 (Trochim & Donnelly, 2008).

Online PSS. Table 9 shows the overall mean score and internal consistency for the oMSPSS for the combined random community sample who spent more than 10 minutes per day on SNSs. The mean score of the overall oMSPSS was M = 46.49, SD = 16.84. Distribution of the total oMSPSS scores for the combined random sample is depicted in Figure 8 below. Normality testing using the Kolmogorov-Smirnov test produced a p-value of less than .05. However, visual inspection of the normality plot and tests for skewness (−.26) and kurtosis (−.60) indicated that the oMSPSS scores were approximately normally distributed. No outliers were detected.

Higher scores on the scale indicated more online PSS. The internal consistency for the oMSPSS was in the excellent range, as measured by the Cronbach's Alpha which was 0.92.

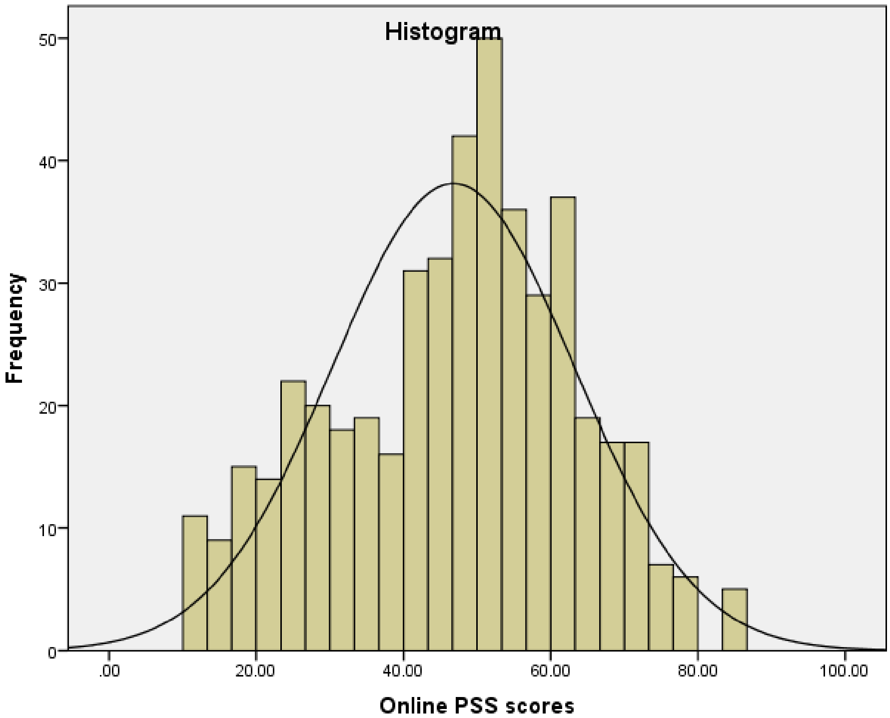

Figure 8. Histogram for the online PSS scores of the combined random sample (N = 472)

Offline PSS. Table 9 shows the overall mean score and internal consistency for the MSPSS for the combined random community sample who spent more than 10 minutes per day on SNSs. The mean score of the overall MSPSS was M = 66.39, SD = 14.38. Higher scores on the scale indicated more online PSS. The internal consistency for the oMSPSS was in the excellent range, as measured by the Cronbach's Alpha which was 0.92.

Psychological wellbeing. Table 9 shows the overall mean score and internal consistency for the MHC-SF for the combined random community sample who spent more than 10 minutes per day on SNSs. The mean score of the overall MHC-SF was M = 58.82, SD = 15.04. The normality testing using Kolmogorov-Smirnov produced a p-value of less than 0.05. However, visual inspection of the normality plot (see Figure 9) and test statistics for skewness and kurtosis indicated that the MHC-SF scores were approximately normally distributed. Higher scores in the scale indicated more psychological wellbeing. The internal consistency for the MHC-SF was in the excellent range, as measured by the Cronbach's Alpha which was 0.91.

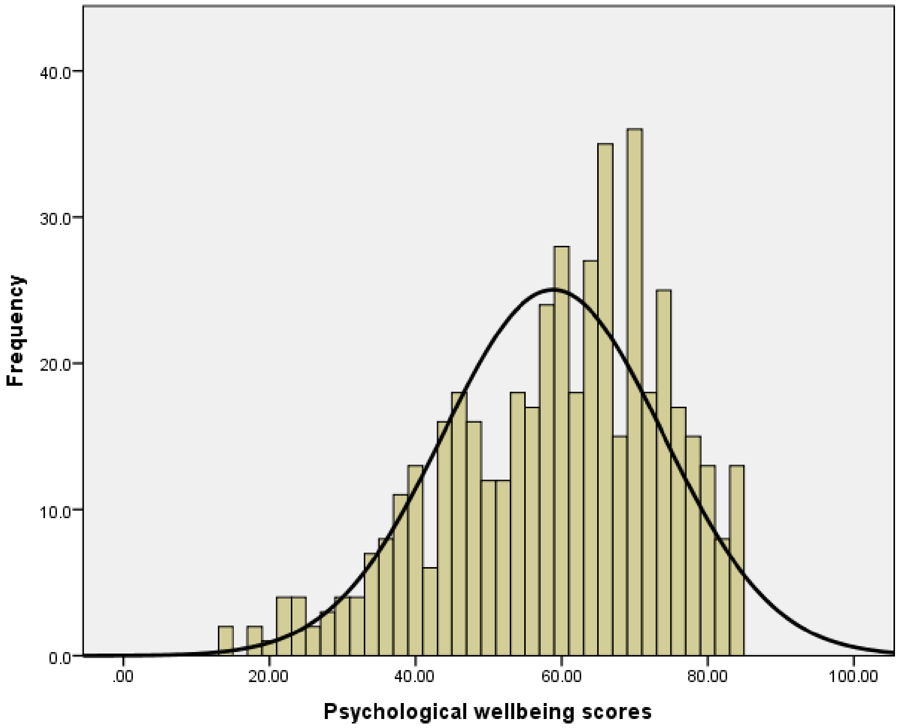

Figure 9. Histogram for the psychological wellbeing scores of the combined random sample (*N* = 472)

Online Self-Disclosure. Participants' online self-disclosure levels were measured using the oSDS. An overall mean score and internal consistency for the scale were calculated for the combined random sample who spent more than 10 minutes a day on SNSs and are displayed in Table 9. The mean score of the overall oSDS was M=39.49, SD = 9.66. Kolmogorov-Smirnov normality testing produced a p-value of less than .05. However, visual inspection of the normality plot (Figure 10 below) and skewness (−.25) and kurtosis (−.29) showed that oSDS scores were approximately normally distributed. No outliers were detected. The results suggested a normal distribution for the oSDS scores in the sample. Higher scores in the scale indicated disclosing more about oneself on SNSs. The internal consistency for the oSDS was good with a calculation of Cronbach's Alpha of 0.82.

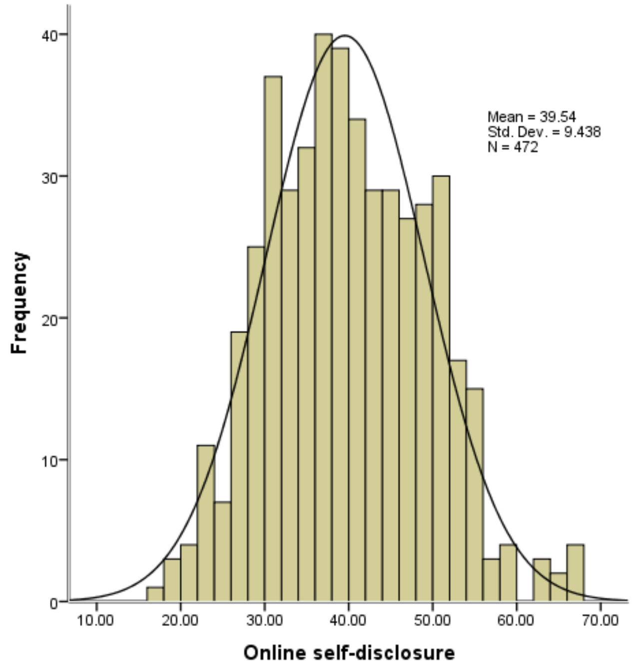

Figure 10. Histogram for the online self-disclosure scores of the combined random sample (*N* = 472)

Personality. Three personality traits were measured using the Extroversion, Conscientiousness, and Neuroticism subscales of the BFI-10. Overall mean scores and internal consistencies for the three scales were calculated and are displayed in Table 9. The mean score of the overall extroversion subscale was M = 7.16, SD = 2.00; the mean score of the overall conscientiousness subscale was M = 8.20, SD = 1.67; and the mean score of the overall neuroticism subscale was M = 5.15, SD = 1.90. The internal consistency for the extroversion, conscientiousness, and neuroticism measured by the Cronbach's Alphas were .51, .45, and .40 respectively. While these may be considered poor, the BFI-10 scales are short (2 items each) making inter-item correlations less representative index of reliability and content validity (Ziegler et al., 2014). As previously noted, reviews (see Chapter three) have indicated that the BFI-10 is psychometrically robust.

Table 9. *Means and Standard Deviations of Participants' Online Social Support, Offline Social Support, Online Self-Disclosure, Psychological Wellbeing and Personality Traits for the Combined Random Community Sample (N = 472)*

Variable	Mean (SD)	Range Minimum	Range Maximum	α	Skew	Kurtosis
oMSPSS	46.49 (16.84)	12	84	0.92	−0.26	−0.60
MSPSS	66.39 (14.38)	12	84	0.92	−1.29	1.98
oSDS	39.49 (9.66)	17	67	0.82	−0.25	−0.29
MHC-SF	58.82 (15.04)	14	84	0.91	−0.58	−0.21
BFI-10						
Extroversion	7.16 (2.00)	2	10	0.51	−0.25	−0.67
Conscientiousness	8.20 (1.67)	2	10	0.45	−0.72	−0.15
Neuroticism	5.15 (1.90)	2	10	0.40	−0.19	−0.29

Note. MSPSS = oMSPSS = Online Multidimensional Scale of Perceived Social Support, Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory, MHC-SF = Mental Health Continuum-Short Form, α = Cronbach's Alpha

Associations Between Psychological Wellbeing, Online/Offline Perceived Social Support, Online Self-disclosure, Personality Traits, and Demographic Characteristics for the Combined Random Community Sample.

Correlations between measures were inspected (see Appendix F-1) to ensure that 1) correlations were in the expected directions, 2) independence of the variables was indicated, and 3) that there were no issues of multicollinearity.

All correlations were in the expected directions (see Appendix F-1). All correlations were less than .5, which is well below the recommended threshold of .7 (Tabachnick, 2014), indicating that there was no problem of multicollinearity across these variables. Correlation coefficients between .10 and .29 represent a small association, coefficients between .30 and .49 represent a moderate association, and coefficients of .50 and above represent a large association or relationship (J. Cohen, 1988). Time spent on SNSs was positively related to online PSS. As expected, there was a positive correlation between time spent on SNSs and online PSS. The correlation between online PSS and offline PSS was also positive. This finding warranted further analyses of the study H_1 using regressions. The correlation between the psychological wellbeing and offline PSS measure scores was positive and significant as expected. Contrary to expectations, the correlation between psychological wellbeing and online PSS was not significant. However, the correlation between online PSS and online PSS was moderate and positive. Therefore, a regression analysis was conducted to explore the effect of online PSS and offline PSS together on wellbeing.

The correlation between the country of residence and psychological wellbeing was moderate and positive, while age, region, and gender were not significantly correlated with psychological wellbeing. However, age, region, and gender were included in the multivariable regression analyses to explore how they contributed to the model. Extroversion was moderately positively related to psychological wellbeing. Similarly, conscientiousness was moderately positively related to psychological wellbeing. On the other hand, neuroticism was moderately negatively related to psychological wellbeing.

Between Group Differences in Variables Measured

The Differences in Time Spent on SNSs Across the Three Sub-samples

Here, I examined whether participants differed in relation to which sub-sample they were in and amount of time participants spent on SNSs per day. A one-way ANOVA was conducted to test for differences in time spent on SNS per day between the three sample groups. There was a significant effect of sample group type. The Levene test for the equality of variance among the levels of time spent on SNS per day showed that the variances were significantly different ($F(2, 855) = 21.40$, $p < .001$), suggesting that an alternative post hoc test for pairwise differences of means should be used. The strength of the relationship between the time spent on SNS per day and the sample group, as assessed by η^2 was small, with the sample group type accounting for 5% of the variance of the dependent variable. Post hoc comparisons using the Games-Howell test indicated that the average time spent on SNS per day for the New Zealand random sample group ($M = 2.82$, $SD = 1.61$) was significantly different than the Maldives random sample group ($M = 3.70$, $SD = 2.13$) and the New Zealand clinical sample ($M = 3.53$, $SD = 1.87$). The average time spent on SNS per day by the New Zealand clinical sample group was not significantly different from the Maldives random sample group. Figure 11 shows graphically the percentage of time spent on SNSs per day for each sample group. Most New Zealanders in the random community sample (almost 33%) used SNSs for 30 minutes or more per day. On the other hand, in the Maldivian random community sample and the New Zealand clinical sample about half of the sample groups used SNSs for 30 minutes or more per day.

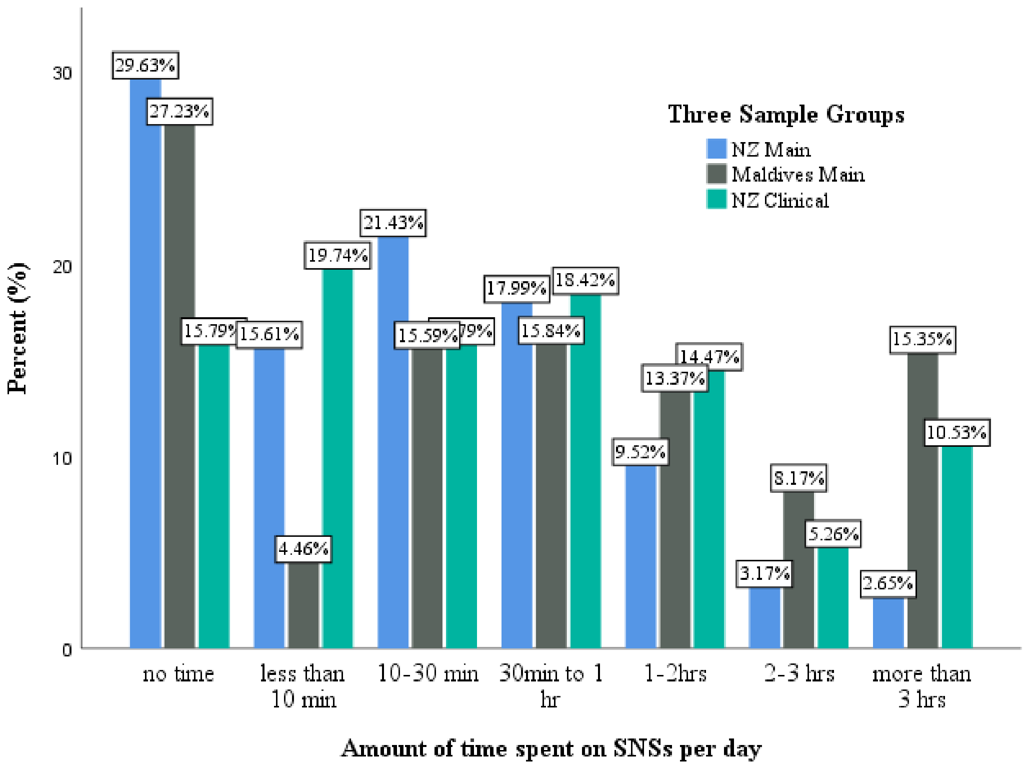

Figure 11. Percentage of time spent on SNSs per day by three sub-samples; NZ random community sample (n = 378), Maldives random community sample (n = 404), and NZ clinical sample (n = 76)

Between-Group Differences in Online/Offline PSS, Online Self-disclosure, and Psychological Wellbeing Scores

The mean differences in online PSS, offline PSS, online self-disclosure, and psychological wellbeing were examined for only between the New Zealand and Maldives community samples by adjusting for the estimated differences in the parameter values thought to have been caused by the MV in the Maldives sample. First, the results from MV estimation are presented.

MV Estimation Results

To apply the MV estimation method, Dr Willink applied two important modelling assumptions.

If there is some MV at the question level, then it seems reasonable to imagine a similar extent of MV at the total score level. Thus, it seems reasonable to require the MV to have the same sign for every question, whether it be positive or negative. So the first assumption is:

Assumption 1: Although different questions (items) might have different amounts of MV, the amounts all have the same sign, i.e. the deviations are all in the same direction.

Also, it seems reasonable to suppose that the MV is negligible for at least one of the questions. So the second assumption is:

Assumption 2: At least one of the questions has measurement invariance.

The first assumption allows us to estimate the absolute value of the MV for each question and the second assumption allows the populations to be registered to each other. Despite making these assumptions, the results depend on which 'direction' the MV is in. So there are two estimates of the MV for each property, one for each direction. The method was applied and the following results were obtained.

- *For online perceived social support, relative to the level α_A (in the NZ sample), MV has acted to increase α_B (in the Maldives sample) by 4.3 points on the scale or by -0.4 (minus 0.4) points on the scale.*
- *For offline perceived social support, relative to the level α_A, MV has acted to increase α_B by 2.1 points on the scale or by -0.0 (minus 0.0) points on the scale.*
- *For online self-disclosure, relative to the level α_A, MV has acted to increase α_B by 6.3 points on the scale or by 0.4 points on the scale.*
- *For wellbeing, relative to the level α_A, MV has acted to increase α_B by 0.0 points on the scale or by -4.5 (minus 4.5) points on the scale.*

The effect of MV of the conclusions can be studied by reversing the estimated differences in the parameter values thought to have been caused by the MV. Thus, before, conducting tests of means to compare

New Zealanders and Maldivians, amended calculations would be carried out by both

1. *subtracting 4.3 from each score of online perceived social support in the Maldives sample,*
2. *subtracting 2.1 from each score of offline perceived social support in the Maldives sample,*
3. *subtracting 6.3 from each score of online self-disclosure in the Maldives sample,*
4. *subtracting 0.0 from each score of wellbeing in the Maldives sample,*

and also

1. *subtracting -0.4 from (i.e. adding 0.4 to) each score of online perceived social support in the Maldives sample,*
2. *subtracting 0.0 from each score of offline perceived social support in the Maldives sample,*
3. *subtracting 0.4 from each score of online self-disclosure in the Maldives sample,*
4. *subtracting -4.5 from each score of wellbeing in the Maldives sample.*

Testing Mean Differences Between

In order to conduct tests of means I first subtracted the estimates of the MV given above from the total scores (for each participant from the Maldives random sample) for each variable. Hence, there are two sets of means testing conducted for each variable. That is, one comparing the New Zealand participants' mean scores with the Maldivian participants' mean scores adjusted with the first set of MV estimates given above and also comparing the New Zealand participants' mean scores with the Maldivian participants' mean scores adjusted with the second set of MV estimates given above.

Independent sample *t*-tests were then conducted to compare the group differences in online PSS, offline PSS, online self-disclosure, and wellbeing scores. First, we restricted the analyses to respondents from the two groups with known values for the four variables. Those who spent 10 minutes or less were not required to complete the online PSS and online self-disclosure measures based on an assumption that those who do not spend time on SNS or use SNSs for less than 10 minutes per day are unlikely to acquire online social support or self-disclose via SNSs. The results are presented in Table 10.

Mean Differences in Online PSS Between Sub-samples

As seen in Table 10, the mean difference in online PSS between New Zealanders and Maldives was not significant when the MV estimate for direction one was applied, $t(447.38) = -0.167$, $p > .05$, but was significant when the MV estimate for the other direction was applied, $t(447.38) = -3.284$, $p < .05$. Therefore, based on these findings, we cannot conclude that there is a significant difference in online PSS levels between the New Zealand and Maldives community samples. This is because there is an over-riding principle to which we can turn when choosing between these estimates, and that is the principle of conservatism. Taking the conservative approach means accepting no positive difference of association is declared until the data are sufficient to permit it. In the same way, the appropriate choice of estimate of MV will be the choice leading to the 'weaker' result so that, if adjusting for one estimate of MV leads to a null conclusion while adjusting for the estimate of MV leads to a positive conclusion, the first is to be preferred.

Mean Differences in Offline PSS Between Sub-samples

Results showed that there was a significant difference in the means between New Zealanders and Maldivians after adjusting the scores for the Maldivian participants using both estimates of MV. That is, the mean offline PSS level for the New Zealand community sample was significantly greater than that of the Maldives community sample in both comparisons, $t(469.89) = 8.28$, $p <.05$ and $t(469.89) = 6.59$, $p < .05$ respectively.

Mean Differences in Online Self-disclosure Between Sub-samples

The mean difference in online self-disclosure between New Zealanders and Maldives was not significant when the MV estimate for one direction was applied, $t(423.16) = -1.24$, $p > .05$ but was significant when the MV estimate for the other direction was applied, $t(434.16) = -9.44$, $p < .05$. Therefore, based on the principle of conservatism, we cannot conclude that there is a significant difference in online self-disclosure levels between the New Zealand and Maldives community samples.

Mean Differences in Wellbeing Between Sub-samples

The mean difference in psychological wellbeing between New Zealanders and Maldives was significant when the MV estimate for one direction was applied, $t(467.40) = 4.73$, $p < .05$ but was not significant when the MV estimate for the other direction was applied, $t(467.40) = 1.35$, $p > .05$. Therefore, taking a conservative approach, we cannot conclude that there is a significant difference in psychological wellbeing between the New Zealand and Maldives community samples.

Table 10. *Between-Group Differences in Mean Scores of Online PSS, Offline PSS, Online Self-disclosure, and Wellbeing in the New Zealand Random Community Sample (n = 205) and Maldives Random Community Sample (n = 267)*

Variable	New Zealand		Maldives		95% CI for Mean Difference	Std. Error Difference			
	Mean	*SD*	*Mean*	*SD*			*t*	*df*	*p*
Online PSS	44.20	15.94	44.45[a]	16.61	−0.251	1.508	−0.167	447.375	0.868
Offline PSS	71.00	11.81	60.71[a]	16.16	10.282	1.242	8.281	469.894	< 0.001
Online SD	35.40	9.06	36.42[a]	8.46	−1.014	0.817	−1.241	423.163	0.215
Wellbeing	62.39	13.11	56.08[a]	15.86	6.307	1.335	4.726	467.397	< 0.001
Online PSS	44.20	15.94	49.15[b]	16.61	−4.951	1.508	−3.284	447.375	0.001
Offline PSS	71.00	11.81	62.81[b]	15.16	8.182	1.242	6.590	469.894	< 0.001
Online SD	35.40	9.06	43.12[b]	8.46	−7.714	0.817	−9.439	423.163	< .001
Wellbeing	62.39	13.11	60.58[b]	15.86	1.807	1.335	1.354	467.397	0.176

Note: Higher mean scores for online PSS = more online support; higher mean scores for offline PSS = more offline support; higher mean scores for online self-disclosure = more online self-disclosure online; and higher mean scores for wellbeing = better wellbeing

aMean scores compared after Maldivian participants' scores were adjusted using the first set of MV estimates

bMean scores compared after Maldivian participants' scores were adjusted using the second set of MV estimates

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Gender Differences in the Mean Online PSS, Offline PSS, Self-disclosure, and Wellbeing Scores in Each Sample Group

Independent sample *t*-tests were conducted to compare means of online PSS, offline PSS and wellbeing in men and women within each group separately. The results are presented in Table 11.

Online PSS

There was a significant difference in the means of online PSS by gender in the New Zealand random community sample, with males (M = 47.79, SD = 14.16) having higher online PSS than females (M = 42.74, SD = 16.43); $t(123) = -2.20$, $p < .05$. There was no significant gender difference in online PSS in either the Maldives random community or the New Zealand Clinical samples.

Offline PSS

There was a significant gender difference in the means of offline PSS in the New Zealand random community sample, with females (M = 72.49, SD = 9.81) having higher offline PSS levels than males (M = 67.29, SD = 15.18); $t(78) = 2.43$, $p < .05$. There was no significant gender difference in the means of offline PSS in the Maldives random community sample. There was no significant gender difference in online PSS in either the Maldives random community or the New Zealand clinical samples.

Online Self-disclosure

There was a trend towards significance in the mean differences of online self-disclosure scores by gender in the New Zealand random community sample, with males (M = 37.19, SD = 7.89) having higher online self-disclosure scores than females (M = 34.68, SD = 9.42); $t(203) = -1.80$, $p = 0.073$. There was a significant gender difference in the means of online self-disclosure scores in the Maldives random community sample, with males (M = 44.12, SD = 9.10) having higher online self-disclosure scores than females (M = 41.69, SD = 7.82); $t(265) = -2.32$, $p < .05$. There was no significant difference in the mean online self-disclosure scores in the New Zealand clinical sample, however, the mean scores for both genders follow a similar trend as that of the New Zealand and Maldives random community sub-samples.

Wellbeing

Females (*M* = 54.51, *SD* = 12.15) were found to have a small but statistically significant higher mean wellbeing level than males (*M* = 46.31, *SD* = 13.41) and $t(43) = 2.10$, $p = .043$ among the New Zealand Clinical sample, but no significant differences were found in any other groups.

Table 11. *Results of t-tests and Descriptive Statistics for Online PSS, Offline PSS, Online Self-disclosure, and Wellbeing by Gender for Three Sub-samples*

Sub-sample	Variable	Gender						95% CI for Mean Difference			
		Male			Female						
		M	*SD*	*n*	*M*	*SD*	*n*		*t*	*df*	η^2
NZ random community sample	Online PSS	47.8	14.2	59	42.7	16.4	146	−9.58, −0.51	−2.07*	203	0.02
	Offline PSS	67.3	15.2	59	72.5	9.8	146	0.95, 9.46	2.43*	203	0.04
	Online SD	37.2	7.9	59	34.7	9.4	146	−5.25, 0.23	−1.80	203	0.02
	Wellbeing	60.9	11.7	59	63.0	13.6	146	−1.92, 6.05	1.02	203	0.01
Maldives random community sample	Online PSS	50.1	15.7	113	47.7	17.2	154	−6.42, 1.68	−1.15	265	0.01
	Offline PSS	62.2	14.9	113	63.2	15.4	154	−2.68, 4.73	0.55	265	0.001
	Online SD	44.1	9.1	113	41.7	7.8	154	-4.46, −0.37	−2.32*	265	0.02
	Wellbeing	56.8	15.9	113	55.6	15.9	154	−5.09, 2.66	-0.62	265	0.001
NZ clinical sample	Online PSS	50.2	12.5	16	46.1	15.0	29	−12.57, 4.40	−0.93	43	0.02
	Offline PSS	65.6	12.2	16	71.9	10.9	29	−0.84, 13.44	1.78	43	0.07
	Online SD	39.6	11.3	16	35.8	7.3	29	−10.35, 2.68	−1.22	43	0.04
	Wellbeing	46.3	13.4	16	54.5	12.2	29	0.30, 16.12	2.09*	43	0.09

Age Differences in Mean Online PSS, Offline PSS, Self-disclosure, and Wellbeing Between Sub-samples

The relationship between age, online and offline social support and wellbeing for each subsample are compared visually using scatter plots. We restricted our analysis to respondents from the three sub-samples (i.e., the New Zealand random community sample, Maldives random community sample, and New Zealand convenience clinical sample) with known values for variables of age, online and offline social support, online self-disclosure, and wellbeing. The results are presented in Figures 12-15. Overall, the figures show significant linear negative relationships between age and online PSS in the two random community samples ($p < .01$) (Figure 12). There was a significant positive relationship between offline PSS and age ($p < .001$) for the New Zealand random community sample. Age was not associated with offline PSS in the Maldives random community sample and the New Zealand clinical sample (Figure 13). Figure 14 shows that the relationship between online self-disclosure and age in the three subsamples were not significant. Figure 15 shows that the relationship between age and wellbeing was not significant. However, age was accounted for in the multivariable regression analyses when exploring relationships between key predictors and outcome variables in later chapters.

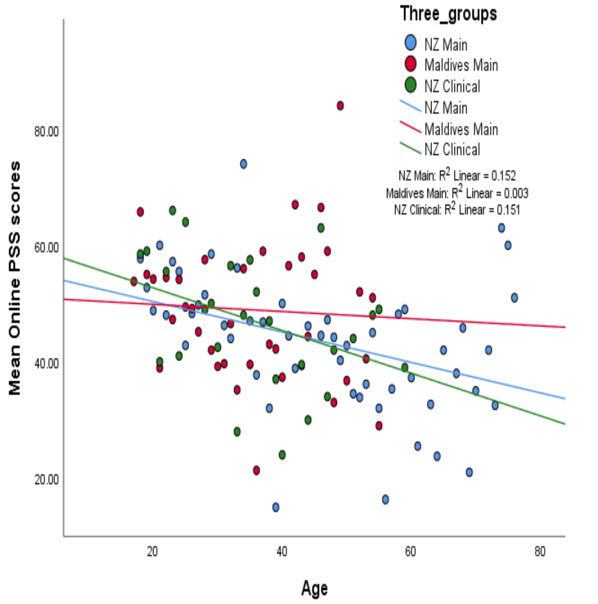

Figure 12. Scatter plot showing mean online PSS scores across age for the three subsamples (NZ Main, *n* = 205, Maldives Main, *n* = 267, NZ clinical, *n* = 45)

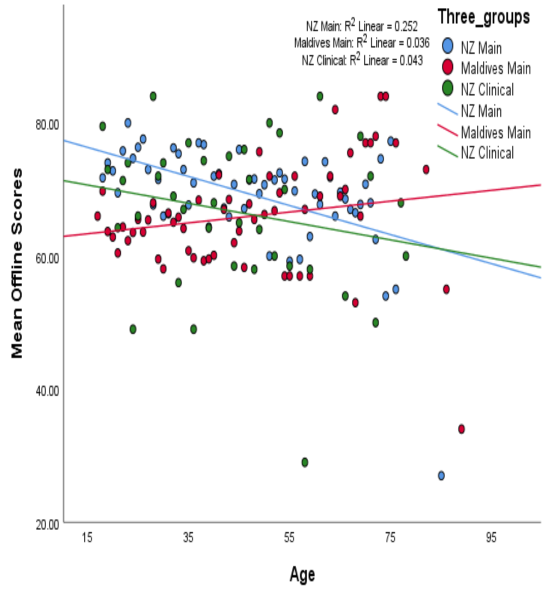

Figure 13. Scatter plot showing mean offline PSS scores across age for the three subsamples (NZ Main, *n* = 205, Maldives Main, *n* = 267, NZ clinical, *n* = 45)

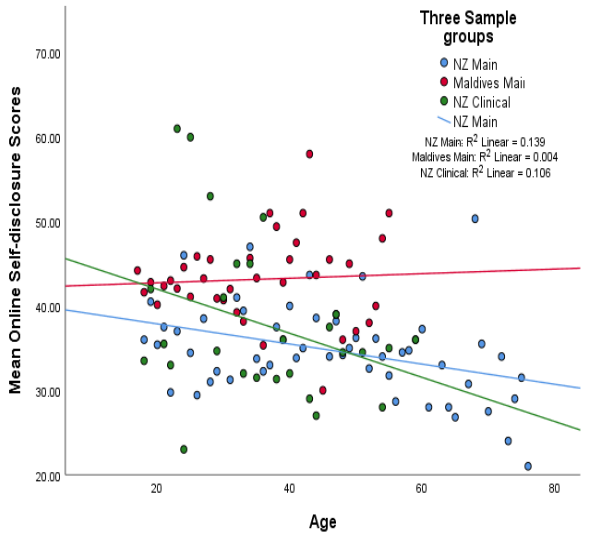

Figure 14. Scatter plot showing mean online self-disclosure scores across age for the three subsamples (NZ Main, *n* = 205, Maldives Main, *n* = 267, NZ clinical, *n* = 45)

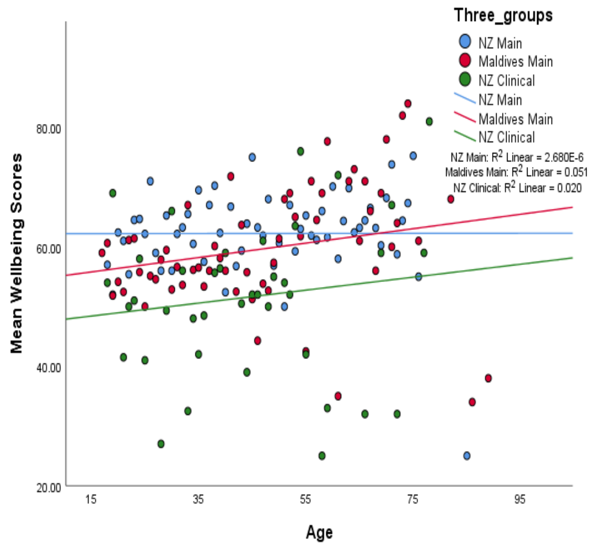

Figure 15. Scatter plot showing mean wellbeing scores across age for the three subsamples (NZ Main, *n* = 205, Maldives Main, *n* = 267, NZ clinical, *n* = 45)

Urban/Rural Differences in Online PSS, Offline PSS, Online Self-disclosure, and Wellbeing Within Groups

Independent sample *t*-tests were conducted to compare means of online PSS and offline PSS and wellbeing in urban and rural residents across the New Zealand random community and Maldives random community samples. The New Zealand clinical sample was excluded from this analysis as all the participants in the New Zealand clinical participants were urban residents. The results are presented in Table 12.

New Zealand Random Community Sample

There were statistically significant differences between urban and rural participants in offline PSS scores, but not in online PSS, online self-disclosure, or wellbeing. The results show that urban residents had higher offline PSS, but no statistical difference exists between urban and rural residents in terms of their online PSS or wellbeing levels.

Maldives Random Community Sample

There were no significant mean differences between urban and rural residents in online PSS, offline PSS, online self-disclosure, and wellbeing levels.

Table 12. *Results of t-tests and Descriptive Statistics for Online PSS, Offline PSS, Online Self-disclosure, and Wellbeing by Region for NZ and Maldives Random Community Samples*

Sub-sample	Variable	Region						95% CI for Mean Difference			
		Urban			Rural						
		M	*SD*	*n*	*M*	*SD*	*n*		*t*	*df*	η^2
NZ random community sample	Online PSS	44.5	16.4	113	43.9	15.4	92	−3.80, 5.05	0.28	203	0.00
	Offline PSS	72.6	10.4	113	69.0	13.1	92	0.34, 6.82	2.18*	203	0.02
	Online SD	35.6	9.8	116	34.3	8.2	97	−1.11, 2.85	1.09	211	0.004
	Wellbeing	62.0	12.8	113	62.9	13.6	92	−4.59, 2.68	−0.52	203	0.001
Maldives random community sample	Online PSS	48.6	17.1	117	48.8	16.3	150	−4.24, 3.84	−0.10	265	0.00
	Offline PSS	64.1	14.5	117	61.8	15.7	150	−1.39, 5.96	1.22	265	0.01
	Online SD	42.1	8.35	122	43.5	9.2	159	−3.52, 0.57	−1.42	279	0.01
	Wellbeing	55.3	15.3	117	56.7	16.3	150	−5.20, 2.51	−0.69	265	0.001

Note: Online SD = Online Self-disclosure and higher mean scores on online SD = more self-disclosure online; higher mean scores for online PSS = more online support; higher mean scores for offline PSS = more offline support; and higher mean scores for wellbeing = better wellbeing.
* *p < .05.*

Relationship Between Personality, Online PSS, Offline PSS, Online Self-disclosure, and Psychological Wellbeing Within Sub-samples

Appendices, F-2 to F-4 show the interrelationships among personality variables and other study variables within the three sub-samples. Correlations between these variables were examined to inform the multivariable regression analyses in Chapter 7 which focuses on testing the study hypotheses across three sub-samples after controlling for the covariates. All correlations were less than .5, well below the recommended threshold of .7 (Tabachnick, 2014), indicating that there was no problem of multicollinearity across these variables.

R1: Is there an Association Between Time Spent on SNSs and Psychological Wellbeing?

This section investigates the association between time spent on SNSs per day and psychological wellbeing for each sample separately. This analysis includes all participants including those who reported no or minimal SNS use (less than 10 minutes per day). The time spent on SNSs per day was treated as a continuous variable for the purpose of linear regression analyses. Bivariate correlations between variables were examined for each subsample separately (see Appendix F-2 to 4) prior to conducting linear regressions. The absence of multicollinearity was determined if no independent variable had correlation coefficients greater than 0.7. There was no evidence of multicollinearity as the condition indexes were less than 15, and the variance inflation factor (VIF) was less than 10 (J. Cohen et al., 2003). Independence of residuals was checked with the Durbin-Watson statistic which indicated that residuals were normally distributed and constantly varied across the populations (homoscedastic).

Multivariable regression analyses were conducted to examine the relationship between time spent on SNSs and online PSS across the three subsamples. In the regression analysis, time spent on SNS was entered as a block with covariates, age, gender, region, and the three personality variables. The results are presented in Table 13.

Table 13 shows that for the New Zealand random sample, the overall model was significant with 28% of the variance in psychological wellbeing explained by all of the predictor variables: $R^2 = .28$, $F(7, 365) = 20.01$, $p < .001$. However, individually, time spent on SNS was not a significant predictor of psychological wellbeing ($\beta = -.06$, $p > .05$). For the Maldives random community sample, the overall model was also significant with 21% of the variance in psychological wellbeing explained by all of the predictor variables: $R^2 = .21$, $F(7,390) = 15.21$, $p < .001$. Similarly, for the New Zealand clinical sample, the overall regression model was significant with 41% of the variance in psychological wellbeing explained by all of the predictors together: $R^2 = .41$, $F(6,62) = 7.29$, $p < .001$. However, individually, time spent on SNS was not a significant predictor of psychological wellbeing in Maldives random community sample ($\beta = -.02$, $p > .05$) or in the New Zealand clinical sample ($\beta = .18$, $p > .05$). In other words, after adjusting for the effects of relevant demographic and personality variables, amount of time spent on SNS use was not significantly correlated with psychological wellbeing in any of the sample groups.

Table 13. *Summary of Multivariable Regression Analyses Predicting Psychological Wellbeing from Time Spent on SNSs per Day Across the Three Subsamples*

	New Zealand Main				Maldives Main				New Zealand Clinical			
Variable	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*
Age	-0.08	0.05	−0.09	−1.81	0.01	0.07	0.01	0.20	0.16	0.12	0.17	1.34
Gender[a]	−1.96	1.23	−0.07	−1.59	−0.33	1.50	-0.01	-0.22	−4.09	3.05	−0.14	−1.34
Region[b]	0.34	1.18	0.01	0.29	0.67	1.47	0.02	0.46				
Extroversion	1.59	0.30	0.25	5.23**	1.81	0.51	0.19	3.52**	1.63	0.66	0.20	2.47*
Conscientiousness	2.00	0.37	0.26	5.42**	1.54	0.51	0.16	2.99**	2.13	0.72	0.30	2.95**
Neuroticism	−1.76	0.31	−0.27	−5.59**	−2.15	0.44	-0.24	-4.91**	-2.40	0.82	-0.33	−2.94**
Time spent on SNS per day	−0.46	0.41	−0.06	−1.12	−0.16	0.44	-0.02	-0.36	1.40	0.99	0.18	1.42
df	7, 365				3, 390				6, 62			
R^2	0.28				0.21				0.41			
F	20.01**				15.21**				7.29*			

Note. [a]Male = 1, [b] Urban = 1, NZ clinical sample were all urban residents. NZ community sample, *n* = 373, Maldives community, *n* = 398, NZ clinical sample, *n* = 69
**p* < .05, **p < .001

Summary of key preliminary results

There were significant differences in the amount of time participants spent on SNSs per day between the three subsamples. Overall, the majority of the New Zealand participants from the community spent the least amount of time on SNSs followed by the New Zealand clinical participants compared to the Maldivian participants from the community. Generally, the number of participants who spent three or more hours a day on SNSs were low in all of the three subsamples.

Mean differences in online PSS, offline PSS, online self-disclosure, and psychological wellbeing between Maldivians and New Zealand participants from the community were compared after adjusting for the measurement variance in the scores for the Maldivian participants. Results showed that compared to the New Zealand community sample, the Maldives community sample had significantly lower offline PSS levels. Results for the mean differences in online PSS, online self-disclosure, and psychological wellbeing were inconsistent when two MI estimations were applied and therefore the findings were not sufficient to conclude that there were any significant differences in the means of these variables between the two groups.

In the New Zealand community sample, males had higher online PSS compared to females whereas women reported having higher offline PSS compared to males. There was no significant gender difference in the online PSS scores for either the Maldives community or New Zealand clinical samples. There was an almost significant gender difference in offline PSS scores in the New Zealand clinical sample.

The scatter plots (12-15) showed the relationship between age and online/offline PSS, online self-disclosure, and psychological wellbeing. Age appeared to be an important factor in online PSS for both the New Zealand community and Maldives community samples. In both groups, older respondents reported having less online PSS than younger respondents. For offline PSS, only the New Zealand community sample showed a significant negative association with age. In contrast, age was not significantly related to either online self-disclosure or wellbeing in either of the other sub-samples.

For both the New Zealand and Maldives community samples, there were statistically significant differences between urban and rural participants in offline PSS scores, but not with online PSS, online self-disclosure, or wellbeing. The results show that urban residents had higher offline PSS, but no statistical difference was found between urban and rural residents in terms of their online PSS or wellbeing levels. Urban and rural differences were not examined in the New Zealand clinical sample.

Analysis conducted to examine the relationship between amount of time spent on SNSs per day and psychological wellbeing showed that after adjusting for the effects of relevant demographic and personality variables, amount of time spent on SNS use was not significantly correlated with psychological wellbeing in any of the sample groups.

CHAPTER 5: RESULTS 2 – RELATIONSHIP BETWEEN TIME SPENT ON ONLINE SOCIAL NETWORKING AND ONLINE PERCEIVED SOCIAL SUPPORT

This chapter presents the associations between time spent on SNSs per day and online PSS for the combined randomly selected general population samples of Maldivians and New Zealanders with known scores for both online PSS and offline PSS (N = 472). Participants who used SNSs for less than 10 minutes per day were not required to complete the online PSS items on the survey form based on the assumption that low SNS users were unlikely to acquire online social support. In this chapter, analyses were undertaken to test the study hypothesis one (H_1) and to explore related variables based on the conceptual model described in Chapter two and illustrated in Figure 2. Descriptive statistics and correlations between variables are presented in Chapter 4. The results in this chapter are reported in two sections: (1) testing of main hypothesis using multivariable regressions, and (2) evaluation of effects of covariates on the relationship between time spent on SNSs and online PSS.

Hypotheses 1: Exploration of the Relationship Between amount of time spent on SNSs and online perceived social support.

This section presents the analyses of the association between time spent on SNSs per day and online PSS. The following analyses were undertaken to test the project's first hypothesis:

> H1: There is a positive relationship between the amount of time spent on SNSs per day and online PSS

Methodological considerations and the selection of covariates for the model are described below.

Methodological Considerations

The hypothesis was tested on the combined New Zealand and Maldives random samples who spent 10 minutes or more per day on SNSs with known values for online social support. The variable 'time spent on SNSs per day' was treated as a continuous variable (with high scores indicating more time spent on SNSs) for the purpose of linear regression analyses. Figure 16 shows that, overall, there is a linear relationship between time spent on SNSs (across all five categories) and online PSS. Therefore, linear regression analysis was considered appropriate for hypothesis testing. In order to test the hypothesis, those who spent 10 minutes or more per day was treated as a continuous variable for the purpose of linear regression analyses.

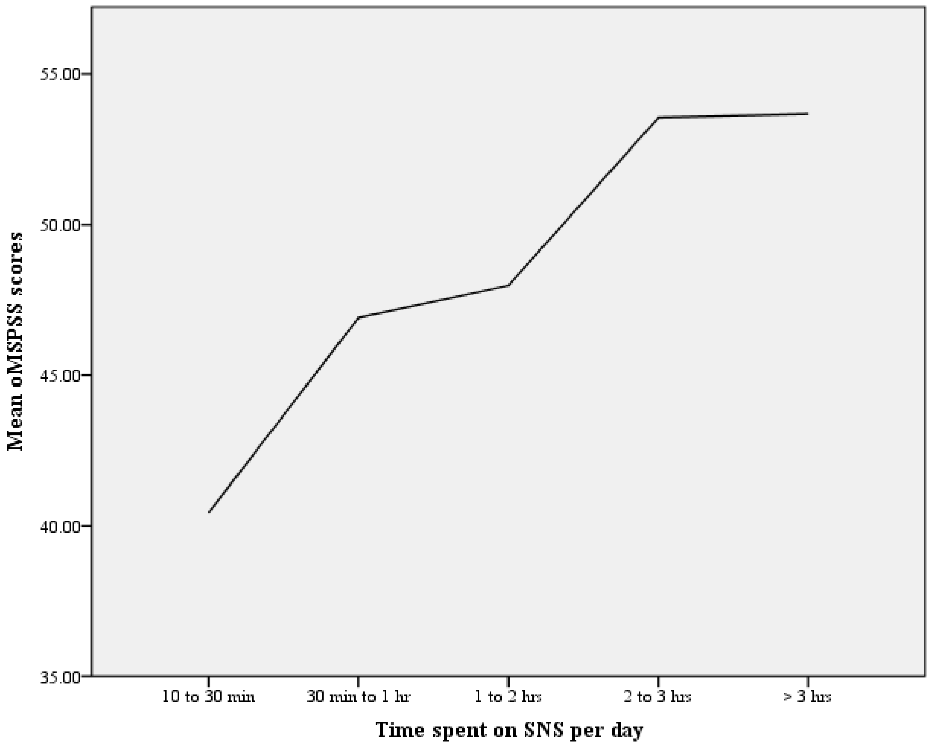

Figure 16. Profile of mean oMSPSS scores over time for combined random sample (*N* = 472)

Multivariate Regression Analyses for Online PSS

The relationship between time spent on SNSs and online PSS was examined using a hierarchical multiple regression with online PSS as the dependent variable. In the first step, the covariates (i.e., age, gender, region, country, extroversion, conscientiousness, neuroticism, and offline PSS) were entered together as a block to control for the effect of these variables on online PSS. Given that online self-disclosure was positively related to online PSS (r = .34, p < .001) its relationship with online PSS was tested in a separate Model. The “Time spent on SNSs” variable was entered in step two. In the third step, online self-disclosure was entered to examine its unique contribution to the model in comparison to the "time spent on SNSs" variable. All results for the Models are presented in Table 14.

In the first Model (see Table 14) the covariates age, gender, region, country, extroversion, conscientiousness, and neuroticism were entered as a block. Taken as a whole, the covariates were significant predictors of online perceived social support – $R^2 = .16$, $F(8,463) = 11.04$, $p < .001$ – accounting for approximately 16% of the variance in online PSS.

Model 2 shows that time spent on SNSs predicted online PSS and was statistically significant, $R^2 = .19$, $F(9,462) = 12,28$, $p < .001$. The addition of the time spent on SNSs variable to the model improved model fit as indicated by the significant increase in R^2 from .16 to .19. Therefore, while, the initial block of covariates together had a significant effect on online PSS, Model 2 shows that adding the time spent on SNSs variable explained significantly more of the variance in online PSS on its own. More online PSS was experienced by people who spent more time on SNSs compared to those who spent less time. Thus, the null hypothesis of no difference between the means of online social support by the amount of time spent on SNSs was rejected, with 4% of the variability in online PSS explained by time spent on SNSs per day.

Online self-disclosure was considered important to control for, given that it is closely linked to communicative behaviour, responsiveness, and reciprocity in relationships (see Chapter One). Support for this link was found in the current study. In Model 3, online self-disclosure was a statistically significant predictor of online PSS: $R^2 = .30$, $F(10,461) = 19.31$, $p < .001$. The addition of the online self-disclosure variable to the model improved model fit significantly as indicated by the significant change in R^2 from .19 to .30. Therefore, while the covariates together with time spent on SNSs variables have a significant effect on online PSS, Model 3 shows that the online self-disclosure explained significantly more of the variance in online PSS on its own. The more participants disclosed online, the greater their perceived online PSS.

Demographic variables

The associations between individual variables with online PSS was examined. Age contributed significantly to the final Model after controlling for all other predictors (β[1]

[1] All β values stand for standardised betas

= -.16, $t(461) = -3.16$, $p < .001$). Age had a significant negative regression weight, indicating that when people's age increased, their online perceived social support level decreased, after controlling for the other variables in the Model. Gender contributed significantly to the model after controlling for all other predictors (β =.09, $t(461)$ = 2.29, p <.05). Men (M = 49.32, SD = 15.20) reported significantly higher levels of online PSS than women (M = 45.31, SD = 17.00). Region of residence did not have a significant effect on online PSS (β = -.03, $t(461)$ = -.73, p > .5). Model 3 shows that the was not significantly associated with online PSS after controlling for all other predictors (β = .05, $t(461)$ =.85, p > .05) although Maldivian participants reported overall higher online PSS levels (M = 48.74, SD = 16.82) than New Zealand participants (M = 44.20, SD = 16.34).

Personality Variables

Neither extroversion nor conscientiousness contributed significantly to online PSS with β = .02, $t(462)$ = .38, p = n.s., and β = -.01, $t(462)$ = -.24, p > .05 respectively. Neuroticism showed only a trend towards significance (β =.07, $t(461)$ = 1.60, p = .070)

To conclude, the results from this section support H_1, indicating that more time spent on SNSs was associated with an increase in online PSS when controlling for demographic variables, personality traits, and online self-disclosure. Another significant finding was that online self-disclosure was associated with greater increase in online PSS compared to time spent on SNSs.

Table 14. *Summary of Multivariable Regression Analyses Predicting online PSS from Time Spent on SNSs per Day for Combined Random Sample (N =472)*

	Model 1				Model 2				Model 3			
Variable	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*
Age	-0.23	0.06	-0.20**	-3.66	-0.18	0.06	-0.15*	-2.72	-0.19	0.06	-0.16**	-3.16
Gender[a]	4.85	1.50	0.14**	3.22	4.73	1.48	0.14**	3.21	3.19	1.39	0.09*	2.29
Region[b]	-1.50	1.43	-0.05	-1.04	-1.38	1.41	-0.04	-0.98	-0.96	1.32	-0.03	-0.73
Country[c]	-3.52	2.00	-0.11	-1.76	-2.41	1.98	-0.07	-1.22	1.64	1.92	0.05	0.85
Extroversion	-0.29	0.43	-0.03	-0.66	-0.24	0.42	-0.03	-0.56	-0.34	0.40	-0.04	-0.85
Conscientiousness	-0.60	0.45	-0.06	-1.31	-0.51	0.45	-0.05	-1.14	-0.13	0.42	-0.01	-0.31
Neuroticism	0.74	0.41	0.08	1.81	0.89	0.40	0.10*	2.22	0.58	0.38	0.07	1.60
Offline PSS	0.32	0.05	0.28**	6.03	0.30	0.05	0.26**	5.70	0.30	0.05	0.26**	6.06
Time spent on SNSs					2.36	0.54	0.20**	4.34	1.74	0.51	0.15**	3.39
oSDS									0.63	0.08	0.36**	8.18
df	8, 463				9, 462				10, 461			
R^2	0.16				0.19				0.30			
F	11.04**				12.28**				19.32**			
ΔR^2					0.03				0.10			

Note. [a]Male = 1, [b] Urban = 1, [c] New Zealand =1, oSDS = online self-disclosure
**p* < .05, **p < .001

Exploratory Analysis: Determinants of Online Self-Disclosure

To further explore the relationship between time spent on SNSs and online self-disclosure, a separate regression was conducted with online self-disclosure as an outcome variable without online PSS in the regression model.

Multivariable Regression Analyses

As an outcome variable, online self-disclosure was tested with a multivariable regression, with time spent on SNSs, age, gender, region, country, and the three personality variables entered together to examine their association with online self-disclosure. These results are summarised in Table 15.

Taken as a whole, the Model was significant (R^2 = .20, F(9,462) = 13.15 , p < .001), suggesting that these variables together explained approximately 20% of variance in the prediction of online self-disclosure scores. As seen in Table 15, when controlling for all of the covariates, the main effect of time spent on SNS variable was significant – β = .14, t(462) = 3.18, p < .001 – indicating that participants who spent more time on SNSs per day self-disclosed significantly more on SNSs. The regression analysis also shows how each of the covariates contributed to the model as described below.

Demographic variables. Age did not contribute significantly to the model after controlling for all other predictors: β = .04, t(462) = .67, p > .05. Gender contributed significantly to the Model after controlling for all other predictors: β = .13, t(462) = 2.95, p < .05. Men (M = 41.73, SD = 9.28) reported significantly higher levels of online self-disclosure than women (M = 38.28, SD = 9.31). There was no difference in online self-disclosure levels between participants living in urban and rural regions. Country contributed significantly to the Model after controlling for all other predictors: β = -.34, t(462) = -5.74, p < .001. Maldivians (M = 42.72, SD = 8.46) reported significantly higher levels of online self-disclosure than New Zealanders (M = 35.40, SD = 9.06).

Personality variables. Extroversion did not contribute significantly to the model: β = .03, t(461) = .65, p > .05. Conscientiousness contributed significantly to the model after controlling for all other predictors: β = -.11, t(462) = -2.39, p < .05. Conscientiousness had a significant negative regression coefficient, indicating that people who scored high on the conscientiousness scale had lower online self-disclosure levels, after controlling for the other variables in the model. Neuroticism had a significant positive regression coefficient, indicating that people who scored high on the neuroticism scale had higher online self-disclosure levels, after controlling for the other variables in the model: $\beta = .10$, $t(462) = 2.21$, $p < .05$.

Table 15. *Summary of Multivariable Regression Analyses Predicting Online Self-Disclosure from Time Spent on SNSs per Day for Combined Random Community Sample (N = 472)*

Variable	*df*	*F*	R^2	*B*	*SE B*	*β*	*t*
	9, 462	13.15**	0.20				
Age				0.02	0.04	0.04	0.67
Gender[a]				2.47	0.84	0.13**	2.94
Region[b]				-0.67	0.80	-0.04	-0.84
Country[c]				-6.48	1.13	-0.34**	-5.75
Extroversion				0.16	0.24	0.03	0.65
Conscientiousness				-0.61	0.25	-0.11*	-2.39
Neuroticism				0.51	0.23	0.10*	2.21
Offline PSS				0.00	0.03	0.00	0.09
Time on SNSs				0.99	0.31	0.14**	3.18

Note. [a]Male = 1, [b] Urban = 1, [c] New Zealand =1
*$p < .05$, ** $p < .001$

Mediating Effects of Online Self-disclosure in the Relationship Between Time Spent on SNSs and Online Perceived Social Support

Given that both time spent on SNS and online-self-disclosure were significantly and positively associated with online PSS, a mediation analysis was performed using PROCESS macro v3.4 (Hayes, 2018) for SPSS to investigate the mediating effects of online self-disclosure in the association between amount of time spent on SNSs and online PSS as depicted in the conceptual model (Figure 2). For this analysis, 5000 bootstrap samples were used, and mediating effect was determined at the 95% confidence interval. The results of the mediation analysis are shown in Figure 17 below (separately taken from Figure 2). As mentioned before, the amount of time spent on SNSs was positively related to online self-disclosure, and online self-disclosure was positively associated with online perceived social support. When statistically controlling for online self-disclosure, the amount of time spent on SNSs was still significantly associated with online perceived social support, which indicated that the direct effect of amount of time on SNSs on online PSS did not fully disappear when online self-disclosure was added to the model. However, the bootstrap confidence interval confirmed that the indirect effect of SNS use on online PSS through online self-disclosure (Table 16). These results indicated that the relationship between amount of time spent on SNSs and online PSS was partially mediated by online self-disclosure.

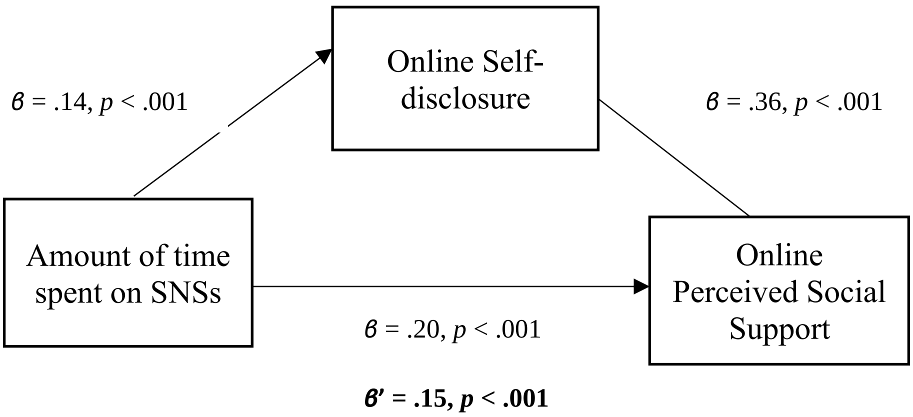

Figure 17. Mediation model showing that the effect of time spent on SNSs on online perceived social support is partially mediated by online self-disclosure. Change in beta weight when the mediator is present is highlighted in bold

Table 16. *Bootstrap Results for Indirect Effects for Combined New Zealand and Maldives Random Sample (N = 472)*

Mediator	**Effect**	**SE**	**LL 95% CI**	**UL 95% CI**
Online Self-disclosure	0.616	0.222	0.204	1.081

Note: SE = standard error of regression coefficient, LL 95% CI = 95% confidence interval lower limit, UL 95% CI = 95% confidence interval upper limit.

R2: Do Demographic and Personality Variables Moderate the Relationship Between Amount of Time Spent on SNSs per day and Online Perceived Social Support, and Online Self-Disclosure?

This section provides results for the moderating effects of the key demographic and personality variables in the relationship between amount of time spent on SNSs and online PSS, offline PSS, and online self-disclosure as depicted in the conceptual model (Figure 2). The results are presented for the combined New Zealand and Maldives random community sample. The moderating effect of the relationship between time spent on SNS per day and offline PSS was not examined because the key focus in this Chapter is on online PSS and online self-disclosure. The data were analysed using IBM SPSS statistics 24 software (SPSS, Inc., Chicago, IL, USA) and PROCESS macro v3.4 (Hayes, 2018) for SPSS. In the moderation analyses, 5000 bootstrap samples were used, and moderation effect was determined at the 95% confidence interval. Statistical significance was defined as a two-tailed *p*-value of < 0.05. Each moderator was examined separately with the key predictor variable while controlling for the covariates. The full models are presented in Appendix K. Table 17 shows the results for the interaction between the moderators and the predictors.

As seen in Table 17 the results, as indicated by the *p*-values, show that none of the demographic and personality variables moderated the relationships between amount of time spent on SNSs per day and online PSS or online self-disclosure. Age did not have a moderating effect on the relationship between the amount of time spent on SNSs and either online PSS or online self-disclosure. There was no significant difference in males and females in the relationship between amount of time spent on SNSs and either online PSS or online self-disclosure. Similarly, there was no significant difference in Maldivians and New Zealanders in the relationship between amount of time spent on SNSs and either online PSS or online self-disclosure. The personality variables (extroversion, conscientiousness, and neuroticism) did not have a moderating effect on the relationship between amount of time spent on SNSs and either online PSS or online self-disclosure.

Separate moderation analyses were carried out for the New Zealand clinical sample (see Appendix L for the results) to examine whether the moderating effects of the demographic and personality variables in the relationship between amount of time spent on SNS per day and online PSS and online self-disclosure. Similar to the findings for the combined random community sample, the results for the New Zealand clinical sample were also non-significant.

Table 17. *Unstandardised Bootstrapped Effects for Moderators in the Relationship Between Time Spent on SNSs per day and Online PSS and Online Self-disclosure for the Combined New Zealand and Maldives Random Community Sample (N = 472)*

	B	***SE***	***t***	***p***	***LLCI***	***ULCI***
Time spent on SNSs x Age → Online PSS	-0.060	0.038	-1.567	0.118	-0.135	0.015
Time spent on SNSs x Gender → Online PSS	-0.855	0.975	-0.877	0.381	-2.771	1.061
Time spent on SNSs x Region → Online PSS	0.835	0.954	0.875	0.382	-1.040	2.710
Time spent on SNSs x Country → Online PSS	0.273	1.077	0.254	0.800	-1.844	2.390
Time spent on SNSs x Extroversion → Online PSS	-0.300	0.251	-1.197	0.232	-0.794	0.193
Time spent on SNSs x Conscientiousness → Online PSS	-0.030	0.272	-0.111	0.912	-0.564	0.503
Time spent on SNSs x Neuroticism → Online PSS	0.396	0.243	1.631	0.104	-0.081	0.872
Time spent on SNSs x Age → Online self-disclosure	0.039	0.022	1.810	0.071	-0.003	0.082
Time spent on SNSs x Gender → Online self-disclosure	0.347	0.556	0.625	0.532	-0.744	1.439
Time spent on SNSs x Region → Online self-disclosure	-0.493	0.543	-0.907	0.365	-1.561	0.575
Time spent on SNSs x Country → Online self-disclosure	0.813	0.611	1.330	0.184	-0.388	2.014
Time spent on SNSs x Extroversion → Online self-disclosure	0.107	0.143	0.748	0.455	-0.174	0.388
Time spent on SNSs x Conscientiousness → Online self-disclosure	0.151	0.154	0.981	0.327	-0.152	0.455
Time spent on SNSs x Neuroticism → Online self-disclosure	0.175	0.138	1.265	0.207	-0.097	0.447

Note: CI LL = 95% confidence interval lower limit; CI UL = 95% confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient. Online SD = Online self-disclosure.

Summary of Results Regarding Hypothesis One, and the Direct, Indirect, and Conditional Relationship Between Time Spent on SNSs and, Online PSS, Online Self-disclosure

This chapter has examined the project's first hypothesis, which predicts that the time spent on SNSs per day would have a positive relationship with online PSS as measured by the oMSPSS. In general, the results supported the hypothesis. Participants who spent more time on SNSs had significantly higher levels of online PSS compared to those who spent less time on SNSs. These findings remained significant even after controlling for age, gender, region, country, extroversion, conscientiousness, and neuroticism. A notable finding was the online self-disclosure variable being a greater predictor of online PSS than time on SNS use.

A look at the associations across individual covariates and online PSS showed that age had a significant main effect on online PSS with younger participants having higher online PSS levels compared to the older participants after controlling for other covariates. Similarly, there was a significant main effect for gender, with men reporting higher levels of online PSS compared to women after controlling for other covariates. Overall, Maldivian participants reported significantly higher online PSS levels than New Zealand participants.

Analysis of the relationship between time spent on SNSs and online self-disclosure showed similar results to those for time spent on SNSs and online PSS. Participants who spent more time on SNSs had significantly higher levels of online self-disclosure compared to those who spent less time on SNSs.

Further multivariable regression analysis showed that age was no associated with online self-disclosure after controlling for other covariates. There was a significant main effect of gender, with men reporting higher levels of online self-disclosure compared to women after controlling for other covariates. Country also showed a significant main effect with Maldivians disclosing more online than New Zealanders after controlling for other variables. In addition, conscientiousness was negatively associated with online self-disclosure (i.e., participants who were more conscientious disclosed significantly less than those who were less conscientious), and neuroticism was positively associated with online self-disclosure, while extroversion was not significantly associated with online self-disclosure.

Mediation analysis showed that online self-disclosure partially mediated the relationship between time spent on SNSs per day and online perceived social support.

Moderation analyses were conducted to examine the moderating effects of demographic and personality variables in the relationship between time spent on SNSs per day and online PSS and online self-disclosure. Results showed that the demographic and personality variables did not significantly moderate the relationship between the amount of time spent on SNSs per day and online PSS or online self-disclosure.

CHAPTER 6: RESULTS 3 - THE RELATIONSHIP BETWEEN PERCEIVED ONLINE SOCIAL SUPPORT AND PERCEIVED OFFLINE SOCIAL SUPPORT WITH WELLBEING

This chapter presents the associations between social support, both online and offline and psychological wellbeing for the combined randomly selected general population samples of Maldivians and New Zealanders. These analyses were undertaken to test hypotheses two (H_2) and three (H_3) and explore related variables based on the conceptual model described in Chapter 2 and illustrated in Figure 2. The results in this chapter are reported in three main sections: (1) testing of main hypotheses, (2) multivariate regressions for building models, and (3) evaluation of potential demographic and psychological covariates.

Hypotheses 2 and 3: Exploration of the Relationship Between Offline and Online Perceived Social Support with Psychological Wellbeing

In this section, the second and third study hypotheses, as described below, were tested. To test the associations hypothesised in H_2 and H_3, the analyses were restricted to respondents from the two random sample groups from New Zealand and the Maldives with known values for the variables of online and offline social support, and wellbeing.

H2: Online social support will be positively correlated to psychological wellbeing

H3: Offline social support will be positively correlated to psychological wellbeing

Methodological considerations and the selection of covariates for the model are described below.

Methodological Considerations

The hypotheses were tested on the combined New Zealand and Maldives random community sample using multivariable regression analysis. Statistical assumptions needed for the multivariable multiple regression models were checked following the guidelines from (J. Cohen et al., 2003). Linearity between the dependent and independent variables was checked using plots of residuals and predicted values. Normal distribution of residuals was identified with histograms and Q-Q plots of residuals (see Appendix G). The absence of multicollinearity was determined if no independent variable had correlation coefficients greater than 0.7. There was no evidence of multicollinearity as the condition index was less than 15, and the variance inflation factor (VIF) was less than 10 (J. Cohen et al., 2003). Independence of residuals was checked with the Durbin-Watson statistic and indicated by a Durbin-Watson statistic of 1.80. Residuals were normally distributed and constantly varied across the population (homoscedastic).

Multivariable Regression Analysis for Psychological Wellbeing

Hypotheses two and three were tested with a series of multivariable regressions with online PSS and offline PSS, as the key potential predictor variables. In the first step, the personality traits, online self-disclosure, gender, age, urban/rural region, and country of residence were included as covariates to derive a more explanatory model for wellbeing. In the second step, online PSS was entered on its own to examine its relationship with psychological wellbeing. In the final step, offline PSS was entered to explore its effect on psychological wellbeing as well as to explore any changes in the relationship between online PSS and psychological wellbeing when offline PSS is considered. Results for all three models are presented in Table 18.

In the first Model (see Table 18) the covariates age, gender, region, country, extroversion, conscientiousness, neuroticism, and online self-disclosure were entered as a block to control for these variables. Taken as a whole, the covariates were significant predictors of psychological wellbeing – $R^2 = .25$, $F(8,463) = 18.79$, $p < .001$ – thus accounting for approximately 25% of variance in psychological wellbeing.

Model 2 was also significant, $R^2 = .25$, $F(9,462) = 17.05$, $p < .001$. However, the addition of the online PSS to the model did not improve model fit, as indicated by the nonsignificant change in R^2 of .245, to .249, $p > .05$. People who reported experiencing greater online PSS did not report having significantly higher levels of psychological wellbeing than people reporting having less online PSS: $\beta = .06$, $t(9,462) = 1.52$, $p > .05$.

Model 3 shows that offline PSS was a statistically significant predictor of psychological wellbeing: β = .28, t(10,461) = 6.39, p < .001. The addition of the offline variable to the model improved model fit significantly as indicated by the significant change in R^2 of .25, to .31. The results show that offline PSS was the strongest predictor of psychological wellbeing. The greater the participants reported experience of perceived offline PSS, the higher their psychological wellbeing levels. Therefore, H_2 was not supported but H_3 was supported. An important finding is that while online PSS and offline PSS were significantly positively correlated (refer to Appendix F-1), only offline PSS was significantly and positively related to psychological wellbeing.

Figure 18 visually depicts the relationship between online/offline PSS and psychological wellbeing separately. These scatter plots show that the relationship between offline social support and psychological wellbeing was marked by a positive and strong correlation, while this was not the case with regard to the relationship between online PSS and psychological wellbeing. The association of covariates with psychological wellbeing is discussed in the next section.

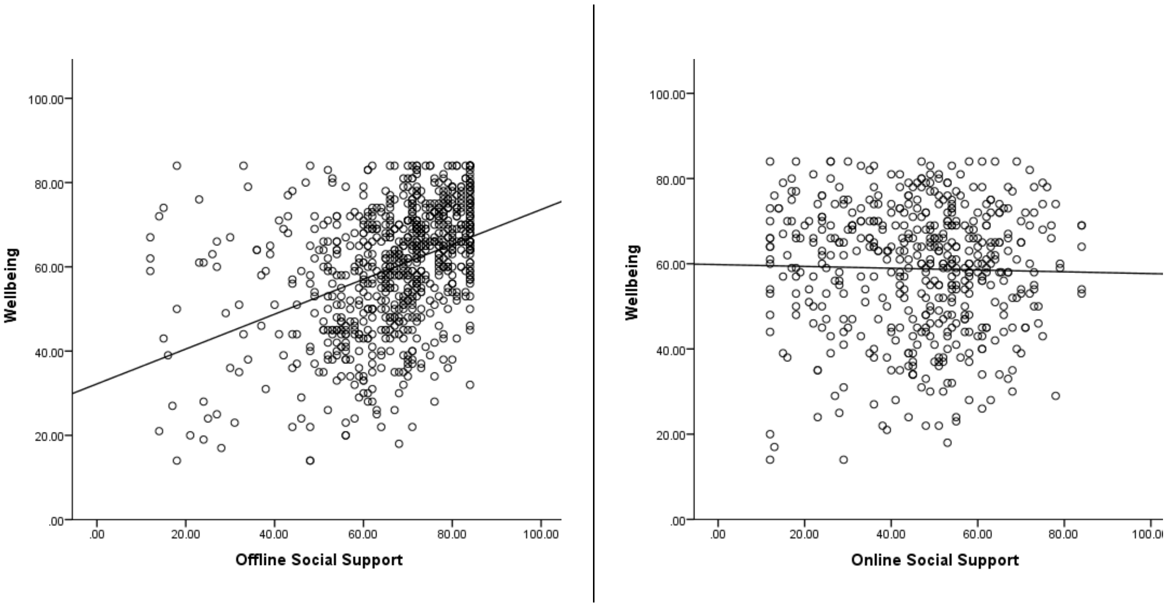

Figure 18. Scatter plots showing the relationship between wellbeing and online and offline social support (N = 472).

Examining the Effect of Potential Confounders (Age, Gender, Region, Country of Residence, Personality Factors, Online Self-disclosure)

The potential covariates included in the regression model were age, gender, region, and country of residence, online self-disclosure, and the three personality traits (i.e., extroversion, conscientiousness, and neuroticism). These variables were selected using the conceptual model informed by the literature for the determinants of wellbeing (see Chapter 1, p. 47.). Each potential covariate was examined to see whether they were individually associated with psychological wellbeing. A summary of the findings for each potential confounding variable is given below: Results are presented in Table 18.

Demographic characteristics. Model 3 shows that age was not significantly associated with wellbeing (β = .002, p = .965). Gender was also not significantly associated with wellbeing (β = 0.01, p =0.746). There was no significant difference between urban and rural residents in their psychological wellbeing levels (β = -0.03, p =0.459). On the other hand, country of residence was associated with wellbeing (β = 0.21, $p < .001$). That is, New Zealanders reported significantly higher levels of psychological wellbeing compared to Maldivians.

Personality traits. All three personality variables were significant predictors of psychological wellbeing when all other variables are controlled for. Extroversion showed a significant and positive relationship with wellbeing (β =.15, $p < .01$). Conscientiousness showed a significant and positive relationship with wellbeing (β = .21, $p < .001$). On the other hand, neuroticism was negatively associated with wellbeing (β = -.22, $p < .001$).

Online self-disclosure. The effect of online self-disclosure was considered important to control for given that it is closely linked to communicative behaviour, responsiveness, and reciprocity in relationships (see Chapter One). Support for this link was found in the current study. There was a moderate to strong positive association between online self-disclosure and online PSS (r = .40, $p < .001$, Appendix F-1). However, in Table 18, Model 3 shows that when controlling for all the other variables, online self-disclosure was not a significant predictor of psychological wellbeing (β = -0.001, $p > .05$).

Table 18. *Summary of Multivariable Regression Predicting Wellbeing from Online Social Support and Offline Social Support for the Combined Random Community Sample (N = 472)*

	Model 1				Model 2				Model 3			
Variable	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*
Age	-0.06	0.06	-0.06	-1.13	-0.06	0.06	-0.06	-1.13	0.00	0.05	0.00	0.04
Gender[a]	-0.20	1.31	-0.01	-0.16	-0.20	1.31	-0.01	-0.16	0.41	1.27	0.01	0.32
Region[b]	-0.17	1.24	-0.01	-0.14	-0.17	1.24	-0.01	-0.14	-0.88	1.19	-0.03	-0.74
Country[c]	10.35	1.69	0.34**	6.14	10.35	1.69	0.34**	6.14	6.30	1.73	0.21**	3.65
Extroversion	1.64	0.37	0.21**	4.46	1.64	0.37	0.21**	4.46	1.15	0.36	0.15*	3.21
Conscientiousness	1.90	0.40	0.21**	4.80	1.90	0.40	0.21**	4.80	1.88	0.38	0.21**	4.96
Neuroticism	-1.88	0.36	-0.23**	-5.29	-1.88	0.36	-0.23**	-5.29	-1.73	0.34	-0.22**	-5.08
Online Self-disclosure	0.002	0.07	0.001	0.03	0.002	0.07	0.001	0.03	0.00	0.07	-0.001	-0.01
Online PSS					-0.06	0.06	-0.06	-1.13	-0.01	0.04	-0.01	-0.19
Offline PSS									0.30	0.05	0.28**	6.39
df	8, 463				9, 462				10, 461			
R^2	0.245				0.249				0.31			
F	18.79**				17.05**				20.76**			
ΔR^2					0.004				0.06**			

Note. [a]Male = 1, [b] Urban = 1, [c] New Zealand =1, *p < .05*, **p < .001

R3: Do Demographic and Personality Variables Moderate the Relationship Between Predictor Variables (Online PSS, Offline PSS, and Online Self-disclosure) and psychological wellbeing?

This section provides results for the moderating effects of the key demographic and personality variables in the relationship between predictor variables (online PSS, offline PSS, and online self-disclosure) and psychological wellbeing as depicted in the conceptual model (Figure 2). The data were analysed using the PROCESS macro v3.4 (Hayes, 2017) for SPSS. In the moderation analyses, 5000 bootstrap samples were used, and moderation effect was determined at the 95% confidence interval. Statistical significance was defined as a two-tailed *p*-value of < .05. Each moderator was examined separately with the key predictor variable while controlling for the covariates. The full models are presented in Appendix M. Table 19 shows the results for the interaction between the moderators and the predictors.

As seen in Table 19, the results of the moderation analyses and indicated by the *p*-values, none of the demographic and personality variables moderated the relationships between the predictor variables (online PSS, offline PSS, and online self-disclosure) and the psychological wellbeing. Age did not have a moderating effect on the relationship between the three predictors and psychological wellbeing. There was no significant difference in males and females in the relationship between the predictors and psychological wellbeing. There was also no significant difference in urban and rural residents in the relationship between the predictors and psychological wellbeing. Similarly, there was no significant difference in Maldivians and New Zealanders in the relationship between the predictors and psychological wellbeing. The personality variables (extroversion, conscientiousness, and neuroticism) did not have a moderating effect on the relationship between the predictors and psychological wellbeing.

Separate moderation analyses were carried out for the New Zealand clinical sample (see Appendix N for the results) to examine whether the moderating effects of the demographic and personality variables in the relationship between predictors (online PSS, offline PSS, and online self-disclosure) and psychological wellbeing. Similar to the findings for the combined random community sample, the results for the New Zealand clinical sample were also non-significant.

Table 19. *Unstandardised Bootstrapped Effects for Moderators in the Relationship Between Online PSS, Offline PSS, and Online Self-disclosure in Predicting Psychological Wellbeing for the Combined New Zealand and Maldives Random Community Sample (N = 472)*

	B	***SE***	***t***	***p***	***LLCI***	***ULCI***
Online PSS x Age → Psychological Wellbeing	-0.002	0.003	-0.721	0.472	-0.007	0.003
Online PSS x Gender → Psychological Wellbeing	-0.082	0.078	-1.056	0.292	-0.235	0.071
Online PSS x Region → Psychological Wellbeing	-0.079	0.071	-1.110	0.268	-0.219	0.061
Online PSS x Country → Psychological Wellbeing	-0.045	0.074	-0.613	0.540	-0.191	0.100
Online PSS x Extroversion → Psychological Wellbeing	-0.017	0.018	-0.908	0.365	-0.053	0.020
Online PSS x Conscient → Psychological Wellbeing	-0.007	0.022	-0.341	0.734	-0.050	0.035
Online PSS x Neuroticism → Psychological Wellbeing	0.019	0.018	1.055	0.292	-0.016	0.055
Offline PSS x Age → Psychological Wellbeing	-0.001	0.003	-0.229	0.819	-0.007	0.005
Offline PSS x Gender → Psychological Wellbeing	-0.022	0.085	-0.257	0.798	-0.189	0.145
Offline PSS x Region → Psychological Wellbeing	-0.083	0.083	-0.995	0.320	-0.246	0.081
Offline PSS x Country → Psychological Wellbeing	0.096	0.092	1.043	0.297	-0.085	0.278
Offline PSS x Extroversion → Psychological Wellbeing	-0.024	0.022	-1.092	0.276	-0.067	0.019
Offline PSS x Conscient→ Psychological Wellbeing	-0.026	0.028	-0.915	0.361	-0.081	0.029
Offline PSS x Neuroticism → Psychological Wellbeing	0.039	0.022	1.748	0.081	-0.005	0.083
Online SD x Age → Psychological Wellbeing	-0.005	0.005	-1.030	0.304	-0.014	0.004
Online SD x Gender → Psychological Wellbeing	0.157	0.133	1.188	0.236	-0.103	0.418
Online SD x Region → Psychological Wellbeing	0.006	0.126	0.049	0.961	-0.241	0.253
Online SD x Country → Psychological Wellbeing	-0.193	0.135	-1.425	0.155	-0.459	0.073
Online SD x Extroversion → Psychological Wellbeing	-0.009	0.032	-0.281	0.779	-0.071	0.053
Online SD x Conscient → Psychological Wellbeing	-0.053	0.036	-1.465	0.144	-0.125	0.018
Online SD x Neuroticism→ Psychological Wellbeing	-0.002	0.035	-0.048	0.961	-0.071	0.067

Note: [a]Male = 1, [b] Urban = 1, [c] New Zealand =1, *p < .05, **p < .001; Online SD = online self-disclosure, Concient = conscientiousness; CI LL = 95% confidence interval lower limit; CI UL = 95% confidence interval upper limit; B = Unstandardised regression coefficients; SE = standard error of regression coefficient

Summary of Key Results

The study findings show that online PSS had a non-significant association with psychological wellbeing after controlling for other variables (Table 18, Model 3). On the other hand, offline PSS shows a significant positive association with psychological wellbeing. Therefore, the results did not provide support for H_2 but provided support for H_3. The results supported those of previous studies in finding a positive relationship between offline social support and wellbeing. Similar to online PSS, online self-disclosure was also not significantly associated with psychological wellbeing.

The effect of potential covariates including demographic and psychosocial variables on the relationship between online and offline social support with wellbeing was examined. Out of the four demographic variables, only country of residence predicted wellbeing, with New Zealanders reporting significantly higher levels of wellbeing compared to Maldivians. All three personality variables were significantly associated with psychological wellbeing in the expected direction as per their characteristics and findings in the literature. Extroversion and conscientiousness were positively associated with psychological wellbeing while neuroticism was negatively related to wellbeing. Offline social support had the strongest effect on wellbeing followed by neuroticism and conscientiousness (both had approximately similar effect sizes).

An analysis of the effects of moderators in the relationship between online PSS, offline PSS, and online self-disclosure in predicting psychological wellbeing was tested (see Table 19). Results showed that none of the demographic and personality variables moderated the relationships between the predictor variables (online PSS, Offline PSS, and online self-disclosure) and the psychological wellbeing in the combined random sample or the New Zealand clinical sample.

Taken together, these results show that, although there is a positive association between online PSS and offline PSS (see Appendix F-1), only offline PSS showed a significant positive association with wellbeing. This relationship was not significantly different between age groups, gender, country, and those scoring high or low in the three personality variables. These findings will be discussed in Chapter Eight in the context of previous findings from published studies in the literature.

In the next chapter, the relationship between wellbeing and online/offline social support was explored across three of the project's subsamples: the New Zealand and Maldives random community samples and the New Zealand clinical sample.

CHAPTER 7: TESTING FOR HYPOTHESES 1-3 ACROSS THE THREE SUBSAMPLES: THE NEW ZEALAND AND MALDIVES RANDOM COMMUNITY SAMPLES AND THE NEW ZEALAND CONVENIENCE CLINICAL SAMPLE

This chapter explores the study's three hypotheses that were previously tested for the combined random sample, but now separately for the subsamples (Group 1 = New Zealand community sample; Group 2 = Maldivian community sample; Group 3 = New Zealand clinical sample). The demographic characteristics of the three sample groups were outlined in Chapter 3, and summarised in Table 6. The means and standard deviations of the key variables for each subsample were given in Chapter Four, Table 10. The MV estimation was examined for hypotheses two and three only given that these two hypotheses involve the four key multi-item variables and address the core objectives of the current project.

Testing Hypothesis 1: The Relationship Between Time Spent on SNS and Online PSS Across the Three Groups

This section investigates the association between time spent on SNSs per day and online PSS by groups separately for those who spent more than 10 minutes per day on SNSs. The time spent on SNSs per day variable was treated as a continuous variable for the purpose of linear regression analysis. Bivariate correlations between variables were examined for each subsample separately (see Appendix F-2 to 4) prior to conducting linear regressions. As expected, there was a significant positive correlation between time spent on SNSs and online PSS across all three subsamples.

A series of multivariable regression analyses were conducted to examine the relationship between time spent on SNSs and online PSS across the three subsamples. As with Chapter 5, covariates (demographic characteristics, personality traits, and offline PSS) were entered first in a block to control for their effects on the dependent variable. In the second step, the key potential predictor variable "time spent on SNSs" was entered. In the third step, the variable online self-disclosure was entered. Online self-disclosure shows a moderate positive relationship with online PSS across all three sub-samples (see Appendixes E-2 to 4). The results from the final steps (Model 3) are presented in Table 20. The results for all the models (Models 1 to 3) for the three subsamples are provided in Appendix H.

New Zealand Random Community Sample: Hypothesis 1

Table 20 shows that all of the predictors together explained 25% of the variance in online PSS and this model was significant: R^2 = .29, F(9,195) = 8.74 , p < .001. Time spent on SNSs was a significant predictor of online PSS. That is respondents' online PSS increased when they spent more time on SNSs. Therefore, H_1 was supported in the New Zealand random community sample.

In the New Zealand random community sample, offline PSS was significantly and positively associated with online PSS (β = .20, p < .05). Another notable significant finding was the significant positive association between online self-disclosure and online PSS. The standardised beta values shown in Table 20 indicate that the relationship between online self-disclosure and online PSS was stronger (β = .33, p < .001) than the relationship between time spent on SNSs and online PSS (β = .15, p < .05). Therefore, this analysis revealed that respondents' online PSS increased more when they disclosed more online relative to the increase in online PSS associated with increased time spent on SNSs in the New Zealand community sample.

None of the personality variables were significantly associated with online PSS in this sample Out of the three demographic variables age, gender, and region, age and gender were significant predictors of online PSS with age being positively associated with online PSS (β = -.21, p < .001). Men reported significantly higher levels of online PSS than women (β = .15, p < .05).

Maldives Random Community Sample: Hypothesis 1

Table 20 shows that for the Maldives random community sample, the overall model was significant with 31% of the variance in online PSS explained by all of the predictor variables: R^2 = .31, F(9,257) = 12.80, p < .001. Time spent on SNSs was a significant predictor of online PSS (β = .15, p < .05). That is respondents' online PSS increased when they spent more time on SNSs. Therefore, H_1 was supported in the Maldives random community sample.

As expected, offline PSS was significantly and positively associated with online PSS (β = .29, p < .001). Similar to the New Zealand random community sample, a positive and stronger relationship between online self-disclosure and online PSS was observed (β = .33, p < .001) than time spent on SNSs and online PSS (β = .15, p < .05) in the Maldives random community sample.

Out of the three personality variables, only neuroticism was significantly associated with increased online PSS (β = .15, p < .05). Of the three demographic variables, age showed a trend towards a negative association with online PSS (β = -.11, p = .067).

New Zealand Convenience Clinical Sample: Hypothesis 1

Table 20 shows for this subsample, the overall model was significant with 45% of the variance in online PSS being explained by all of the predictors together: R^2 = .45, F(8,36) = 3.70, p < .05. Amount of time spent on SNSs was significantly associated with online PSS: (β = .34, p < .05) after controlling for the potential covariates. Therefore, H_1 was supported in the New Zealand convenience clinical sample.

Online self-disclosure was not significantly associated with online PSS in this sample group: (β = .23, p > .05). As expected, offline PSS was a significant predictor of online PSS (β = .42, p < .05) None of the personality traits or demographic characteristics were significantly associated with online PSS in the New Zealand clinical sample. Similarly, neither age, gender, or personality traits moderated the relationship between amount of time spent on SNS per day and online PSS. Although online PSS and offline PSS were significantly correlated, online PSS did not mediate the relationship between time spent on SNSs and offline PSS.

Table 20. *Summary of Multivariable Regression Analyses Predicting online PSS from Time Spent on SNSs per Day across the Three Subsamples*

	New Zealand Main				Maldives Main				New Zealand Clinical			
Variable	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*
Age	−0.22	0.07	−0.21	-2.99*	-0.21	0.11	-0.11	-1.84[c]	0.03	0.19	0.02	0.16
Gender[a]	5.37	2.24	0.15	2.40*	2.22	1.84	0.07	1.21	5.41	4.50	0.19	1.20
Region[b]	−2.77	2.01	-0.09	-1.37	0.53	1.80	0.02	0.30	-	-	-	-
Extroversion	-0.92	0.54	-0.11	-1.69	0.33	0.60	0.03	0.55	-1.68	0.90	-0.26	-1.86
Conscientiousness	-0.07	0.62	-0.01	-0.11	-0.21	0.59	-0.02	-0.35	0.83	0.98	0.11	0.85
Neuroticism	-0.38	0.53	-0.05	-0.71	1.41	0.55	0.15	2.58*	0.52	1.07	0.07	0.48
Offline PSS	0.27	0.09	0.20	3.07**	0.31	0.06	0.29	5.18**	0.51	0.16	0.42	3.15*
Time spent on SNSs	2.18	0.92	0.15	2.37*	1.74	0.64	0.15	2.69*	3.76	1.77	0.34	2.13*
Online self-disclosure	0.58	0.11	0.33	5.23**	0.65	0.11	0.33	6.12**	0.36	0.23	0.23	1.59
df	9, 195				9, 257				8, 36			
R^2	0.29				0.31				0.45			
F	8.74**				12.80**				3.70*			
ΔR^2	0.10**				0.10**				0.04			

Note. [a]Male = 1, [b]Urban = 1, NZ clinical group were all urban residents, NZ random community sample, *n*= 205, Maldives random community sample, *n* = 267, NZ Clinical, *n* = 45
**p* < .05, **p < .001, [c]*P* = 0.056

Testing Hypotheses 2 and 3 Across the Three Subsamples: the New Zealand and Maldives Random Community Samples and the New Zealand Clinical Sample

Prior to conducting linear regression analysis for the purpose of detecting associations between key predictors (online PSS and offline PSS) and psychological wellbeing, MV was estimated for the regression slopes. The hypotheses were tested by first adjusting the estimated differences in the parameter values thought to have been caused by the MV. Thus, before carrying out linear regressions of wellbeing against online perceived social support, offline perceived social support and online disclosure offline, calculations were carried out by using both sets of estimates for scores obtained by the Maldivians for each variable as described below and in Chapter 3, the section on MV estimation. The New Zealand clinical sample was not included in the MV estimation because it is a small convenience sample. However, results from the linear regression are presented for this group for exploratory purpose.

MV Estimation Results

The method of analysis involved estimating the difference between β_A and β_B by matching the sample covariance matrices to the theoretical covariance matrices. Again, assumptions 1 and 2 are applicable (see Appendix O) but again the results depend on which ‘direction’ the MV is in. Therefore, there are two estimates of the MV for each property, one for each direction (i.e., assuming MI to considered to be greater than or less than 1). After applying this method, the following results were obtained.

- *For online perceived social support, relative to the slope β_A (in the NZ sample), MV has acted to reduce β_B (in the Maldives sample) to 0.99 times its true value or to reduce β_B to 0.89 of its true value.*
- *For offline perceived social support, relative to the slope β_A, MV has acted to increase β_B to 1.02 times its true value or to reduce β_B to 0.99 of its true value.*
- *For online disclosure, relative to the slope β_A, MV has acted to increase β_B to 1.58 times its true value or to reduce β_B to 0.51 of its true value.*

- *For wellbeing, relative to the slope β_A, MV has acted to reduce β_B to 0.98 times its true value or to reduce β_B to 0.73 of its true value.*

  The effect of MV of the conclusions can be studied by reversing the estimated differences in the parameter values thought to have been caused by the MV. Thus, with a linear regression of psychological wellbeing against online perceived social support, offline perceived social support and online disclosure offline, amended calculations would be carried out by both

1. *dividing each score of online perceived social support in the Maldives sample by 0.99,*
2. *dividing each score of offline perceived social support in the Maldives sample by 1.02,*
3. *dividing each score of online disclosure in the Maldives sample by 1.58,*
4. *dividing each score of wellbeing in the Maldives community by 0.98,*

   and also

1. *dividing each score of online perceived social support in the Maldives sample by 0.89,*
2. *dividing each score of offline perceived social support in the Maldives sample by 0.99,*
3. *dividing each score of online disclosure in the Maldives sample by 0.51,*
4. *dividing each score of wellbeing in the Maldives sample by 0.73,*

Based on these estimates, the Maldivian participant's scores were adjusted accordingly, by dividing the total scores for each variable in the Maldives random sample by the two estimates of the MV separately and conducting two regression analyses using the two sets of adjusted scores.

Potential covariates including age, gender, and three personality variables, were controlled for in the regression analyses for each group. Region was explored for the New Zealand and Maldives random community samples only. The New Zealand clinical group participants were all urban residents. The statistical assumptions needed for the multivariable multiple regression models were checked following guidelines from (J. Cohen et al., 2003). The linearity between the dependent and independent variables was checked using plots of residuals and predicted values. The normal distribution of residuals was identified with histograms and Q-Q plots of residuals (see Appendix I). The absence of multicollinearity was determined if no independent variable had correlation coefficients greater than 0.7. There was no evidence of multicollinearity (see Appendix F-2 to 4). The condition index was less than 15, and the variance inflation factor (VIF) was less than 10 (J. Cohen et al., 2003) for all three subsamples. Independence of residuals was checked with the Durbin-Watson statistic and indicated by a Durbin-Watson statistic greater than 1.75 obtained for all three subsamples. The residuals were normally distributed and constantly varied across the populations, consistent with their being homoscedastic.

A series of multivariable regression analyses were conducted to examine the relationship between online PSS and offline PSS with psychological wellbeing across the three subsamples. Two separate regression analyses were conducted for the Maldives random sample with the two MV estimates. As with Chapter 6, covariates (demographic characteristics, personality traits, and online self-disclosure) were entered first as a block to control for their effects on the dependent variable. In the second step, the key potential predictor, online PSS was entered. In the third step, the key potential predictor, offline PSS was entered. The results from the final steps (Model 3) are presented in Table 21. The results from all the models (Models 1 to 3) for the three subsamples are provided in Appendix J.

New Zealand Random Community Sample: Hypotheses 2 and 3

Table 21 shows that for the New Zealand random community sample, the overall model was significant with 38% of the variance in psychological wellbeing explained by all of the predictor variables: $R^2 = .38$, $F(9, 195) = 13.16$, $p < .001$. However, individually, online PSS was not a significant predictor of psychological wellbeing ($\beta = -.04$, $p > .05$). In other words, people who reported experiencing more online PSS did not report having significantly higher levels of psychological wellbeing than people who reported experiencing less online PSS once all the other covariates were controlled for. Therefore, H_1 was not supported in the New Zealand random sample.

On the other hand, the results show that offline PSS was a significant predictor of psychological wellbeing for the New Zealand random community sample, (β = .32, p < .001). That is, perceiving oneself as having offline social support from family and friends was associated with improvements in psychological wellbeing once all the other covariates were controlled for. Therefore, in the New Zealand random community sample, H_2 was not supported but H_3 was.

None of the demographic factors were significantly related to psychological wellbeing for this sample. Online self-disclosure was not significantly related to psychological wellbeing. All three personality variables were significant predictors of psychological wellbeing. Extroversion showed a significant and positive relationship with wellbeing (β =.16, p < .05). Conscientiousness also showed a significant and positive relationship with wellbeing (β = .23, p < .001). Conversely, neuroticism was negatively associated with wellbeing, (β = −.32, p < .001).

Maldives Random Community Sample: Hypotheses 2 and 3

Table 21 shows two sets of linear regression results for the Maldives random community sample as the scores for Maldivian participants were adjusted using the two MV estimates separately for online PSS, offline PSS, online self-disclosure, and psychological wellbeing. The two regression analyses produced identical standardised betas and *t*-scores as shown in Table 21. The overall model was significant, with 24% of the variance in psychological wellbeing explained by all of the predictor variables: R^2 = .24, F(9, 257) = 8.92, p < .001. However, individually, online PSS was not a significant predictor of psychological wellbeing (β = .001, p > .05) once all the other covariates were controlled for. In other words, people who reported experiencing more online PSS did not report having significantly higher levels of psychological wellbeing than people who reported experiencing less online PSS. Therefore, H_2 was not supported in the Maldives random sample.

Similar to the findings from the New Zealand random community sample, the Maldives random community sample results show that offline PSS was a significant predictor of psychological wellbeing (β = .25, p < .001). That is, perceiving greater offline social support from family and friends was associated with improvements in psychological wellbeing. Therefore, in the Maldives random community sample, H_2 was not supported but H_3 was.

None of the demographic factors were significantly related to psychological wellbeing in this sample. Similarly, online self-disclosure was not significantly related to psychological wellbeing. Extroversion showed a trend towards a significant and positive relationship with wellbeing (β =.12, p = 0.061). Conscientiousness also showed a significant and positive relationship with wellbeing (β = .21, p < .001). On the other hand, neuroticism was negatively associated with wellbeing (β = −.16, p < .05).

New Zealand Clinical Sample: Hypotheses 2 and 3

Table 21 shows that for the New Zealand clinical sample, the overall model was significant with 38% of the variance in psychological wellbeing explained by all of the predictor variables together: R^2 = .38, F(8, 36) = 2.80, p < .05. However, individually, only neuroticism was a significant predictor of psychological wellbeing. Those who scored high on the neuroticism scale reported having lower levels of psychological wellbeing (β = -.45 p < .001). Neither online PSS nor offline PSS was significantly associated with psychological wellbeing once all the other covariates were controlled for. While non-significant, the magnitude of the effect of online PSS was relatively large (β = .22, p > .05) compared to the magnitude of the effects of offline PSS (β = −.01, p > .05). Taken together, reporting greater perceived online or offline social support was not associated with increased psychological wellbeing for the New Zealand clinical group. Therefore, the results did not provide support for either H_2 or H_3 in this subsample.

With regard to the demographic factors, none revealed significant associations with psychological wellbeing. Only gender showed a trend towards significance (β = -.29, p = .082), with the mean wellbeing score for women being higher than that for men.

Section summary

Figure 19 shows the proportion of variance in psychological wellbeing explained by online PSS, online self-disclosure, and offline PSS for the three subsamples. From the chart below, it can be seen that by far the greatest variance in wellbeing was explained by offline PSS for all three subgroups. Online social support and online self-disclosure had very little or almost no effect on wellbeing across all three subsamples.

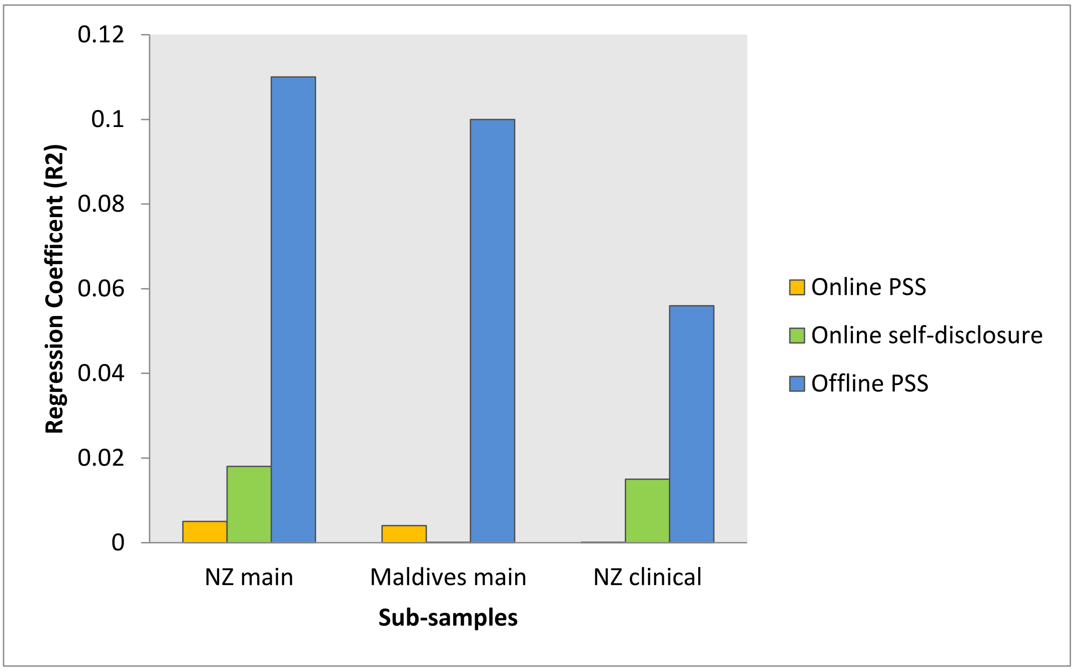

Figure 19. The proportion of variance (R^2) in wellbeing explained by online PSS, online self-disclosure and offline PSS

Table 21. *Summary of Multivariable Regression Analyses Predicting Psychological Wellbeing from online PSS Across the Three Subsamples*

	New Zealand Main				Maldives Main[c]				Maldives Main[d]				New Zealand Clinical			
Variable	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*	*B*	*SE B*	*β*	*t*
Age	-0.03	0.06	-0.04	-0.57	0.05	0.11	0.03	0.46	0.07	0.15	0.03	0.46	0.02	0.17	0.02	0.12
Gender[a]	0.37	1.72	0.01	0.21	0.56	1.88	0.02	0.30	0.76	2.53	0.02	0.30	-7.76	4.34	-0.29	-1.79
Region[b]	-1.35	1.56	-0.05	-0.87	-0.55	1.84	-0.02	-0.30	-0.74	2.47	-0.02	-0.30	-	-	-	-
Extroversion	1.09	0.42	0.16	2.61*	1.16	0.62	0.12	1.88	1.56	0.83	0.12	1.88	1.32	0.93	0.22	1.42
Conscientiousness	1.82	0.47	0.23	3.84**	1.99	0.61	0.21	3.29**	2.67	0.81	0.21	3.29**	0.12	0.97	0.02	0.13
Neuroticism	-2.08	0.41	-0.32	-5.07**	-1.52	0.55	-0.16	-2.75**	-2.04	0.74	-0.16	-2.75**	-3.16	1.06	-0.45*	-3.00
Online self-disclosure	-0.08	0.09	-0.05	-0.87	0.12	0.18	0.04	0.65	0.05	0.08	0.04	0.65	-0.13	0.22	-0.09	-0.59
Online PSS	-0.03	0.05	-0.04	-0.59	0.01	0.06	0.01	0.10	0.01	0.08	0.01	0.10	0.20	0.15	0.22	1.29
Offline PSS	0.28	0.07	0.32	5.06**	0.28	0.07	0.25	4.14**	0.36	0.09	0.25	4.14**	-0.01	0.17	-0.01	-0.06
df	9, 195				9, 257				9, 257				8, 36			
R^2	0.38				0.24				0.24				0.38			
F	13.16**				8.92**				8.92**				2.80*			
ΔR^2	0.08**				0.05**				0.05**				0.00			

Note. [a]Male = 1, [b] Urban = 1, NZ clinical sample were all urban residents. NZ community sample, *n* = 205, Maldives community, *n* = 267, NZ clinical sample, *n* = 45

[c]Regression slopes compared after Maldivian participants' scores were adjusted using first set of MV estimates

[d]Regression slopes compared after Maldivian participants' scores were adjusted using second set of MV estimates

**p* < .05, **p < .001

Summary of Key Results for Hypotheses 1, 2, and 3 across the New Zealand and Maldives Community Samples and the New Zealand Clinical Sample

This chapter analysed the group differences in the relationship between time spent on SNSs, online PSS, online self-disclosure, offline PSS, and wellbeing. The key findings from this chapter are summarised below.

- Overall, the results showed that those who spent more time on SNSs per day reported having higher online PSS than those who spent less time on SNS per day across the New Zealand and Maldives community participants. A similar pattern was observed for the New Zealand clinical sample as well. Therefore hypothesis 1 was supported across all three subsamples.

- There were some group differences in the associations between several predictor variables and wellbeing. Online PSS and online self-disclosure had little or no effect on wellbeing in any of the sub-groups. In both New Zealand and Maldives random community samples, offline PSS was positively related to psychological wellbeing. This was not the case for the New Zealand clinical sample. Therefore, hypothesis 2 was not supported in any of the three sub-samples. On the other hand, hypothesis 3 was supported in New Zealand and Maldives random community samples but not the New Zealand clinical sample group.

- In New Zealand and Maldives random community samples, personality factors predicted wellbeing, with both extroversion and conscientiousness having a positive association with wellbeing, and neuroticism having a negative association with wellbeing. In the New Zealand clinical group, a high level of neuroticism was associated with low levels of psychological wellbeing, while extroversion and conscientiousness did not statistically predict wellbeing. However, the directions of these relationships were consistent for the random community samples.

- None of the demographic variables were significantly associated with psychological wellbeing in New Zealand and Maldives random community samples or the New Zealand clinical sample. However, in the New Zealand clinical sample, a marginal relationship between gender and wellbeing was found, with females having relatively lower mean wellbeing levels than males.

CHAPTER 8: DISCUSSION

This chapter concludes the thesis with a discussion of the findings relating to the hypotheses presented in Chapter Two. This chapter is organised into five sections. First, the purpose of the study is reviewed. Next, the findings are summarised and integrated with the extant literature, and their implications for research and practice are outlined. Then, the strengths and limitations of the study are addressed. The project's limitations are then discussed with suggestions for future research offered. Finally, conclusions are summarised before the significance of this project is presented.

Purpose of the Study

The aim of the current project was to explore the role of social support in determining psychological wellbeing, with an emphasis on social support acquired from online social networking. Robust research has consistently shown that face-to-face social support is important for psychological wellbeing (Kawachi & Berkman, 2001; Siedlecki et al., 2014). However, it is not known how the significant increase in SNS use has affected the experience and consequences of social support. This project collected data on time spent on SNSs per day, online PSS and offline PSS to examine their relationships with psychological wellbeing and also to allow for considerations of key variables including gender, age, urban versus rural residence, and culture.

Using a cross-sectional survey design, the participants' time spent on SNSs per day, online PSS and offline PSS, online self-disclosure, personality traits, and how these related to psychological wellbeing, were measured in a random community sample of 385 New Zealanders and 411 Maldivians. These two community samples were randomly selected using Electoral Rolls accessed from New Zealand and Maldives. In addition, study hypotheses were also tested on a small convenience clinical sample from New Zealand for comparison.

R1: Is there an association between time spent on SNSs and psychological wellbeing Within the Three Subsamples (Chapter 4)

Given that previous research has found mixed results, the current study examined the association between time spent on SNSs per day and psychological wellbeing while controlling for demographic and personality variables. Our results found that there was no significant association between time spent on SNSs per day and psychological wellbeing in any of the subsamples after accounting for the demographic and personality variables. As noted earlier, studies that have found similar results to the current study. In Maldives, no previous data is available on social media use and psychological outcomes. However, a study conducted in New Zealand with a large national sample of adults reported that, although there was a significant positive association between social media use and psychological distress, this association was weak (Stronge et al., 2019). Although the current study did not find significant results, the direction of the association between time spent on SNSs and psychological wellbeing was negative for both New Zealand and Maldives random community samples but positive for the New Zealand clinical sample. Our sample sizes were much smaller compared to the New Zealand study and in the current study, a relatively low number of participants indicated that they used SNSs for more than 3 hours a day. Stronge and colleagues (2019) argued that people would need to be using social media constantly for it to be the main contributor of psychological distress. The current study found that personality traits had stronger and significant correlations with psychological wellbeing compared to amount of time spent on SNSs. Therefore, in line with previous research, the current study found that spending time on SNSs was not a major concern in terms of its impact on psychological wellbeing.

Hypothesis 1: The Relationship Between Time Spent on SNS Per Day and Online Perceived Social Support in the Combined Random Community Sample (Chapter 5)

The findings supported the first hypothesis, which posited a significant positive relationship between those who spent more than 10 minutes per day on SNSs and online PSS. As predicted, more time spent on SNSs was associated with greater perceived social support. These findings remained significant even after controlling for online self-disclosure, age, gender, country, and levels of extroversion, conscientiousness, and neuroticism. As with the random sample as a whole, time spent on SNSs was significantly and directly related to online PSS for both New Zealanders and Maldivians when examined separately with almost similar effects (β = .15 and β = .20 respectively). These findings provide support for the fundamental theoretical notion that communication between people can help develop social relations (Barrera & Ainlay, 1983; Catherine & Barbara, 2008).

Cross-sectional studies have found a positive association between intensity of SNS use or online interaction and social support measures (Hu et al., 2017; Jang et al., 2016; Johnston et al., 2013; Nick et al., 2018; Olsen et al., 2012; N. Park, 2012; Seo et al., 2016; Smedema & McKenzie, 2010). The data from this study are consistent with such findings. Although the majority of these studies were conducted using college students, Nick and colleagues (2018) used both community and college samples in their study. They examined the relationship between SNS use and online social support in the United States using a combined sample of undergraduate students (aged 18-23) from a South-Eastern university and a community sample (aged 18-42) selected via an online survey system. The authors concluded that greater use of SNSs was associated with greater online PSS (Nick et al., 2018). Similar findings were reported by Park (2012) in his study that examined the relationship between frequency of online communication and PSS (non-specified) in a South Texas rural random sample. Therefore, in general, findings from the current project and previous research suggest that time spent on online social networking is associated with an increase in online PSS for college students as well as general community members. Although the underlying mechanisms that link SNS use and online PSS were not explored in the current study or in the studies discussed above, others have investigated possible behaviours that specifically influence online social support. For instance, Utz and Breuer (2017) in their longitudinal study revealed that very specific activities, such as explicitly asking for advice helped people gain social support via SNSs.

There are some notable differences in the specific ways both ‘time spent on SNSs’ and online PSS were measured in this project, which distinguishes it from many previous studies. The majority of previous studies used measures of perceived social capital rather than measures of online PSS. However, the overall findings of the studies discussed provide support for a positive association between SNS use and ‘online social support’, which is consistent with the current study findings. For instance, Nicole

Ellison, one of the most frequently cited researchers on communication technology and social processes, measured intensity of Facebook use by using a scale developed with her colleagues. They concluded that the intensity of Facebook use was positively associated with online bonding social capital (Ellison et al., 2007). Bonding social capital is considered by some to be equivalent to perceived social support (Trepte et al., 2014). Johnston and colleagues (2013) using the same measures used in the study by Ellison and colleagues (2007) found that intensity of Facebook use was positively associated with bonding social capital in a randomly selected sample of university students from South Africa (Ellison et al., 2007; Johnston et al., 2013). Notably C.-Y. Liu and Yu (2013) found that the intensity of Facebook use, measured using Ellison and colleagues' Facebook Intensity Scale, was positively related to online PSS in a sample of university students in Taiwan. In conclusion, these research findings provide further support for the positive association between the amount of time spent on online social networking and online PSS despite the different measures used.

Other Key Findings on Online PSS and Online Self-disclosure for the Combined Random Community Sample (Chapter 5)

In addition to the support found for the main hypothesis (H_1), other findings also emerged with regard to the relationship between SNS use and online social support within the overall random community sample. Most importantly, online self-disclosure was positively associated with online PSS. It was also found that age was negatively correlated with online PSS, and male gender was significantly associated with higher online PSS. Maldivians reported a significantly higher level of online PSS than New Zealanders (discussed in the cross-sectional differences section). Finally, neither region, levels of extroversion, conscientiousness, nor neuroticism were significantly related to online PSS. These findings are discussed below.

Online Self-disclosure and Online PSS. The results in this sample replicate previous findings, which have reported a positive association between online self-disclosure and online PSS (Jeong et al., 2014; K.-T. Lee et al., 2013; D. Liu & Brown, 2014; Nguyen et al., 2012; Trepte & Reinecke, 2013; Utz, 2015). Our findings showed that online self-disclosure had a stronger positive effect on online PSS *(*Table 14: Model 3*,* $R^2\Delta$ = .10) compared to the effects of time spent on SNSs on online PSS

(Table 14: Model 2, $R^2\Delta$ = .03). In addition, mediation analysis showed that online self-disclosure partially mediated the relationship between amount of time spent on SNSs and online PSS. This suggests that increased SNS use is associated with increase in online perceived social support (direct effect) and that increased online self-disclosure also associated with increased online perceived social support (indirect effect). These findings provide support for Taylor and Altman's (1987) social penetration model being applicable to the online context, which suggests that self-disclosure is an integral part of developing and maintaining social relationships.

Interestingly, our findings showed that online self-disclosure was not significantly associated with offline PSS. This suggests that online self-disclosure may be different from face-to-face disclosure which has been found to be a predictor of offline social support (Jeong et al., 2014). Jeong and colleagues (2014) who compared online and offline self-disclosure and online and offline social capital in a random community sample in South Korea. Their results showed that online self-disclosure was positively associated with online social capital (bridging and bonding) but not offline social capital. Similarly, offline self-disclosure affected only offline social capital (Jeong et al., 2014). Therefore, findings from Jeong and colleagues' study and the current project suggest that online contacts may be different from offline contacts in that they may be two separate social groups. While this may suggest a distinct separation between online and offline domains of social support, over time, online self-disclosure may likely facilitate offline social relationships. Self-disclosure has the potential to convert an anonymous or known online contact into a reciprocal sharing in an "authentic" interactive relationship. Further in-depth examination of different aspects of online self-disclosure (such as the types of online self-disclosure, including the quality and depth of reciprocity), may help determine whether, consistent with Taylor and Altman's model, online self-disclosure could facilitate positive changes in offline social relationships. In conclusion, the finding from the current project provides support for the importance of online self-disclosure in enhancing online perceived social support.

Age and online PSS. In the current study, a significant negative association between age and online PSS was observed. Literature on the relationship between perceived social support from face-to-face contact and age suggests that it is a complex phenomenon. In general, compared to young adults, older adults are more at risk of loss of social support due to loss of a partner or health-related issues (van Baarsen, 2002). This may be balanced by their greater acceptance of smaller but more stable social networks (Martire et al., 1999; van Tilburg, 1998). The negative association between age and online PSS found in the current project is generally in line with previous studies which have reported that face-to-face social interaction is generally less intense in older age brackets (Krause, 1999; van Baarsen, 2002). Generally, people maintain social connections with numerous others, more particularly when younger. During the latter part of adulthood, rates of social interaction begin to decline, due to loss of significant others or family and friends, and living alone (Krause, 1999; van Tilburg, 1998). With increasing accessibility and use of SNS platforms, one might expect little difference between old and young cohorts in terms of their online PSS. In fact, one could assume that SNS use would be a substitute means of building or maintaining social relations for older adults much as it is for young people, because they are able to interact with family and friends living elsewhere whom they may not be able to meet with otherwise. A possible explanation for why older people had less online PSS in the current study may be because young people still dominate SNS use compared to older generations (Clement, 2019b). The current study findings provide support for this conclusion by finding a significant negative association between SNS use and age (see Appendix F-1). Another reason why older generations are not using SNSs as much as their younger counterparts may also be due to their low IT efficacy. C.-P. Lin and Bhattacherjee (2009) based on their study concluded that IT usage was significantly related to IT efficacy, or having the knowledge and skills to use SNS platforms which in turn had a positive effect on online social support through increase in technology use. Therefore, a scale assessing IT efficacy may have added value to the study.

Gender and online PSS. Contrary to previous findings regarding gender differences in traditional social support, in the current study men reported obtaining higher online PSS than women. Previous studies have supported the general assumption that women are more likely than men to both seek and provide and receive offline social support (Reevy & Maslach, 2001; B. R. Sarason et al., 1985; Stansfeld et al., 1998; Vaux, 1985). Only a few studies have explored gender differences in online PSS. H. Kim (2014) found no significant association between gender and online perceived social support in their survey of undergraduate students in the United States. Similarly, Frison and Eggermont (2016) reported no gender differences in online PSS obtained from public Facebook interactions in their study of adolescents. However, private Facebook interactions had a positive association with girls' perceptions of online social support but not boys' online PSS in the same study by Frison and Eggermont (2016). Luan and colleagues (2015) also concluded that women had more online social support than men based on their findings that women had more 'likes' and comments on Facebook than men (Luarn et al., 2015). These two studies contradict the findings of the current project, and suggest that there may be gender differences in online social support that warrant further explanation. While the latter two studies used convenience samples, the current study used a robust fully powered random community sample. The results from the current study may be explained by factors such as 'social roles' (Matud et al., 2003). That is, although women seem to dominate most popular social media use and communicate online as much as men, men may perceive themselves to be getting more online support than women do due to differences in the online and offline contexts where interactions occur. Perhaps men find it easier to seek social support online due to the anonymity that the SNS technology provides when talking about sensitive issues which make them appear weak. Women may find it easier to provide and seek support face-to-face due to their gender-specific characteristics such as better interpersonal skills, and more nurturing behaviour compared to men (Reevy & Maslach, 2001). The cross-cultural differences in the relationship between gender and online PSS are discussed later in this chapter.

Region and online PSS. There was no significant difference between urban and rural dwellers with regard to their online PSS in the combined random community sample. To the best of the author's knowledge, the current study is the first to examine the urban/rural differences in online PSS. Studies have reported that generally, compared to rural dwellers, urban dwellers had lower offline social support in both western and non-western countries (J.-M. Kim et al., 2004; Romans et al., 2011; Tobiasz-Adamczyk & Zawisza, 2017). These findings do not seem to apply to online social support levels which need further investigation.

Personality and online PSS. Despite growing research interest in the role of personality in internet use behaviours, to the author's knowledge, no studies have specifically explored the association between personality traits and online PSS.

Although this was not the primary area of study in this project, some interesting findings emerged, highlighting potential differences between online PSS and offline PSS. Previous researchers have argued that traditional perceived social support is likely to be a stable trait-like construct (I. G. Sarason et al., 1983) and therefore related to personality traits such as the big five factors (I. G. Sarason et al., 1983). Evidence from the current study suggests that people who are more extroverted have higher offline PSS, but not online PSS (i.e., there was no significant association between extroversion and online PSS). With regard to offline PSS, the literature tends to support the claim that extroversion typically correlates with the psychological attributes that make a person sociable (Asendorpf & Van Aken, 2003; Bolger & Eckenrode, 1991; Chay, 1993; Digman, 1990; Finch & Graziano, 2001; Halamandaris & Power, 1997; Swickert et al., 2010), while those who score high on neuroticism tend to have a lower level of sociability (Furukawa et al., 1998; Russell et al., 1997; I. G. Sarason et al., 1983). Individuals who are more extroverted generally have more friends (Demir & Weitekamp, 2007; Hills & Argyle, 2001; Pullen et al., 2014), and are thus likely to report having more social support than those who are less extroverted. The current study did not find a significant association between conscientiousness and online PSS when controlling for other variables. However, as reported in Appendix F-1, a significant negative bivariate correlation between conscientiousness and online PSS was found, as well as a significant positive correlation between conscientiousness and offline PSS. No studies have examined the association between conscientiousness and online PSS. The results regarding the positive association between conscientiousness and offline PSS are consistent with previous literature that reported that individuals who are high in conscientiousness report greater levels of satisfaction with support providers (Asendorpf & Van Aken, 2003; Swickert et al., 2010).

With regard to neuroticism, the current study found a trend towards a significant positive relationship between neuroticism and online PSS after controlling for other variables. There was no significant correlation between neuroticism and offline PSS (see Appendix F-1). Notably, the direction of the relationship between neuroticism and online PSS and the non-significant relationship between extroversion and online PSS suggests that the 'social compensation' hypothesis may be more applicable than the 'rich get richer' hypothesis. The social compensation hypothesis proposes that those with high neuroticism personality-related characteristics or mental health symptoms report having more online social relationships to compensate for poor social interaction offline (e.g.,Valkenburg et al., 2005; Zywica & Danowski, 2008). A more psychometrically powerful measure of personality traits may have produced significant associations. An alternative reason why the current study did not find any significant associations between personality characteristics and online PSS may have been because unlike offline PSS, online PSS is more a context-specific construct rather than a trait-like construct.

R2: Is the association between amount of time spent on SNSs and online perceived social support and online self-disclosure moderated by demographic and personality variables? (Chapter 5: Combined Random Sample)

In this study, age, gender, region, country, and personality variables did not moderate the relationship between amount of time spent on SNS per day and online PSS. Only a small number of previous studies have examined potential moderators in SNS use and online social support research and the findings are mixed. Although the current study found a significant negative correlation between age and time spent on SNSs, age did not moderate the relationship between time spent on SNSs and online PSS. In the current study, the age of participants ranged between 17 to 75 years for the combined random community sample. However, Liu and colleagues (2018), based on their meta-analysis, reported that the relationship between SNS use and social support was stronger among college students compared to middle schoolers. It is likely that although teenagers, in general, spend more time on SNS, they do not perceive interactions with online contacts as always supportive compared to college age groups. Unlike the findings reported by Liu and colleagues (2018), the current study did not find a moderating role of gender in the relationship between time spent on SNSs and online PSS in the combined community sample.

It is only recently that researchers have started looking at cross-cultural differences in time spent on SNSs and online PSS. To my knowledge, no such studies have been conducted in either New Zealand or Maldives. In the current project there was a significant positive association between time spent on SNSs and online PSS, for both the Maldivian ($\beta = .20$, $p < .001$) and New Zealander ($\beta = .15$, $p < .05$) general samples. However, moderation analysis showed that the strengths of these relationship were not significantly different between the two countries despite Maldivians spending relatively more time on SNSs. On the contrary, Liu and colleagues (2018) found that Asians received more support via generic SNS use than Europeans and Americans. Overall, Maldivians spent more time on SNS than do New Zealanders; over 50% of Maldivians reported spending more than 30 minutes or more per day on SNSs while only 33% of the New Zealand participants in the random community sample reported the same amount of time spent on SNSs. Due to the wide availability of SNS technology, it has become a particularly attractive and convenient means of keeping in touch with family and friends for Maldivians given that more than two thirds of the country's population are dispersed across 200 islands. Therefore, Maldivians are likely to spend more time on SNSs than New Zealanders. There may also be attitudinal differences towards social networking between Maldivians and New Zealanders. Maldivians may see SNS use more favourably and be less worried about privacy than New Zealanders. This speculation is somewhat supported by this study's finding that overall, Maldivians self-disclosed significantly more online than did New Zealanders, and that self-disclosure online was a stronger indicator of online PSS than time spent on SNSs for both countries.

Unlike previous studies, the current study findings showed that the three personality variables (extroversion, conscientiousness, and neuroticism) did not moderate the relationship between time spent on SNSs and online PSS. Therefore, the current study did not find support for the "rich get richer" hypothesis (Amichai-Hamburger & Vinitzky, 2010; Gosling et al., 2011; J. H. Lin et al., 2011; Pfeil, Zaphiris, et al., 2009; P. Sheldon, 2008; Swickert et al., 2002) or the "social compensation" hypothesis (e.g.,Valkenburg et al., 2005; Zywica & Danowski, 2008). Further results on the moderating effects of personality traits are discussed later in this chapter.

Cross-cultural Differences in Other Key Findings on Online PSS Across New Zealand and Maldives Random Community Samples (Chapter 7).

In this section, the discussion focused on the differences in the **direct** relationship between covariates (i.e., demographic, online PSS, and personality variables) and online PSS in the two random community samples separately. The previous section discussed the results of moderation effects of these variables in the relationship between time spent on SNSs and online PSS. The results showed that online PSS and online self-disclosure were positively associated in both New Zealand and Maldives community samples when examined separately. This is consistent with previous findings, which have reported a positive association between online self-disclosure and online PSS regardless of culture (Jeong et al., 2014; K.-T. Lee et al., 2013; D. Liu & Brown, 2014; Nguyen et al., 2012; Trepte & Reinecke, 2013; Utz, 2015).

Although the study found only a marginally significant relationship between neuroticism and online PSS when the random samples were combined, when examined separately, higher levels of neuroticism were significantly associated with higher online PSS for Maldivians but not for New Zealanders. Extroversion and conscientiousness were not significantly related to online PSS in either group**.** This suggests that there may be cross-cultural differences in the relationship between some personality traits and online PSS. The significant relationship between neuroticism and online PSS for Maldivians may highlight a possible cultural difference in relation to Maldivians who are shy or anxious (often associated with high neuroticism) seeking more support online. Unlike New Zealanders, Maldivians may be more likely to be reluctant to talk about mental health problems face-to-face due to stigma and negative attitudes towards mental illness (Maldives Ministry of Health, 2017).

Some interesting cross-cultural differences emerged in relation to age and gender and their association with online PSS. For New Zealanders, greater age was associated with lower online PSS. The results for Maldivians also showed a similar direction as those for New Zealanders; however, the relationship was not as strong although significant. A similar pattern of results also emerged for offline PSS: age was significantly negatively associated with offline PSS for New Zealanders while for Maldivians a similar relationship showed only a trend towards significance. This is interesting and probably suggests some cross-cultural differences in online PSS and offline PSS across the lifespan. It is possible that in Maldives, there was a likely to be a smaller difference between online PSS and offline PSS levels across age because Maldivians face fewer challenges in terms of losing social connections as people age. In Maldives, the elderly are looked after by their families throughout their lives, and there are no rest home facilities. Therefore, the elderly are very much more integrated into the community, thereby maintaining their social networks. In contrast, the significant negative associations between age and online and offline PSS in the New Zealand sample suggests that the general literature on age-related loss of social relationships is more applicable to New Zealanders than Maldivians.

Male gender was significantly associated with higher online PSS than female gender for New Zealanders. The result for Maldivian participants was in the same direction as that for New Zealanders, but the relationship was not significant. This might suggest that New Zealand men gain social support in an online context more than women perhaps because of the factors discussed earlier such as anonymity and ability to freely express oneself. It also suggests that the gender difference in online PSS applies more to New Zealanders than Maldivians. It is hard to know why it does not apply to Maldivians. In the current study, time on SNS use across genders within national samples was not examined but it is likely that in Maldives, there is no significant gender difference in the amount of time spent on SNSs compared to New Zealand. Therefore, in general, both Maldivian men and women reported having similar levels of online PSS.

As noted previously, to date, no studies have examined urban/rural differences in online PSS. Contrary to previous research, the current study found that urban residents had significantly higher offline PSS but no significant difference in online PSS in the New Zealand community sample. On the other hand, there was no significant difference between urban and rural Maldivian residents in either online or offline PSS levels. It is likely that there is no significant difference in online PSS between urban and rural residents because there is no significant difference in amount of time spent on SNSs between the two groups regardless of culture. These findings need further investigation with urban and rural residents more clearly defined for Maldivians.

Taken together, findings from the current project and previous research suggest that engaging in online social interaction has a positive association with online PSS across two diverse cultures. In the next section, the results from the clinical sample are discussed in relation to their time spent on SNSs and online PSS.

The Relationship Between Times Spent on SNS and Online Perceived Social Support in the Clinical Sample (Chapter 7)

The results from the current study showed a significant positive relationship between time spent on SNSs and online PSS after controlling for potential covariates and for the New Zealand clinical sample. Prior research has found that people with mental illness are characterised by deficits in their offline social relationships (Leskelä et al., 2004; Leskelä et al., 2008). As reported earlier, results from the current study indicate that this may also apply in their online social relationships as well. Current study findings showed that neither online PSS nor offline PSS was significantly associated with psychological wellbeing in this group. Age and gender were also not associated with online PSS. Regarding the three personality traits, none of them were significantly associated with online PSS. On the other hand, online self-disclosure showed a trend towards a positive association with online PSS. These findings suggest that SNS communication where this involves high self-disclosure may allow people with mental illness or high neurotic symptoms to acquire online PSS by offering easily accessible interaction. While often not effective in an offline context (Joiner et al., 1999), self-disclosure in the online context may be more functional. In the online context, it appears that generally, people may be more willing to provide supportive comments to negative disclosures than in the offline context because online interactions with people who have mental health problems may not disrupt offline social relationships as much (Ren et al., 2018). Therefore, the current study's findings provide possible evidence that SNS use and online self-disclosure may help people with mental illness to acquire online PSS. This also provides support for the potential benefit of online support groups for those who have difficulty accessing social support in the face-to-face context.

Hypothesis 2: Relationship Between Online Perceived Social Support and Wellbeing; and Hypothesis 3: Relationship Between Offline Perceived Social Support and Wellbeing in the Combined Random Community Sample (Chapter 6)

The association between online social support and psychological wellbeing was tested in a research model derived from the theories of offline social support (S. Cohen & Wills, 1985). Additional variables (online self-disclosure, age, gender, country, region, and personality), identified from the literature review as important were also explored, as either independent variables or covariates.

The current study did not find a significant association between online PSS and psychological wellbeing in the overall random community sample. The current study's finding that offline social support was strongly associated with better psychological wellbeing agrees with the historical literature that indicates social support is a key contributor and a strong predictor of psychological wellbeing (Berkman et al., 2000; S. Cohen, 2004; Helliwell & Putnam, 2004; Kawachi & Berkman, 2001; Ryff & Singer, 2000). Therefore, the study findings provided no support for hypothesis 2 (H_2) but did support hypothesis 3 (H_3).

The failure to find an association between online PSS and wellbeing implies that, although participants perceived that they were getting online PSS from spending time on SNSs, the online PSS had no net additional positive effect on their wellbeing levels. This finding was surprising at first, and differs from previous studies which suggest that the more online PSS people perceive having, the more likely their level of wellbeing will increase or their depressive symptoms will decrease (see review in Chapter 2). Theoretically one would expect a positive relationship between online social support and wellbeing extrapolating from the research findings and theory pertaining to offline social support (S. Cohen & Wills, 1985).

The growing literature on online social support and wellbeing has generated mixed findings with no clear explanation for the contrasting results that have emerged. The results from the current study are in line with those from previous studies that have found no or only weak relationships between online social support or supportive interactions and different indicators of wellbeing (Grieve et al., 2013; H. Kim, 2014; J. Kim & Lee, 2011; Trepte et al., 2014; Utz & Breuer, 2017; van Ingen et al., 2015).

There are a number of points to highlight which may explain why the current study did not find a positive relationship between online PSS and psychological wellbeing. C.-Y. Liu and Yu (2013) also found that the relationship between online social support and wellbeing was weak compared to the relationship between offline social support and wellbeing. They concluded that the relationship between online social support and wellbeing was mediated through offline social support. That is, that online social support helped to increase offline social support and subsequently enhance wellbeing. Although our study did not find support for such a mediation process through regression analyses, a strong positive correlation between online PSS and offline PSS was found; this suggests that although online PSS was not beneficial for wellbeing, it may have helped enhance offline PSS by maintaining or consolidating online contact with participants' friends and family which in turn enhances their wellbeing. Further research using more complex statistical models is needed to explore this relationship.

Although this project did not find a significant overall relationship between online PSS and wellbeing, it is possible that for certain groups, online PSS does have a positive effect on wellbeing. Two such groups may be college students or people who are highly anxious. As our review showed in Chapter two, the majority of the studies that found a positive association between online social support and psychological wellbeing measures used college student samples. For college students, online social networking may help maintain contact with offline networks, and create new offline networks and friendships, which in turn may have a positive effect on wellbeing. Indian and Grieve (2014) found that Facebook social support was related to improved wellbeing for a group with high social anxiety compared to a low social anxiety group. For the low social anxiety group, Facebook social support was not related to wellbeing (Indian & Grieve, 2014). J. Park and colleagues (2016) found that participants who met the criteria for major depressive disorder (MDD) reported having more Facebook social support only when they disclosed negative feelings online. The data from the small clinical sample in the current project did not find a significant relationship between online PSS and psychological wellbeing. However, the direction of the relationship was positive. This needs to be explored with a bigger robust clinical sample to see whether online social support may be perhaps beneficial for psychological wellbeing for people with mental health conditions.

Although the current study found no significant difference in the level of psychological wellbeing between low and high SNS users, Utz and colleagues found that people who are less satisfied with their life were more likely to ask for advice on SNS and that high stress levels were consistently related to asking for advice (Utz &

Breuer, 2017). Therefore, individuals with lower wellbeing may be more likely to turn to SNSs for social support thus showing no statistically significant relationship between online PSS and psychological wellbeing. This relationship could be expected in a longitudinal cohort study aimed at distinguishing temporal pathways.

It is also possible that the lack of a statistically significant relationship between online PSS and psychological wellbeing was due to the overall lower online PSS levels that participants had reported compared to their overall offline PSS levels. That is, the level of online PSS may not have been sufficient to have a positive association on wellbeing. The results from the current study indicate that the mean level of online PSS was significantly lower than the mean level of offline PSS in both New Zealand and Maldives random community samples.

There are other factors that were not explored in this study that may have influenced the relationship between online PSS and psychological wellbeing. For instance, although people perceived themselves as having online social support from SNSs, they are also likely to be at risk of negative experiences such as cyberbullying and trolling which can have a negative effect on their wellbeing. Cole and colleagues found that while spending more time online increases the extent of social support from one's online social network it also increases one's risk for cyber-victimisation (Cole et al., 2017). It is also possible that SNSs may have positive and negative impacts which may cancel each other out, showing no significant associations with psychological wellbeing. Therefore, the research field needs instruments which are able to tap into both positive and negative impacts of SNS use. Furthermore, the effects on both social support and wellbeing may depend on the type of SNS used. For example, Facebook appears to provide more opportunities for personalised communication, whereas Twitter is a tool for news and political and less personal communication. It appears that the majority of people use more than one SNS site and the impact of using one or several social media sites needs to be explored for better understanding. In the interest of keeping the questionnaire short, data on functions of different types of SNSs and negative experiences of SNS use was not collected in the current project. In addition, the main focus of the study was on replicating the positive effects of SNS use using a large robust random sample as previous studies have predominantly used unrepresentative and underpowered convenience samples.

Another reason why the current study did not find a statistical relationship between online PSS and wellbeing may be because the online support measure used did not assess the full range of different support types available from online networks. At the time of research design and selection of measures, a comprehensive search for valid measures of online social support was conducted (Ali et al., in preparation). Based on the review, the oMSPSS was chosen as the most appropriate measure of online PSS available at the time. However, in addition to online perceived social support from family and friends, support from online groups or online contacts such as anonymous 'followers' or 'friends' may be as important to consider. More details regarding the limitations of the measures used in the current study are discussed later in this chapter.

There are also differences in the social support measures used in this study compared to other work, which may have contributed to the failure to replicate previous results. For instance, Burke and colleagues used the Bonding Social Capital subscale from Williams' (2006) Internet Social Capital scales to measure online support very broadly with statements such as "There are several people I trust to help solve my problems" (Burke et al., 2010; Williams, 2006). This measure does not differentiate support from friends, family, and significant others on SNS the way the oMSPSS used in the current study does. Perhaps, in the online context, measuring social support from wider online networks (e.g., online groups, online-only friends, followers) may be more appropriate as these sources could provide online social support in addition to family and friends. The oMSPSS used in this study did not specifically measure social support from 'online groups' or 'online friends' or 'followers' that you may not interact face-to-face with, which are important to consider in the online context. Moreover, there may be different effects from 'received' and 'perceived' support on wellbeing. Zhang found a positive relationship between 'received support' from Facebook and satisfaction with life (Zhang, 2017). This is different from 'perceived social support' as 'received support' measured the frequency of encouragement from Facebook friends to feel better about oneself, tangible help from Facebook friends to deal with difficulties, advice from Facebook friends to solve problems, and information provided by Facebook friends to understand a situation. Therefore, it may be that for SNS users, it may not be the perceived social support that is associated with positive psychological wellbeing. Rather the amount of emotional, tangible (e.g., financial donations), and informational support one receives from others online may be more important.

It is also likely that SNSs are not always ‘places’ where you can form stronger bonds by just spending more time there. Offline perceived social support comes from strong enduring ties which usually occur face-to-face over time in association with full disclosure and reciprocity (Antonucci & Jackson, 1990). This idea is supported by some studies. For instance, Grieve and colleagues (2013) found that when social connectedness is strong on SNSs, there is an increase in satisfaction with life (Grieve et al., 2013). A study using Spanish teenagers found a positive relationship between online friendship strength and wellbeing (Apaolaza et al., 2013). Burke and Kraut (2016) also found that ‘composed’ communication rather than ‘one-click’ communication from ‘strong ties’ was also associated with an increase in psychological wellbeing (Burke & Kraut, 2016).

Taken together, these findings suggest that perceived online social support may not benefit everyone the same way, and it may also come with some risks. It also suggests that online social support may be more beneficial for those who are socially more anxious or spend less time in face-to-face social interaction. Given that our random sample group came from the community, the majority of the participants most likely do not have significant anxiety problems. The results from our clinical sample show a trend towards a positive association between online PSS and psychological wellbeing, but the results were not significant possibly because it was a much smaller sample and therefore, was underpowered. Our results highlight the need for more research to tease apart the separate roles of online and offline social interactions in wellbeing using longitudinal designs, which include more sophisticated measures of online relating.

Other Key Findings Concerning Psychological Wellbeing in the Combined New Zealand and Maldives Random Community Sample (Chapter 6)

In addition to the support for the main hypothesis, other notable findings also emerged in relation to other predictors of wellbeing. These findings are discussed next.

Online self-disclosure and psychological wellbeing. The results of the regression analyses showed that online self-disclosure did not have a significant association with wellbeing after controlling for demographic and personality variables.

Although our study found a positive association between online self-disclosure and online PSS, which is consistent with the literature on self-disclosure and social connection (N. Park et al., 2011; Utz, 2015), self-disclosure did not directly or indirectly have an effect on wellbeing. Therefore, our results suggest that online self-disclosure may not have any benefits in terms of enhancing psychological wellbeing despite having a positive relationship with online social support. This contradicts previous studies on the health-related effects of online self-disclosure in the context of internet support groups for individuals coping with various health and emotional issues (Barak & Gluck-Ofri, 2007; Shaw et al., 2006; Shim et al., 2011). Those studies indicated that self-disclosure in closed forums or online support groups had positive effects on the users' emotional wellbeing. Therefore, it may be likely that online self-disclosure is beneficial when shared with people with similar interests or concerns mostly in closed groups. Our study did not differentiate between public and private disclosure. Contrary to our findings, Lee and colleagues (2011) found evidence that self-disclosure on social networking sites can improve subjective wellbeing in college students (G. Lee et al., 2011). This suggests that online self-disclosure may be beneficial in certain groups such as college students who use SNSs as a means of communicating and sharing their experiences with offline social networks, but this may not generalise to the broader population.

Another explanation for the lack of a significant relationship between online self-disclosure and psychological wellbeing in the current study may be the potential negative effects of online disclosure such as online harassment, cyberbullying, and negative attention despite its benefits in building social relationships. This may be particularly germane if the online self-disclosure occurs in the public SNS spaces. As previously noted, the current study did not measure risk factors associated with SNSs and therefore, they were not controlled for.

Personality and psychological wellbeing. As expected, all three personality variables were significantly associated with wellbeing. Both extroversion and conscientiousness were positively associated with wellbeing while neuroticism was negatively associated with wellbeing. The results from the multivariable regressions showed an additional increase of 14% variance in wellbeing when the personality variables were added to the final model. This is consistent with previous literature which states that personality factors could account for a significant amount of variance in the relationship between social support and psychological wellbeing (I. G. Sarason et al., 1983). In particular, sociability, which is a facet of extroversion has been related to increased positive affect (Emmons & Diener, 1985). That is sociable individuals spend more time in social situations, which in turn has been associated with happiness. Further support for the association between life satisfaction and personality traits has been demonstrated by the results of the meta-analysis reported by Steel and colleagues (2008). Although the strongest associations observed involved neuroticism and extroversion, conscientiousness and agreeableness also had moderate associations with subjective wellbeing (Steel et al., 2008). The current study found that when personality variables were entered simultaneously in the model that also included social support variables as predictors, extroversion, conscientiousness, and neuroticism had significant associations with wellbeing. This provides further support for the robust literature on the link between personality variables and psychological wellbeing. Our results showed that personality traits were significantly associated with psychological wellbeing, even after controlling for some of its well-known determinants (i.e., social support, age, gender, and self-disclosure). This suggests that personality traits can help to explain some of the variations in wellbeing and therefore are important to consider or control for.

Other correlates of psychological wellbeing. In relation to demographic factors controlled for in the regression model looking at the relationship between online PSS and offline PSS and wellbeing, being a New Zealander was associated with higher wellbeing while the other three covariates of age, gender, and region did not produce significant associations.

The significant difference in wellbeing between New Zealanders and Maldivians is consistent with research findings that focus on cultural factors related to wellbeing (Suh & Oishi, 2002). The difference in wellbeing level between Maldives and New Zealand could be explained by the individualist versus collectivist cultural characteristics which are found to be related psychological wellbeing. Two reviews of literature have concluded that members from individualist cultures are happier than members of collectivist cultures (Diener et al., 1995; Suh & Oishi, 2002). As discussed in Chapter three, Maldives has a generally more collectivist culture compared to New

Zealand. In addition, in recent years, Maldives has experienced significant political and economic instability which are also factors that affect wellbeing. In highly individualist cultures such as the United States and Western/Northern Europe, the rights, liberty, and distinctive emotions of each individual is highlighted over the in-group's expectations and needs, such as family. In individualist cultures, a sense of freedom and self-worth are associated with higher wellbeing (Inglehart et al., 2008). In more collectivist societies (e.g., East Asia, Central/South America), the goals and needs of a significant in-group tend to take precedence over an individual's thoughts, values, and preferences of an individual, particularly comprising the experience of subjective wellbeing (Fischer & Boer, 2011; Suh & Oishi, 2002).

The covariates age, gender, and region were not related to wellbeing. The non-significant R^2 change when these demographic variables were added to the regression model suggests that these variables did not either directly or indirectly relate to psychological wellbeing. The non-significant relationship between age and wellbeing supports the literature on the stability of wellbeing across the lifespan (Diener & Suh, 1997). Although this study did not explore the difference in wellbeing between different age groups, others have found a U-shaped relationship between life satisfaction and age, with the lowest level of life satisfaction occurring in the age group 35-50 (Blanchflower & Oswald, 2008). Similar to age, gender also did not predict wellbeing.

R3: Is the association between online perceived social support/offline perceived social support and psychological wellbeing moderated by demographic and personality variables in the combined community sample?

Further moderation analysis provided essential details regarding the relationship between key predictors (i.e., online PSS, offline PSS, and online self-disclosure) and psychological wellbeing. Results from the current study showed that age, gender, region, country, and personality variables did not moderate the relationship between the three predictors and psychological wellbeing. Some have reported age differences in terms of social support structures or social network sizes and/or support seeking behaviours (van Baarsen, 2002; Vaux, 1985). However, the association between offline social support and wellbeing may not vary with age (Siedlecki et al., 2014; Segrin, 2006; Vaux, 1985). Overall, it appears that whilst everyone benefits from social support regardless of age in terms of wellbeing, the structure of social support changes as people get older with fewer close contacts. Van Baarsen's (2002) study findings suggest that there may be other factors, such as loneliness after partner loss and self-esteem which may affect support seeking behaviour or perceived social support levels. Results from the current study support previous literature indicating that the association between social support and wellbeing may not vary with age. Moderation analysis from the current study showed that the relationship between perceived social support (both online and offline) and psychological wellbeing did not significantly vary with age.

Although studies have found some evidence to support gender difference in online social support (Luarn et al., 2015; Teoh et al., 2015), in the current project the association between online social support and psychological wellbeing did not vary between males and females. Similarly, the relationship between offline PSS or online self-disclosure and psychological wellbeing also did not vary between males and females.

As reported in Chapter one, cultural differences are an important phenomenon potentially influencing how social support is communicated and provided. Westerners appear to be more strongly encouraged to request for social support in the offline context in times of stress than non-Westerners (H. S. Kim et al., 2008). A recent meta-analysis reported that Asians were found to receive more social support via SNS than Europeans and Americans (D. Liu et al., 2018), but there seems to be a lack of research exploring the cultural differences in the relationship between online social support and psychological wellbeing. Moderation analyses from the current study for both these associations (i.e. online PSS and wellbeing/ offline PSS and wellbeing) were similar across cultures. That is, online PSS was not associated significantly with wellbeing in either cultural sample while offline PSS was associated significantly with wellbeing in both cultures. There were no cross-cultural differences in the relationship between online self-disclosure and wellbeing.

The link between perceived social support (online and offline) and psychological wellbeing was not moderated by the three personality variables extroversion, conscientiousness, and neuroticism. Unlike previous findings, the current study findings did not find a significant difference in the relationship between online self-disclosure and psychological wellbeing between those scoring high and low on the personality variables (Seidman, 2013). In conclusion, this study findings did not support either the rich-get-richer or the social compensation hypotheses (Zywica & Danowski, 2008). Future research could further address whether specific SNS platforms can serve as an enhancer for extraverted users and a compensatory tool for users scoring high on neuroticism, to promote psychological wellbeing for both groups.

Cross-cultural Differences in the Relationship Between Online PSS, Offline PSS, and Psychological Wellbeing Across the New Zealand and Maldives Random Community Samples (Chapter 7)

The analyses carried out to explore the cultural differences in relation to the study hypotheses two and three. These analyses were carried out after adjusting the estimated measurement variance which is considered important in cross-cultural research to achieve reliable and valid comparisons. Across both New Zealand and Maldives, the results were consistent for both hypotheses two and three after taking MV estimates into consideration. That is, a non-significant association between online PSS and wellbeing was found in both sub-samples. The significant positive association between offline PSS and wellbeing was found for both Maldivian and New Zealand groups independently. These findings are in line with the previous research that did not find a significant relationship between online PSS and wellbeing in samples from both America (Hu et al., 2017; H. Kim, 2014) and Europe (Trepte et al., 2014; Utz & Breuer, 2017). Overall, the results demonstrate the universal importance of offline social support for psychological wellbeing irrespective of culture.

With regard to personality factors, there were no cross-cultural differences in the relationships between either conscientiousness or neuroticism and wellbeing. Across both groups, conscientiousness was positively associated with wellbeing while neuroticism was negatively related to wellbeing. When groups were explored separately, the relationship between extroversion and wellbeing remained significant and positive for the New Zealand random community sample. However, this relation was not significant for the Maldivian random community sample but the direction of the relationship was similar to the New Zealand group and showed a trend towards significance. These findings provide some support for the well-established literature on personality and wellbeing, and the cross-cultural validity of some of the factors of the five-factor model of personality. However, further studies using more comprehensive measures of personality factors will be important.

With regard to age, gender, and region, none of these variables significantly predicted wellbeing in any of the subsamples after controlling for other variables. That is, neither age, gender, nor region was directly associated with psychological wellbeing (no main effect). These findings need to be discussed in light of previous research findings which are complex and beyond the aims of the current study.

The Relationship Between Online/Offline PSS and Psychological Wellbeing in the Clinical Sample (Chapter 7)

Interestingly, our results showed that neither online PSS nor offline PSS was significantly associated with psychological wellbeing in the clinical sample. Although the results were not significant (likely influenced by the small sample size), the direction and strength of the relationship between online PSS and wellbeing was large and positive compared to the small negative effect of offline PSS on wellbeing. Overall, the results from the current study point to the possibility that perceived social support (online or offline) may not, of themselves, help improve the psychological wellbeing of people with mental health conditions. Some argue that an important factor which may contribute to this difference is a low level of "resilience" in 'at-risk' groups such as those with mental health problems (Zautra et al., 2010). Zautra and colleagues argued that social support is a form of resilience which promotes adaptation to adversity. Another interesting finding from this sample group was the negative association between neuroticism and psychological wellbeing. Compared to the two community samples, the clinical sample had higher mean scores for neuroticism. This is consistent with the presence of negative psychological symptomatology in the clinical sample. The non-significant finding between perceived offline social support and psychological wellbeing highlights the possibility of mental health problems disrupting offline social relationships or reflecting difficult offline relationships as previous literature has reported (S. Henderson, 1981). Characteristics associated with mental health problems can influence the ability to feel a sense of belonging or have biases in social information processing (Gotlib et al., 2004; Joiner & Coyne, 1999; Ren et al., 2018; Steger & Kashdan, 2009).

In addition to the non-significant main effects between online PSS and offline PSS on psychological wellbeing, the moderation analyses carried out for the New Zealand clinical sample showed that none of the demographic or personality variables moderated the relationship between predictors (online PSS, offline PSS, and online self-disclosure) and psychological wellbeing.

Implications for Research and Practice

The findings from this research project have a number of implications for researchers, health practitioners/educators, and policymakers. First, despite people perceiving themselves as getting social support from spending time on SNSs, this support did not have an empirically demonstrable positive effect on their psychological wellbeing. Therefore, unlike the well-established main effects theory linking offline PSS and wellbeing, this study found no evidence to conclude the same association exists for online PSS in a large randomly selected representative community sample. Spending time on SNS use may be beneficial for acquiring social support. This may be particularly true for cultures like Maldives where people depend on SNSs for social interactions due to the geographical nature of the country, with most of the island communities separated by ocean. However, perceived social support acquired from SNSs appears to be inadequate for users to experience increased wellbeing. It is possible that negative consequences of SNS use (i.e., cyberbullying, negative self-comparison to others, greater exposure to undesirable material from others, and online addiction) outweighed the potential benefits of SNS use (i.e., easier access to potentially supportive friends and loved ones, and access to information related to social events). Perhaps SNS use and online PSS may benefit wellbeing when used moderately and only with offline contacts. Given that online PSS is a relatively new phenomenon and research findings are inconsistent, research needs to continue with more comprehensive measurement tools and exploratory research designs.

One of the most influential variables on psychological wellbeing, that persisted even when controlling for demographic variables and personality variables, was offline PSS. This study was able to provide further support for the idea that engagement in meaningful and intimate social relationships is one of the key components through which social factors may influence wellbeing (Berkman et al., 2000; S. Cohen, 2004;

Kawachi & Berkman, 2001; Ryff & Singer, 2000). The main positive effect of offline PSS on wellbeing, alongside no effect from online PSS, was consistently detected in both the community random samples. That is, the primary finding that offline social support was strongly and positively related to wellbeing, where online social support was not, was found consistently across combined, and Maldives and New Zealand community samples. Another important finding from the current study was the non-significant association between offline social support and psychological wellbeing in the clinical sample. This finding may reflect the presence of a ‘plaintive set’ or tendency to describe having inadequate social support among the psychiatric population. Statistical associations found between offline perceived social support and wellbeing in the general population sample imply that developing appropriate social support interventions for people lacking such support would be beneficial in terms of their psychological wellbeing and promoting resilience in the general population. With regard to developing perceived social support interventions, one way forward may be to focus on raising awareness about the risks associated with SNS use, strengthening face-to-face social interaction, and increasing opportunities for social integration.

Other Important Contributions from the Project

In addition to finding support for the main effects of offline social support, this research found support for the well-established role of personality variables in psychological wellbeing. The current study has successfully confirmed the importance of personality factors (extroversion, conscientiousness, and neuroticism) in predicting psychological wellbeing. The multivariable regression analyses showed that personality variables added significant variance over and above the other variables in the models predicting psychological wellbeing. Tailoring health and wellness programmes to improve quality of life with special attention given to individual personality characteristics (especially the Big Five) could enhance lifestyle health behaviours that promote psychological wellbeing. In particular, focusing on developing interventions to manage emotion regulation difficulties associated with neuroticism would be important (Bolger & Zuckerman, 1995; Purnamaningsih, 2017).

The current study provides support for a positive association between online self-disclosure and online PSS in both New Zealand and Maldives community samples. This is an important finding given that there is only one study that has examined the relationship between online self-disclosure and online PSS using a relatively small convenience sample of college students (K.-T. Lee et al., 2013). The current project contributes to the literature on the importance of online self-disclosure and social relationships formed online. Furthermore, it has provided support for the importance of controlling for online self-disclosure in the relationship between time on SNS use and online PSS.

This study has also shed some light on cross-cultural similarities and differences in SNS use, social support, and psychological wellbeing. As noted, the consistent finding that offline PSS was associated with wellbeing across both countries adds to the existing literature on the importance of offline social support in promoting mental health. This finding is particularly important for Maldives where research on mental health and wellbeing is scarce. More than half of the sampled Maldivians reported spending a greater amount of time online and disclosing more online compared to those in the New Zealand sample. Although Maldivians may find SNS communication more beneficial to maintain social connections than New Zealanders, this may inadvertently increase their risk of exposure to the harmful effects of SNS use such as cyber-victimisation. It is relevant that the overall offline PSS and wellbeing levels for Maldivians were significantly lower than New Zealanders'. This may indicate possibly that in Maldives there is a decrease in offline social relating as a result of increased time on SNSs. Therefore, it may be important to take preventive measures to increase awareness of the importance of offline PSS. This may be particularly important among the younger generations who spend more time on SNSs than older cohorts, as indicated by the negative relationship between age and time spent on SNS found in the current study.

Strengths

The current study has a number of key strengths. First and foremost, it was conducted within a coherent theoretical model of online PSS built from the existing literature on constructs pertaining to online social behaviour as well as offline social support and wellbeing. The study measures were selected based on a clear definition of perceived social support and the expected theoretical mechanisms by which the measures would have expected effects. Selection of uniform online and offline social support measures made it possible to compare their effects on wellbeing. Therefore, there was consistency across the theoretical frameworks used for the measures selected, and the interpretation of findings. Despite the fact that not all tenets of the proposed model were supported in the present study, the key findings provide a general framework within which to interpret the results and consider future research directions.

Random and Adequate Sizing of the Primary Samples

This study is based on representative samples of the general population aged 18 and above from each country. The response rate for the current study was considered adequate for a postal survey design. The sample size was sufficient to permit multivariable regression analyses and the evaluation of the unique associations of several independent variables and one dependent variable in the model. The application of multiple regressions using several predictors of wellbeing strengthened the conclusions of the study. The ability to control for other independent variables (i.e., demographic factors, personality traits, and online self-disclosure) was important in understanding the interrelated effects of demographic variables, online self-disclosure, and personality variables and in uncovering a mediating effect in the association between both online PSS and offline PSS with psychological wellbeing.

Another strength of the current study is its novel contribution to the literature on online social support perceived in a general population sample from Maldives and New Zealand. The diversity of the sample (on some key dimensions) is another asset of the present study. Whereas the sample was limited in terms of ethnicity for the New Zealand sample, in both samples both genders, a broad range of ages, and urban/rural residents were represented. The ability to generalize the results of this study is restricted by limitations that will be discussed in the next section; however, the diversity of the sample enhances the likelihood that these results can be applied to the larger population.

Choice of Instruments

The choice of measure for online PSS was based on a review of available online PSS measures and evaluation of their psychometric properties (Ali, Bell, & Romans, in preparation). Based on the review, the MSPSS was adapted (called oMSPSS) for the online context given that it has been a widely used measure both in the offline context (Eker et al., 2000; Zimet et al., 1998) and online context (Y-K. Cho & Yoo, 2016; Obst & Stafurik, 2010). The oMSPSS performed well in terms of its reliability, which provides an important indication of its usefulness in evaluating online support. Clearly there is an urgent need to develop more psychometrically robust comprehensive instruments for online social support.

Cross-cultural Comparisons

All of the hypotheses were tested on subsamples from two contrasting countries, which enabled the author to assess the replicability of the study's findings across two cultural groups. An emergent strength of the study was that most of the statistically significant associations were observed in both random samples even after MV was considered. The consistency of the findings across two different cultures appears meaningful, suggesting some cross-cultural generalisability within the field of social support that invites replication and further research.

Limitations and Recommendations for Future Research

A number of limitations that point to interesting opportunities for further research were observed. These limitations do not undermine the importance of this research, but are important to acknowledge. These limitations are noted, possible future research is recommended, and theoretical implications are proposed.

Cross-sectional, Correlational Survey Design

Ultimately, social support researchers want to know whether, when, and how social support causes changes in the recipient's mood or wellbeing. Given the cross-sectional nature of this study, its results can only be used to generate suggestions for how social support and wellbeing might be causally related. Any proposals regarding causal relations must be considered tentative because the constructs were all measured at the same point in time. The researcher, therefore, did not have the ability to control for previous wellbeing levels or previous levels of support when estimating the associations of interest. However, two recent cohort studies have reported no longitudinal relationships between online social support and psychological wellbeing in large samples of SNS users (Trepte et al, 2014; Utz and Bruer, 2017). This suggests that online PSS may not have the same benefits as offline PSS in enhancing psychological wellbeing, particularly for people from the general population.

Although survey designs have distinct advantages (such as easy implementation and less expense) over experimental or longitudinal designs, they do have limitations. First, causal inferences cannot be made with cross-sectional designs because the data is measured at one time interval unlike longitudinal studies. Furthermore, the use of a survey design in the current project is associated with challenges to internal validity due to limitations in controlling all potentially related variables. The author of this project did consider some key variables such as age and gender and personality variables that are likely to be associated with social support and wellbeing as a way to address this challenge. However, future research could consider conducting longitudinal studies while controlling for important factors such as cyber-victimisation, and online addiction if and when it becomes formalised. In spite of the weaknesses associated with the use of non-experimental or non-longitudinal designs, survey studies are still quite commonly used in studies looking at novel psychological areas. This is possibly because (apart from its potential problems with causal links) studies of this nature can still be a useful first step towards inferring causation by demonstrating correlations that support theory-based predictions.

Taking into account the limitations of using a cross-sectional survey design, future research to measure people's online social support and wellbeing should consider the use of non-college samples in longitudinal cohort studies that may uncover causal relationships. Adolescents and older adults are worth studying in the future as their use of SNSs can be vastly different.

Measurement Issues

First of all, as the data coming from this study covered a variety of topics including online and offline social support, personality, online self-disclosure, and psychological wellbeing, short or abbreviated scales were chosen to minimise responder fatigue and the non-response rate. Although care was taken to select measures with strong psychometric properties, there are some limitations that need to be addressed.

The literature review revealed that there is a lack of validated measures of online social support. The online social support measure (oMSPSS) used in this study was adapted from a measure designed to measure offline perceived social support (MSPSS) (Zimmet et al, 1988) and later used to assess online PSS. Although the oMSPSS demonstrated excellent internal consistency across both sub-samples, it is possible that the oMPSS failed to tap into some unique aspects of social support acquired from SNSs. Therefore, other measures should be considered in future research. Very recently (after the data collection phase of this project had been completed), a promising scale to measure online social support was developed by Nick and colleagues (2018) which was based on previous empirical and theoretical work on offline social support. Their 40-item measure called the Online Social Support Scale (OSSS) broadly covers people's perception of having four types of support (emotional support, social companionship, informational support, and tangible support) and the items are specifically designed for the online context. For example, some of the items are "when I am online, people help me understand my situation better", "I am part of groups online", and "I contact people online to get help or raise money for things I think are important" (Nick et al., 2018). Future researchers could use the OSSS to measure online social support and the effects on psychological variables, and interactions with personality traits. It is possible that a different measure of support availability might capture some support more specifically related to the online context. Inclusion of measures of the negative effects of online SNSs may also be important for SNS use and wellbeing research, given research discussing the potential harms of cyberbullying and 'trolling'. Future research can build on the current study findings and further examine the potential moderators of the relationship between online PSS and psychological wellbeing such as cyberbullying or negative life events.

Methodological concerns also arise from the use of self-report measures. The reliance on self-reported data could lead to errors such as social desirability bias (Nederhof, 1985) or self-selection bias (Jones et al., 2016). Therefore, it would be more accurate to observe people's actual communication behaviours online. For example, Park and colleagues (2013) developed a Facebook web application or diary to gather social activity data from Facebook users and provide online screening for depression (S. Park et al., 2013). Another study employed a similar approach to collect participants' status updates, 'wall posts', and private messages on Facebook, and asked participants to rate the intimacy and personal relevance of each post (Bazarova et al., 2015). Future research might also consider this approach for data collection.

It would be useful to broaden the scope of the research by comparing the different types of SNS applications. Lenhard (2015) found that the use of different SNS platforms has diversified with young adults using multiple SNS applications compared to older cohorts. Individuals' online social interaction may differ according to the characteristics of the different SNS applications. For example, Facebook confession boards enable users to discuss taboo topics and explore stigma related topics giving rise to new opportunities and risks (Bazarova et al., 2015). Furthermore, Panger (2014) reported that unfavourable social comparisons were more common on Facebook than Twitter and therefore the former platform left users more vulnerable to poor wellbeing.

The current study used an estimation approach to MI to draw valid conclusions regarding the mean differences in key variables and their correlations across New Zealanders and Maldivians. Future research would be important to 'test' for cross-cultural MI of measures used and revise/adapt the measures if necessary, to ensure that cross-cultural comparisons are valid and meaningful.

Conclusion

This research was carried out to study SNS use, online PSS and its role in psychological wellbeing in comparison to offline PSS in two robust community samples from two distinct cultures. The use of a small convenience clinical sample added value by providing clinical versus nonclinical comparisons in the associations between variables examined in the current research. The findings from this project provided information relevant to public concerns regarding the increase in social media use and its potentially negative impact on psychological wellbeing. In line with many previous studies, this study found no significant association between amount of time spent on SNSs and psychological wellbeing. Current study findings showed a significant relationship between time spent on SNSs per day and online PSS. However, this perception of having support from online interaction was not associated with better psychological wellbeing. On the other hand, regardless of cultural background, perceived social support from offline social networks was positively related to wellbeing. These findings suggest that while individuals may report that support provided by friends and family on SNSs is beneficial, this support may not translate to measurable improvements in wellbeing. However, it may be the case that an intrinsic confounding of social networking affects online social support: individuals who are in more distress access social support resources more often when compared with those in less distress. Hence, in cross-sectional research, it is difficult to determine whether social support predicts worse wellbeing or whether more distressed individuals access social support resources more frequently to cope with this distress. This uncertainty may account for these seemingly paradoxical study findings.

Either way, the results suggest that greater offline social support is associated with increased psychological wellbeing. This is particularly important given that more and more people are interacting online. This is a particularly an important message to be shared with young people given that they are spending an increasing amount of time on SNSs which may put them at risk of neglecting important offline social networks.

In conclusion, the current project can be considered to have made a unique and important contribution to the understanding of both online and offline social support in two contrasting cultures. This is particularly important for Maldives where social science research is scarce. It provides exploratory evidence for practitioners to address the importance of maintaining face-to-face social support in a world where social media is taking up a significant amount of people’s time, and functions as a reference point for the development of further online behaviour research. This study not only provided an expansion of this research to a new cultural context (i.e., Maldives) but also provided a unique contribution to the literature examining the role of cultural context in understanding psychological processes.

Significance of this Project

The role of offline social support in psychological wellbeing has been an area of academic interest for decades. More recently, with the growing use of SNSs around the globe, researchers have begun to look at social support received on SNSs and whether this online social support has the same benefits as offline support for wellbeing. Given that SNS behaviour is a relatively new topic in the literature and that the findings in the literature have been inconsistent in relation to online PSS and psychological wellbeing, there is a need for continuing research in the area that is based on theory and which uses robust samples and study designs. With regard to future investigations, the current project provides an initial reference point from which to further develop psychological measures and study designs with which to explore the role of online PSS and psychological wellbeing.

The current research addresses gaps in the literature by examining the impact of potentially relevant correlates of online PSS. Of the demographic factors, personality traits, online self-disclosure, age, and online self-disclosure were shown to be important predictors of online PSS across both New Zealand and Maldives. There may be cultural differences in the effects of gender and personality traits on online PSS. There were no urban/rural differences in online PSS in either New Zealand or Maldives. These findings highlight the importance of controlling for potential confounders such as age, gender, personality traits, and online self-disclosure in future studies.

Finally, the current research project is the first well-powered study to examine the relationship between online social support from SNS use and psychological wellbeing using robust community samples from two nations. The current study shows that ‘the new way of being and relating to others’ in today’s digitalised world should not replace the importance of promoting and keeping offline relationships. Face-to-face interaction or interacting through a variety of means with ‘real’ friends with whom people can establish caring and close relationships are fundamental for psychological wellbeing.

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APPENDICES

APPENDIX. A-1: Survey Questionnaire for New Zealand Participants

Survey Questionnaire for New Zealanders

Information Sheet

Dear (*participant first name*)

My name is Afiya Ali and I am researching the impact of online social networking (or use of online communication) for social support and psychological wellbeing. Please help us to understand how online social networking affects social relationships and psychological wellbeing (positive experience in life) by completing this questionnaire. Details of this study are provided below.

1. What is the study about? You are invited to take part in a research study to examine the impact of online social networking on social support and psychological wellbeing. The information gained from this research will identify issues related to social support and wellbeing in the changing world of social interaction. This research is my PhD project at the University of Otago which is supervised by Dr Elliot Bell and Professor Sarah Romans.

2. How much time will I need to spend? It will generally take 20-25 minutes to complete the questionnaire. We appreciate your valuable time. When you complete the questionnaire within 3 weeks from the date on this information sheet, you are eligible to enter a lucky draw to either win a Samsung tablet 16 GB or a $400 shopping voucher.

3. How do I decide if I want to be involved in the study? Participation is entirely up to you. Feel free to talk to others such as a support person, friend, family, or whanau about the study to decide whether to take part in it. If you decide to take part and send us the completed questionnaire you may not be able to withdraw your responses as it then becomes part of the research data. These data, which would not identify you, may be used in future studies.

4. What will I be asked to do for the study? You can return this questionnaire by post (in the freepost envelop provided), or email (scan and send to aliaf675@student.otago.ac.nz) or fax to (04 385 5877), or if you would like to complete it online go to (web address), click on the 'take survey' link, and then enter your personal code (give here)

If you decide you want to take part in the research project, you will be asked to sign the consent form provided. By signing it you are telling us that you:

- understand what you have read;
- consent to take part in the research project

5. Who is being asked to take part in the study? You are one of 1000 adults selected from New Zealand and Maldives by random sampling using the electoral rolls. We are very keen to receive responses from all those who are selected, as this is how we ensure that the views we gather represent a full range of adults. By comparing these two groups, we may detect differences in use of social network sites and online social support between the two countries.

Go to next page →

6. Why is this study beingundertaken? People are spending more and more time interacting with others through online social network sites. This has the potential to significantly change social relationships and psychological wellbeing. Learning about the impact of online social networking on social support and wellbeing can guide us to use online social network sites effectively.

7. How will being involved in the study affect me? This is an observational study with no associated health risks. However, you can stop answering the questionnaire if you become upset or distressed as a result of your participation in the research. If you do become upset or distressed as a result of your participation in the research, please let me know and I will discuss this with my supervisors to find you the most appropriate help. Generally people are advised to call 0800 543 354, the 24/7 helpline which offers free, anonymous and confidential support, or to contact their GP.

8. Who will know that I have taken part in the study? Your response will be treated with full confidentiality by the research team. No identifying information about you will be made public. Your code will only be used to distribute the prizes and the key linking your name will be destroyed after the prize draws. All records and materials associated with the study will be stored securely and destroyed after ten years.

9. How will I know about the results? At the end of the research, a report will be written and the results may be published in peer reviewed journals and conference presentations. This report will be posted online in due course and you will be given the link to the site, so you can learn about the findings.

10. Where do I get information about my rights? If you have any concerns about your rights as a participant in this study you can talk to a health and disability advocate about your concerns (Freephone 0800 555 050 or email: advocacy@hdc.org.nz). This study has been approved by the University of Otago, Human Ethics Committee (Health). If you have any concerns about the ethical conduct of the research you may contact the Committee through the Human Ethics Committee Administrator (phone: +64 3 479 8256 or email: gary.witte@otago.ac.nz). Any issues you raise will be treated in confidence and investigated and you will be informed of the outcome.

If you want any more information about any aspect of the study please contact Afiya Ali

PhD Candidate (Co-investigator):	**Supervisor(Principal Investigator):**	**Supervisor (Co-investigator):**
Afiya Ali Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0210500953 Fax: 04 385 5877 E-mail: afiya.ali@postgrad.otago.ac.nz	Dr Elliot Bell Lecturer and clinical psychologist Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0274 739 886 Fax: 04 385 5877 E-mail: elliot.bell@otago.ac.nz	Professor Sarah Romans Professor Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0211157137 Fax: 04 385 5877 E-mail: sarah.romans@otago.ac.nz

Go to next page

Response by: post in envelope provided; scan and email to ***afiya.ali@postgrad.otago.ac.nz****; fax to* ***04 385 5877****; or complete online at* ***(web link)*** *– your access code is ….*

UNIVERSITY of OTAGO
Te Whare Wānanga o Otāgo
NEW ZEALAND

CONSENT FORM

STUDY: **The impact of online social networking on social support and psychological wellbeing**

Please tick the boxes next to the statements if you agree with them:

☐ I have read the Information Sheet concerning the study titled "The impact of online social networking, on social support and psychological wellbeing**"** exploring '*my thoughts and feelings about online social networking'*.

☐ All my questions about the project have been answered to my satisfaction, and I understand that I am free to request further information at any stage.

☐ I understand that if I do not wish to take part, I do not have to complete the questionnaire. If I do complete and return the questionnaire it may not be possible to withdraw my answers.

☐ I understand that my participation in this study is confidential and any personal identifying information will not appear in any spoken or written report of the study.

☐ I understand the nature and size of the risks of discomfort or harm which are explained in the Information Sheet.

☐ I have had time to consider whether to take part.

☐ I know who to contact if I have any queries about the study.

Go to next page →

Response by: *post in envelope provided; scan and email to* ***afiya.ali@postgrad.otago.ac.nz****; fax to* ***04 385 5877****; or complete online at (****web link****) – your access code is ….*

Please tick "yes" or "no" to show if you agree/consent to the following:

- I wish to receive a copy of the results, when available once published (approximately 2 years)

  ○ YES (If YES, email address: ______________________________)
  ○ NO

I ____________________ (full name) hereby consent to take part in this study.

Signature:

Date:

PhD Candidate (Co-investigator):	**Supervisor(Principal Investigator):**	**Supervisor (Co-investigator):**
Afiya Ali Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0210500953 Fax: 04 385 5877 E-mail: afiya.ali@postgrad.otago.ac.nz	Dr Elliot Bell Lecturer and clinical psychologist Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0274 739 886 Fax: 04 385 5877 E-mail: elliot.bell@otago.ac.nz	Professor Sarah Romans Professor Dept. of Psychological Medicine University of Otago, Wellington P.O. Box 7343, Wellington 6242 Phone: 0211157137 Fax: 04 385 5877 E-mail: sarah.romans@otago.ac.nz

Please turn over the page and start the survey → ***Go to next page to question*** **1**

Please answer ALL questions   Mark your answer like this ✓   If you make a mistake, draw a cross like this then tick the correct response X

1	**Do you use any Social Networking Sites (SNS) such as Facebook, Twitter, Instagram?**
	Yes ◯ | No ◯ If NO, go to Question 52

2	Which SNS do you use (list all, starting with the most frequently used SNS)
	1.
	2.
	3.
	4.
	5.

The next five statements focus on your reasons-for using SNS. Place a check mark in the circle that best describes how much you agree with each of the following statements:

	I use SNS mainly to	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
3	Express how I feel and what I think	◯	◯	◯	◯	◯
4	Maintain relationships I have made offline	◯	◯	◯	◯	◯
5	Search for people with professional expert knowledge that I need to access	◯	◯	◯	◯	◯
6	To communicate with friends and family	◯	◯	◯	◯	◯
7	Share content/information that I want others to know, e.g., music and videos	◯	◯	◯	◯	◯

8	Approximately how much time, in hours and minutes, do you spend on SNS on a typical day?	Less than 10 min	10 to 30 min	More than 30 min, up to 1 hr	More than 1 hr, up to 2 hrs	More than 2 hrs, up to 3 hrs	More than 3 hrs
		◯	◯	◯	◯	◯	◯

Go to Q 52

Instructions: We are interested in understanding your relationship with people in your online social networks. Online Social Networks (SNSs) are web-based platforms which allow users to connect with new people and interact with people they already know over the internet, share ideas, pictures, posts, activities, events, and interests with people in their network. Examples of popular SNSs are Facebook, Twitter, Instagram, Google+.

The next questions (5 -16) are concerned with the *online social networking (SNS)* context only even though you may interact with some of these people offline as well. Read each statement carefully. Indicate how you feel about each statement

	Please rate each statement as	Very Strongly Disagree	Strongly Disagree	Mildly Disagree	Neutral	Mildly Agree	Strongly Agree	Very Strongly Agree
9	There is a special person(s) (in my online social network) who is around when I am in need.							
10	There is a special person(s) (in my online social network) with whom I can share my joys and sorrows.							
11	My family really tries to help me through SNSs							
12	I get the emotional help and support I need from my family through SNSs.							
13	I have a special person(s) (in my online social network) who is a real source of comfort to me.							
14	My friends really try to help me through SNSs							
15	I can count on my friends that I talk on SNSs when things go wrong.							
16	I can talk about my problems with my family through SNSs							
17	I have friends in my online social networks with whom I can share my joys and sorrows.							
18	There is a special person(s) (in my online social network) who cares about my feelings.							
19	My family that I talk on SNSs are willing to help me make decisions							
20	I can talk about my problems with my friends on SNSs.							

The next questions (17-29) also relate to your experience of using *online social networking sites (SNS)* only. Read each statement carefully. Indicate how you feel about each statement:

	Please rate each statement as	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
21	For me, SNSs are good for getting any kind of real help or support.					
22	The supports I get on SNSs are of practical help to me.					
23	The supports I get on SNSs makes me feel better.					
24	I'm happy when people comment on my posts.					
25	I'm happy when people ''Like'' my posts.					
26	I get excited when I get an SNSs notification.					
27	I'm disappointed if I log on and don't have any new notifications.					
28	I get a lot of negative responses on SNSs.					
29	It freaks me out if my friend/follower/contact or equivalent number decreases.					
30	I get upset if somebody doesn't accept my friend/follower/contact or equivalent request.					
31	SNSs actually makes me feel less close to people					
32	If I needed help with something, I could post it on SNSs and I'd get the help I need.					
33	If I needed information about something, I could post it on social media and I'd get the information I need.					
34	People respond to me on social media as much as I want them to.					

Instructions: **Please mark the following statements to reflect how *you* communicate *on online social networking sites (SNS).* NOTE: For the purposes of this survey, "disclosures" are pieces of information that you share about yourself both which is shared with wider online community or with individuals through private messaging on SNS.**

	Please rate each statement as	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
35	I do not often talk about myself on SNS.					
36	On SNS, my statements of my feelings are usually brief.					
37	I usually write fairly long SNS posts about myself.					
38	My SNS posts are shortest when I am discussing myself.					
39	I often write about myself on SNS.					
40	I often discuss my feelings about myself on SNS.					
41	I frequently express my personal beliefs and opinions on SNS.					
42	I intimately disclose who I really am, openly and fully on SNS.					
43	Once I get started, my disclosures on SNS last a long time.					
44	I often disclose intimate, personal things about myself on SNS without hesitation.					
45	I feel that I sometimes do not control my disclosure of personal or intimate things I tell about myself on SNS.					
46	Once I get started, I intimately and fully reveal myself in my disclosures on SNS.					
47	My SNS posts are limited to just a few specific topics.					
48	My SNS posts range over a wide variety of topics.					
49	Once I get started writing on SNS, I move easily from one topic to another.					

50	My SNS posts address a variety of subjects.					
51	My SNS posts tend to centre around one subject of interest.					

Please answer all the questions below:

I now want you to answer these questions which you may have completed earlier, but this time consider them only in relation to your offline social relationships. For those of you who do not use SNS, also answer the questions below based on your offline social relationships.

Read each statement carefully. Mark how you feel about each statement.

	Please rate each statement as	Very Strongly Disagree	Strongly Disagree	Mildly Disagree	Neutral	Mildly Agree	Strongly Agree	Very Strongly Agree
52	There is a special person(s) who is around when I am in need.							
53	There is a special person(s) with whom I can share my joys and sorrows.							
54	My family really tries to help me.							
55	I get the emotional help and support I need from my famil							
56	I have a special person(s) who is a real source of comfort to me.							
57	My friends really try to help me.							
58	I can count on my friends when things go wrong.							
59	I can talk about my problems with my family.							
60	I have friends with whom I can share my joys and sorrows.							
61	There is a special person(s) in my life who cares about my feelings.							
62	My family is willing to help me make decisions.							
63	I can talk about my problems with my friends.							

Please answer the following questions about how you have been feeling during the past month. Place a check mark in the circle that best represents how often you have experienced or felt the following:

	During the past month, how often did you feel…	Never	Once or Twice	About Once a Week	About 2 or 3	Almost Every Day	Every Day

					Times a week		
64	happy						
65	interested in life						
66	satisfied with life						
67	that you had something important to contribute to society						
68	that you belonged to a community (like a social group, or your neighbourhood)						
69	that our society is a good place for all people						
70	that people are basically good						
71	that the way our society works makes sense to you						
72	that you liked most parts of your personality						
73	good at managing the responsibilities of your daily life						
74	that you had warm and trusting relationships with others						
75	that you had experiences that challenged you to grow and become a better person						
76	confident to think or express your own ideas and opinions						
77	that your life has a sense of direction or meaning to it						

Please rate the following statements about yourself?

	I see myself as someone who …	Disagree strongly	Disagree a little	Neither agree nor disagree	Agree a little strongly	Agree strongly
78	… is reserved					

79	… is generally trusting	○	○	○	○	○
80	…. tends to be lazy	○	○	○	○	○
81	… is relaxed, handles stress well	○	○	○	○	○
82	… has few artistic interests	○	○	○	○	○
83	… is outgoing, sociable	○	○	○	○	○
84	… tends to find fault with others	○	○	○	○	○
85	… does a thorough job	○	○	○	○	○
86	… gets nervous easily	○	○	○	○	○
87	… has an active imagination	○	○	○	○	○

PLEASE ALSO ANSWER THE FOLLOWING QUESTIONS TO COMPLETE THE SURVEY

88 How old are you?

Years. (e.g. 39) ☐☐

89 Are you ○ Female ○ Male

90 Which ethnic group do you belong to (please tick the space or spaces which apply to you)

○	Maldivian
○	New Zealand European
○	Maori
○	Cook Islands Maori
○	Tongan
○	Niuean
○	Chinese

◯	Indian
◯	Other such as Dutch, Japanese, Tokelauan, Please state:

91	Are you

◯	Never Married
◯	Living together
◯	Married
◯	Divorced
◯	Widowed

◯	NCEA Level
◯	Some tertiary
◯	Completed tertiary
◯	Post tertiary
◯	Other (specify here) ___________________________

94	What is your postcode (4 digit number)	

93	Which type of area do you live in?	Urban ◯	Rural ◯
	(Choose from right, which definition applies the best for where you live)	Urban areas are very developed, meaning there is a density of human structures such as houses, commercial buildings, roads, bridges, and railways. "Urban area" can refer to towns, cities, and suburbs.	A rural is an area that is located outside towns and cities with a low population density and small settlements. Farming, agriculture, and forestry are commonly rural areas.

95	**Please indicate if you would like to go in the draw for a prize (either a Samsung Tablet 16GB Wi Fi & 3G or $400 Prezzy card (shop anywhere in NZ) – drawn on (date)**

I would like to enter the prize draws (If yes, email ________________________)	I would not like to enter the prize draws

Thank you so much for taking the time to complete this survey

APPENDIX A-2: Reminder Postcard for NZ Main Group

Front page

A friendly Reminder

Dear participant,

We have not yet received your response to the invitation to participate in a study on online social networking and psychological wellbeing. If you have already completed the questionnaire, please accept my sincere thanks. If not, please return your completed questionnaire as soon as possible or complete the online questionnaire online at http://bit.do/afiya-ali and enter your access code **XXXX**

Your participation in this study is very valuable. We appreciate you taking the time from your normal schedule to help us learn as much possible about how online social networking impacts social support and wellbeing. You can still enter the lucky draw to win a Tablet or a $400 gift voucher if you complete the questionnaire and post it to us before 19 July 2016.

If by some chance you did not receive the questionnaire, or it was misplaced, please call me at 0210500953, and I will get another one in the mail to you immediately.

Many thanks
Afiya

UNIVERSITY of OTAGO
Te Whare Wānanga o Otāgo
NEW ZEALAND

Address side

Afiya Ali

Dept of Psychological
Medicine
University of Otago,
Wellington
P.O. Box 7343, Wellington

PLEASE
PLACE
STAMP
HERE

Mailing Address Line 1
Mailing Address Line 2
Mailing Address Line 3
Mailing Address Line 4
Mailing Address Line 5

APPENDIX A-3 – Reminder Letter for NZ Main Group

Second reminder letter sent to the non-responders on NZ main group

Dear..

We still have not yet received your response to the invitation to participate in the study on online social networking and psychological wellbeing. If you have already completed the questionnaire, please accept my sincere thanks. If not, I would be really appreciative if you completed the same questionnaire which I have enclosed with this letter or complete the online questionnaire online at **http://bit.do/afiya-ali** and enter your access code **XXXX**

You are one of my participants in a randomly selected sample. Hence I am not able to replace you by someone else. It is important that everyone in my sample did complete the survey to ensure the scientific strength of my research findings. The strength of random sampling is that you get the opinion of everyone in a given community.

It doesn’t matter whether you use social media or not as my study focuses on both offline and online social interaction with your friends and family. Your responses are valuable for my study goal which is to advance social science research for community wellbeing and shaping offline and online social support interventions for various groups. We appreciate you taking the time from your normal schedule to help us learn as much possible about how online social networking impacts social support and wellbeing. You are still eligible to win a $100 Prezzy card if you complete the questionnaire and post it to us before 30 August 2016.

I will send you a reminder about this questionnaire in a couple of weeks if you have not responded. If you are not interested in this particular project, please drop me a reply by email and I will not send a reminder.

However, I really hope you will help us in this way. I view this research topic as very important in improving our understanding of modern mental health.

If you have any questions about this, please contact me at afiya.ali@postgrad.otago.ac.nz

Thank you for your consideration

Yours sincerely,

Afiya Ali

APPENDIX A-4: Final Reminder Letter for NZ Main Group

Third and final reminder to the non-responders from the NZ main group

Dear..

Over the last few months we have sent you two copies of a survey on online social networking and psychological wellbeing, as well as a postcard. We are asking again if you could please fill in this survey. It will only take 15-20 minutes.

The reason why we are trying so hard to get you to reply is that your views are really important.

Social support (face-to-face) is really important for wellbeing but this may be affected by changes in society especially with increase in time spent online. Hence we need to find out how online social networking is affecting our social networks. You are one of my participants in a randomly selected sample. Hence I am not able to replace you by someone else. It is important that everyone in my sample did complete the survey to ensure the scientific strength of my research findings. The strength of random sampling is that you get the opinion of everyone in a given community.

It doesn't matter if you do not use online social networks, you can still complete the survey.

My study focuses on both offline and online social interaction with your friends and family. We have received a good number of replies overall, but adding your views will make the survey even more useful.

I have enclosed the same questionnaire with this letter or you can complete the questionnaire online at **http://bit.do/afiya-ali** and enter your access code **XXXX**

If you have any questions about this, please contact me at afiya.ali@postgrad.otago.ac.nz

Look forward to hearing back from you soon

Yours sincerely,

Afiya Ali

APPENDIX A-5: Survey Questionnaire for Maldivians

Survey Questionnaire for Maldivians

ސާވޭ އާއިބެހޭ މައުލޫމާތު ކަރުދާސް

އަޅުގަނޑަކީ ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ ގައި ޕީ.އެޗް.ޑީ އެއް ހާސިލުކުރުމަށް ކުރިއަށްގެންދާ ދަރިވަރެކެވެ. މި ދިރާސާ އަކީ ސޯޝަލް މީޑިއާ ނުވަތަ އިންޓަރނެޓްގެ ސަހަރޯން އިޖްތިމާއީ ގުޅުންތައް ނަގާލާ ދިރާސާއެއް ހުރިހާ ދިރާސާތަކެވެ. މިއީ އޮނިވަރސިޓީ އޮފް އޮޓާގޯގެ ޑިސިޕްލިނަރީ ދާއިރާ ގެ. އެވިއަޅު ބޭނުމަކީ ފަހުމުވުން ސާފު ކުރަމުންދާ ބޭނުންވާ މަޢުލޫމާތު ކަރުދާސް ދިރާސާއަށް ކަރުދާސް ދިރާސާއެކެވެ.

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ފޭސްބުކް، ޓްވިޓަރ، އަދި އިންސްޓަގްރާމް ފަދަ ސޯޝަލް މީޑިއާގެ ސަހަރޯން އަޅުގަނޑުމެންގެ ނަފްސާނީ ދުނިޔޭއާބެހޭގޮތުން ކުރާ އަސަރު ދެނެގަތުމަށް މިދިރާސާކުރަމެވެ. ހާއްސަކޮށް މިހާރު ބަދަލުވަމުންދާ ދުނިޔެއަށް އަޅުގަނޑުމެން އިޖްތިމާއީ ގުޅުންތަކާއި އެކަކު އަނެކަކާއި ބާއްވާ ގުޅުން މިހާރު ވަނީ ވަރަށް ބޮޑަށް ބަދަލުވެފައެވެ. ކޮންމެ ސޯޝަލް މީޑިއާ ގުޅުމެއް ހުރިނަމަ ވާނީ މިކަމުގެ ސަހަރޯން ކަމަށް އަސަރުކުރާ ދުނިޔެއަކަށް ޚާއްޞަ ދިރާސާއެއް ބޭނުންގެ އެއްބާރުލުން މިދިރާސާ ކަރުދާސް ވަރަށް މުހިއްމެވެ.

2. އަހަރެން ހިއާ ވަޑައިގެން ދޫކޮށް ޝާމިލް މި ދިރާސާއަށް؟

މިގައި ހިމެނޭ ސުވާލު ކަރުދާސް ފުރިހަމަ ކުރުމަށް ގާތްގަނޑަކަށް 15 މިނެޓް ވާނެއެވެ. އެހެންކަމުން ތިޔަބޭފުޅުން ދެއްވާ ވަގުތު އަޅުގަނޑަށް ކުރުމުގެ ގޮތުން މި ސުވާލު ކަރުދާސް ލިބުމާ 3 ހަފްތާ ތެރޭގައި ސުވާލުކަރުދާސް ފުރިހަމަކޮށްދިނަމަ ގުޅުއްވުން ދޭ އަހަރެމެން ގައި ބައިވެރިވުމުގެ ފުރުސަތު އެބައޮތެވެ.

3. އަހަރެން މިދިރާސާގައި ބައިވެރިވާން ނިންމާނީ ކިހިނެއް؟

މި ދިރާސާގައި ބައިވެރިވުމަކީ އަމިއްލަ އިޚްތިޔާރުގައި ކުރާކަމެކެވެ. މި ދިރާސާގައި ބައިވެރިވާނީ ނުވަތަ ނޫނީ ނިންމުމަކީ އެއީ މުޅިން ތިޔަ ހައްގެއް ކަމުގައި ވާނެއެވެ. އަދި މިގޮތަށް ބައިވެރިވާން ނިންމައިފިނަމަ ސުވާލުކަރުދާސް ފުރިހަމަކޮށް ހަވާލުކުރުމަށް ހުށަހަޅާނީ ތިބާގެ އިހުތިޔާރެވެ. އަދި ތިޔަބޭފުޅުން ދެއްވާ ޖަވާބުތަކަކީ ސިއްރު ފަރާތެއް ހާމަނުކުރެވޭނެ ކަމެކެވެ.

4. ސުވާލުކަރުދާހަށް ޖަވާބުދޭނީ ކިހިނެއް؟

މި ސުވާލުކަރުދާސް ފުރިހަމަ ކުރުމަށްފަހު ސީލުކުރެވިފައިވާ ސުވާލުކަރުދާސް ބަލާ އަންނަ ފަރާތް ހަވާލުކުރައްވާށެވެ.
އެހެން ނޫނީ ސުވާލުކަރުދާސް ފުރިހަމަކޮށް ސްކޭންކޮށް afiya.ali@postgrad.otago.ac އަށް އީމެއިލް ކުރައްވާށެވެ. އެހެން ނޫނީ މި ސުވާލުކަރުދާހުގެ ބަދަލުގައި އޮންލައިން ކޮށް މި ސުވާލުކަރުދާސް ފުރިހަމަ ކުރެވިދާނެއެވެ. ސާވޭ ކަރުދާސް އޮންލައިންކޮށް ފުރިހަމަ ކުރުމަށް މި ލިންކް ބޭނުންކުރައްވާ.
މި ދިރާސާގައި ބައިވެރިވާ ނިންމައިފިކަމަށް ވާނަމަ ސުވާލުކަރުދާހާއި އެއްގައިވާ އެއްބަސް ވުމުގައި ސޮއިކުރައްވާ. މި އެއްބަސްވުމުގެ ސުވާލުތަކުގެ ވާހަކައި މިދިރާސާ އާއި ބެހޭ ގޮތުން ލިޔުމުގައިވާ ކަރުދާސް ކިޔައިދިނުމަށްފަހު އަދި މިދިރާސާގައި ބައިވެރިވާން ނިންމިކަމަށް.

5. މި ދިރާސާގައި ބައިވެރިވުން ކޮންބައެއް؟

މި ދިރާސާ އަކީ ރާއްޖެއާއި ނިއުޒިލެންޑްގެ އާއްމު ރައްޔިތުންނަށް އަމާޒުކޮށްގެން ހެދި ދިރާސާއެކެވެ. މި ދިރާސާގައި ބައިވެރިވާ މީހުން ހުރި ދ ގައުމުގެ ވެޓްފާރމުންގެ ލިސްޓު ބޭނުންކޮށްގެން ފަރާތްތަކަށް ދިމާވާ ނަންބަރުތަކުގެ ހިލާފު މީހާގެ ނަން

ހުވައިގެންނެވެ. އެހެން ކަމުން މިދިރާސާގައި އިޚްތިޔާރުކުރުން ބައިވެރި ވުމަކީ އަމިއްލަގޮތުން މިދިރާސާގެ ހުރިހާކަމަކަށް ވަކިން މުހިއްމު ކަމެކެވެ.

6. މިދިރާސާގައި ބައިވެރިވުމުން ކުރާނީ ކޮންކަހަލަ އަސަރުތަކެއް؟

މިދިރާސާ އަކީ ސިއްރީ ތަޖުރިބާތަކެއް ނުވަތަ ފަރުވާއެއް ދީ ދިރާސާކުރާކަން ނުވާތީ މިގޮތުން އެއްވެސް ކަހަލަ ސިއްރު ނަތީޖާތަކެއް ދިމާވުމަކީ ނާދިރުކަމެކެވެ. އެހެންނަމަވެސް މި ދިރާސާއަށް ޖަވާބުދިނުމުން ދާ ވަގުތު އެއްވެސްކަހަލަ އުނދަގުލެއް ނުވަތަ ހިތްޕަސޭހަ ނުވާކަމެއް ދިމާވެއްޖެނަމަ ޖަވާބުދިނުން ހުއްޓާލުމުގެ ފުރުސަތު އެބައޮތެވެ. އަދި މިފަދަ ކަމެއް ދިމާވެއްޖެނަމަ އަޅުގަނޑާ ގުޅުއްވާނީއެވެ. އަދި އަޅުގަނޑުގެ ސުޕަވައިޒަރުންނާއި މަޝްވަރާ ކުރުމަށް ފަހު އެކަމާ އެކަށީގެންވާ އެހީތެރިކަމެއް ފޯރުކޮށް ދެވޭނެއެވެ.

7. ކޮންކޮން ބައިކަށް އެދޭނީ އަހަރެން މި ދިރާސާގައި ބައިވެރިވުމަށް؟

ތިޔަފަރާތުން މިދިރާސާއަށް ދެއްވާ ޖަވާބުތަކަކީ ފުރިހަމައަށް ސިއްރުކުރެވޭނެ މަޢުލޫމާތެވެ. އަދި ތިޔަފަރާތުން ދެއްވާ ޖަވާބު ތިޔަފަރާތުގެ ނަމާއި އެއްވެސް ގޮތަކުން ގުޅިގެން ނުހުންނާނެއެވެ. ތިޔަފަރާތުގެ ދުވަހުގެ ހާލަތު ކުރިއަށްދާ ގޮތް ބަލާ ދެ ބައެއްގެ ބޭނުމަށް ގުޅައިގެން ދުވަސް ނަގާނެއެވެ. މި ދިރާސާއާއި ބެހޭ ހުރިހާ މަޢުލޫމާތު ސިއްރުކޮށް ރައްކާކުރެވޭނީ އަހަރެން ގޮވާލި ގޮތަށް ނުވަތަ ފަހު 10 އަހަރަށް ފަހު މިލިކު ނައްތާލެވޭނެއެވެ.

8. މިދިރާސާގެ ނަތީޖާ އަހަރެންނަށް އެނގޭނީ ކިހިނެއް؟

މި ދިރާސާ ނިމުމުން ބޭނުންވާ ނަމަ އެއްވެސް ފަރާތަކަށް ވަގުތީގޮތުން ލިބޭނެއެވެ. އަދި ނަތީޖާ މިދިރާސާއިން ލިބޭ މަޢުލޫމާތުތައް އެކި ފަރާތްތަކުގެ ސަރުކާރާއި ކުންފުނިތަކުގެ ހިއްސާދާރުންނަށް އެކަށީގެން ވާނެއެވެ. އަދި މިރިޕޯޓް އިންޓަރނެޓް މެދުވެރިކޮށް ބޭނުންވާ ފަރާތްތަކަށް ހިއްސާކުރެވޭނެއެވެ. ރިޕޯޓް ހިއްސާ ބޭނުންވާ ފަރާތްތަކަށް ރިޕޯޓް ހިއްސާ ބޭނުންވާ ލިންކު ފޮނުވޭނެއެވެ.

9. އަހަރެންގެ ހައްޤުތަކާއި ބެހޭ މައުލޫމާތު ލިބޭނީ ކޮންތާކުން؟

މި ދިރާސާއާއި ބެހޭ ގޮތުން އެއްވެސް ކަހަލަ ކަންބޮޑުވުމެއް ނުވަތަ ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ އާއި ގުޅުއްވުން އެދެމެވެ. މި ދިރާސާ ވަނީ ޔުނިވަރސިޓީ އޮފް އޮޓާގޯގެ އިންސާނީ އެތިކްސް ކޮމިޓީގެ ހުއްދަ ލިބިގެން ކުރިއަށްގެންދާ ދިރާސާއެކެވެ. މިދިރާސާ އާއި ބެހޭގޮތުން އެއްވެސް ޝަކުވާއެއް ހުށަހަޅުއްވަން ބޭނުންވާނަމަ އެކަމަށް ބަލާ އެކަމާ ނުހަމަ ތިޔަފަރާތަށް ޚިދުމަތްދޭނެ ކަމުގެ ޔަޤީންކަން އަރުވަމެވެ.

މިދިރާސާއާއި ބެހޭ ގޮތުން އިތުރު މަޢުލޫމާތު ބޭނުންނަމަ ގުޅުއްވާނީ އާފިޔާ އަލީ އާއެވެ.

އާފިޔާ އަލީ	ޑރ. އެލިއަޓް ބެލް	ޕްރޮފެސަރ ސާރާ ރޮމާންސް
ޕީ.އެޗް.ޑީ ކެންޑިޑޭޓް	ސުޕަވައިޒަރ	ސުޕަވައިޒަރ
ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން	ލެކްޗަރަރ، ކްލިނިކަލް ސައިކޮލޮޖިސްޓް	ޕްރޮފެސަރ
ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ	ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން	ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން
ވެލިންގްޓަން 6242، ނިއުޒީލޭންޑް	ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ	ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ
ފޯން: 7999462	ވެލިންގްޓަން 6242، ނިއުޒީލޭންޑް	ވެލިންގްޓަން 6242، ނިއުޒީލޭންޑް
އީމެއިލް afiya.ali@postgrad.otago.ac.nz	ފޯން: 0274739886	ފޯން: 0211157137
	އީމެއިލް: elliot.bell@otago.ac.nz	އީމެއިލް sarah.romans@otago.ac.nz

އެއްބަސްވުން

ދިރާސާ: ސޯޝަލް މީޑިއާގެ ސަޕޯޓުން އިޖްތިމާޢީ ގުޅުންތަކާއި ނަފްސާނީ ދުޅަހެޔޮކަމަށް ކުރާ އަސަރު ދެނެގަތުން

އެއްބަސްވާނަމަ ތިރީގައިވާ ގޮޅިތަކުގައި ނިޝާނު ފާހަގަކޮށް ދެއްސަވާ!

- ☐ މި ދިރާސާއާއި ބެހޭ ގޮތުން ތައާރަފުކޮށްދީފައިވާ މަޢުލޫމާތު ކަރުދާސް އަހަރެން ރަނގަޅަށް ކިޔައިފިމެވެ.
- ☐ ހިތަށްއަރާ ސުވާލުތަކަށް އަހަރެންގެ ސުވާލުތަކަށް ޖަވާބު ލިބިއްޖެއެވެ. އަދި އަހަރެން ބޭނުންވެއްޖެނަމަ އިތުރު މަޢުލޫމާތު ލިބޭނެކަން އެނގެއެވެ.
- ☐ މިދިރާސާގައި ބައިވެރިވުން ބޭނުން ނުވާނަމަ މި ސުވާލު ކަރުދާސް ފުރިހަމަ ނުކުރުމަށް ނިންމިދާނެކަން އެނގެއެވެ. ނަމަވެސް ސުވާލުކަރުދާސް ފުރިހަމަ ކޮށްފައި ހުށަހަޅައިފިނަމަ އަލުން ނަގައިގަނެވޭނެ ކަމެއް ނެތްކަން އެނގެއެވެ.
- ☐ މި ސުވާލު ކަރުދާހަށް އަހަރެން ދޭ ޖަވާބުތަކަކީ ސިއްރު މަޢުލޫމާތުކަން އެނގެއެވެ. އަހަރެންނަކީ ކާކުކަން އެނގޭގޮތަށް އެއްވެސް މަޢުލޫމާތެއް މި ދިރާސާގެ ރިޕޯޓްތަކުގައި ނުހިމެނޭނެކަން އެނގެއެވެ.
- ☐ މި ދިރާސާގެ ސަބަބުން ލިބިދާނެ އުނދަގޫތައް ނުވަތަ ގެއްލުމެއް ވާނަމަ އެކަމާއި ބެހޭ ތަފްސީލު މަޢުލޫމާތު ކަރުދާހުގައި ލިޔެފައިވެއެވެ.
- ☐ މި ދިރާސާގައި ބައިވެރިވާނީ ވިސްނަން ވަގުތު ލިބުނެވެ.
- ☐ މި ދިރާސާއާއި ބެހޭގޮތުން ސުވާލެއް އޮތްނަމަ ގުޅާނީ ކާކާކަން އެނގެއެވެ.

އަހަރެން ______________________ (ފުރިހަމަ ނަން) މި ދިރާސާ ގައި ބައިވެރިވާން

އެއްބަސް ވަމެވެ.

ސޮއި: ތާރީޚް:

އާފިޔާ އަލީ ޕީ.އެޗް.ޑީ ކެންޑިޑޭޓް ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ ވެލިންގްޓަން 6242، ނިއުޒީލެންޑް ފޯން: 7580261 afiya.ali@postgrad.otago.ac.nz	ޑރ. އެލިއަޓް ބެލް ސުޕަރވައިޒަރ ޕްރޮފެސަރ، ކްލިނިކަލް ސައިކޮލޮޖިސްޓް ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ ވެލިންގްޓަން 6242، ނިއުޒީލެންޑް ފޯން: 0274739886 އީމެއިލް: elliot.bell@otago.ac.nz	ޕްރޮފެސަރ ސާރާ ރޮމަންސް ސުޕަރވައިޒަރ ޕްރޮފެސަރ ޑިޕާޓްމަންޓް އޮފް ސައިކޮލޮޖިކަލް މެޑިސިން ޔުނިވަރސިޓީ އޮފް އޮޓާގޯ ވެލިންގްޓަން 6242، ނިއުޒީލެންޑް ފޯން: 0211157137 sarah.romans@otago.ac.nz

ސުވާލު ނަމްބަރ 1 އަށް ޖަވާބު ދިނުމަށް އަނެއްސަފްހާއަށް ދޭ

ހުރިހާ ސުވާލަކަށް ޖަވާބު ދެއްވާ	ޖަވާބު ދިނުމަށް މިގޮތަށް ފާހަގަ ޖައްސަވާ ✓	ނުރަނގަޅު ޖަވާބު ދެވިއްޖެނަމަ މިގޮތަށް × ފާހަގަ ޖައްސަވާފައި ރަނގަޅު ގޮޅީގަ އަލުން ފާހަގަ ޖައްސަވާ.

1	ޓްވިޓަރު، ފޭސްބުކް، ނުވަތަ އިންސްޓަގްރާމް ފަދަ އެއްވެސް ކަހަލަ ސޯޝަލް މީޑިއާއެއް ބޭނުންކުރައްވަންތަ؟
	އާން ◯ ނޫން ◯ ← ނޫންނަމަ ސުވާލު ނަންބަރު 51 އަށް ދޭ

2	ޓްވިޓަރު، ފޭސްބުކް، ނުވަތަ އިންސްޓަގްރާމް ފަދަ އެއްވެސް ކަހަލަ ސޯޝަލް މީޑިއާއެއް ބޭނުންކުރައްވަންތަ؟
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ތިރީގައިވާ 5 ސުވާލު ބިނާވެގެންވަނީ ސޯޝަލް މީޑިއާ ބޭނުންކުރާ ސަބަބުތަކުގެ މައްޗަށެވެ. ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދިނުމަށް އެއްވެ އެކަށީގެންވާ ބޮޑުގައި ހުރި ފާހަގަޖައްސަވާ

	އަހަރެން އެއްމެފަހުން ސޯޝަލް މީޑިއާ ބޭނުން ކުރަނީ	ބޮޑަށް ދެބަސްވަން	ދެބަސްވަން	އެއްބަސްވެސްނުވެ ދެބަސްވެސްނުވަން	އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން
3	އަހަރެންގެ އިޙްސާސްތަކާއި ޚިޔާލުތައް ފާޅުކުރުމަށް	◯	◯	◯	◯	◯
4	ސޯޝަލް މީޑިއާގެ ބޭނުން (އޮފްލައިން ކޮށް) ބައްދަލުވެ އުފެދިފައިވާ ގުޅުންތައް ދެމެހެއްޓުމަށް	◯	◯	◯	◯	◯
5	ބޭނުންވާ އާ އާ ފަންނީ އިލްމުވެރިން ހޯދުމަށްޓަކައި	◯	◯	◯	◯	◯
5	އާއިލާގެ މެމްބަރުންނާއި ރަހުމަތްތެރިންނާއި މުވާސަލާތު ކުރުމަށް	◯	◯	◯	◯	◯
7	އަހަރެން މިހުންނަން އަންގައިދޭން ބޭނުންވާ މައުލޫމާތު ހިއްސާކުރުމަށް (މިސާލަކަށް ފީޗާ އާއި ތަޅާ)	◯	◯	◯	◯	◯

8	އާއްމުކޮށް ދުވަހެއްގައި ސޯޝަލް މީޑިއާގައި ހޭދަކުރަނީ ކިހާ ވަގުތެއް	10 މިނެޓަށް ވުރެމަދުން	10 މިނެޓާއި 30 މިނެޓާއި ދެމެދު	30 މިނެޓާއި 1 ގަޑިއިރާއި ދެމެދު	1 ގަޑި އިރާއި 2 ގަޑި އިރާއި ދެމެދު	2 ގަޑިއިރާއި 3 ގަޑިއިރާއި ދެމެދު	3 ގަޑިއިރަށް ވުރެ ގިނައިން

ސުވާލު ނަމްބަރ 51 އަށް ދޭ

އިރުޝާދު: ތަފުސީލުކޮށް ސައިބަރބުލީއިންގ ސޯޝަލް މީޑިއާ ޓެކްނޮލޮޖީގެ ބޭނުން ކުރުމުން މީހުންނާއި ދެކޮށް ބަހުލާ ގޮތާއި ގުޅި ހެދި ދެވޭ. ސޯޝަލް މީޑިއާ އަކީ އިންޓަރނެޓް ޓެކްނޮލޮޖީ ބޭނުން ކުރާ ގޮތް ހިތާއި، ޕޯސްޓްތަކާއި، ހަރަކާތްތަކާއި، ސައިބަރބުލީއާ ގުޅޭ ކޮމެންޓްތަކާއި، އަދި ފޮޓޯތައް ދައްކަން މީހުންނާއި ދެކޮށް ދިމާވާ މީހުންނާއި ހިއްސާކުރުމަށް ބޭނުންކުރާ ވެބްސައިޓްތަކެވެ. މިގޮތުން އެއްވެ އާއްމުކޮށް ބޭނުންކުރާ ސޯޝަލް މީޑިއާ ތަކަކީ ފޭސްބުކް، ޓްވިޓާ، ޕިންޓަރެސްޓް، އިންސްޓަގްރާމް އަދި ޔޫޓިއުބް ފަދަ ސައިޓްތައް ނުވަތަ އެހެން ތަކެވެ.

ދެންއަންނަ ސުވާލު ތަކަކީ (9 -20) ބިނާވެފައިވަނީ ހަމައެކަނި އޮންލައިން ކޯސް ނުވަތަ ސޯޝަލް މީޑިއާ ޓެކްނޮލޮޖީ އެހެން މީހުންނާ މުޢާމަލާތްކުރުމުގައި ބޭނުން ކުރުމުގެ ބައިގައެވެ. ސޯޝަލް މީޑިއާ ޓެކްނޮލޮޖީ ވާހަކަދައްކާ މީހުންގެ ތެރޭގައި އެހެން ޤަބޫލުކުރަން ބޭއްބޭފުޅު ވާހަކަ ދައްކާ މީހުންނާ ގުޅުވުން އެކަކީ ކޮން ފޯމެއް. މިވާ ޤަބޫލުކުރާ ސުވާލުތަކަށް ޖަވާބުދިނުމަށް އެއްމެ އެކަކީ ކޮންފާ ބޮޑުގައި ޖެހޭ ފާހަގަކުރައްވާ!

	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދޭ	ވަރަށްބޮޑަށް ދެކޮޅުވަން	ބޮޑަށް ދެކޮޅުވަން	ކުޑަކޮށް ދެކޮޅުވަން	ވަކިކޮޅެއް ނޫން	ކުޑަކޮށް އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން	ވަރަށްބޮޑަށް އެއްބަސްވަން
9	ބޭނުމެއްނެތި ވަގުތުތަކުގައި (ސޯޝަލް މީޑިއާ ޕްލެޓްފޯމްތަކުން) އަނިޔާވެރިވުމަށް ހާއްސަ މީހެއް ހުރޭ.							
10	އެކަލާއި ހިތާމަވާ ހިއްސާ ކުރާން ހާއްސަ މީހެއް ސޯޝަލް މީޑިއާ ޕްލެޓްފޯމްތަކުން ވާހަކަ ދައްކާ މީހުންގެ ތެރޭގައި ހުރޭ.							
11	ސޯޝަލް މީޑިއާ ޕްލެޓްފޯމް އަހަރެންގެ އާއިލާއިން އަހަރެން އަނިޔާވެރިވުމުން މަސައްކަތް ކުރޭ.							
12	ސޯޝަލް މީޑިއާ ޕްލެޓްފޯމް ނަފްސާނީ ގޮތުން ލިބުނު އެއްބާރުލުމާއި ރައްކާތެރިކަން އާއިލާގެ ފަރާތުން ލިބޭ.							
13	އަހަރެންނަށް ހިތްހަމަޖެހުން ގެންނަ ހާއްސަ މީހެއް (ސޯޝަލް މީޑިއާގައި) ހުރޭ.							
14	ސޯޝަލް މީޑިއާ ޕްލެޓްފޯމް ވާހަކަދައްކާ އަހަރެންގެ ރަހުމަތްތެރިން އަހަރެން އަނިޔާވެރިވުމުން މަސައްކަތް ކުރޭ							

#	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދެއްވާ	ވަރަށްބޮޑަށް ދެބަސްވަން	ބޮޑަށް ދެބަސްވަން	ކުޑަކޮށް ދެބަސްވަން	ވަކިކޮޅެއް ނޫން	ކުޑަކޮށް އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން	ވަރަށްބޮޑަށް އެއްބަސްވަން
15	ކަމެއް ޕޯސްޓްކޮށް ހިނގައިދިޔަގޮތް ސޯޝަލް މީޑިއާ ގްރޫޕްތަކުން ވާހަކަދައްކާ އަހަރެންގެ ރަހުމަތްތެރިންނަން ބަހުސް ކުރެވޭ							
16	ދިރިއުޅުމުގައި ކުރިމަތިވާ މައްސަލަތައް (ސޯޝަލް މީޑިއާ ގްރޫޕްތަކުން) އާއިލާއާ ހިއްސާކުރެވޭ							
17	ސޯޝަލް މީޑިއާ ގްރޫޕްތަކުން ވާހަކަދައްކާ ރަހުމަތްތެރިންގެ ތެރޭގައި އަހަރެންގެ ދުވަހު ހިތްމަގޮތް ހިއްސާކުރާނެ މީހުން ލިބޭ							
18	އަހަރެންގެ ދިރާސާތަކާބެހޭ އަގުވާ ހާއްސަ މީހުން (ސޯޝަލް މީޑިއާގައި) ހުރި							
19	އަހަރެންގެ ނިންމުންތައް ނިންމަން (ސޯޝަލް މީޑިއާ ގްރޫޕްތަކުން) އާއިލާއިން އެހީތެރިވޭ							
20	ދިރިއުޅުމުގައި ކުރިމަތިވާ މައްސަލަތައް (ސޯޝަލް މީޑިއާ ގްރޫޕްތަކުން)ރަހުމަތްތެރިންނާ ހިއްސާކުރެވޭ							

ދެންއަންނަ ސުވާލު (21 -34) ތަކުގައި ބިނާކޮށްފައިވަނީ ހަމައެކަނި އޮންލައިން ކާރު ނުވަތަ ސޯޝަލް މީޑިއާ ބޭނުންކުރުމުގައި ކުރެވޭ ތަޖުރިބާތަކުގެ މައްޗަށް. މިހާ ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދިނުމުގައި އެއްވެސް އުޅަދިގެންވާ ބޮލުގައި ނުޖަހާ ފާހަގަކޮށްލާ!

#	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދެއްވާ	ބޮޑަށް ދެބަސްވަން	ދެބަސްވަން	އެއްބަސްވެސް ދެބަސްވެސް ނުވަން	އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން
21	ސޯޝަލް މީޑިއާ އަކީ އަހަރެންނަށް ބޭނުންވާ ކޮންމެކަހަލަ އިންފޮމޭޝަން ހޯދުމަށް ރަގަޅު އެއްޗެއް					
22	ސޯޝަލް މީޑިއާ އިން ލިބޭ އިންފޮމޭޝަނަކީ އަހަރެންނަށް ބޭނުންތެރި އެއްޗެއް					
23	ސޯޝަލް މީޑިއާއިން އަހަރެންނަށް ލިބޭ އިންފޮމޭޝަނުގެ ސަބަބުން އަހަރެންނަށް ހިތްހަމަޖެހުން ލިބޭ					
24	ސޯޝަލް މީޑިއާ ގައި އަހަރެން ލިޔާ އެއްޗެހިތަކަށް (ޕޯސްޓް ތަކަށް) އެހެންމީހުން ޖަވާބު ދިނުމުން ނުވަތަ ކޮމެންޓް ކުރުމުން އަހަރެން އުފާވޭ					

25	ސޯޝަލް މީޑިއާގައި އަހަރެން ލިޔާ އެއްޗެހިތަކަށް (ޕޯސްޓް ތަކަށް) އެހެން މީހުން 'ލައިކް' ކުރުމަ އަހަރެން އުއްމީދު					
26	ސޯޝަލް މީޑިއާ އިން މެސޭޖެއް ލިބުނުކަން އަންގައިދޭ ނޯޓިސް (ނޮޓިފިކޭޝަން) އެއް ލިބުމުން އަހަރެންގެ ހިތް އަވަސް ވެގެން ދޭ					
27	ސޯޝަލް މީޑިއާ ހުޅުވާލުމުގެ ނޯޓިސް (ނޮޓިފިކޭޝަން) އެއް ނުބެލިނަމަ އަހަރެން ހިތްހަމަ ނުޖެހޭ					
28	ސޯޝަލް މީޑިއާ އިން އަހަރެންނަށް ވަރަށް ގިނަ ނުރައްކަލު ޖަވާބުތަކެއް ލިބޭ					
29	އަހަރެންގެ ސޯޝަލް މީޑިއާ ރައްޓެހިން ނުވަތަ ކޮންޓެކްޓްތަކުގެ ނުވަތަ ފޮލޯވަރުސް މަދުވެއްޖެނަމަ އަހަރެން ވަރަށް ކަންބޮޑުވޭ					
30	ސޯޝަލް މީޑިއާ އިން އަހަރެން ފޮލޯ ކުރާ ފަރާތެއް ނުވަތަ ފޮލޯވަރ ރިކުއެސްޓެއް އެޕްރޫވްކުރުމަށް އެކަން ގަބޫލު ނުކުރުމުން އަހަރެން ދެރަވޭ					
31	ސޯޝަލް މީޑިއާގެ ސަބަބުން އެހެން މީހުންނާ އަސްލު އެއާ ގާތް ގުޅުމެއް އަހަރެން ނެތޭ					
32	އަހަރެން ކަމަކަށް އެހީއެއް ބޭނުން ވެއްޖެނަމަ އެކަމެއް ސޯޝަލް މީޑިއާގައި ލިޔުމުން އެ ބޭނުންވާ އެހީތެރިކަމެއް އަހަރެންނަށް ލިބޭ					
33	އަހަރެން ކަމަކާ ބެހޭ މަޢުލޫމާތެއް ބޭނުން ވެއްޖެނަމަ އެކަމެއް ސޯޝަލް މީޑިއާގައި ލިޔުމުން އެ ބޭނުންވާ މަޢުލޫމާތެއް އަހަރެންނަށް ލިބޭ					
34	އަހަރެން ބޭނުންވާ ވަރަށް ސޯޝަލް މީޑިއާއިން އެހެން މީހުން އަހަރެންނަށް ޖަވާބު ދޭ					

އިރުޝާދު: އިންޓަރނެޓް ނުވަތަ ސޯޝަލް މީޑިއާ ބޭނުންކުރުމުން މުޢާމަލާތުތަކާ ގުޅޭ ގޮތުން ބަލާ ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބު ދެއްވާ. ނޯޓް: މި ސުވާލު ގެ ބޭނުމަކީ "ފޭކްނިއުސް" ފަދަ ކުރުފުސީ އިންޓަރނެޓް ނުވަތަ ސޯޝަލް މީޑިއާ ބޭނުންކުރުމުން ލިބިގެންވާ ބަދަލުތަކުން އެކަށީގެން ފެންނަގޮތަކީ ނުވަތަ ވަކި ބަޔަކާއި ނުވަތަ ވަކިމީހަކާއި ހިއްސާ ކުރާ މަޢުލޫމާތެވެ.

	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދޭށެވެ	ބޮޑަށް ދެކޮޅުވަން	ދެކޮޅުވަން	އެއްބަސްވެސް ދެކޮޅުވެސް ނުވަން	އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން
35	އަމިއްލަ ނަފުސާއިބެހޭ ގޮތުން އާރާހިތިން އަހަރެން ސޯޝަލް މީޑިއާ ގައި ވާހަކަ ދައްކަން					
36	ސޯޝަލް މީޑިއާގައި އަހަރެންގެ އިހްސާސްތައް ފާޅުކުރަނީ އާއްމުކޮށް ތިރިކޮށް					
37	އާއްމުކޮށް އަހަރެން ސޯޝަލް މީޑިއާގައި އަމިއްލަ ނަފްސާބެހޭ ގޮތުން ލިޔަނީ ނުވަތަ ޕޯސްޓް ކުރަނީ ފުރަތަމަ ކަމަކަށް ދުރުކޮށް					
38	އަހަރެންގެ އަމިއްލަ ނަފްސާއިބެހޭ ބޮޑަށް ސޯޝަލް މީޑިއާގައި ލިޔާ ޕޯސްޓްތަކެއް ހުންނާނީ ކުރުކޮށް					
39	ސޯޝަލް މީޑިއާގައި އާއްމުކޮށް އަހަރެން އަމިއްލަ ނަފްސާއިބެހޭ ބޮޑަށް ލިޔަން					

40	އަހަރެންގެ އަމިއްލަ ނަފްސާއިމެދު ހެޔޮވާ އިހްސާސްތައް އާއްމުކޮށް އަހަރެން ސޯޝަލް މީޑިއާގައި މަޝްވަރާކުރަން					
41	އަހަރެންގެ އަމިއްލަ ހިޔާލުތަކާއި ގޮންޖެހުންތަކާ ކަންތައްތައް އާއްމުކޮށް ސޯޝަލް މީޑިއާގައި ހިއްސާކުރަން					
42	އަހަރެންނަކީ ހާލުކަށި ވަގުތު ފުންކޮށް އަދި ވަރަށް ހާމަކަންބޮޑުކޮށް ސޯޝަލްމީޑިއާގައި ފާޅުކުރަން					
	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދެއްވާ	ބޮޑަށް ދެބަސްވަން	ދެބަސްވަން	އެއްބަހެއްވެސް ދެބަހެއްވެސްނުވަން	އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން
43	ފެއްޓުމަށްފަހު ވަރަށް ގިނައިރުވަންދެން ސޯޝަލްމީޑިއާގައި އަހަރެންގެ ވާހަކަތައް ހިއްސާކުރަން ވަގުތު ހޭދަކުރަން					
42	އެއްވެސް ޚިޔާލުކުރުމެއްނެތި ސޯޝަލް މީޑިއާގައި އަހަރެންނާއި ބެހޭ ޚާއްޞަ ނުވަތަ އަމިއްލަ ވާހަކަތައް ގިނައިން ފާޅުކުރަން					
44	އަހަރެން ދުރާ ގޮތުގައި އަހަރެންގެ ޚާއްޞަ ކަންތައްތަކާއިބެހޭ ވާހަކަތައް ސޯޝަލް މީޑިއާގައި ފާޅުކުރުން އެއްބައިވަރަށް ކަންޖެހޭގޮތެއް ނުކުރެވޭ					
45	ފެއްޓުމަށްފަހު އަހަރެންގެ ޚާއްޞަ ނުވަތަ އަމިއްލަ ވާހަކަތައް އެއްކޮށް ފާޅުކުރަން					
46	އަހަރެން ސޯޝަލް މީޑިއާގައި ލިޔާ ޕޯސްޓުތައް ހުންނަނީ ވަކި ހާއްސަ މައުޟޫޢަކަށް އެކަނި					
47	އަހަރެން ސޯޝަލް މީޑިއާގައި ލިޔާ ޕޯސްޓުތައް ހުންނަނީ ތަފާތު އެކި ކަންކަމާބެހޭ ގޮތުން					
48	ސޯޝަލް މީޑިއާގައި ލިޔަން ފެއްޓުމަށްފަހު އަހަރެން ވަރަށްފަސޭހައިން އެއް މައުޟޫއިން އަނެއް މައުޟޫއަށް ބަދަލުކޮށްލެވޭ					
49	ސޯޝަލް މީޑިއާގައި އަހަރެން ލިޔާ ޕޯސްޓުތައް ހުންނަނީ އެކި ތަފާތު މައުޟޫތަކާބެހޭގޮތުން					
50	ސޯޝަލް މީޑިއާގައި އަހަރެން ލިޔާ ޕޯސްޓުތައް ހުންނަނީ ވަކި ޚާއްސަ މައުޟޫއެއްގެ މައްޗަށް ބިނާވެފަ					

ތިރީގައިމިވާ 12 ސުވާލު ބިނާވެގެންވަނީ ސޯޝަލް މީޑިއާގެ ބޭނުން ދަންނަ މިންވަރުގެ މައްޗަށެވެ.

އިރުޝާދު: ސޯޝަލް މީޑިއާގެ ބޭނުން (އޮޕަރޭޝަނަލް) އެހެންނަމަވެސް ބައެއްފަހަރު އުފާވާ ގުޅުންތަކަށް ވިސްނާ ތިރީގައި މިވާ ކޮންމެ ޖުމްލައަކާ ދިމާ ދާ ގޮތް ފާހަގަ ކުރޭ

	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދެއްވާ	ވަރަށްބޮޑަށް ދެބަސްވަން	ބޮޑަށް ދެބަސްވަން	ކުޑަކޮށް ދެބަސްވަން	ވަކިކޮޅަކަށްނުޖެހި	ކުޑަކޮށް އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން	ވަރަށްބޮޑަށް އެއްބަސްވަން
51	ބޭނުމެއްނެތި ވަގުތުގައި އިންޓަރނެޓާ ސޯޝަލް މީޑިއާ ބަލަން							

	ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދެއްވާ	ވަރަށްބޮޑަށް ދެބަސްވަން	ބޮޑަށް ދެބަސްވަން	ކުޑަކޮށް ދެބަސްވަން	ވަކިކޮޅެއް ނޫ	ކުޑަކޮށް އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން	ވަރަށްބޮޑަށް އެއްބަސްވަން
52	އުފާފާއި ހިތާމަޔަށް ހިއްސާ ކުރަން ހާއްސަ މީހެއް ހުރި							
53	އަޅުގަނޑުގެ އާއިލާ އަޅުގަނޑަށް އެހީތެރިވެދިނުމަށް މަސައްކަތް ކުރޭ							
54	ނަފްސާނީ ގޮތުން ލިބެންވާ އެއްބާރުލުމާއި ރައްކާތެރިކަން އާއިލާގެ ފަރާތުން ލިބޭ							
55	އަޅުގަނޑަށް ހިތާމަޖެހުން ގެންސުދޭ ހާއްސަ މީހެއް ހުރި							
56	އަޅުގަނޑުގެ ރަހުމަތްތެރިން އަޅުގަނޑަށް އެހީތެރިވެދިނުމަށް މަސައްކަތް ކުރޭ							
57	ކަމެއް ގޯސްކޮށް ހިނގައިދިޔަމަ އަޅުގަނޑުގެ ރަހުމަތްތެރިންނަށް ބަރޯސާ ކުރެވޭ							
58	ދަރިއުމުރުގައި ކުރިމަތިވާ މައްސަލަތައް އާއިލާއާ ހިއްސާކުރެވޭ							
59	އުފާފާއި ހިތާމަތައް ހިއްސާކުރާނެ ރަހުމަތްތެރިން ތިބޭ							
60	އަޅުގަނޑުގެ އިޙްސާސްތަކާމެދު އާއިލާ ހާއްސަ މީހެއް އަޅުގަނޑުގެ ހާލަތުގަ ހުރި							
61	އަޅުގަނޑުގެ ނިންމުންތައް ނިންމަން އާއިލާއިން އެހީތެރިވޭ							
62	ދަރިއުމުރުގައި ކުރިމަތިވާ މައްސަލަތައް ރަހުމަތްތެރިންނާ ހިއްސާކުރެވޭ							

ތިރީގައިވާ ސުވާލުތަކަށް ޖަވާބުދޭނީ ފާއިތުވެދިޔަ މަހުގެ ތެރޭގައި ކުރެވުނު އިޙްސާސްތަކަށް ބިނާކޮށްގެންނެވެ.
އެންމެ އެކަށީގެންވާ ބޮކްސްގައި ޓިކް ފާހަގަކުރައްވާ

	ފާއިތުވިދިޔަ މަހުގެ ތެރޭގައި، އަހަރެން....	އެއްގޮތަކަށް ވެސް ނޫން	އެއްފަހަރު ނޫނީ ދެފަހަރު	ގާތްގަނޑަކަށް ހަފްތާއަކު އެއްފަހަރު	ހަފްތާއަކު ދެތިން ފަހަރު	ގާތްގަނޑަކަށް ކޮންމެ ދުވަހަކު	ކޮންމެ ދުވަހަކު ވެސް
63	އުފާވެރިކަން އިޙްސާސްކުރިން						
64	ދިރިއުޅުމާމެދު ޝައުޤުވެރިވި						
65	ދިރިއުޅުމާއި ދޭތެރޭ ހިތްހަމަޖެހުން އިޙްސާސްވި						
66	މުޖުތަމަޢަށް ބޭނުންތެރި ކަމެއް ކޮށްދެވުނު ކަމުގެ އިޙްސާސްވުން						
67	މުޖުތަމަޢުއަށް ނިސްބަތްވާ ފަރުދެއް ކަމުގެ އިޙްސާސްވި						
68	މި މުޖުތަމަޢަކީ އެންމެންނަށް ރަގަޅު ތަނެއްކަމުގެ އިޙްސާސްވި						
69	އެންމެންނަކީވެސް އާއްމު ގޮތެއްގައި ރަގަޅު ބައެއްކަމުގެ އިޙްސާސްވި						
70	މުޖުތަމަޢު ތެރޭގައި ކަންތައްތައް ހިނގަމުން އެންމެ ހަމަޖެހޭ އުސޫލަކުން ކަން ވަޒަންކުރެވުން						
71	ތިމާގެ ޝަޚްސިއްޔަތުގައި ހުރި ގިނަ ސިފަތަކެއް ތިމާއަށް ކަމުދާކަން އިޙްސާސްވި						
72	އާއްމު ދިރިއުޅުމުގެ ޒިންމާތައް ރަގަޅަށް އަދާކުރެވޭކަން އިޙްސާސްވި						
73	ތިމާއާއި އެހެން މީހުންނާއި އޮތް ގުޅުމަކީ ހިތްހަމަޖެހޭ އަދި އިތުބާރުކުރެވޭ ގުޅުމެއްކަން އިޙްސާސްވި						
74	ތިމާގެ ނަފްސު އިތުރަށް ހަރުދަނާކޮށް ތަރައްޤީކުރުމުގައި އުނދަގޫތަކާއި ގޮންޖެހުންތައް ތަޖުރިބާ ކުރިން						
75	އަމިއްލަ އަށް ވިސްނާ ފިކުރުކޮށް އެކިއާރާއި ފިކުރުތައް ހާމަ ކުރަން ކެރޭ ކަމުގެ އިޙްސާސްވި						
76	ދިރިއުޅުމުގެ މަޤްޞަދަކާއި ދިރިއުޅުން ގެންދަން ބޭނުންވާ ވަކި ދިމާއެއް އޮތްކަން އިޙްސާސްވި						

ތިރީގައިވާ ބުނެވުންތަކަށް ޖަވާބުދިނުމަށް އެންމެ އެކަށީގެންވާ ބޮޑުގައި ހުރި ފާހަގަކުރައްވާ

	ބޮޑަށް ދެބަސްވަން	ދެބަސްވަން	އެއްބަސްވެސް ދެބަސްވެސްނުވަން	އެއްބަސްވަން	ބޮޑަށް އެއްބަސްވަން
ކުރަށުންގެ އަމިއްލަ ނަޒަރާ ގުޅޭ ދެކޭނީ :					
77 އުނގެނުމަކީ އަދި އުނގެނުމަށް ޖަހާލުމުގެ ކަންތައްތައް ބުއްދި ނުކުރާ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
78 ޒާތުގެ ތެރޭގައި އުނގެނުމުގައި އިތުބާރު ކުޑަ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
79 ކަންނެތް މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
80 ހާސްކަން، ކަންބޮޑުވާ ކަމަކާ ކަމުގެ ދިރާސާއި ބުނުމަ ފަސޭހައިން ރުއްސޭނެ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
81 ކަންކުރާ ދަތިކަން ފަންނުވެރި ހުނަރުތައް ހުނަރ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
82 މުސްތާގު ގެއްލި އަދި އުފާވެރި މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
83 ފިނިފިނިކަން އުނގެނުމުގެ ކުރިއަރާ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
84 މަސައްކަތްތަކާ ފުރުސަތު ފުރިހަމަކުރާ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
85 އަމަލު ހާސްވި ޖާގަ މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○
86 ހުރުމަ ތަނަވަސް މިޒާޖުގެ ގޮތުގައި	○	○	○	○	○

މި ސަރުވޭ ފުރިހަމަ ކުރުމަށްޓަކައި ތިރީގައި މިވާ ސުވާލުތަކަށްވެސް ޖަވާބުދެއްވަން ވާނެއެވެ.

87 އުމުރު:

88 ޖިންސު: އަންހެން ○ ފިރިހެން ○

89 ރަށްފުރިފައިވާ ރަށް:

90 މިހާރު ދިރިއުޅުއްވާ ރަށް:

91 30 ޖޫން 2016 ގައި އެންމެ ނަސީބު ގެދޮރުއަޅުގައި ބައި ފިރިފަހައްޓަވަން ބޭނުންފުޅުވޭތޯ؟ ގެދޮރުވެރިން
ހޯދުމަށް ނަސީބުވުން ބޭނުމަކަށް އަޅާލާފައި ލިޔެވުމުގައި ދެއްވާށެވެ.

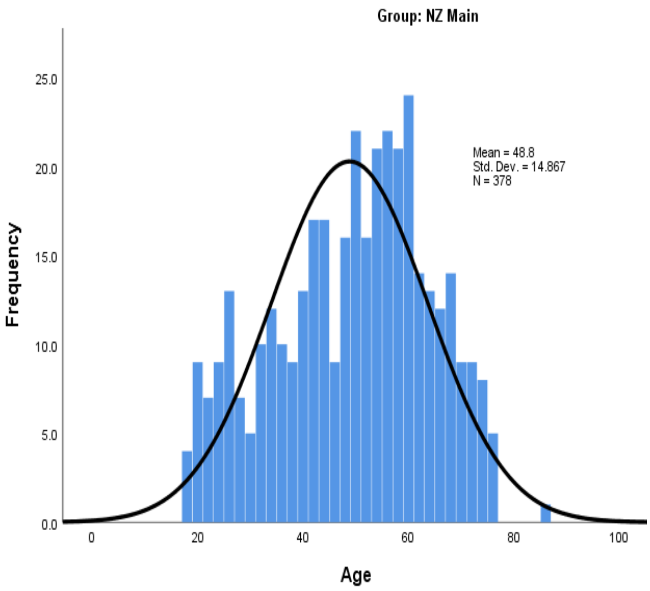
ބައިވެރިވާކަށް ބޭނުމެއްނޫން	ބައިވެރިވާން ބޭނުން (އީމެއިލް އެޑްރެސް ____________________________)

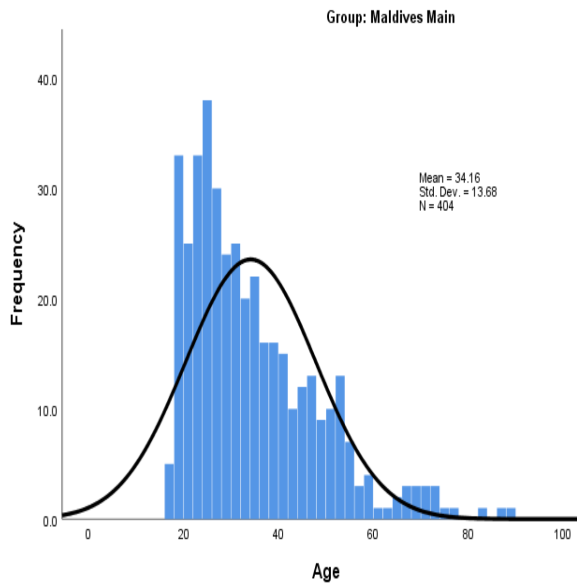
މި ދިރާސާއާއި ބެހޭ ރިޕޯޓް ތަރުޖަމާކުރުމުން އޭގެ ކޮޕީއެއް އަރުވަމާ ބޭނުން	92

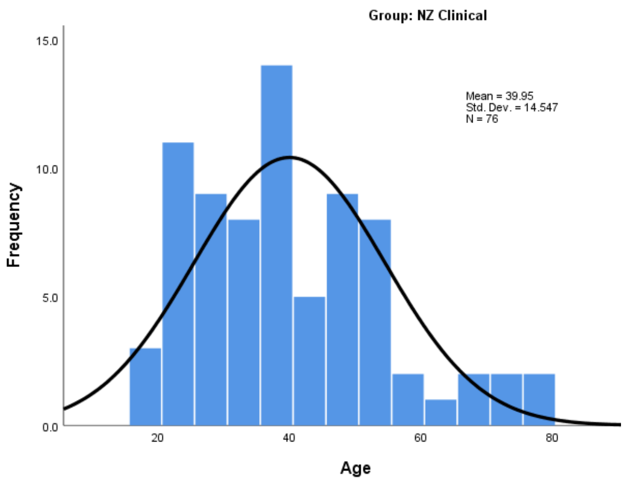
ނޫން	އާނ
	އާނ ނަމަ އީމެއިލް އެޑްރެސް:

މި ސާރވޭގައި ބައިވެރިވެދެއްވީތީ ވަރަށް ބޮޑަށް ޝުކުރިއްޔާ

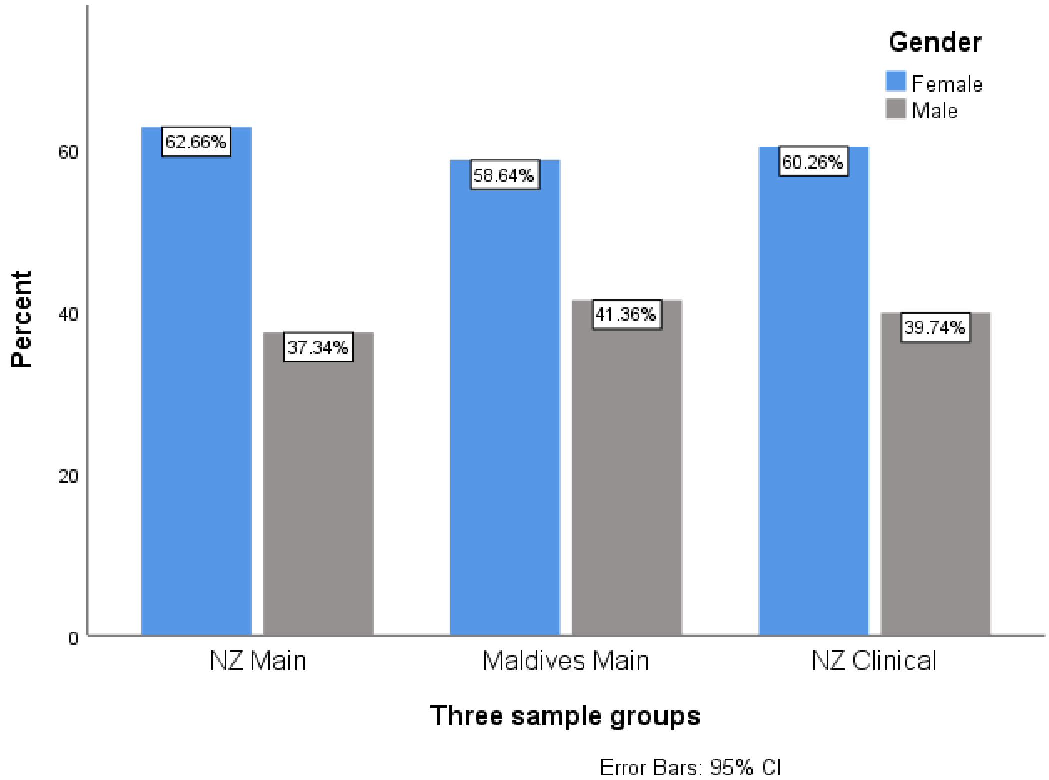
APPENDIX. B: Graph Showing the Distribution of Age for the Three Subsamples (NZ Main, n = 378, Maldives Main, n = 404, NZ Clinical, n = 76)



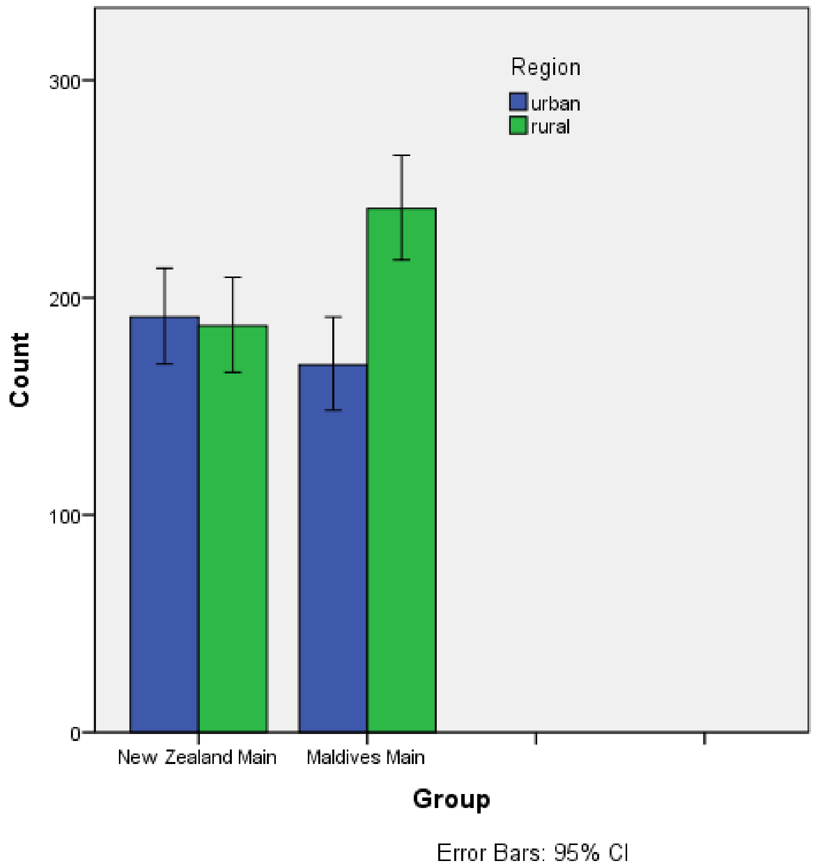




APPENDIX C: Percentage of Men and Women in Each of the Three Sample Groups (NZ Main, *n* = 378, Maldives Main, *n* = 404, NZ Clinical, *n* = 76)



APPENDIX D: Number of people living in either urban or rural regions in the Maldives Main and New Zealand Main groups including those who spent less than 10 minutes on SNSs ((NZ Main, *n* = 378, Maldives Main, *n* = 404)



APPENDIX. E: Frequency Table Showing the Distribution of MSPSS Scores for the Combined Random Sample ($N = 472$)

Valide	Score	Frequency	Percent	Valid Percent	Cumulative Percent
	12	3	0.4	0.4	0.4
	14	2	0.3	0.3	0.6
	15	2	0.3	0.3	0.9
	16	1	0.1	0.1	1
	17	1	0.1	0.1	1.1
	18	3	0.4	0.4	1.5
	21	1	0.1	0.1	1.7
	23	2	0.3	0.3	1.9
	24	3	0.4	0.4	2.3
	25	1	0.1	0.1	2.4
	26	1	0.1	0.1	2.5
	27	3	0.4	0.4	2.9
	28	1	0.1	0.1	3
	29	1	0.1	0.1	3.2
	30	2	0.3	0.3	3.4
	31	1	0.1	0.1	3.6
	32	2	0.3	0.3	3.8
	33	2	0.3	0.3	4.1
	34	2	0.3	0.3	4.3
	36	2	0.3	0.3	4.6
	37	2	0.3	0.3	4.8
	38	2	0.3	0.3	5.1
	39	2	0.3	0.3	5.3
	40	1	0.1	0.1	5.5
	41	2	0.3	0.3	5.7
	42	2	0.3	0.3	6
	43	3	0.4	0.4	6.4
	44	6	0.8	0.8	7.1
	45	3	0.4	0.4	7.5
	46	3	0.4	0.4	7.9
	47	1	0.1	0.1	8
	48	9	1.1	1.1	9.1
	49	7	0.9	0.9	10
	50	2	0.3	0.3	10.3
	51	8	1	1	11.3
	52	13	1.6	1.7	13
	53	9	1.1	1.1	14.1
	54	18	2.3	2.3	16.4
	55	11	1.4	1.4	17.8
	56	15	1.9	1.9	19.7
	57	7	0.9	0.9	20.6
	58	10	1.3	1.3	21.9
	59	15	1.9	1.9	23.8
	60	20	2.5	2.5	26.3
	61	19	2.4	2.4	28.7
	62	26	3.3	3.3	32
	63	10	1.3	1.3	33.3
	64	14	1.8	1.8	35.1
	65	21	2.6	2.7	37.7
	66	29	3.6	3.7	41.4
	67	20	2.5	2.5	44
	68	20	2.5	2.5	46.5
	69	23	2.9	2.9	49.4
	70	30	3.8	3.8	53.2
	71	34	4.3	4.3	57.6
	72	46	5.8	5.8	63.4
	73	24	3	3	66.5
	74	15	1.9	1.9	68.4
	75	13	1.6	1.7	70
	76	17	2.1	2.2	72.2
	77	24	3	3	75.2
	78	25	3.1	3.2	78.4
	79	23	2.9	2.9	81.3
	80	24	3	3	84.4
	81	15	1.9	1.9	86.3
	82	18	2.3	2.3	88.6
	83	12	1.5	1.5	90.1
	84	78	9.8	9.9	100
	Total	787	98.9	100	
Missing	System	9	1.1		
Total		796	100		

Appendix F-1: Correlation Matrix for the Combined Sample who spent SNSs for 10 mins or more per day (*N* = 472)

	oMSPSS	MSPSS	MHC-SF	oSDS	Extroversion	Conscientiousness	Neuroticism	Time on SNSs	Age	Gender	Region	Country
oMSPSS	1.00	0.22**	-0.02	.040**	0.01	-0.14**	0.07	0.28**	-0.27**	0.12*	-0.01	-0.14**
MSPSS		1.00	0.36**	-0.11*	0.08	0.05	-0.02	0.04	0.02	-0.13**	0.13**	0.28**
MHC-SF			1.00	-0.13**	0.22**	0.33**	-0.29**	-0.06	0.18**	-0.03	-0.02	0.21**
oSDS				1.00	0.11*	-0.15**	0.02	0.24**	-.023**	0.18**	-0.08	-0.38**
Extroversion					1.00	0.27**	-0.31**	0.09	-0.10*	0.01	-0.07	-0.36**
Conscientiousness						1.00	-0.22**	-0.10*	0.24**	-0.07	-0.06	0.05
Neuroticism							1.00	-0.09	-0.07	-0.15**	0.10*	0.16**
Time on SNS (> 10 min per day)								1.00	-0.35**	0.05	-0.02	-0.29**
Age									1.00	0.00	-0.05	0.54**
Gender (male = 1)										1.00	-0.10*	-0.14**
Region (urban = 1)											1.00	0.11*
Country (NZ =1)												1.00

Note: MHC-SF = Mental Health Continuum-Short Form, oMSPSS = Online Multidimensional Scale of Perceived Social Support, MSPSS = Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory

**. Correlation is significant at the .01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed).

Appendix F-2: Correlations between variables for New Zealand Random Sample who used SNSs for 10 mins or more per day (*N* = 205)

	MSPSS	MHC-SF	oRDS	Extroversion	Conscientiousness	Neuroticism	Time on SNSs	Age	Gender	Region
oMSPSS	.165*	-0.071	.373**	-0.116	-.167*	0.056	.204**	-.292**	.144*	0.019
MSPSS	1	.332**	-0.086	.173*	-0.051	-0.005	0.020	-.250**	-.200**	.151*
MHC-SF		1	-.151*	.360**	.313**	-.416**	-.147*	0.071	-0.071	-0.036
oSDS			1	-0.006	-.165*	0.053	.192**	-0.074	0.126	0.067
Extroversion				1	.174*	-.331**	-0.063	0.111	-0.076	0.050
Conscientiousness					1	-.186**	-.140*	.260**	-0.096	-0.096
Neuroticism						1	0.076	-.254**	-0.090	0.075
Time on SNS (> 10 min per day)							1	-.231**	-0.068	-0.008
Age								1	0.035	-.244**
Gender									1	0.010
Region										1

Note: MHC-SF = Mental Health Continuum-Short Form, oMSPSS = Online Multidimensional Scale of Perceived Social Support, MSPSS = Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory

**. Correlation is significant at the .01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Appendix F-3: Correlations between variables for Maldives Random Sample who used SNSs for 10 minutes or more per day (*N* = 267)

	MSPSS	MHC-SF	oRDS	Extroversion	Conscientiousness	Neuroticism	Time on SNSs	Age	Gender	Region
oMSPSS	.330**	0.06	.388**	0.02	-0.10	.134*	.214**	-.180**	0.071	-0.006
MSPSS	1	.319**	0.049	.242**	0.09	-.121*	.183**	-0.110	-0.033	0.075
MHC-SF		1	0.003	.312**	.33**	-.279**	0.058	0.095	0.038	-0.042
oSDS			1	-0.069	0	.131*	0.088	0.025	.141*	-0.120
Extroversion				1	.440**	-.221**	0.023	.147*	-0.017	-0.115
Conscientiousness					1	-.275**	-0.026	.278**	-0.036	-0.043
Neuroticism						1	-.165**	-0.105	-.158**	0.087
Time on SNS							1	-.251**	0.077	0.067
Age								1	.163**	0.014
Gender									1	-.145*
Region	-	-	-	-	-	-	-	-	-	1

Note: MHC-SF = Mental Health Continuum-Short Form, oMSPSS = Online Multidimensional Scale of Perceived Social Support, MSPSS = Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory

**. Correlation is significant at the .01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed).

Appendix F-4: Correlations between variables for NZ Clinical Sample who spent 10 mins or more per day ($N = 45$)

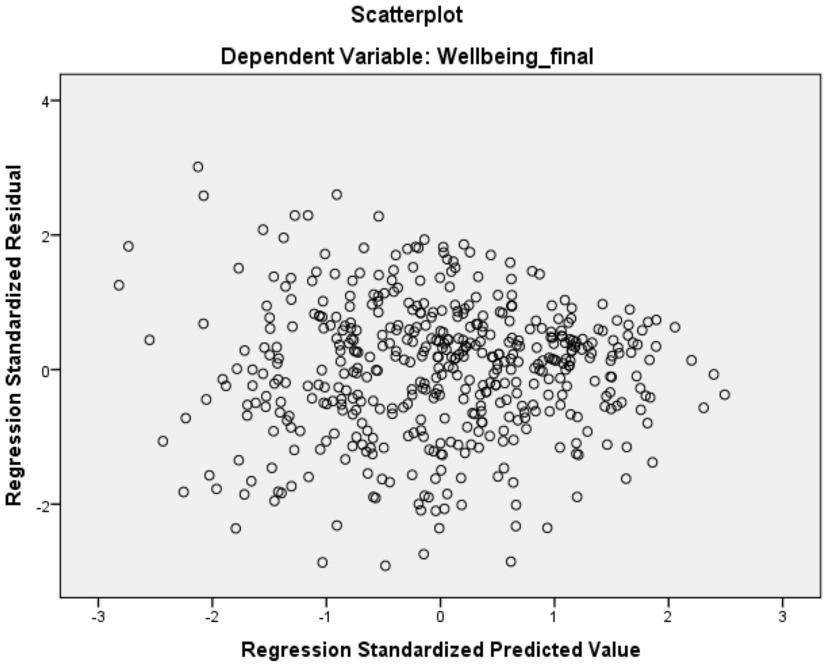
Correlations between variables for New Zealand Clinical Sample (n = 45)

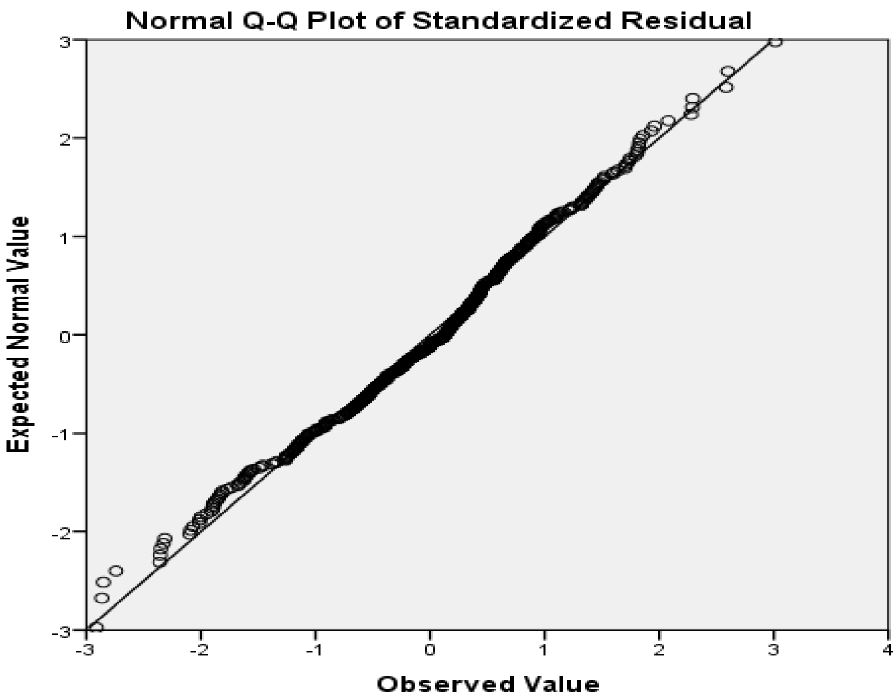
	MSPSS	MHC-SF	oRDS	Extroversion	Conscientiousness	Neuroticism	Time on SNSs	Age	Gender
oMSPSS	.302*	0.016	.396**	-0.190	0.057	0.168	.412**	-0.207	0.140
MSPSS	1	0.242	0.015	0.251	0.182	-0.118	-0.053	0.033	-0.262
MHC-SF		1	-0.107	.362*	0.187	-.443**	0.027	0.137	-.304*
oSDS			1	0.083	-0.081	0.126	.375*	-0.194	0.206
Extroversion				1	0.206	-0.205	-0.025	-0.057	-.326*
Conscientiousness					1	0.003	-0.004	-0.065	-.373*
Neuroticism						1	0.288	-.321*	-0.112
Time on SNS							1	-.613**	0.032
Age								1	-0.057
Gender									1

Note: MHC-SF = Mental Health Continuum-Short Form, oMSPSS = Online Multidimensional Scale of Perceived Social Support, MSPSS = Multidimensional Scale of Perceived Social Support Scale, oSDS = Online Self-Disclosure Scale, BFI-10 = 10-item Big Five Inventory

**. Correlation is significant at the .01 level (2-tailed).
*. Correlation is significant at the .05 level (2-tailed).

Appendix G: Scatterplot, and Q-Q plots for residuals for dependent variable, psychological wellbeing for combined random sample ($N = 472$)





Appendix H: Multivariable Regression Analysis Showing All Three Models for the Three Subsamples Who Use SNS for more than 10 minutes per day (H_1)

Model Summary

						Change Statistics				
Subsample	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
New Zealand Main (n = 205)	1	.380a	0.144	0.114	15.00984	0.144	4.739	7	197	0.000
	2	.433b	0.188	0.154	14.66167	0.043	10.467	1	196	0.001
	3	.536c	0.288	0.255	13.76482	0.1	27.373	1	195	0.000
Maldives Main (n = 267)	1	.419d	0.175	0.153	15.28545	0.175	7.864	7	259	0.000
	2	.457e	0.209	0.184	14.99898	0.034	10.988	1	258	0.001
	3	.556f	0.309	0.285	14.04137	0.1	37.391	1	257	0.000
New Zealand Clinical (n = 45)	1	.515g	0.265	0.149	13.03927	0.265	2.282	6	38	0.056
	2	.642h	0.413	0.302	11.81111	0.148	9.314	1	37	0.004
	3	.672i	0.451	0.329	11.57533	0.038	2.523	1	36	0.121

ANOVA[a]

Three_groups			Sum of Squares	df	Mean Square	F	Sig.
NZ Main	1	Regression	7473.456	7	1067.637	4.739	.000[b]
		Residual	44383.152	197	225.295		
		Total	51856.608	204			
	2	Regression	9723.540	8	1215.442	5.654	.000[c]
		Residual	42133.069	196	214.965		
		Total	51856.608	204			
	3	Regression	14909.891	9	1656.655	8.744	.000[d]
		Residual	36946.717	195	189.470		
		Total	51856.608	204			
Maldives Main	1	Regression	12861.368	7	1837.338	7.864	.000[e]
		Residual	60514.072	259	233.645		
		Total	73375.440	266			
	2	Regression	15333.315	8	1916.664	8.520	.000[f]
		Residual	58042.125	258	224.969		
		Total	73375.440	266			
	3	Regression	22705.310	9	2522.812	12.796	.000[g]
		Residual	50670.130	257	197.160		
		Total	73375.440	266			
NZ Clinical	1	Regression	2328.253	6	388.042	2.282	.056[h]
		Residual	6460.859	38	170.023		

	Total	8789.111	44			
2	Regression	3627.522	7	518.217	3.715	.004[i]
	Residual	5161.590	37	139.502		
	Total	8789.111	44			
3	Regression	3965.537	8	495.692	3.700	.003[j]
	Residual	4823.574	36	133.988		
	Total	8789.111	44			

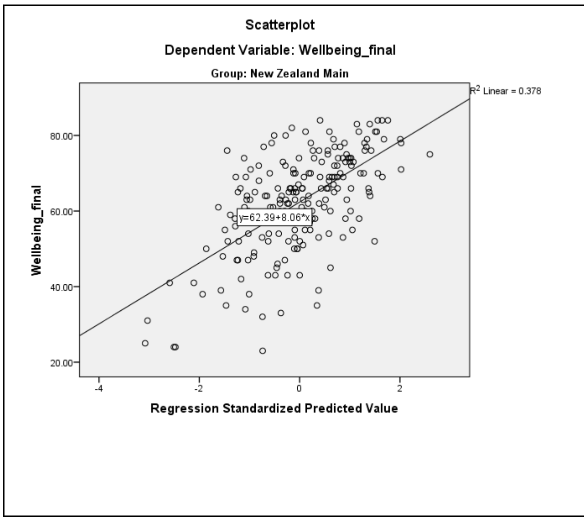
Coefficients

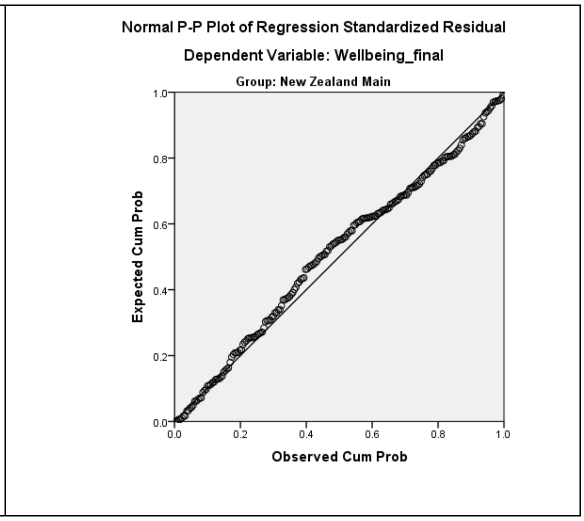
Subsamples	Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
			B	Std. Error	Beta		
NZ Main	1	(Constant)	52.562	11.267		4.665	0
		Age	-0.27	0.079	-0.253	-3.428	0.001
		Gender	5.88	2.4	0.167	2.45	0.015
		Region	-2.164	2.194	-0.068	-0.986	0.325
		Extro	-0.793	0.588	-0.097	-1.35	0.179
		Consc	-0.693	0.667	-0.073	-1.039	0.3
		Neuro	-0.265	0.581	-0.033	-0.456	0.649
		Offline PSS	0.213	0.096	0.158	2.22	0.028
	2	(Constant)	40.617	11.608		3.499	0.001
		Age	-0.224	0.078	-0.21	-2.867	0.005
		Gender	6.816	2.363	0.194	2.885	0.004
		Region	-2.286	2.143	-0.071	-1.067	0.287
		Extro	-0.732	0.574	-0.09	-1.275	0.204
		Consc	-0.456	0.655	-0.048	-0.695	0.488
		Neuro	-0.289	0.568	-0.036	-0.508	0.612
		Offline PSS	0.23	0.094	0.171	2.449	0.015
		Time of SNS	3.107	0.96	0.217	3.235	0.001
	3	(Constant)	17.95	11.728		1.531	0.127
		Age	-0.22	0.073	-0.206	-2.992	0.003
		Gender	5.371	2.235	0.153	2.403	0.017
		Region	-2.767	2.014	-0.087	-1.374	0.171
		Extro	-0.916	0.54	-0.112	-1.695	0.092
		Consc	-0.065	0.62	-0.007	-0.105	0.916
		Neuro	-0.38	0.533	-0.048	-0.713	0.477
		Offline PSS	0.272	0.089	0.201	3.065	0.002
		Time on SNS	2.177	0.919	0.152	2.368	0.019
		Online SD	0.584	0.112	0.331	5.232	0
Maldives Main	1	(Constant)	25.36	8.235		3.079	0.002
		Age	-0.257	0.118	-0.131	-2.169	0.031
		Dum_M	4.204	1.977	0.125	2.126	0.034
		Dum_Urb	-0.896	1.938	-0.027	-0.463	0.644
		Extro	0.193	0.656	0.019	0.294	0.769
		Consc	-0.534	0.642	-0.055	-0.831	0.407
		Neuro	1.659	0.579	0.173	2.867	0.004
		Offline PSS	0.376	0.065	0.343	5.77	0
	2	(Constant)	16.132	8.547		1.887	0.06
		Age	-0.141	0.121	-0.072	-1.163	0.246
		Dum_M	3.566	1.95	0.106	1.829	0.069

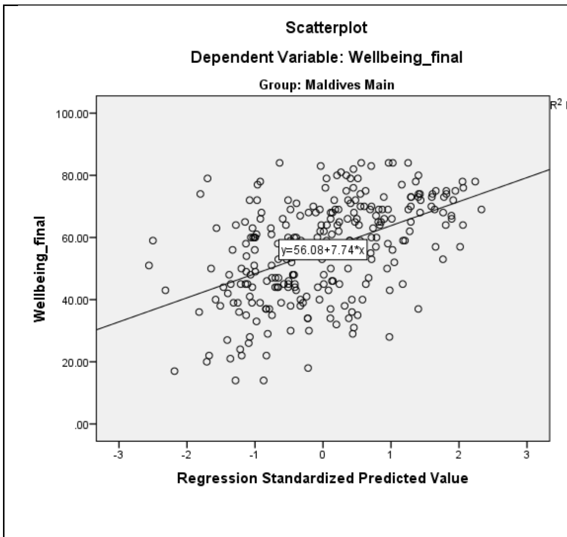
		Dum_Urb	-0.937	1.901	-0.028	-0.493	0.622
		Extro	0.189	0.644	0.019	0.293	0.77
		Consc	-0.507	0.63	-0.052	-0.804	0.422
		Neuro	1.944	0.574	0.203	3.386	0.001
		Offline PSS	0.346	0.065	0.316	5.367	0
		Time on SNS	2.261	0.682	0.198	3.315	0.001
	3	(Constant)	-7.157	8.862		-0.808	0.42
		Age	-0.21	0.114	-0.107	-1.84	0.067
		Dum_M	2.215	1.839	0.066	1.205	0.229
		Dum_Urb	0.531	1.796	0.016	0.295	0.768
		Extro	0.332	0.603	0.033	0.551	0.582
		Consc	-0.209	0.592	-0.022	-0.353	0.725
		Neuro	1.406	0.545	0.147	2.58	0.01
		Offline PSS	0.314	0.061	0.287	5.182	0
		Time on SNS	1.736	0.644	0.152	2.694	0.008
		Online SD	0.653	0.107	0.333	6.115	0
NZ Clinical	1	(Constant)	12.404	22.472		0.552	0.584
		Age	-0.214	0.19	-0.17	-1.126	0.267
		Gender	6.383	4.789	0.219	1.333	0.191
		Extro	-1.434	0.996	-0.226	-1.44	0.158
		Consc	0.699	1.098	0.097	0.637	0.528
		Neuro	1.069	1.192	0.141	0.898	0.375
		OffPSS	0.511	0.18	0.421	2.843	0.007
	2	(Constant)	-9.806	21.617		-0.454	0.653
		Age	0.064	0.195	0.051	0.328	0.745
		Gender	7.663	4.358	0.262	1.758	0.087
		Extro	-1.378	0.902	-0.217	-1.528	0.135
		Consc	0.791	0.995	0.109	0.794	0.432
		Neuro	0.736	1.085	0.097	0.679	0.502
		Offline PSS	0.531	0.163	0.437	3.261	0.002
		Time on SNS	4.967	1.628	0.453	3.052	0.004
	3	(Constant)	-13.486	21.312		-0.633	0.531
		Age	0.031	0.192	0.024	0.161	0.873
		Gender	5.408	4.501	0.185	1.202	0.237
		Extro	-1.678	0.904	-0.264	-1.856	0.072
		Consc	0.828	0.976	0.114	0.848	0.402
		Neuro	0.52	1.072	0.068	0.485	0.631
		Online PSS	0.506	0.16	0.417	3.154	0.003
		Time on SNS	3.762	1.766	0.343	2.13	0.04
		OnSD	0.364	0.229	0.232	1.588	0.121

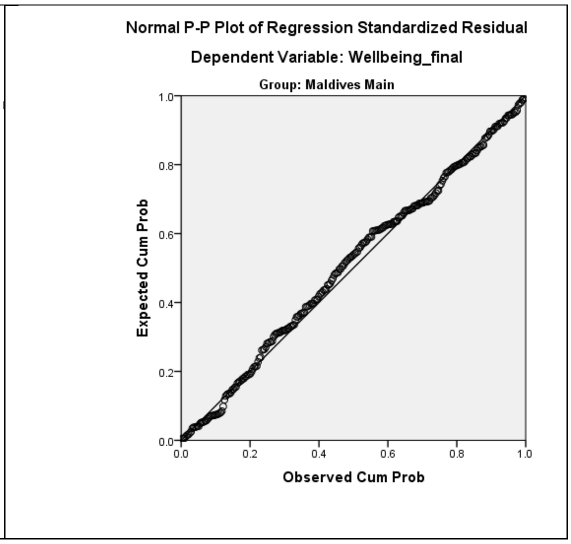
Dependent Variable: Online PSS

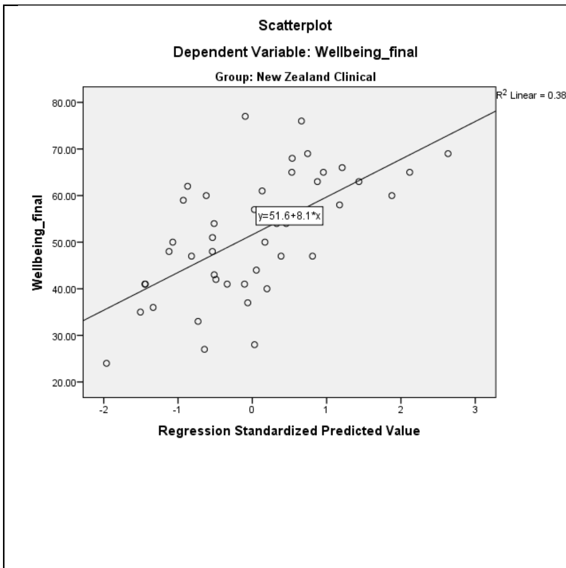
Appendix I: Scatterplot and P-P plots for residuals for dependent variable, psychological wellbeing for three subsamples separately

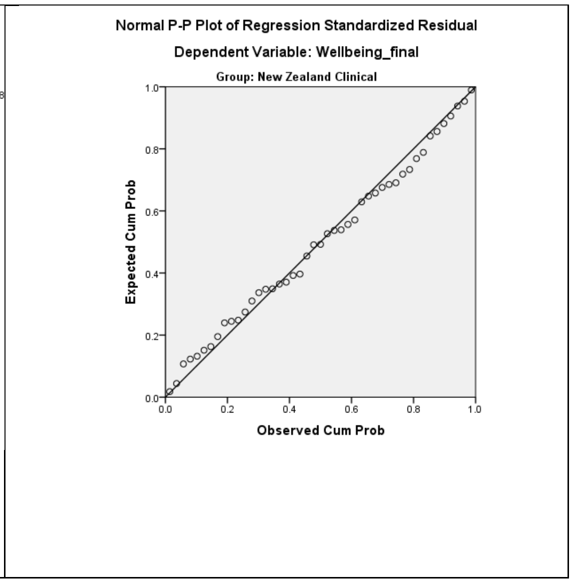












Appendix J: Multivariable Regression Analysis Showing All Three Models for the Three Subsamples who use SNS for more than 10 minutes per day (H_2 and H^3)

Model Summary: MV estimated in one direction

Groups		R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	Sig. F Change	Durbin-Watson
NZ Main	1	.544[a]	0.296	0.271	11.20064	0.296	11.806	0.000	
	2	.544[b]	0.296	0.267	11.22387	0.001	0.185	0.667	
	3	.615[c]	0.378	0.349	10.57982	0.082	25.589	0.000	1.917
Maldives Main	1	.424[e]	0.180	0.158	14.85013	0.180	8.131	0.000	
	2	.433[f]	0.187	0.162	14.81588	0.007	2.199	0.139	
	3	.488[g]	0.238	0.211	14.37208	0.051	17.179	0.000	1.759

ANOVA[a]

Three_groups			Sum of Squares	df	Mean Square	F	Sig.
NZ Main	1	Regression	10368.071	7	1481.153	11.806	.000[b]
		Residual	24714.485	197	125.454		
		Total	35082.556	204			
	2	Regression	10391.401	8	1298.925	10.311	.000[c]
		Residual	24691.155	196	125.975		
		Total	35082.556	204			
	3	Regression	13255.699	9	1472.855	13.158	.000[d]
		Residual	21826.857	195	111.933		
		Total	35082.556	204			
Maldives Main	1	Regression	12551.899	7	1793.128	8.131	.000[e]
		Residual	57116.310	259	220.526		
		Total	69668.209	266			
	2	Regression	13034.585	8	1629.323	7.423	.000[f]
		Residual	56633.625	258	219.510		
		Total	69668.209	266			
	3	Regression	16583.107	9	1842.567	8.920	.000[g]
		Residual	53085.102	257	206.557		
		Total	69668.209	266			

Groups	Model	Variables	B	Std. Error	β	t	Sig.	Collinearity Statistics: Tolerance	VIF
NZ Main	1	(Constant)	60.536	7.268		8.329	0.000		
		Age	-0.091	0.057	-0.104	-1.598	0.112	0.843	1.187
		Gender	-1.345	1.770	-0.047	-0.760	0.448	0.953	1.049
		Region	-0.548	1.632	-0.021	-0.336	0.738	0.929	1.077

		Extro	1.495	0.432	0.223	3.458	0.001	0.859	1.164
		Consc	1.713	0.502	0.218	3.415	0.001	0.875	1.142
		Neuro	-2.139	0.434	-0.326	-4.933	0.000	0.821	1.218
		Online SD	-0.141	0.089	-0.097	-1.593	0.113	0.955	1.047
	2	(Constant)	59.436	7.718		7.701	0.000		
		Age	-0.084	0.060	-0.096	-1.407	0.161	0.774	1.291
		Gender	-1.428	1.784	-0.049	-0.800	0.425	0.942	1.062
		Region	-0.495	1.640	-0.019	-0.302	0.763	0.924	1.083
		Extro	1.511	0.435	0.226	3.475	0.001	0.853	1.173
		Consc	1.720	0.503	0.219	3.419	0.001	0.875	1.143
		Neuro	-2.129	0.435	-0.324	-4.891	0.000	0.819	1.222
		Online SD	-0.156	0.095	-0.108	-1.638	0.103	0.833	1.200
		Online PSS	0.024	0.056	0.029	0.430	0.667	0.765	1.306
	3	(Constant)	33.568	8.892		3.775	0.000		
		Age	-0.033	0.057	-0.037	-0.573	0.568	0.750	1.333
		Gender	0.365	1.719	0.013	0.213	0.832	0.902	1.109
		Region	-1.353	1.555	-0.051	-0.870	0.385	0.913	1.096
		Extro	1.092	0.418	0.163	2.610	0.010	0.819	1.221
		Consc	1.824	0.475	0.232	3.843	0.000	0.873	1.146
		Neuro	-2.082	0.410	-0.317	-5.073	0.000	0.818	1.222
		Online SD	-0.079	0.091	-0.054	-0.868	0.386	0.810	1.235
		Online PSS	-0.032	0.054	-0.039	-0.595	0.553	0.733	1.364
		Offline PSS	0.352	0.070	0.317	5.059	0.000	0.813	1.231
Maldives Main	1	(Constant)	30.707	8.608		3.567	0.000		
		Age	-0.029	0.114	-0.015	-0.253	0.800	0.887	1.127
		Gender	0.458	1.938	0.014	0.237	0.813	0.901	1.110
		Region	0.501	1.883	0.015	0.266	0.790	0.946	1.057
		Extro	1.810	0.619	0.186	2.922	0.004	0.785	1.273
		Consc	2.011	0.626	0.213	3.212	0.001	0.718	1.392
		Neuro	-1.764	0.565	-0.189	-3.123	0.002	0.867	1.154
		Online SD	0.206	0.176	0.068	1.170	0.243	0.935	1.070
	2	(Constant)	29.420	8.632		3.408	0.001		
		Age	0.008	0.116	0.004	0.065	0.948	0.848	1.180
		Gender	0.234	1.939	0.007	0.121	0.904	0.896	1.117
		Region	0.325	1.882	0.010	0.172	0.863	0.942	1.061
		Extro	1.706	0.622	0.175	2.743	0.007	0.775	1.290
		Consc	2.028	0.625	0.215	3.246	0.001	0.718	1.393
		Neuro	-1.842	0.566	-0.197	-3.254	0.001	0.859	1.164
		Online SD	0.097	0.190	0.032	0.512	0.609	0.796	1.256
		Online PSS	0.090	0.061	0.093	1.483	0.139	0.793	1.261
	3	(Constant)	17.951	8.819		2.036	0.043		
		Age	0.053	0.113	0.028	0.465	0.642	0.840	1.191
		Gender	0.564	1.883	0.017	0.299	0.765	0.894	1.119
		Region	-0.555	1.838	-0.017	-0.302	0.763	0.930	1.075
		Extro	1.160	0.618	0.119	1.879	0.061	0.740	1.351
		Consc	1.992	0.606	0.211	3.286	0.001	0.718	1.393
		Neuro	-1.522	0.554	-0.163	-2.745	0.006	0.843	1.187
		Online SD	0.119	0.185	0.039	0.646	0.519	0.796	1.257
		Online PSS	0.007	0.062	0.007	0.105	0.917	0.710	1.408
		Offline PSS	0.275	0.066	0.253	4.145	0.000	0.797	1.254

Model Summary: MV estimated in the second direction

Groups	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
NZ Main	1	.544[a]	0.296	0.271	11.20064	0.296	11.806	7	197	0.000	
	2	.544[b]	0.296	0.267	11.22387	0.001	0.185	1	196	0.667	
	3	.615[c]	0.378	0.349	10.57982	0.082	25.589	1	195	0.000	1.917
Maldives Main	1	.424[e]	0.180	0.158	19.93579	0.180	8.131	7	259	0.000	
	2	.433[f]	0.187	0.162	19.88981	0.007	2.199	1	258	0.139	
	3	.488[g]	0.238	0.211	19.29403	0.051	17.179	1	257	0.000	1.759

ANOVA[a]

Groups	Model		Sum of Squares	df	Mean Square	F	Sig.
NZ Main	1	Regression	10368.071	7	1481.153	11.806	.000[b]
		Residual	24714.485	197	125.454		
		Total	35082.556	204			
	2	Regression	10391.401	8	1298.925	10.311	.000[c]
		Residual	24691.155	196	125.975		
		Total	35082.556	204			
	3	Regression	13255.699	9	1472.855	13.158	.000[d]
		Residual	21826.857	195	111.933		
		Total	35082.556	204			
Maldives Main	1	Regression	22621.212	7	3231.602	8.131	.000[e]
		Residual	102935.831	259	397.436		
		Total	125557.043	266			
	2	Regression	23491.115	8	2936.389	7.423	.000[f]
		Residual	102065.928	258	395.604		
		Total	125557.043	266			
	3	Regression	29886.313	9	3320.701	8.920	.000[g]
		Residual	95670.730	257	372.260		
		Total	125557.043	266			

Coefficients[a]

Group	Model	Variable	B	Std. Error	Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
NZ Main	1	(Constant)	60.536	7.268		8.329	0.000		
		Age	-0.091	0.057	-0.104	-1.598	0.112	0.843	1.187
		Gender	-1.345	1.770	-0.047	-0.760	0.448	0.953	1.049
		Region	-0.548	1.632	-0.021	-0.336	0.738	0.929	1.077
		Extro	1.495	0.432	0.223	3.458	0.001	0.859	1.164
		Consc	1.713	0.502	0.218	3.415	0.001	0.875	1.142
		Neuro	-2.139	0.434	-0.326	-4.933	0.000	0.821	1.218
		Online SD	-0.141	0.089	-0.097	-1.593	0.113	0.955	1.047
	2	(Constant)	59.436	7.718		7.701	0.000		
		Age	-0.084	0.060	-0.096	-1.407	0.161	0.774	1.291
		Gender	-1.428	1.784	-0.049	-0.800	0.425	0.942	1.062
		Region	-0.495	1.640	-0.019	-0.302	0.763	0.924	1.083
		Extro	1.511	0.435	0.226	3.475	0.001	0.853	1.173
		Consc	1.720	0.503	0.219	3.419	0.001	0.875	1.143
		Neuro	-2.129	0.435	-0.324	-4.891	0.000	0.819	1.222
		Online SD	-0.156	0.095	-0.108	-1.638	0.103	0.833	1.200
		Online PSS	0.024	0.056	0.029	0.430	0.667	0.765	1.306
	3	(Constant)	33.568	8.892		3.775	0.000		
		Age	-0.033	0.057	-0.037	-0.573	0.568	0.750	1.333
		Gender	0.365	1.719	0.013	0.213	0.832	0.902	1.109
		Region	-1.353	1.555	-0.051	-0.870	0.385	0.913	1.096
		Extro	1.092	0.418	0.163	2.610	0.010	0.819	1.221
		Consc	1.824	0.475	0.232	3.843	0.000	0.873	1.146
		Neuro	-2.082	0.410	-0.317	-5.073	0.000	0.818	1.222
		Online SD	-0.079	0.091	-0.054	-0.868	0.386	0.810	1.235
		Online PSS	-0.032	0.054	-0.039	-0.595	0.553	0.733	1.364
		Offline PSS	0.352	0.070	0.317	5.059	0.000	0.813	1.231
Maldives Main	1	(Constant)	41.224	11.556		3.567	0.000		
		Age	-0.039	0.153	-0.015	-0.253	0.800	0.887	1.127
		Gender	0.615	2.601	0.014	0.237	0.813	0.901	1.110
		Region	0.673	2.528	0.015	0.266	0.790	0.946	1.057
		Extro	2.430	0.832	0.186	2.922	0.004	0.785	1.273
		Consc	2.700	0.840	0.213	3.212	0.001	0.718	1.392
		Neuro	-2.369	0.758	-0.189	-3.123	0.002	0.867	1.154
		oSD	0.089	0.076	0.068	1.170	0.243	0.935	1.070
	2	(Constant)	39.495	11.588		3.408	0.001		
		Age	0.010	0.156	0.004	0.065	0.948	0.848	1.180
		Gender	0.314	2.603	0.007	0.121	0.904	0.896	1.117
		Region	0.436	2.527	0.010	0.172	0.863	0.942	1.061
		Extro	2.291	0.835	0.175	2.743	0.007	0.775	1.290
		Consc	2.723	0.839	0.215	3.246	0.001	0.718	1.393
		Neuro	-2.473	0.760	-0.197	-3.254	0.001	0.859	1.164

	Online SD	0.042	0.082	0.032	0.512	0.609	0.796	1.256
	Online PSS	0.109	0.073	0.093	1.483	0.139	0.793	1.261
3	(Constant)	24.099	11.839		2.036	0.043		
	Age	0.071	0.152	0.028	0.465	0.642	0.840	1.191
	Gender	0.757	2.528	0.017	0.299	0.765	0.894	1.119
	Region	-0.745	2.468	-0.017	-0.302	0.763	0.930	1.075
	Extro	1.558	0.829	0.119	1.879	0.061	0.740	1.351
	Consc	2.674	0.814	0.211	3.286	0.001	0.718	1.393
	Neuro	-2.044	0.744	-0.163	-2.745	0.006	0.843	1.187
	Online SD	0.052	0.080	0.039	0.646	0.519	0.796	1.257
	Online PSS	0.008	0.075	0.007	0.105	0.917	0.710	1.408
	Offline PSS	0.359	0.087	0.253	4.145	0.000	0.797	1.254

New Zealand Clinical Sample Results

Model Summary

						Change Statistics				
Sample	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
NZ Clinical (n = 45)	1	.592[g]	0.350	0.248	11.34403	0.350	3.412	6	38	0.009
	2	.619[h]	0.384	0.267	11.19682	0.033	2.006	1	37	0.165
	3	.619[i]	0.384	0.247	11.35067	0.000	0.004	1	36	0.952

ANOVA[a]

Three_groups			Sum of Squares	df	Mean Square	F	Sig.
NZ Clinical	1	Regression	2634.690	6	439.115	3.412	.009[h]
		Residual	4890.110	38	128.687		
		Total	7524.800	44			
	2	Regression	2886.158	7	412.308	3.289	.008[i]
		Residual	4638.642	37	125.369		
		Total	7524.800	44			
	3	Regression	2886.640	8	360.830	2.801	.016[j]
		Residual	4638.160	36	128.838		
		Total	7524.800	44			

Coefficients							
Sample	Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
			B	Std. Error	Beta		
NZ Clinical	1	(Constant)	71.143	17.317		4.108	0.000
		Age	-0.01	0.166	-0.009	-0.062	0.951
		Gender	-7.542	4.227	-0.279	-1.784	0.082
		Extro	1.002	0.874	0.17	1.146	0.259
		Consc	0.321	0.953	0.048	0.337	0.738
		Neuro	-3.108	1.043	-0.441	-2.979	0.005
		Online SD	-0.008	0.202	-0.006	-0.042	0.967
	2	(Constant)	65.33	17.578		3.717	0.001
		Age	0.02	0.166	0.017	0.121	0.905
		Gender	-7.704	4.174	-0.285	-1.846	0.073
		Extro	1.303	0.888	0.222	1.467	0.151
		Consc	0.122	0.951	0.018	0.128	0.899
		Neuro	-3.154	1.03	-0.448	-3.062	0.004
		Online SD	-0.129	0.217	-0.089	-0.593	0.556
		Online PSS	0.195	0.137	0.21	1.416	0.165
	3	(Constant)	65.913	20.207		3.262	0.002
		Age	0.021	0.168	0.018	0.123	0.903
		Gender	-7.762	4.338	-0.287	-1.79	0.082
		Extro	1.317	0.928	0.224	1.42	0.164
		Consc	0.123	0.965	0.018	0.127	0.899
		Neuro	-3.163	1.055	-0.449	-2.999	0.005
		Online SD	-0.13	0.221	-0.09	-0.589	0.56
		Online PSS	0.199	0.154	0.215	1.29	0.205
		Offline PSS	-0.011	0.173	-0.009	-0.061	0.952

a Dependent Variable: Wellbeing

Appendix K: Unstandardized bootstrapped effects of Moderators (Age, Gender, Country, Region, Extroversion, Conscientiousness, and Neuroticism) in the Relationship Between Time Spent on SNSs per day and Outcome Variables (Online PSS, Offline PSS, and Online Self-disclosure) for the Combined New Zealand and Maldives Random Community Sample (*N* = 472)

Model 1: Moderator = Age, Outcome Variable = Online PSS						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	-1.676	7.623	-0.220	0.826	-16.657	13.304
Time on SNSs	3.619	1.304	2.776	0.006	1.057	6.182
Age	-0.061	0.102	-0.591	0.555	-0.262	0.141
Time on SNSs x Age	-0.060	0.038	-1.567	0.118	-0.135	0.015
Extro	-0.357	0.397	-0.900	0.368	-1.137	0.422
Consc	-0.065	0.421	-0.154	0.878	-0.892	0.763
Neuro	0.616	0.379	1.626	0.105	-0.129	1.360
Offline PSS	0.298	0.049	6.054	0.000	0.201	0.395
Online self-disclosure	0.633	0.076	8.273	0.000	0.482	0.783
Gender	3.152	1.391	2.265	0.024	0.417	5.886
Region	-0.988	1.316	-0.751	0.453	-3.574	1.597
Country	1.660	1.915	0.867	0.386	-2.102	5.423
R^2	0.299					
df	11,460					
F	17.838					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Time on SNSs x Age	0.004	2.459	1	461	0.118

Model 2: Moderator = Gender, Outcome Variable = Online PSS						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	2.322	7.011	0.331	0.741	-11.455	16.099
Time on SNS	2.066	0.633	3.261	0.001	0.821	3.310
Gender	5.352	2.836	1.887	0.060	-0.221	10.925
Time on SNS x Gender	-0.855	0.975	-0.877	0.381	-2.771	1.061
Age	-0.190	0.060	-3.158	0.002	-0.309	-0.072
Region	-1.076	1.325	-0.812	0.417	-3.679	1.528
Country	1.620	1.918	0.845	0.399	-2.149	5.389
Extro	-0.305	0.399	-0.766	0.444	-1.089	0.478

Consc	-0.130	0.420	-0.310	0.757	-0.955	0.695
Neuro	0.578	0.379	1.525	0.128	-0.167	1.322
Online self-disclosure	0.626	0.076	8.189	0.000	0.476	0.776
Offline PSS	0.302	0.049	6.105	0.000	0.205	0.399
R^2	0.296					
df	11,460					
F	17.620					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, *B* = Unstandardised regression coefficients, *SE* = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):	ΔR^2	*F*	*df1*	*df2*	*p*
Time spent on SNS x gender	0.001	0.769	1	460.000	0.381

Model 3: Moderator = Region, Outcome variable = Online PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	4.093	6.905	0.593	0.554	-9.477	17.663
Time on SNSs	1.296	0.723	1.792	0.074	-0.125	2.718
Region	-3.036	2.718	-1.117	0.265	-8.376	2.305
Time on SNS x region	0.835	0.954	0.875	0.382	-1.040	2.710
Age	-0.191	0.060	-3.170	0.002	-0.310	-0.073
Gender	3.331	1.404	2.373	0.018	0.573	6.089
Country	1.678	1.918	0.875	0.382	-2.092	5.448
Extro	-0.289	0.401	-0.721	0.471	-1.077	0.499
Consc	-0.134	0.420	-0.320	0.749	-0.959	0.690
Neuro	0.602	0.380	1.585	0.114	-0.144	1.348
Online self-disclosure	0.627	0.076	8.199	0.000	0.477	0.777
Offline PSS	0.299	0.049	6.054	0.000	0.202	0.396
R^2	0.296					
df	11,460					
F	17.620					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Region	0.001	0.765	1	460.000	0.382

Model 4: Moderator = Country, Outcome Variable = Online PSS

Variables	*B*	*SE*	*t*	*p*	*LLCI*	*ULCI*
constant	3.745	6.934	0.540	0.589	-9.881	17.371
Time on SNSs	1.658	0.611	2.712	0.007	0.457	2.859
Country	0.990	3.199	0.309	0.757	-5.296	7.276
Time on SNS x country	0.273	1.077	0.254	0.800	-1.844	2.390
Age	-0.190	0.060	-3.138	0.002	-0.308	-0.071
Gender	3.215	1.400	2.297	0.022	0.465	5.966
Region	-0.967	1.319	-0.733	0.464	-3.560	1.626
Extro	-0.337	0.398	-0.847	0.398	-1.118	0.445
Consc	-0.129	0.420	-0.306	0.760	-0.954	0.697
Neuro	0.571	0.380	1.501	0.134	-0.176	1.318
Online self-disclosure	0.624	0.077	8.132	0.000	0.473	0.774
Offline PSS	0.300	0.050	6.054	0.000	0.203	0.397
R^2	0.295					
df	11,460					
F	17.529					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Country	0.000	0.064	1	460.000	0.800

Model 5: Moderator = Extroversion, Outcome variable = Online PSS

Variables	*B*	*SE*	*t*	*p*	*LLCI*	*ULCI*
constant	-2.344	8.441	-0.278	0.781	-18.932	14.243
Time on SNSs	3.968	1.930	2.056	0.040	0.176	7.760
Extro	0.440	0.761	0.579	0.563	-1.055	1.935
Time spent on SNS x Extro	-0.300	0.251	-1.197	0.232	-0.794	0.193
Age	-0.194	0.060	-3.212	0.001	-0.312	-0.075
Gender	3.399	1.404	2.420	0.016	0.639	6.158
Region	-1.126	1.324	-0.850	0.396	-3.729	1.477
Country	1.793	1.921	0.934	0.351	-1.982	5.568
Consc	-0.105	0.420	-0.251	0.802	-0.931	0.720
Neuro	0.566	0.379	1.494	0.136	-0.178	1.310
Online self-disclosure	0.627	0.076	8.201	0.000	0.476	0.777
Offline PSS	0.299	0.049	6.075	0.000	0.203	0.396
R^2	0.297					
df	11,460					
F	17.706					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time spent on SNS x Extro	0.002	1.433	1	460.000	0.232

Model 6: Moderator = Conscientiousness, Outcome variable = Online PSS						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	2.809	9.440	0.298	0.766	-15.741	21.359
Time on SNSs	1.983	2.237	0.886	0.376	-2.413	6.379
Consc	-0.046	0.876	-0.052	0.958	-1.768	1.676
Time on SNS x Conscientiousness	-0.030	0.272	-0.111	0.912	-0.564	0.503
Age	-0.190	0.060	-3.152	0.002	-0.309	-0.072
Gender	3.192	1.396	2.286	0.023	0.448	5.935
Region	-0.954	1.319	-0.723	0.470	-3.546	1.638
Country	1.630	1.921	0.849	0.396	-2.145	5.406
Extro	-0.337	0.398	-0.849	0.397	-1.119	0.444
Neuro	0.579	0.379	1.527	0.128	-0.166	1.324
Online self-disclosure	0.626	0.077	8.166	0.000	0.475	0.776
Offline PSS	0.299	0.049	6.054	0.000	0.202	0.396
R^2	0.295					
df	11,460					
F	17.523					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Conscientiousness	0.000	0.012	1	460.000	0.912

Model 7: Moderator = Neuroticism, Outcome variable = Online PSS						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	8.983	7.633	1.177	0.240	-6.017	23.983
Time on SNSs	-0.343	1.377	-0.249	0.803	-3.049	2.363
Neuro	-0.432	0.725	-0.596	0.552	-1.857	0.993
Time on SNS x Neuroticism	0.396	0.243	1.631	0.104	-0.081	0.872
Age	-0.194	0.060	-3.224	0.001	-0.313	-0.076
Gender	3.322	1.393	2.384	0.018	0.584	6.061
Region	-0.887	1.316	-0.674	0.500	-3.473	1.698

Country	1.389	1.920	0.723	0.470	-2.385	5.162
Extro	-0.330	0.396	-0.834	0.405	-1.110	0.449
Consc	-0.118	0.419	-0.283	0.778	-0.941	0.705
Online self-disclosure	0.614	0.077	8.010	0.000	0.463	0.764
Offline PSS	0.305	0.049	6.179	0.000	0.208	0.402
R^2	0.299					
df	11,460					
F	17.864					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Neuroticism	0.004	2.660	1	460	0.104

Model 1: Moderator = Age, Outcome Variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	49.300	6.556	7.520	0.000	36.417	62.184
Time on SNSs	0.244	1.198	0.204	0.838	-2.110	2.599
Age	-0.152	0.093	-1.631	0.104	-0.335	0.031
SNS use x age	0.008	0.035	0.219	0.827	-0.061	0.076
Gender	-2.619	1.269	-2.063	0.040	-5.113	-0.125
Region	2.477	1.194	2.074	0.039	0.130	4.823
Country	12.588	1.645	7.654	0.000	9.356	15.819
Extro	1.608	0.354	4.543	0.000	0.913	2.304
Consc	0.105	0.384	0.275	0.784	-0.648	0.859
Neuro	-0.525	0.345	-1.519	0.129	-1.204	0.154
Online self-disclosure	-0.150	0.074	-2.017	0.044	-0.296	-0.004
Online PSS	0.248	0.041	6.054	0.000	0.167	0.328
R^2	0.237					
df	11,460					
F	12.987					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNSs x Age	0.000	0.048	1	460.000	0.827

Model 2: Moderator = Gender, Outcome Variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	50.430	5.908	8.536	0.000	38.820	62.040
Time on SNSs	-0.087	0.581	-0.150	0.881	-1.229	1.055
Gender	-6.386	2.565	-2.490	0.013	-11.425	-1.346
SNS use x gender	1.489	0.882	1.687	0.092	-0.245	3.222
Age	-0.134	0.055	-2.437	0.015	-0.242	-0.026
Region	2.668	1.196	2.231	0.026	0.318	5.018
Country	12.544	1.640	7.651	0.000	9.322	15.766
Extro	1.543	0.355	4.349	0.000	0.846	2.240
Consc	0.111	0.381	0.293	0.770	-0.636	0.859
Neuro	-0.518	0.344	-1.508	0.132	-1.193	0.157
Online self-disclosure	-0.151	0.074	-2.048	0.041	-0.297	-0.006
Online PSS	0.248	0.041	6.105	0.000	0.168	0.328
R^2	0.242					
df	11,460					
F	13.321					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, *B* = Unstandardised regression coefficients, *SE* = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR²	***F***	***df1***	***df2***	***p***
Time spent on SNS x gender	0.005	2.848	1.000	460	0.092

Model 3: Moderator = Region, Outcome variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	48.564	5.862	8.285	0.000	37.044	60.083
Time on SNSs	0.545	0.660	0.826	0.409	-0.751	1.842
Region	2.752	2.472	1.113	0.266	-2.106	7.611
SNS x region	-0.112	0.869	-0.129	0.897	-1.820	1.595
Age	-0.135	0.055	-2.454	0.014	-0.244	-0.027
Gender	-2.641	1.279	-2.066	0.039	-5.154	-0.129
Country	12.587	1.645	7.651	0.000	9.354	15.819
Extro	1.599	0.357	4.477	0.000	0.897	2.301
Consc	0.114	0.382	0.300	0.765	-0.636	0.865
Neuro	-0.523	0.346	-1.513	0.131	-1.202	0.156
Online self-disclosure	-0.149	0.074	-2.009	0.045	-0.295	-0.003
Online PSS	0.247	0.041	6.054	0.000	0.167	0.327
R^2	0.237					
df	11,460					
F	12.984					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Region	0.000	0.017	1.000	460	0.897

Model 4: Moderator = Country, Outcome Variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	46.881	5.890	7.960	0.000	35.307	58.455
Time on SNSs	1.021	0.556	1.837	0.067	-0.071	2.114
Country	16.699	2.791	5.983	0.000	11.214	22.184
Time on SNS x Country	-1.767	0.972	-1.817	0.070	-3.677	0.144
Age	-0.139	0.055	-2.534	0.012	-0.247	-0.031
Gender	-2.798	1.268	-2.206	0.028	-5.291	-0.306
Region	2.525	1.190	2.122	0.034	0.186	4.863
Extro	1.595	0.353	4.523	0.000	0.902	2.288
Consc	0.097	0.380	0.255	0.799	-0.651	0.845
Neuro	-0.471	0.344	-1.366	0.173	-1.147	0.206
Online self-disclosure	-0.139	0.074	-1.881	0.061	-0.285	0.006
Online PSS	0.246	0.041	6.054	0.000	0.166	0.326
R^2	0.242					
df	11,460					
F	13.357					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Time on SNS x Country	0.005	3.303	1.000	460.000	0.07

Model 5: Moderator = Extroversion, Outcome variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	51.015	7.305	6.984	0.000	36.660	65.370
Time on SNSs	-0.430	1.764	-0.244	0.808	-3.897	3.037
Extro	1.286	0.690	1.865	0.063	-0.069	2.642
Time spent on SNS x Extro	0.123	0.229	0.539	0.590	-0.326	0.573
Age	-0.134	0.055	-2.423	0.016	-0.242	-0.025
Gender	-2.711	1.280	-2.118	0.035	-5.226	-0.196
Region	2.542	1.200	2.117	0.035	0.182	4.901

Country	12.519	1.650	7.590	0.000	9.278	15.761
Consc	0.103	0.382	0.271	0.787	-0.647	0.854
Neuro	-0.515	0.345	-1.495	0.136	-1.192	0.162
Online self-disclosure	-0.150	0.074	-2.023	0.044	-0.296	-0.004
Online PSS	0.248	0.041	6.075	0.000	0.168	0.328
R^2	0.290					
df	11,460					
F	13.016					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Time spent on SNS x Extro	0.000	0.290	1.000	460	0.590

Model 6: Moderator = Conscientiousness, Outcome variable = Offline PSS

Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	51.082	8.242	6.198	0.000	34.886	67.279
Time on SNSs	-0.343	2.035	-0.169	0.866	-4.341	3.655
Conscientiousness	-0.179	0.796	-0.225	0.822	-1.744	1.386
Time on SNS x Conscientiousness	0.103	0.247	0.419	0.676	-0.382	0.588
Age	-0.136	0.055	-2.463	0.014	-0.244	-0.027
Gender	-2.641	1.270	-2.080	0.038	-5.137	-0.146
Region	2.465	1.194	2.065	0.040	0.119	4.811
Country	12.618	1.645	7.669	0.000	9.385	15.851
Extro	1.608	0.354	4.545	0.000	0.913	2.303
Neuro	-0.524	0.345	-1.520	0.129	-1.201	0.153
Online self-disclosure	-0.150	0.074	-2.023	0.044	-0.296	-0.004
Online PSS	0.247	0.041	6.054	0.000	0.167	0.327
R^2	0.237					
df	11,460					
F	13.003					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Time on SNS x Conscientiousness	0.000	0.175	1	460	0.676

Model 7: Moderator = Neuroticism, Outcome variable = Offline PSS						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	41.935	6.655	6.301	0.000	28.857	55.013
Time on SNSs	2.853	1.242	2.296	0.022	0.412	5.295
Neuro	0.636	0.658	0.967	0.334	-0.657	1.929
Time on SNS x Neuroticism	-0.452	0.220	-2.059	0.040	-0.884	-0.021
Age	-0.129	0.055	-2.340	0.020	-0.237	-0.021
Gender	-2.775	1.266	-2.192	0.029	-5.262	-0.288
Region	2.377	1.189	1.999	0.046	0.040	4.714
Country	12.753	1.639	7.782	0.000	9.533	15.974
Extro	1.586	0.352	4.502	0.000	0.894	2.279
Consc	0.099	0.380	0.261	0.794	-0.648	0.846
Online self-disclosure	-0.138	0.074	-1.871	0.062	-0.284	0.007
Online PSS	0.251	0.041	6.179	0.000	0.171	0.331
R^2	0.244					
df	11,460					
F	13.487					
p	< .001					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Time on SNS x Neuroticism	0.007	4.240	1	460	0.040

Appendix L: Unstandardised Bootstapped Effects for Moderators in the Relationship Between Time Spent on SNSs per day and Online PSS and Online Self-disclosure for the New Zealand Clinical Sample (N = 45)

Time on SNS x Gender

Model Summary

R	R-sq	MSE	F	df1	df2	p
.548	.300	170.904	1.928	8.000	36.000	.086

Model

	coeff	se	t	p	LLCI	ULCI
constant	22.306	21.871	1.020	.315	-22.051	66.662
Time on SNS	3.057	2.642	1.157	.255	-2.301	8.414
Gender	1.304	9.566	.136	.892	-18.098	20.706
Intere	.503	3.303	.152	.880	-6.195	7.202
Extro	-1.379	1.031	-1.337	.189	-3.469	.712
Consc	1.081	1.103	.980	.334	-1.157	3.318
Online SD	.431	.259	1.666	.104	-.094	.957
Neuro	.158	1.205	.131	.897	-2.287	2.602
Age	.004	.224	.017	.987	-.451	.459

Product terms key:

Int_1 : Time on SNSs x Gender

Test(s) of highest order unconditional interaction(s):

R2-chng	F	df1	df2	p

X*W	.000	.023	1.000	36.000	.880

Online PSS x Age

Model Summary

R	R-sq	MSE	F	df1	df2	p
.548	.301	170.764	1.934	8.000	36.000	.085

Model

	coeff	se	t	p	LLCI	ULCI
constant	19.222	22.321	.861	.395	-26.047	64.492
TimeonSN	4.505	5.514	.817	.419	-6.678	15.688
Q88_Age	.095	.420	.227	.821	-.756	.947
Int_1	-.041	.179	-.230	.819	-.404	.322
Gender	2.455	4.993	.492	.626	-7.672	12.583
Extro	-1.418	1.055	-1.344	.187	-3.558	.722
Consc	1.039	1.105	.941	.353	-1.201	3.279
Online SD	.444	.260	1.707	.096	-.084	.971
Neuro	.110	1.213	.091	.928	-2.351	2.571

Product terms key:

Int_1 : Time on SNS x Age

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.001	.053	1.000	36.000	.819

Online PSS x Extroversion

Model Summary

R	R-sq	MSE	F	df1	df2	p
.566	.320	166.000	2.118	8.000	36.000	.059

Model

	coeff	se	t	p	LLCI	ULCI
constant	34.903	24.202	1.442	.158	-14.181	83.987
TimeonSN	-.603	4.243	-.142	.888	-9.208	8.003
Extro	-3.183	2.022	-1.574	.124	-7.283	.917
Int_1	.721	.691	1.043	.304	-.681	2.122
On_SD	.387	.258	1.501	.142	-.136	.911
Q88_Age	.042	.215	.195	.846	-.395	.479
Dum_Male	1.533	5.003	.306	.761	-8.614	11.679
Neuro	.014	1.193	.011	.991	-2.406	2.433
Consc	.837	1.105	.758	.453	-1.403	3.078

Product terms key:
Int_1: Time on SNS x Extro

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.021	1.088	1.000	36.000	.304

Online PSS x Conscientiousness

Model Summary

R	R-sq	MSE	F	df1	df2	p
.548	.300	170.934	1.927	8.000	36.000	.086

Model

	coeff	se	t	p	LLCI	ULCI
constant	19.833	23.099	.859	.396	-27.015	66.681
TimeonSN	3.987	5.460	.730	.470	-7.087	15.060
Consc	1.313	2.189	.600	.552	-3.126	5.753
Int_1	-.108	.829	-.131	.897	-1.789	1.572
On_SD	.431	.260	1.660	.106	-.096	.958
Q88_Age	.006	.223	.026	.980	-.447	.458
Dum_Male	2.513	4.987	.504	.617	-7.600	12.627
Neuro	.169	1.214	.139	.890	-2.294	2.632
Extro	-1.330	1.026	-1.297	.203	-3.411	.750

Product terms key:

Int_1 : Time on SNS x Consc

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.000	.017	1.000	36.000	.897

Online PSS x Neuroticism

Model Summary

R	R-sq	MSE	F	df1	df2	p
.551	.303	170.139	1.957	8.000	36.000	.081

Model

	coeff	se	t	p	LLCI	ULCI
constant	9.849	33.437	.295	.770	-57.966	77.663
TimeonSN	7.326	9.513	.770	.446	-11.967	26.620

Neuro	1.339	3.018	.444	.660	-4.781	7.459
Int_1	-.477	1.108	-.430	.669	-2.723	1.770
Extro	-1.303	1.018	-1.281	.208	-3.367	.761
Consc	1.107	1.100	1.006	.321	-1.125	3.339
On_SD	.453	.260	1.740	.090	-.075	.980
Q88_Age	.026	.219	.121	.904	-.417	.470
Dum_Male	2.461	4.972	.495	.624	-7.623	12.545

Product terms key:
Int_1 : Time on SNS x Neuro

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.004	.185	1.000	36.000	.669

Appendix M: Unstandardized bootstrapped effects of Moderators (Age, Gender, Region, Country, Extroversion, Conscientiousness, and Neuroticism) in the Relationship Between Independ Variables (Online PSS, Offline PSS, and Online Self-disclosure) and Psychological Wellbeing in Combined New Zealand and Maldives Random Community Sample (N = 472)

Model 1: Moderator = Age						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	19.865	7.327	2.711	0.007	5.466	34.263
Online PSS	0.056	0.098	0.572	0.568	-0.137	0.249
Age	0.084	0.125	0.669	0.504	-0.163	0.330
Online PSS x Age	-0.002	0.003	-0.721	0.472	-0.007	0.003
Gender	0.387	1.268	0.305	0.760	-2.104	2.878
Region	-0.925	1.194	-0.775	0.439	-3.271	1.421
Extroversion	1.146	0.360	3.188	0.002	0.440	1.853
Conscientiousness	1.896	0.380	4.988	0.000	1.149	2.643
Neuroticism	-1.735	0.341	-5.084	0.000	-2.405	-1.064
Online Self-disclosure	0.000	0.074	-0.003	0.998	-0.145	0.145
Offline PSS	0.294	0.046	6.332	0.000	0.203	0.385
Country	6.270	1.729	3.626	0.000	2.872	9.667
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, B = Unstandardised regression coefficients, SE = standard error of regression coefficient.

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online PSS x Age	0.001	0.519	1	460	.472

Model 2: Moderator = Age						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	21.203	9.272	2.287	0.023	2.983	39.423
Offline PSS	0.321	0.118	2.711	0.007	0.088	0.553
Age	0.049	0.210	0.233	0.816	-0.364	0.462
Offline PSS x Age	-0.001	0.003	-0.229	0.819	-0.007	0.005
Gender	0.358	1.288	0.278	0.781	-2.173	2.889
Region	-0.884	1.193	-0.741	0.459	-3.228	1.461
Extroversion	1.153	0.360	3.206	0.001	0.446	1.860
Conscientiousness	1.874	0.380	4.931	0.000	1.127	2.621
Neuroticism	-1.733	0.341	-5.076	0.000	-2.404	-1.062
Online self-disclosure	0.000	0.074	-0.005	0.996	-0.146	0.145
Country	6.270	1.735	3.615	0.000	2.861	9.679
Online PSS	-0.009	0.042	-0.209	0.834	-0.091	0.073
R^2	0.311					
df	11,460					
F	18.897					
p	< .001					

Test(s) of highest order unconditional interaction(s):					
	Δ*R*²	***F***	***df1***	***df2***	***p***
Offline PSS x Age	0.001	0.052	1	460	0.819

Model 3: Moderator = Age						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	16.424	8.684	1.891	0.059	-0.641	33.489
Online self-disclosure	0.164	0.176	0.929	0.353	-0.183	0.510
Age	0.172	0.173	0.992	0.322	-0.168	0.512
Online SD x Age	-0.005	0.005	-1.030	0.304	-0.014	0.004
Gender	0.477	1.268	0.376	0.707	-2.015	2.969
Region	-0.791	1.195	-0.662	0.508	-3.139	1.557
Extroversion	1.172	0.360	3.258	0.001	0.465	1.879
Conscientiousness	1.897	0.380	4.998	0.000	1.151	2.643
Neuroticism	-1.742	0.341	-5.107	0.000	-2.413	-1.072
Country	6.467	1.735	3.727	0.000	3.057	9.876
Online PSS	-0.008	0.042	-0.198	0.843	-0.090	0.074
Offline PSS	0.294	0.046	6.354	0.000	0.203	0.385
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	Δ*R*²	***F***	***df1***	***df2***	***p***
Online SD x Age	0.002	1.060	1	460	0.304

Model 4: Moderator = Gender						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	20.984	6.321	3.320	0.001	8.561	33.406
Online PSS	0.016	0.047	0.341	0.733	-0.077	0.109
Gender	4.400	3.986	1.104	0.270	-3.433	12.233
Online PSS x gender	-0.082	0.078	-1.056	0.292	-0.235	0.071
Age	-0.001	0.054	-0.009	0.993	-0.107	0.106
Region	-0.865	1.192	-0.726	0.468	-3.207	1.476
Extroversion	1.169	0.360	3.251	0.001	0.462	1.876
Conscientiousness	1.900	0.380	5.005	0.000	1.154	2.646
Neuroticism	-1.697	0.343	-4.955	0.000	-2.370	-1.024
Country	6.359	1.728	3.679	0.000	2.962	9.755
Offline PSS	0.300	0.046	6.456	0.000	0.208	0.391
Online self-disclosure	0.000	0.074	0.001	0.999	-0.145	0.145
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Online PSS x Gender	0.002	1.115	1	460	0.292

Model 2: Moderator = Gender						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	22.248	6.464	3.442	0.001	9.546	34.951
Offline PSS	0.305	0.059	5.187	0.000	0.190	0.421
Gender	1.832	5.689	0.322	0.748	-9.348	13.012
Offline x gender	-0.022	0.085	-0.257	0.798	-0.189	0.145
Age	0.001	0.055	0.014	0.989	-0.106	0.108
Region	-0.887	1.193	-0.743	0.458	-3.231	1.458
Extroversion	1.150	0.360	3.199	0.002	0.444	1.857
Conscientiousness	1.873	0.380	4.927	0.000	1.126	2.620
Neuroticism	-1.732	0.341	-5.075	0.000	-2.403	-1.061
Country	6.302	1.729	3.644	0.000	2.904	9.700
Online self-disclosure	0.001	0.074	0.011	0.991	-0.145	0.147
Online PSS	-0.009	0.042	-0.204	0.839	-0.090	0.073
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Offline PSS x Gender	0.000	0.066	1	460	0.798

Model 2: Moderator = Gender						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	25.829	6.591	3.919	0.000	12.877	38.780
Online self-disclosure	-0.062	0.090	-0.688	0.492	-0.238	0.114
Gender	-6.003	5.546	-1.083	0.280	-16.901	4.895
Online SD x Gender	0.157	0.133	1.188	0.236	-0.103	0.418
Age	0.001	0.054	0.010	0.992	-0.106	0.107
Region	-0.800	1.193	-0.671	0.503	-3.145	1.545
Extroversion	1.149	0.359	3.199	0.002	0.443	1.854
Conscientiousness	1.859	0.379	4.901	0.000	1.114	2.605
Neuroticism	-1.760	0.342	-5.151	0.000	-2.432	-1.089
Country	6.367	1.728	3.685	0.000	2.972	9.763
Online PSS	-0.004	0.042	-0.086	0.932	-0.086	0.078
Offline PSS	0.287	0.047	6.138	0.000	0.195	0.379
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):

	ΔR^2	*F*	*df1*	*df2*	*p*
Online SD x Gender	0.002	1.411	1	460	0.236

Model 2: Moderator = Country						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	22.342	6.133	3.643	0.000	10.290	34.394
Online PSS	0.011	0.052	0.209	0.835	-0.091	0.112
Counry	8.491	3.970	2.139	0.033	0.689	16.292
Online PSS x Country	-0.045	0.074	-0.613	0.540	-0.191	0.100
Region	-0.873	1.193	-0.732	0.465	-3.217	1.470
Age	-0.003	0.055	-0.046	0.963	-0.110	0.105
Gender	0.428	1.268	0.338	0.736	-2.063	2.919
Extroversion	1.141	0.360	3.171	0.002	0.434	1.849
Conscientiousness	1.882	0.380	4.960	0.000	1.136	2.628
Neuroticism	-1.747	0.342	-5.106	0.000	-2.420	-1.075
Offline PSS	0.293	0.047	6.275	0.000	0.201	0.384
Online self-disclosure	-0.001	0.074	-0.007	0.995	-0.145	0.145
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Online PSS x Country	0.001	0.376	1	460	0.540

Model 2: Moderator = Country						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	24.168	6.220	3.885	0.000	11.944	36.391
Offline PSS	0.266	0.054	4.899	0.000	0.159	0.373
Country	-0.381	6.634	-0.057	0.954	-13.417	12.655
Offline PSS x Country	0.096	0.092	1.043	0.297	-0.085	0.278
Region	-0.914	1.192	-0.766	0.444	-3.256	1.429
Age	0.010	0.055	0.178	0.859	-0.097	0.117
Gender	0.491	1.269	0.387	0.699	-2.002	2.985
Extroversion	1.136	0.360	3.161	0.002	0.430	1.843
Conscientiousness	1.899	0.380	5.003	0.000	1.153	2.645
Neuroticism	-1.737	0.341	-5.095	0.000	-2.408	-1.067
Online self-disclosure	0.002	0.074	0.031	0.975	-0.143	0.147
Online PSS	-0.005	0.042	-0.132	0.895	-0.087	0.076
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*

Offline PSS x Country	0.002	1.088	1	460	0.297	

Model 2: Moderator = Country						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	19.387	6.532	2.968	0.003	6.552	32.223
Online self-disclosure	0.091	0.098	0.927	0.355	-0.102	0.283
Country	13.948	5.637	2.474	0.014	2.870	25.026
Online SD x Country	-0.193	0.135	-1.425	0.155	-0.459	0.073
Region	-0.716	1.196	-0.599	0.550	-3.066	1.634
Age	-0.003	0.054	-0.053	0.958	-0.109	0.104
Gender	0.378	1.265	0.298	0.766	-2.109	2.864
Extroversion	1.176	0.359	3.273	0.001	0.470	1.881
Conscientiousness	1.872	0.379	4.942	0.000	1.128	2.616
Neuroticism	-1.757	0.341	-5.151	0.000	-2.427	-1.087
Online PSS	-0.009	0.042	-0.213	0.832	-0.090	0.073
Offline PSS	0.290	0.046	6.248	0.000	0.199	0.381
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online SD x Country	0.003	2.031	1	460	0.155

Model 2: Moderator = Extroversion						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	16.614	9.140	1.818	0.070	-1.348	34.576
Online PSS	0.118	0.145	0.815	0.416	-0.167	0.403
Extroversion	1.916	0.915	2.093	0.037	0.117	3.715
Online PSS x Extro	-0.017	0.018	-0.908	0.365	-0.053	0.020
Region	-0.921	1.193	-0.773	0.440	-3.265	1.422
Age	0.006	0.054	0.115	0.909	-0.100	0.113
Gender	0.437	1.267	0.345	0.731	-2.054	2.927
Country	6.145	1.736	3.539	0.000	2.733	9.557
Conscientiousness	1.910	0.381	5.015	0.000	1.161	2.658
Neuroticism	-1.701	0.343	-4.962	0.000	-2.374	-1.027
Offline PSS	0.296	0.046	6.403	0.000	0.205	0.387
Online self-disclosure	-0.003	0.074	-0.035	0.972	-0.147	0.142
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online PSS x Extroversion	0.001	0.824	1	460	0.365

Model 2: Moderator = Extroversion						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	10.761	12.597	0.854	0.393	-13.995	35.516
Offline PSS	0.468	0.164	2.848	0.005	0.145	0.791
Extroversion	2.767	1.523	1.817	0.070	-0.225	5.760
Offline PSS x Extro	-0.024	0.022	-1.092	0.276	-0.067	0.019
Region	-0.840	1.192	-0.705	0.481	-3.183	1.502
Age	0.007	0.054	0.123	0.902	-0.100	0.113
Region	0.383	1.267	0.302	0.763	-2.106	2.872
Country	6.234	1.728	3.607	0.000	2.837	9.630
Conscientiousness	1.898	0.379	5.001	0.000	1.152	2.644
Neuroticism	-1.732	0.341	-5.081	0.000	-2.402	-1.062
Online self-disclosure	0.004	0.074	0.059	0.953	-0.141	0.149
Online PSS	-0.008	0.042	-0.190	0.850	-0.090	0.074
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Offline PSS x Extroversion	0.002	1.192	1	460	0.276

Model 2: Moderator = Extroversion						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	20.135	11.278	1.785	0.075	-2.027	42.297
Online SD	0.063	0.238	0.263	0.793	-0.406	0.531
Extroversion	1.489	1.251	1.191	0.234	-0.969	3.946
Online SD x Extro	-0.009	0.032	-0.281	0.779	-0.071	0.053
Region	-0.913	1.198	-0.762	0.446	-3.266	1.441
Age	0.003	0.054	0.059	0.953	-0.103	0.110
Gender	0.430	1.270	0.339	0.735	-2.065	2.926
Country	6.267	1.734	3.615	0.000	2.860	9.674
Conscientiousness	1.893	0.383	4.942	0.000	1.140	2.646
Neuroticism	-1.722	0.343	-5.021	0.000	-2.396	-1.048
Online PSS	-0.007	0.042	-0.177	0.860	-0.089	0.075
Offline PSS	0.297	0.047	6.382	0.000	0.206	0.389
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***

Online SD x Extroversion	0.000	0.079	1	460	0.779

Model 2: Moderator = Conscientiousness						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	19.604	11.199	1.750	0.081	-2.405	41.612
Online PSS	0.053	0.184	0.289	0.773	-0.309	0.415
Consc	2.241	1.129	1.985	0.048	0.022	4.460
Online PSS x Conscient	-0.007	0.022	-0.341	0.734	-0.050	0.035
Region	-0.904	1.194	-0.757	0.449	-3.251	1.443
Age	0.004	0.054	0.066	0.948	-0.103	0.110
Gender	0.425	1.269	0.335	0.738	-2.068	2.917
Country	6.284	1.730	3.633	0.000	2.885	9.684
Extroversion	1.154	0.360	3.209	0.001	0.447	1.861
Neuroticism	-1.726	0.342	-5.049	0.000	-2.397	-1.054
Offline PSS	0.297	0.046	6.395	0.000	0.205	0.388
Online SD	0.001	0.074	0.008	0.994	-0.145	0.146
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online PSS x Conscient	0.000	0.116	1	460	0.734

Model 2: Moderator = Conscientiousness						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	8.063	17.230	0.468	0.640	-25.797	41.922
Offline PSS	0.510	0.239	2.134	0.033	0.040	0.980
Conscientiousness	3.611	1.931	1.869	0.062	-0.185	7.406
Offline PSS x Concient	-0.026	0.028	-0.915	0.361	-0.081	0.029
Region	-0.818	1.194	-0.685	0.494	-3.164	1.528
Age	0.006	0.054	0.103	0.918	-0.101	0.112
Gender	0.273	1.276	0.214	0.831	-2.233	2.780
Country	6.114	1.740	3.514	0.000	2.695	9.533
Extroversion	1.144	0.359	3.184	0.002	0.438	1.850
Neuroticism	-1.732	0.341	-5.079	0.000	-2.402	-1.062
Online SD	0.007	0.074	0.097	0.922	-0.139	0.153
Online PSS	-0.008	0.042	-0.198	0.843	-0.090	0.073
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Offline PSS x Concient	0.001	0.836	1	460	0.361

Model 2: Moderator = Conscientiousness						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	4.856	13.673	0.355	0.723	-22.013	31.726
Online SD	0.424	0.300	1.417	0.157	-0.164	1.013
Consc	4.012	1.505	2.667	0.008	1.056	6.969
Online SD x Conscient	-0.053	0.036	-1.465	0.144	-0.125	0.018
Region	-1.009	1.193	-0.845	0.398	-3.354	1.336
Age	0.002	0.054	0.046	0.964	-0.104	0.109
Gender	0.498	1.266	0.393	0.694	-1.991	2.987
Country	6.283	1.725	3.641	0.000	2.893	9.674
Extro	1.185	0.359	3.297	0.001	0.479	1.892
Neuro	-1.726	0.341	-5.068	0.000	-2.395	-1.057
Online PSS	-0.003	0.042	-0.070	0.944	-0.085	0.079
Offline PSS	0.301	0.046	6.492	0.000	0.210	0.392
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online SD x Conscient	0.003	2.147	1	460	0.144

Model 2: Moderator = Neuroticism						
Variables	***B***	***SE***	***t***	***p***	***LLCI***	***ULCI***
constant	27.511	7.541	3.648	0.000	12.691	42.331
OnPSS	-0.106	0.102	-1.041	0.298	-0.306	0.094
Neuro	-2.597	0.888	-2.924	0.004	-4.342	-0.852
Online PSS x Neuro	0.019	0.018	1.055	0.292	-0.016	0.055
Region	-0.897	1.192	-0.753	0.452	-3.239	1.444
Age	0.004	0.054	0.081	0.935	-0.102	0.111
Gender	0.362	1.267	0.286	0.775	-2.128	2.853
Country	6.222	1.729	3.599	0.000	2.824	9.620
Extro	1.132	0.360	3.147	0.002	0.425	1.839
Consc	1.883	0.379	4.967	0.000	1.138	2.628
Offline PSS	0.297	0.046	6.413	0.000	0.206	0.388
Online self-disclosure	-0.008	0.074	-0.109	0.914	-0.153	0.137
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	***F***	***df1***	***df2***	***p***
Online PSS x Neuroticism	0.002	1.113	1	460.000	0.292

Model 2: Moderator = Neuroticism						
Variables	*B*	*SE*	*t*	*p*	*LLCI*	*ULCI*
constant	36.269	9.807	3.698	0.000	16.997	55.542
Offline PSS	0.097	0.123	0.785	0.433	-0.145	0.338
Neuroticism	-4.425	1.578	-2.804	0.005	-7.527	-1.324
Offline PSS x Neuro	0.039	0.022	1.748	0.081	-0.005	0.083
Region	-0.821	1.189	-0.691	0.490	-3.159	1.516
Age	0.009	0.054	0.157	0.875	-0.098	0.115
Gender	0.254	1.267	0.201	0.841	-2.235	2.744
Country	6.066	1.729	3.508	0.000	2.668	9.463
Extroversion	1.118	0.359	3.114	0.002	0.412	1.823
Conscientiousness	1.877	0.378	4.961	0.000	1.134	2.620
Online self-disclosure	0.012	0.074	0.157	0.875	-0.134	0.157
Online PSS	-0.008	0.041	-0.202	0.840	-0.090	0.073
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Offline PSS x Neuroticism	0.005	3.054	1	460	0.081

Model 2: Moderator = Neuroticism						
Variables	*B*	*SE*	*t*	*p*	*LLCI*	*ULCI*
constant	22.459	9.407	2.387	0.017	3.972	40.945
Online SD	0.008	0.206	0.040	0.968	-0.397	0.414
Neuro	-1.667	1.385	-1.203	0.229	-4.389	1.055
Online SD x Neuroticism	-0.002	0.035	-0.048	0.961	-0.071	0.067
Region	-0.882	1.193	-0.739	0.460	-3.226	1.462
Age	0.002	0.054	0.044	0.965	-0.104	0.109
Gender	0.407	1.269	0.321	0.748	-2.086	2.901
Country	6.308	1.735	3.635	0.000	2.898	9.718
Extro	1.154	0.361	3.192	0.002	0.443	1.864
Consc	1.877	0.380	4.936	0.000	1.130	2.625
Online PSS	-0.008	0.042	-0.186	0.853	-0.090	0.074
Offline PSS	0.295	0.047	6.315	0.000	0.204	0.387
R^2	0.311					
df	11,460					
F	18.897					
p	< .000					

Test(s) of highest order unconditional interaction(s):					
	ΔR^2	*F*	*df1*	*df2*	*p*
Online SD x Neuroticism	0.000	0.002	1	460	0.961

Note: CI LL = 95% bias corrected confidence interval lower limit; CI UL = 95% bias corrected confidence interval upper limit, *B* = Unstandardised regression coefficients, *SE* = standard error of regression coefficient.

Appendix N: Unstandardized bootstrapped effects of Moderators (Age, Gender, Country, Extroversion, Conscientiousness, and Neuroticism) in the Relationship Between Independ Variables (Online PSS, Offline PSS, and Online Self-disclosure) and Psychological Wellbeing in the New Zealand Clinical Sample (*N* = 45)

Age x online PSS = Wellbeing

Model Summary

R	R-sq	MSE	F	df1	df2	p
.63	.39	130.97	2.50	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	52.31	29.35	1.78	.08	-7.28	111.89
OnPSS	.50	.49	1.02	.32	-.49	1.49
Age	.43	.66	.65	.52	-.91	1.77
Int_1	-.01	.01	-.64	.52	-.04	.02
Dum_M	-7.91	4.38	-1.81	.08	-16.80	.98
Extro	1.17	.96	1.21	.23	-.79	3.12
Consc	.23	.99	.23	.82	-1.77	2.23
Neuro	-3.19	1.06	-3.00	.00	-5.35	-1.03
OnSD	-.14	.22	-.61	.55	-.59	.32
OffPSS	-.01	.17	-.06	.95	-.36	.34

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.41	1.00	35.00	.52

Gender x online PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.63	.40	129.64	2.56	9.00	35.00	.02

Model

	coeff	se	t	p	LLCI	ULCI
constant	72.06	21.44	3.36	.00	28.55	115.58
OnPSS	.15	.17	.88	.39	-.19	.48
Dum_M	-20.65	15.25	-1.35	.18	-51.62	10.32
Int_1	.26	.30	.88	.38	-.34	.87
Age	.02	.17	.14	.89	-.32	.37
Extro	1.25	.93	1.34	.19	-.64	3.15
Consc	.26	.98	.26	.80	-1.73	2.24
Neuro	-3.29	1.07	-3.08	.00	-5.45	-1.12
OnSD	-.19	.23	-.82	.42	-.66	.28
OffPSS	-.03	.17	-.16	.87	-.38	.33

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.78	1.00	35.00	.38

Extroversion x Online PSS = wellbeing

R	R-sq	MSE	F	df1	df2	p
.63	.40	128.44	2.62	9.00	35.00	.02

Model

	coeff	se	t	p	LLCI	ULCI
constant	86.31	27.96	3.09	.00	29.54	143.08
OnPSS	-.13	.35	-.38	.71	-.84	.58
Extro	-1.35	2.70	-.50	.62	-6.83	4.12
Int_1	.06	.05	1.05	.30	-.05	.16
Age	.02	.17	.13	.90	-.32	.36
Dum_M	-8.43	4.38	-1.93	.06	-17.32	.46
Consc	-.21	1.01	-.21	.84	-2.27	1.85
Neuro	-3.34	1.07	-3.13	.00	-5.50	-1.17
OnSD	-.18	.23	-.79	.43	-.64	.28
OffPSS	.01	.17	.05	.96	-.35	.36

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.02	1.11	1.00	35.00	.30

Conscientiousness x Online PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.38	132.34	2.43	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	69.97	27.79	2.52	.02	13.56	126.39
OnPSS	.10	.49	.20	.84	-.90	1.09
Consc	-.54	3.22	-.17	.87	-7.08	6.00
Int_1	.01	.07	.22	.83	-.12	.15
Age	.02	.17	.12	.91	-.33	.37
Dum_M	-7.60	4.46	-1.70	.10	-16.66	1.46
Extro	1.28	.95	1.35	.19	-.65	3.22
Neuro	-3.10	1.11	-2.79	.01	-5.35	-.84
OnSD	-.13	.22	-.57	.57	-.58	.33
OffPSS	-.01	.18	-.06	.95	-.37	.35

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.05	1.00	35.00	.83

Neuroticism x Online PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.39	132.16	2.44	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	59.47	29.21	2.04	.05	.16	118.78
OnPSS	.34	.48	.71	.48	-.63	1.31
Neuro	-2.33	2.90	-.80	.43	-8.22	3.57
Int_1	-.02	.06	-.31	.76	-.13	.10
Age	.02	.17	.12	.91	-.33	.37
Dum_M	-7.64	4.41	-1.73	.09	-16.60	1.31
Extro	1.38	.96	1.44	.16	-.57	3.34
Consc	.03	1.03	.03	.98	-2.06	2.11
OnSD	-.14	.23	-.63	.54	-.60	.32
OffPSS	.00	.18	-.01	.99	-.36	.36

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.10	1.00	35.00	.76

Age x Offline PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.63	.39	130.43	2.52	9.00	35.00	.02

Model

	coeff	se	t	p	LLCI	ULCI
constant	94.18	42.90	2.20	.03	7.09	181.27
OffPSS	-.48	.65	-.74	.47	-1.80	.84
Age	-.86	1.19	-.72	.47	-3.27	1.55
Int_1	.01	.02	.75	.46	-.02	.05
Dum_M	-7.29	4.41	-1.65	.11	-16.24	1.67
Extro	1.44	.95	1.52	.14	-.48	3.37
Consc	.20	.98	.21	.84	-1.78	2.18
Neuro	-2.96	1.10	-2.70	.01	-5.18	-.74
OnSD	-.11	.22	-.51	.61	-.57	.34
OnPSS	.20	.16	1.31	.20	-.11	.52

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.56	1.00	35.00	.46

Gender x Offline PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.38	132.51	2.42	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	65.41	23.39	2.80	.01	17.92	112.90
OffPSS	.00	.24	-.02	.99	-.48	.47
Dum_M	-6.71	23.90	-.28	.78	-55.24	41.82
Int_1	-.02	.35	-.04	.96	-.73	.70
Age	.02	.17	.12	.91	-.33	.37
Extro	1.31	.95	1.39	.17	-.61	3.23
Consc	.12	.98	.12	.90	-1.88	2.11
Neuro	-3.16	1.07	-2.96	.01	-5.33	-.99
OnSD	-.13	.25	-.51	.61	-.63	.38
OnPSS	.20	.16	1.23	.23	-.13	.52

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.00	1.00	35.00	.96

Extroversion x Offline PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.38	132.40	2.43	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	73.43	47.81	1.54	.13	-23.64	170.49
OffPSS	-.11	.58	-.18	.86	-1.28	1.07
Extro	-.17	8.59	-.02	.98	-17.60	17.27
Int_1	.02	.12	.17	.86	-.22	.26
Age	.02	.17	.12	.91	-.33	.37
Dum_M	-7.92	4.49	-1.76	.09	-17.04	1.20
Consc	.05	1.07	.04	.97	-2.13	2.22
Neuro	-3.17	1.07	-2.96	.01	-5.34	-1.00
OnSD	-.13	.23	-.56	.58	-.58	.33
OnPSS	.20	.16	1.24	.22	-.12	.51

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.03	1.00	35.00	.86

Conscientiousness x Offline PSS = wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.39	131.35	2.48	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	91.15	49.59	1.84	.07	-9.52	191.83
OffPSS	-.38	.68	-.56	.58	-1.76	1.00
Consc	-3.76	7.01	-.54	.60	-18.00	10.48
Int_1	.06	.10	.56	.58	-.15	.26
Age	.03	.17	.17	.87	-.32	.37
Dum_M	-7.69	4.38	-1.75	.09	-16.58	1.21
Extro	1.21	.96	1.27	.21	-.73	3.15
Neuro	-2.99	1.11	-2.71	.01	-5.24	-.75
OnSD	-.12	.22	-.54	.60	-.58	.33
OnPSS	.18	.16	1.12	.27	-.15	.50

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.31	1.00	35.00	.58

Neuroticism x Offline PSS = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.39	131.03	2.49	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	91.51	45.45	2.01	.05	-.76	183.78
OffPSS	-.42	.67	-.62	.54	-1.78	.94
Neuro	-6.75	5.79	-1.17	.25	-18.50	5.01
Int_1	.05	.08	.63	.53	-.12	.22
Age	.05	.17	.26	.79	-.31	.40
Dum_M	-7.68	4.38	-1.76	.09	-16.57	1.20
Extro	1.24	.94	1.32	.20	-.67	3.16
Consc	.32	1.02	.31	.76	-1.75	2.39
OnSD	-.08	.24	-.32	.75	-.56	.41
OnPSS	.16	.16	.99	.33	-.17	.50

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.40	1.00	35.00	.53

Age x Online self-disclosure = wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.38	132.35	2.43	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	61.00	30.84	1.98	.06	-1.61	123.61
OnSD	.04	.85	.05	.96	-1.67	1.76
Age	.22	.94	.23	.82	-1.69	2.13
Int_1	-.01	.03	-.21	.83	-.06	.05
Dum_M	-7.90	4.44	-1.78	.08	-16.92	1.12
Extro	1.25	.99	1.26	.22	-.76	3.26
Consc	.15	.99	.15	.88	-1.85	2.15
Neuro	-3.22	1.10	-2.92	.01	-5.45	-.98
OnPSS	.20	.16	1.28	.21	-.12	.52
OffPSS	-.02	.18	-.10	.92	-.38	.35

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.05	1.00	35.00	.83

Gender x Online self-disclosure = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.62	.38	132.51	2.42	9.00	35.00	.03

Model

	coeff	se	t	p	LLCI	ULCI
constant	66.89	26.33	2.54	.02	13.42	120.35
OnSD	-.14	.33	-.43	.67	-.82	.53
Dum_M	-8.78	17.94	-.49	.63	-45.20	27.63
Int_1	.03	.44	.06	.95	-.88	.93
Age	.02	.17	.12	.91	-.33	.37
Extro	1.32	.94	1.40	.17	-.59	3.23
Consc	.12	.98	.13	.90	-1.86	2.11
Neuro	-3.18	1.12	-2.84	.01	-5.45	-.91
OnPSS	.20	.16	1.27	.21	-.12	.52
OffPSS	-.02	.19	-.08	.94	-.40	.37

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.00	.00	1.00	35.00	.95

Extroversion x Online self-disclosure = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.63	.40	129.42	2.57	9.00	35.00	.02

Model	coeff	se	t	p	LLCI	ULCI
constant	88.17	31.64	2.79	.01	23.93	152.41
OnSD	-.62	.58	-1.07	.29	-1.81	.56
Extro	-1.80	3.53	-.51	.61	-8.97	5.37
Int_1	.08	.09	.92	.37	-.10	.26
Age	.03	.17	.15	.88	-.32	.37
Dum_M	-8.26	4.38	-1.88	.07	-17.15	.64
Consc	-.11	1.00	-.11	.92	-2.13	1.92
Neuro	-3.36	1.08	-3.12	.00	-5.56	-1.17
OnPSS	.17	.16	1.10	.28	-.15	.49
OffPSS	.00	.17	.03	.98	-.35	.36

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.84	1.00	35.00	.37

Conscientiousness x online self-disclosure = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.65	.43	122.87	2.92	9.00	35.00	.01

Model	coeff	se	t	p	LLCI	ULCI
constant	3.36	42.58	.08	.94	-83.07	89.80
OnSD	1.75	1.15	1.52	.14	-.59	4.09
Consc	9.76	5.89	1.66	.11	-2.19	21.72
Int_1	-.28	.17	-1.66	.11	-.63	.06
Age	.03	.16	.21	.84	-.30	.37
Dum_M	-9.05	4.31	-2.10	.04	-17.79	-.31
Extro	1.96	.99	1.99	.05	-.04	3.96
Neuro	-3.70	1.08	-3.43	.00	-5.89	-1.51
OnPSS	.23	.15	1.54	.13	-.07	.54
OffPSS	-.05	.17	-.29	.77	-.40	.30

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.04	2.75	1.00	35.00	.11

Neuroticism x online self-disclosure = Wellbeing

R	R-sq	MSE	F	df1	df2	p
.63	.40	129.80	2.55	9.00	35.00	.02

Model	coeff	se	t	p	LLCI	ULCI
constant	87.12	31.99	2.72	.01	22.17	152.07
OnSD	-.81	.82	-.98	.33	-2.48	.86
Neuro	-6.18	3.68	-1.68	.10	-13.64	1.28
Int_1	.09	.10	.86	.40	-.12	.30
Age	.04	.17	.21	.83	-.31	.38
Dum_M	-8.25	4.39	-1.88	.07	-17.17	.66
Extro	1.08	.97	1.11	.27	-.89	3.05
Consc	.29	.99	.29	.77	-1.72	2.29
OnPSS	.19	.15	1.25	.22	-.12	.51
OffPSS	.02	.18	.11	.91	-.34	.38

Test(s) of highest order unconditional interaction(s):

	R2-chng	F	df1	df2	p
X*W	.01	.73	1.00	35.00	.40

APPENDIX O: AN ASSESSMENT OF MEASUREMENT INVARIANCE

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(Supplementary Analyses provided by Dr Willink in Consultation with the Candidate)

The report discusses one aspect of the analysis of the results from a questionnaire administered to samples of participants from two populations. The questionnaire was designed to simultaneously measure the magnitudes of several properties of each participant so that relationships among these magnitudes can be examined. The context is one of comparing these relationships from population to population *after* the questionnaire has been used. The samples are 'large' in the sense that sample variances can be taken as accurate estimates of the underlying population variances, so that estimated standard errors in the estimation of means can be regarded as exact. This is a standard assumption in statistical analysis, certainly acceptable for sample means calculated from $n = 215$, (Table 7, oSDS, NZ) which I take to be the smallest relevant sample size.

The report considers the 'measurement invariance' of the questionnaire with the two populations. The populations/samples are A='New Zealand Community' and B='Maldives Community', and all references to these populations/samples are now given using the labels A and B. The labels A and B are also used to indicate non-specific populations/samples, and there is no need to identify A with 'New Zealand Community' and B with 'Maldives Community' until specific numerical results are described.

Measurement invariance

The concept of 'measurement invariance' (MI) (or 'measurement equivalence') of a questionnaire Q is the idea that the questionnaire behaves in the same way in both groups, A and B. If the questionnaire behaves differently in A and B then there is a corresponding component of measurement error, but if the behaviours in A and B are the same then, notwithstanding the presence of other sources of error, the scores on the questionnaire can be regarded as accurate. So a lack of MI results in a false difference between scores from different populations, and if this difference can be estimated from the sample data then we can examine the robustness of the conclusions previously drawn. This report describes the estimation process and the results.

If there is MI then it is associated with ‘the questionnaire and populations A and B’ as a combination. For example, there might not be MI for the questionnaire with populations A and C. So all that follows must be understood in terms of only two identified populations, A and B. So the goal to estimate the amount of non-MI that exists for the triplet (Q, A, B). We envisage a direction from A to B, so that all differences correspond to ‘B minus A’, not ‘A minus B’. (So the triplet (Q, A, B) is not the same as the triplet (Q, B, A).) This step is necessary so that the meaning of the sign, + or −, of the non-MI is clear. Henceforth, we shall refer to *measurement variance* (MV) instead of non-MI. This will be explained further below.

An estimation approach to measurement invariance

The concepts of ‘estimate’, ‘true value’ and ‘error’ are foundational, as is the relationship described by:

‘(observed) score = true value + error’.

The true value is the unknown magnitude of the property (in the participant or population), and the questionnaire is a means of approximating or estimating this magnitude. The word `estimation’ perhaps has a weaker connotation than the word `approximation’, but the terms `estimation’, `estimate’ and `estimator’ are standard when discussing measurement processes: in particular, `estimator’ has a technical definition. The term `score’ here stands for the noun `estimate’: in this context the `score’ is the sum of the relevant responses on the questionnaire. The term `error’ is standard, and it does not imply that the researcher has made a mistake. The error is a signed quantity: it is negative if the result is smaller than the true value.

The approach taken here is based on the idea that the error *can never be exactly equal to zero*: real-world processes simply do not work that way. So the analysis takes as a starting point the assertion that

$$\text{true value} \neq \text{score.}$$

When this premise is held, the concept of approximating the extent of MV is more logically satisfactory than the concept of testing the hypothesis of strict MI. However, almost all the literature relating to MI is based on the `testing' approach. Therefore, adopting the `estimation' approach means that the results of the study will, to some extent, be exploratory and experimental. Nevertheless, this work has been carried out with a view to providing the candidate with figures representing best estimates of the numerical effect of MV on scores obtained from A and B. Several reasons for adopting the estimation approach will be given shortly.

Our approach of 'estimation' differs fundamentally from the approach of 'testing' found in most of the relevant literature. In the great majority of the literature, the approach taken is to *test for the existence* of MI to see if the questionnaire can be declared a valid instrument: the output is a pass/fail decision of some sort. In contrast, here we *estimate the size* of a difference in behaviour caused by a lack of MI, and the output is a number, e.g. 1.4 units (out of the scale-maximum, say 84 units). This sample-based number, i.e. the estimate, acts as an approximation to the corresponding magnitude at the population level, (which is unknown and unknowable without administering the questionnaire to everybody). The quality of this approximation is related to the sample size in the usual way.

The conceptual and practical differences between the testing and estimation approaches are large, so we need to adopt new terminology relating to the idea of 'not MI'. The term 'non-invariance' has been used to describe 'not MI', but this term has a binary, pass/fail, yes/no, connotation, like 'invariance', and so it alludes to the testing approach. In contrast, the term 'measurement variance' (MV) seems to convey the right idea and it has not been widely used, and so this term is adopted here. (A basic search on Scopus for "measurement variance" in the title field gave 28 results, and the great majority of these were from the physical sciences. One exception is a paper of Beath *et al* [1], but

Beath *et al* do not use the term “measurement variance” anywhere else in their paper, and they do not define this term. So we are free to use this term here, and we can avoid confusion with the fundamental statistical idea of the ‘variance’ of a random variable by always using the phrase ‘measurement variance’ or writing just MV.)

There are a number of reasons for focusing on MV rather than MI, and these are now stated in the form of assertions.

1. Measurement invariance is an ideal that will never be strictly achieved in cross-cultural research, simply because of the existence of the kinds of differences between cultures that the questionnaire is designed to uncover. So the idea of ‘demonstrating MI’, ‘achieving MI’ or ‘establishing MI’ [2] via a test is loose and somewhat illogical. An alternative approach would estimate the degree of measurement variance instead. This idea that effect testing is not as meaningful as effect-size estimation can be expressed well using the language of hypothesis testing.

   Suppose E is the amount of error when using a measuring instrument. The conventional idea of assessing the quality of the instrument is to initially hypothesize that E is equal to zero and subsequently examine the data to possibly demonstrate statistically that E is not equal to zero. The null hypothesis is “$E = 0$” and the alternative hypothesis is “$E \neq 0$”. (The test is a ‘goodness-of-fit’ test, and in this kind of test the analyst does not want the instrument to be found to perform badly, e.g. does not want the questionnaire to fail the test and be denied the status of ‘invariant’. The opposite is true with the usual type of hypothesis test, where the analyst usually wants to show that the null hypothesis is false, and so chooses a large sample size.) However, it is reasonable to suggest that even though E might be very small, E can never be *exactly* zero. Similarly, it is not possible for a questionnaire to truly be *strictly* invariant: it is not possible for there to be exactly no MV. There must be some unwanted effect causing a small error somewhere, even if it is only a minor effect related to slightly different uses of one word in different cultures.

   So it is not possible for the null hypothesis “$E = 0$” to be true. But if we carry out a hypothesis test and get an inconclusive result then our standard interpretation would be ‘‘I have not got enough statistical evidence to reject the null hypothesis, so I am going to continue to trust it: (I am going to continue to trust that E is equal to zero)''. But how can I trust a hypothesis that common sense tells me is false? It would not make logical sense to do so. This is the first principle behind the very strong argument that the task of studying measurement invariance must be reformulated to be one of estimation.

2. The estimation approach makes the idea of 'fitness-for-purpose' more central. If the questionnaire is used in populations that differ greatly then a small amount of MV will not matter. The testing approach does not accommodate this idea because it focuses on the concept of a fixed criterion.
3. When the focus is on estimation, not testing, there is no need for the hierarchical tests of *configural invariance*, *metric invariance*, *scalar invariance* and *residual invariance* that a conventional analysis of MI involves. Such tests require arbitrary pass/fail criteria such as '$p < 0.05$'. Accordingly, we can read statements such as ''This emphasis on statistical tests and empirically derived cut-off values has been criticized for several reasons'' [3].
4. Adopting the estimation approach leads to a more natural terminology, and a clearer interpretation of the meaning of the results.
5. In the general field of statistical analysis, there is an ongoing shift away from the concept of `hypothesis tests' to the concept of estimation using 'confidence intervals'.
6. The idea of testing MI fits with the idea of *refining* the questionnaire but, in this case, the questionnaire is one that has already been administered.
7. Last but not least, the estimation process (potentially) allows us to focus on the validity of the particular conclusions. If a test was carried out and the questionnaire failed the test then we would not know what to do. With estimation, we can make appropriate adjustments to the scores and restate our conclusions if necessary. Thus, in considering the alternative, 'testing', approach we can read ''Focusing on equality of measurement parameters and not on whether measurement equality matters for conclusions of interest may lead to problematic situations when exact equality does not hold'' [4].

In my opinion, the first of these reasons is sufficient in itself to adopt the 'estimation' approach. The task becomes more 'logical' in its process, and so it ultimately becomes more meaningful.

So the approach taken is to accept that there is some MV, to estimate its size, and then examine whether the result changes the conclusions, thus making it possible for the candidate to makes appropriate adjustments to here analysis. So we do not test MI but instead we estimate the size of the MV while, in effect, asking *in the context of* ***this*** *questionnaire and* ***these*** *populations* ‘‘when is MV small enough to ignore?’’.

With this in mind, we can consider the ‘alignment method’ [5] mentioned by the examiner. This method assumes that ‘‘a majority of the parameters are invariant and a minority of the parameters are noninvariant.’’[6]. The method goes some way toward our goal but it does not seem to answer the question adequately. It involves accepting that there is some MV and trying to adjust for it by refitting the model to minimise a certain measure of MV, whether this be the real size of the MV or not. The full estimation approach seems more satisfactory.

Existing methods of estimation

Adopting the estimation approach means that the ‘testing’ methods suggested in various papers, e.g. the standard MI methodology and the alignment method, lose some relevance. There are only a few articles that do not exclusively use a testing approach. Nye and Drasgow [3] define an effect size index d_{MACS} to assist in studying MV with regard to the mean and covariance structure, but for the variances they assume that the variances of the property in the two populations are the same (‘$\phi_{\mathrm{R}} = \phi_{\mathrm{F}}$’ in their paper), and this is not assumed here. Meuleman [7] gives a brief method for examining MV of item-intercepts (c.f. ‘scalar invariance’) to obtain an estimate of overall additive MV, but his method does not address the multiplicative form of MV (c.f. ‘metric invariance’) that we shall see is relevant here. Oberski [4] introduces the expected-parameter-change-interest (EPC-interest) as an important variation of the EPC of earlier writers, with Oberski’s emphasis being on the effect of MV on the parameters of interest rather than the parameter ‘in question’. Martin et al [8] describe a Bayesian method that involves estimating the MV but they do not fully abandon the idea of testing. To use a Bayesian method in this study would be inappropriate: Bayesian methods are based on a subjective view of probability, and they have not been used in the body of the thesis.

Thus, it is not surprising that, in 2016, Putnick and Bornstein [2] concluded that ‘‘research aimed at quantifying the impact of noninvariance in real-world models is still in its infancy.’’.

Formulation and terminology

We consider a *questionnaire* that has been administered to *participants* in samples drawn from two populations, A and B, in order to measure (the magnitude of) four personal *properties* symbolized by θ, these being *online perceived social support, offline perceived social support, online self-disclosure* and *wellbeing*. The questionnaire addresses these properties simultaneously, with any particular property θ being measured using *m questions* (items), each of which has a numerical *response* on a Likert scale, e.g. 1, 2, ..., 7.

For each participant, the *m* responses to the questions are summed to give the score on that property for that participant. This score is regarded as being an estimate of the underlying, unknown, *true value* or *true level* of that property for that participant. The scores and responses differ from the true levels by amounts known as *error*, with error being positive or negative, as above. The error is made up of different components. In particular, when attention is centred on measuring a property of a population rather than an individual participant, there is *sampling error* associated with the use of a sample of a finite size. This error is expressed in the study of the populations by regarding the true value of **property** θ for **participant *i*** as the outcome of an independent random variable T_i having unknown mean κ and unknown variance τ^2. That is, the participant’s true level of the property is seen as having been randomly drawn from an infinite population with this mean and variance. Also, we can define the random variable $D_i \equiv T_i - \kappa$, so that this is the deviation of the level of the property from the population mean.

Let $X_{\theta qi}$ indicate the response to question q of participant i for property θ. The subscript ‘θ’ is meaningful, but it will be omitted. This response is described by

$$X_{qi} = \alpha_q + \beta_q D_i + E_{qi} \qquad D_i \sim \left(0, \tau^2\right) \tag{1}$$

where α_q and β_q are unknown and E_{qi} is the measurement error when employing question q with participant i. All the random variables on the right-hand side are independent except for variables differing only in the index q: this allows different questions to behave similarly, which is realistic. The corresponding score for participant i on property θ is

$$X_i = X_{1i} + X_{2i} + \cdots + X_{mi} \tag{2}$$

These equations become more complete as a model of the measurement when a statistical assumption is made about the error. A standard assumption is that E_{qi} and E_{qk} have been drawn independently from a distribution with mean zero and unknown variance ψ_q^2. So

$$E_{qi} \sim \left(0, \psi_q^2\right). \tag{3}$$

The model obtained is compatible with Confirmatory Factor Analysis (CFA).

The quantities α_q, β_q and ψ_q^2 describe the behavior of question q in the population, so they are quantities of interest. Strict MI would require that their values are the same when the questionnaire is administered in populations A and B. So we now indicate the population being studied. The model at the question level given by (1) and (3) can then be written as

$$\begin{aligned} X_{qi} &= \alpha_{\mathrm{A}q} + \beta_{\mathrm{A}q} D_i + E_{qi} \qquad & D_i \sim \left(0, \tau_{\mathrm{A}}^2\right) \qquad & E_{qi} \sim \left(0, \psi_{\mathrm{A}q}^2\right) \\ X_{qj} &= \alpha_{\mathrm{B}q} + \beta_{\mathrm{B}q} D_j + E_{qj} \qquad & D_j \sim \left(0, \tau_{\mathrm{B}}^2\right) \qquad & E_{qj} \sim \left(0, \psi_{\mathrm{B}q}^2\right) \end{aligned}$$

Note that $D_i = T_i - \kappa_{\mathrm{A}}$ and $D_j = T_j - \kappa_{\mathrm{B}}$. The corresponding equations for the scores are

$$\begin{aligned} X_i &= \alpha_{\mathrm{A}} + \beta_{\mathrm{A}} D_i + E_i \qquad & D_i \sim \left(0, \tau_{\mathrm{A}}^2\right) \qquad & E_i \sim \left(0, \psi_{\mathrm{A}}^2\right) \\ X_j &= \alpha_{\mathrm{B}} + \beta_{\mathrm{B}} D_j + E_j \qquad & D_j \sim \left(0, \tau_{\mathrm{B}}^2\right) \qquad & E_j \sim \left(0, \psi_{\mathrm{B}}^2\right), \end{aligned} \tag{4}$$

with several terms in these expressions being formed by summing over $q = 1, \cdots, m$. Strict MI would require that the unknown true values of the parameters are the same in each population, e.g. $\boldsymbol{\alpha}_{\mathrm{A}q} = \boldsymbol{\alpha}_{\mathrm{B}q}$ and so $\boldsymbol{\alpha}_{\mathrm{A}} = \boldsymbol{\alpha}_{\mathrm{B}}$.

Chapter 4: Comparisons of group mean levels

In chapter 4 of the thesis, attention is centred on comparing the mean levels of properties in different groups. Here we consider the comparison of the NZ community-sample/population with the Maldives community-sample/population for each of the four variables, *online perceived social support*, *offline perceived social support*, *online self-disclosure* and *wellbeing*. If MI were to exist with regard to the testing of means, then $\alpha_{\mathrm{A}q} = \alpha_{\mathrm{B}q}$ for each **question** q. So to estimate the size of the corresponding component of MV, we seek to estimate the differences $\delta_q \equiv \alpha_{\mathrm{B}q} - \alpha_{\mathrm{A}q}$ for $q = 1, \cdots, m$ using the sample data.

Method and results

The method is based on equation (4), but it is considerably more complex to describe. It makes use of the following two modelling assumptions, which seem necessary and appropriate. If there is some MV at the question level, then it seems reasonable to imagine a similar extent of MV at the exam level. Thus, it seems reasonable to require every value of δ_q to have the same sign, whether it be positive or negative. So the first assumption is:

Assumption 1: Although different questions (items) might have different amounts of MV, the amounts all have the same sign, i.e. the deviations are all in the same direction.

Also, it seems reasonable to suppose that the MV is negligible for at least one of the questions. So the second assumption is:

Assumption 2: At least one of the questions has measurement invariance.

The first assumption allows us to estimate each δ_q and the second assumption allows the populations to be registered to each other. Despite making these assumptions, the results depend on which 'direction' the MV is in. So there are two estimates of the MV for each property, one for each direction.

The method was applied and the following results were obtained.

- For *online perceived social support*, relative to the level α_A (in the NZ sample), MV has acted to increase α_B (in the Maldives sample) by 4.3 points on the scale or by −0.4 (minus 0.4) points on the scale.
- For *offline perceived social support*, relative to the level α_A, MV has acted to increase α_B by 2.1 points on the scale or by −0.0 (minus 0.0) points on the scale.
- For *online self-disclosure*, relative to the level α_A, MV has acted to increase α_B by 6.3 points on the scale or by 0.4 points on the scale.
- For *wellbeing*, relative to the level α_A, MV has acted to increase α_B by 0.0 points on the scale or by −4.5 (minus 4.5) points on the scale.

The effect of MV of the conclusions can be studied by reversing the estimated differences in the parameter values thought to have been caused by the MV. Thus, for the tests of means described in chapter 4 of the thesis, amended calculations would be carried out by

1. subtracting 4.3 from each score of *online perceived social support* in the Maldives sample,
2. subtracting 2.1 from each score of *offline perceived social support* in the Maldives sample,
3. subtracting 6.3 from each score of *online self-disclosure* in the Maldives sample,
4. subtracting 0.0 from each score of *wellbeing* in the Maldives sample,
5. and then rerunning the analysis,

and also by

5. subtracting −0.4 from (i.e. adding 0.4 to) each score of *online perceived social support* in the Maldives sample,
6. subtracting 0.0 from each score of *offline perceived social support* in the Maldives sample,
7. subtracting 0.4 from each score of *online self-disclosure* in the Maldives sample,
8. subtracting −4.5 from each score of *wellbeing* in the Maldives sample,
9. and then rerunning the analysis.

It is highly unusual to encounter a method in which there are two different estimates of the same quantity, each of which is deemed to be equally reliable. This arises here because Assumption 1 permits MV to arise in either direction while Assumption 2 fixes the associated estimate of MV by assuming that the smallest deviation due to MV is zero. The combined result of these assumptions is the existence of two estimates, neither of which is to be preferred on theoretical grounds. No other assumption seems reasonable, so the method must be accepted as having produced two estimates. Nevertheless, there is an over-riding principle to which we can turn when choosing between these estimates, and that is the principle of conservatism. Throughout the thesis, and in much statistical analysis, the procedure has been to hypothesize that there is no difference between groups or no relationship between properties and then to use the data to show otherwise. This is a conservative process: no positive difference of association is declared until the data are sufficient to permit it. In the same way, the appropriate choice of estimate of MV will be the choice leading to the weaker result so that, if adjusting for one estimate of MV leads to a null conclusion while adjusting for the estimate of MV leads to a positive conclusion, the first is to be preferred. This is both a responsible and scientific choice.

Chapter 7: Testing hypotheses 1-3 across the subsamples

In chapter 7 of the thesis, the analysis of the three hypotheses involves linear regression for the purpose of detecting positive associations between the properties. These associations are indicated by regression coefficients statistically significant from zero. These coefficients represent slopes and they do not depend on intercepts, so there is no requirement in chapter 7 for the questionnaire to have $\boldsymbol{\alpha_{Aq} = \alpha_{Bq}}$. Furthermore, the effect of non-zero values of $\psi^2_{\mathrm{A}q}$ and $\psi^2_{\mathrm{B}q}$ is only to weaken the ability of the questionnaire to detect true differences between individuals or populations. Therefore, for the comparison of populations using the results of two separate analyses in chapter 7, the estimation of MV arising from **differences between** $\psi^2_{\mathrm{A}q}$ and $\psi^2_{\mathrm{B}q}$ could not alter original conclusions drawn that the hypotheses are *true*. On the other hand, it seems plausible that estimation of MV of this sort could affect an original conclusion that one of the hypotheses was *false*, but no such conclusion is reached in the thesis, where null results are correctly interpreted as implying unsupported hypotheses, not incorrect hypotheses.

These considerations suggest that the estimation of the relevant MV centres on the differences between $\beta_{\mathrm{A}q}$ and $\beta_{\mathrm{B}q}$ and that **differences between** $\alpha_{\mathrm{A}q}$ and $\alpha_{\mathrm{B}q}$ and between $\psi^2_{\mathrm{A}q}$ and $\psi^2_{\mathrm{B}q}$ can be neglected. The unknown values of $\alpha_{\mathrm{A}q}$ and $\alpha_{\mathrm{B}q}$ become irrelevant, but the values of $\psi^2_{\mathrm{A}q}$ and $\psi^2_{\mathrm{B}q}$ remain relevant because they affect the correlation coefficients on which the method will be based. The analysis for property θ and populations A and B is therefore based around the *m* x *m* covariance matrices of the responses to the corresponding questions, which contains all the information available about $\beta_{\mathrm{A}q}$, $\beta_{\mathrm{B}q}$, $\psi^2_{\mathrm{A}q}$ and $\psi^2_{\mathrm{B}q}$ for quantities , all the information about τ^2_{A} and τ^2_{B}, and all the information available about correlations between the responses to these questions.

Method and results

The method of analysis involved estimating the products $\beta_{\mathrm{A}q}\,\tau_{\mathrm{A}}$ and $\beta_{\mathrm{B}q}\,\tau_{\mathrm{B}}$ by matching the sample covariance matrices to the model-implied covariance matrices. Assumptions 1 and 2 are again applicable but, instead of assuming every value of δ_q to be positive or negative, here we assume that every value of $\beta_{\mathrm{B}q}/\beta_{\mathrm{A}q}$ is greater than or less than 1, which is the value that would exist if there was MI. Assumption 1 allows us to estimate τ_{A} and τ_{B} so that from the products $\beta_{\mathrm{A}q}\,\tau_{\mathrm{A}}$ and $\beta_{\mathrm{B}q}\,\tau_{\mathrm{B}}$ we can obtain estimates of the $\beta_{\mathrm{A}q}$ and $\beta_{\mathrm{B}q}$ parameters. As before, Assumption 2 allows us to register the populations to each other. Again, despite making these assumptions, the results depend on which ‘direction’ the MV is in. So there are again two estimates of the MV for each property, one for each direction.

The method was applied and the following results were obtained.

- For *online perceived social support*, relative to the slope β_A (in the NZ sample), MV has acted to reduce β_B (in the Maldives sample) to 0.99 times its true value or to 0.89 times its true value.
- For *offline perceived social support*, relative to the slope β_A, MV has acted to increase β_B to 1.02 times its true value or to reduce β_B to 0.99 of its true value.
- For *online disclosure*, relative to the slope β_A, MV has acted to increase β_B to 1.58 times its true value or to reduce β_B to 0.51 of its true value.
- For *wellbeing*, relative to the slope β_A, MV has acted to reduce β_B to 0.98 times its true value or to reduce β_B to 0.73 of its true value.

The effect of MV of the conclusions can be studied by reversing the estimated differences in the parameter values thought to have been caused by the MV. Thus, with a linear regression of *wellbeing* against *online perceived social support, offline perceived social support and online disclosure offline*, amended calculations would be carried out by both

5. dividing each score of *online perceived social support* in the Maldives sample by 0.99,
6. dividing each score of *offline perceived social support* in the Maldives sample by 1.02,
7. dividing each score of *online disclosure* in the Maldives sample by 1.58,
8. dividing each score of *wellbeing* in the Maldives community by 0.98,
9. and then rerunning the analysis,

and also

5. dividing each score of *online perceived social support* in the Maldives sample by 0.89,
6. dividing each score of *offline perceived social support* in the Maldives sample by 0.99,
7. dividing each score of *online disclosure* in the Maldives sample by 0.51,
8. dividing each score of *wellbeing* in the Maldives sample by 0.73,

9. and then rerunning the analysis.

It is reasonable to expect that multiplying (or dividing) each score by a constant might have no effect on the statistical significance of the measured (linear) regression coefficients, even though different properties might be multiplied by different factors. Multiplying each score by some factor will also multiply the standard error of the regression coefficient by the same factor, in which case the *t*--statistic might stay the same, even though co-variates are involved. If the *t*-statistic stays the same then the *p*-value stays the same also, in which case the conclusions of the thesis will be unaltered.

Conclusion

The results obtained here are point estimates obtained by a new method. Standard errors are not available for these estimates because this method is new, and undoubtedly each figure could be in error by ±10% or more. After further development, this method could find application in many problems.

The analysis is very unusual in that the structure of the problem gives two estimates of MV for each property, neither of which is *a priori* more realistic than the other. The analysis has been carried out assuming that the first figures of MV for each property apply simultaneously (i.e. ‘go together’) and assuming that the second figures of MV for each property apply simultaneously. I would argue that much of any MV could be due to differences in the understandings of the adjective ‘Strongly’ in ‘Strongly disagree’ and ‘Strongly agree’, in which case the MV could be expected to work in the same direction for each property. So these assumptions seem sound. However, it would be reasonable to examine the effect of interchanging individual values from the first set of figures with those in the second set, e.g. by swapping the figures 0.98 and 0.73 for *wellbeing* in the analysis for chapter 7. This would allow a more conservative assessment of MV.

The analysis suggests that there has been some measurement variance, as might be expected. However, the amount of measurement variance seems unlikely to affect the conclusions of the thesis. This can be determined by carrying out the analyses suggested.

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