Network Models of Mindfulness

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Abstract

Contemporary mindfulness research at the level of self-report has often represented mindfulness as a latent (trait) variable. Recently, a novel psychometric methodology has been developed which allows mindfulness to be modelled as a complex system or network at the level of self-report. This *network perspective* is argued to provide a more plausible conceptualisation of mindfulness.

A network perspective implies that a more densely connected network of practices may be indicative of a greater level of development of mindfulness. It also implies that certain practices may be more strongly interconnected or central than others. These highly central practices may be potentially useful targets for interventions.

Mindfulness networks were estimated for practitioners and non-practitioners using the Friedberg Mindfulness Inventory (Study 1) and an adapted version of the Applied Mindfulness Process Scale (Study 2). A total of 371 regular mindfulness practitioners, 224 non-practitioners and 59 irregular practitioners were recruited online from the Amazon Mechanical Turk database.

Across both measures, comparisons between practitioners and non-practitioners' networks indicated that network density did not significantly differ, whereas evidence was found in support of a significant difference in network structure. Exploratory analyses revealed practitioners' networks to be characterised by greater differentiation in their community structures relative to non-practitioners across both measures. In Study 1, *Acceptance* was revealed to be much more central to the practitioners' network relative to non-practitioners; and *Returning to the Present* much more peripheral. The practice of *Attending to Actions* and/or the negative path it shared with *Self-kindness* were identified as possible targets to facilitate mindfulness in non-practitioners. In Study 2, highly *eudemonic*

practices were revealed to be more central to the practitioners' network relative to non-practitioners, whilst more foundational *de-centering* practices were more peripheral.

These studies provide support for the plausibility of investigating mindfulness as a complex network at the level of self-report. However, the lack of difference in network density indicates that future research is needed to examine network dynamics in the context of regular mindfulness practice. Future research is also required to establish whether the networks estimated are behavioural or semantic.

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Introduction

Mindfulness has become a rapidly expanding phenomenon. Perhaps the most well-known definition comes from Kabat-Zinn (1994) who described mindfulness as “paying attention in a particular way: on purpose, in the present moment, and non-judgmentally” (p. 4). This was later expanded to include “an affectionate, compassionate quality within the attending, a sense of openhearted, friendly presence and interest” (Kabat-Zinn, 2003, p. 145). A number of contemporary authors have suggested that mindfulness be considered an umbrella term for a number of practices, procedures and processes largely defined in relation to the capacities of attention, awareness, memory/retention, and acceptance/discernment (Van Dam et al., 2018). In this thesis, mindfulness will be referred to as a practice or set of practices in both the sense of the verb (i.e., an activity) and noun (i.e., a habit or point of repetition). This represents a pragmatic definition of mindfulness, for the noun form simply reflects the verb form at a later point in time.

In contemporary mindfulness, practices generally resemble each other in their basic procedures and goals (Bishop et al., 2004). Meditation has generally been considered core to mindfulness (Bishop et al., 2004; Kabat-Zinn, 1994; Griffiths, 1983) and a description of a sitting meditation is illustrative. Sitting meditations are often one of the first meditations a novice practitioner may cultivate, especially in the Vipassana, Zen and Tibetan traditions (Sharf, 2015). In a sitting meditation, the practitioner sits upright on the floor, a cushion or straight-backed chair. They will typically be instructed to focus their attention on a physical marker of their breath, such as the rise and fall of their chest, or the sensation of the breath through the nostril. The practitioner will regularly be instructed to simply notice when and perhaps where, their attention wanders, as it invariably will. On these occasions, the practitioner is encouraged to intentionally return their attention to the breath in a non-judgemental or compassionate manner. Thus, the instruction of mindfulness closely resembles its popular definition (i.e., “paying attention in a particular way: on purpose, in the present moment, and non-judgmentally”; Kabat-Zinn, 1994, p. 4).

Beyond formal meditation, the practitioner is typically encouraged to utilise the above refocusing procedure whenever they perceive themselves to be engaging in unhelpful thinking styles or practices. Through encouraging such anchoring practices, a mindful state is believed to emerge, which is claimed to provide a non-elaborative and non-judgmental space between one’s perception and response (Bishop et al., 2004). The practitioner is thus afforded an ability to disengage from habitual responding and flexibly pursue more adaptive practices (Garland, Farb, Goldin, & Fredrickson, 2015a; Shapiro, Carlson, Astin, & Freedman, 2006). As a practice develops, the practitioner may shift from a focused monitoring on the breath to a more *open monitoring* practice in which the practitioner concurrently monitors all present moment experiences in addition to that of the breath (Lutz et al. 2008). In an open monitoring practice, the practitioner may be concurrently monitoring a number of sensations in their environment (such as sound and touch), in addition to internal phenomena such as thoughts and feelings. As practices of these sort become more refined, the practitioner is believed to come into contact with a *pure* or *bare* experience, stripped of projective and associative meanings (Thera, 1973; Chisea, 2013; although see Bodhi, 2011; Sharf, 1995 for critique).

Van Dam and colleagues (2018) suggest that investigations of mindfulness first gained traction with researchers in 1987 following the establishment of the Mind and Life Institute. The Mind and Life Institute facilitated formal regular dialogues between the Dalai Lama and prominent scientists and clinicians. From 2004 onwards, these exchanges came to include regular summer meetings, coinciding with a period of exponential growth in mindfulness publications (see Figure 1). Many empirical reviews now attest to the efficacy of mindfulness beyond its initial application to pain reduction (e.g., Kabat-Zinn, 1982). Mindfulness interventions have been shown to be beneficial for persons suffering from psychiatric symptoms (e.g., Hofmann, Sawyer, Witt & Oh, 2010; Piet & Hougaard, 2011; Khoury et al., 2013; Kuyken et al., 2016; Blanck et al., 2018; Wang et al., 2018), health conditions such as substance abuse (Li, Howard, Garland, McGovern & Lazar, 2017; Black, 2014), obesity (e.g., O'Reilly, Cook, Spruijt-Metz & Black, 2014), cancer (Haller et al., 2017), fatigue (Ulrichsen et al., 2016), and chronic pain (Hilton et al., 2017). Brain imaging studies have revealed positive relationships between mindfulness and various neural functions associated with well-being (Farb et al., 2007; Hölzel et al., 2007; Tang et al., 2007, 2009; Tomasino & Fabbro, 2016; Zeidan et al., 2015). Effects on the immune system and stress parameters have also been reported (Black & Slavich, 2016; Pascoe, Thompson, Jenkins & Ski, 2017).

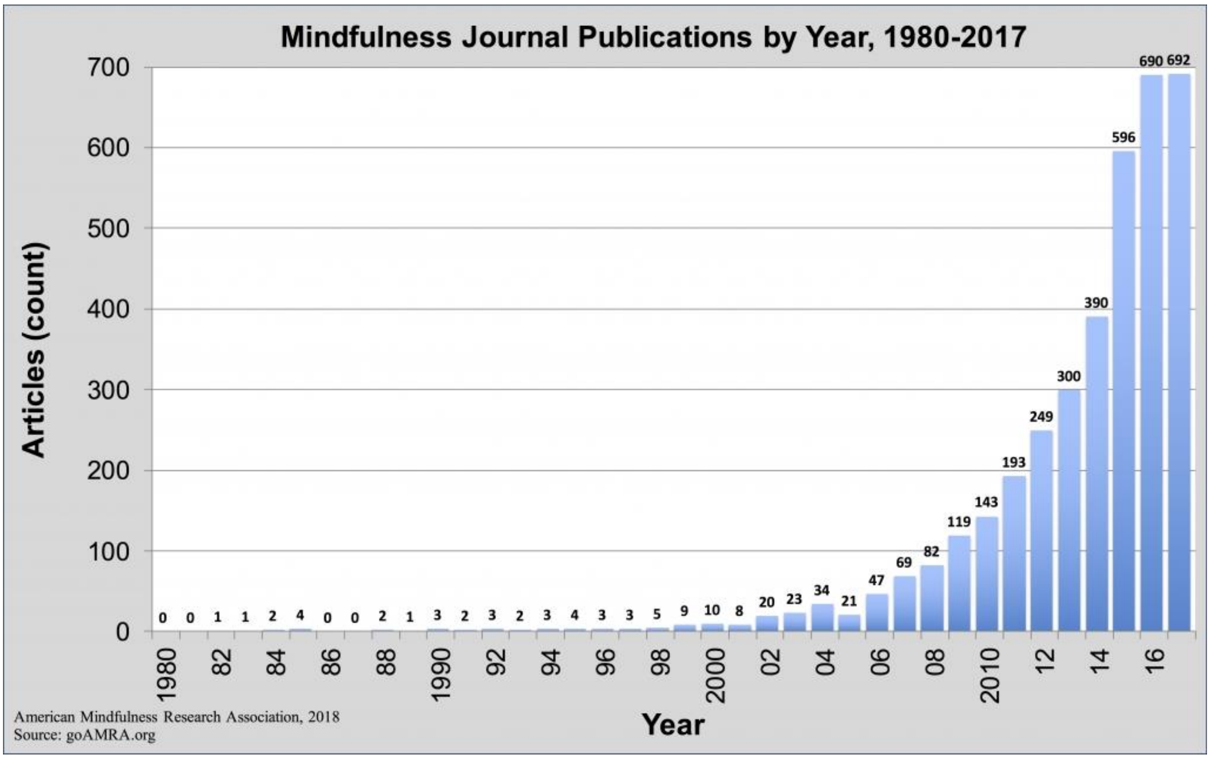


Figure 1. Mindfulness journal publications by year, 1980-2017 Figure reprinted with permission from American Mindfulness Research Association, 2018 (https://goamra.org/resources/)

The growing literature around mindfulness has encouraged the expansion of mindfulness practices into different segments of society. Mindfulness is now offered as a standard psychotherapy in the United Kingdom's National Health Service, and many psychotherapies have come to incorporate mindfulness principles (Mindfulness-Based Stress Reduction, Mindfulness-Based Cognitive Therapy, Acceptance and Commitment Therapy, Dialectical Behaviour Therapy, Mindfulness-Based Relapse Prevention, Mindfulness-Based Trauma Therapy, and Mindfulness-Based Eating Awareness Training). Mindfulness is also gaining momentum in the educational system (Bender, Roth, Zielenski, Longo & Chermak, 2018) where it has become part of standard education for approximately 6,000 school children in London (Torjesen, 2015). In New Zealand, several programmes are being piloted in primary and secondary schools (e.g., Bernay, 2014; Bernay, Graham, Devcich, Rix, & Rubie-Davies, 2016). Mindfulness has also been adapted for use in prison populations with promising results (Dafoe and Stermac 2013; Didonna 2009; Shonin, Van Gordon, Slade, & Griffiths, 2013).

The rapid expansion of mindfulness into diverse settings has been criticised for proceeding beyond the available evidence (Farias & Wikholm, 2016; van Dam et al., 2018). In experimental studies, the efficacy of a given mindfulness intervention is often determined by quantifying the difference between the intervention group and a control group; however, the efficacy of an intervention can often be overstated if the control group is of poor quality. Many studies included in mindfulness reviews have used wait-list controls (participants who are assigned to a waiting list for a mindfulness intervention but receive this after the experimental study) or no control conditions at all (Goyal et al., 2014). Such studies cannot disentangle the effects of the mindfulness intervention (the *active ingredient*) from other *non-specific* aspects involved in an intervention, such as group support, expectation effects, homework tasks, associated retreats and other activities (see Jensen et al., 2012; Quaglia, Braun, Freeman, McDaniel & Brown, 2016 for a discussion of possible non-specific factors). Control groups which aim to replicate non-specific aspects of an intervention without the active ingredient are known as *active controls*. Experimental designs with active controls allow greater confidence that observed effects are associated with the active treatment. When mindfulness interventions are matched to such active controls, the results are less conclusive. In a meta-analysis of the pro-social effects of mindfulness, Kreplin, Farias and Brazil (2018) found that mindfulness meditation had little influence on aggression, prejudice and connectedness, but caused a modest increase in compassion and empathy. These effects declined when active controls were used. In their highly influential meta-analysis, Goyal and colleagues (2014) reviewed 18,753 citations and found that only 47 trials (3%) included an active control or suitable psychological control (i.e., a placebo condition). Limited to these studies, mindfulness meditation programs had moderate evidence of improved anxiety, depression, and pain, and low evidence of improved stress reduction and quality of life. They found no evidence that mindfulness influenced other variables such as positive mood, attention, sleep or substance use. Furthermore, no difference was found between mindfulness and other interventions such as physical exercise, relaxation or anti-depressant medication. This latter finding replicated a previous meta-analysis by Khoury and colleagues (2013), and a lack of any comparative advantage in mindfulness treatments over other treatment options has also been reported in the areas of obesity (Daubenmier et al., 2016), smoking cessation (Vidrine et al., 2016) and back pain (Cherkin et al., 2016). Recently, mindfulness was found to demonstrate moderate relief for psychiatric symptoms in suitably controlled studies, but again, no difference was found between mindfulness therapies and other first line therapies (Cognitive Behavioural Therapy and antidepressant medication; Goldberg et al., 2018).

The task of measuring a practice relevant to many areas of society necessitated the development of reliable self-report measures. Such measures sought to determine whether a given practice or intervention was actually cultivating mindfulness, as opposed to some other quality. Mindfulness constructs in popular mindfulness measures have been shown to be sensitive to change with mindfulness training (e.g., Khoury et al., 2013; Quaglia et al., 2016), and these changes have been shown to mediate important outcomes (e.g., Bränström, Kvillemo, & Moskowitz, 2012; Nyklícek & Kuijpers, 2008; Raes, Dewulf, Van Heeringen & Williams, 2009; (Shapiro, Oman, Thoresen, Plante, & Flinders, 2008; Vøllestad, Sivertsen, & Nielsen, 2011; although see Gu, Strauss, Bond & Cavanagh, 2015; Visted, Vøllestad, Nielsen, & Nielsen, 2015, for methodological weaknesses).

Although proving useful (i.e., predicting various outcomes), substantial heterogeneity exists in how these scales have conceptualised mindfulness. Mindfulness has now come to be defined as anything from how well a person might describe and observe their experiences (Kentucky Mindfulness Scale, KMS; Baer, Smith & Allen, 2004; Five Factor Mindfulness Questionnaire, FFMQ; Baer, Smith, Hopkins, Krietemeyer & Toney, 2006), to their novelty seeking and producing abilities (Langer Mindfulness Scale, LMS; Pirson, Langer, Bodner & Zilcha-Mano, 2012), to how often they think they experience lapses in attention (Mindfulness Attention and Awareness Scale, MAAS; Brown & Ryan, 2003), to how people characterise their openness and personal identification with present experience (Freiburg Mindfulness Inventory, FMI; Buchheld, Grossman & Walach, 2001; Toronto Mindfulness Scale, TMS; Lau et al., 2006). Mindfulness has further been conceptualised as both a uni-dimensional general construct (FMI; Cognitive and Affective Mindfulness Scale-Revised, CAMS-R; Feldman, Hayes, Kumar, Greeson & Laurenceau, 2007; Southampton Mindfulness Questionnaire, SMQ; Chadwick, Hember, Symes, Peters, Kuipers & Dagnan, 2008) and a set of two to five constructs (KIMS, FFMQ, TMS, Philadelphia Mindfulness Scale, PHLMS; Cardaciotto, Herbert, Forman, Moitra, & Farrow, 2008). Validation studies have hence established mindfulness to be simultaneously holistic (Leary & Tate, 2007; Walach et al., 2006) yet modular (Baer et al., 2004, 2006; Cardaciotto et al., 2008; Lau et al., 2006).

This diversity of definitions has led commentators to question the claims that each measure accurately measures mindfulness (Bergomi, Tschacher, & Kupper, 2013; Grossman, 2008; Sauer et al., 2013; Siegling & Petrides, 2016). Despite demonstrating good psychometric properties, correlations between these measures have been found to be only modest (Baer et al., 2004; Carmody, Reed, Kristeller, & Merriam, 2008; Thompson & Waltz, 2007), raising concerns around what construct validity represents in contemporary psychometrics.

Construct validity is often thought to refer to *whether a measure actually measures what it purports to*, and arguably this represents the working definition of many researchers (Borsboom, Mellenbergh, & van Heerden, 2003, 2004). Formulated in this way, construct validity refers to a property of a test, and it tends to demand a *realist* conceptualisation of the attribute being measured; namely, that the attribute *really exists* independent of the measuring procedure (Borsboom et al., 2004). Implicit in this idea is also the assumption that the attribute being measured should cause the changes observed in a measure (i.e., the changes observed in questionnaire item responses). Taken together, the postulation of a really existing attribute with causal properties constitutes a casual theory of measurement advanced by Borsboom and colleagues (2004); specifically, “a test is valid for measuring an attribute if and only if (a) the attribute exists and (b) variations in the attribute causally produce variations in the outcomes of the measurement procedure” (p. 1061).

Interestingly, establishing construct validity in contemporary psychometrics refers to something quite different. In this domain, construct validity is often established by investigating how a construct relates to similar or different constructs in a *nomological network* (i.e., Cronbach & Meehl, 1955). The nomological network represents these constructs, their observable manifestations, and their inter-relations. Construct validity hence shifts from a property of a test (i.e., whether the test measures what it should) to a property of test score interpretations (i.e., how to interpret the construct with respect to its nomological network). In this latter system, researchers need not make any commitment as to whether the construct really exists beyond their measurement procedures, thus the situation emerges where one can create a valid measure of an attribute which at the same time, need not exist.

Maul, Torres Irribarra and Wilson, (2016) attribute this confusion to the continuing influence of the philosophies of *Logical Positivism* and *Operationalism* in mainstream psychometric conceptualising (philosophies long abandoned in other scientific fields). Logical positivism advanced the idea that “statements regarding unobservable (theoretical) entities or forces should only be regarded as meaningful if such statements can be linked to observations in a clear and consistent manner” (Maul et al., 2016, p. 3). Operationalism maintained that theoretical attributes were synonymous with the way they are measured (Bridgeman, 1927). For the operationalist, “there [was] neither a need nor a place for postulating attributes which are prior to the measurement operation” (Borsboom, 2005, p. 93). Taken together, these systems created a context in which psychological attributes were equated with statistical representations, and their identities (i.e., what the attribute refers to), fixed by the relationships observed between these statistical constructs and other constructs.

Although contemporary researchers need not explicitly consider the question of whether their constructs *really exist* in validation, it will be argued here that a realist position is typically endorsed. It is argued that the mindfulness construct of contemporary questionnaires is thus treated as referring to something really existing (i.e., that it has material referents to the physical world), despite no evidence being offered to support this assumption. This is termed *reification* in the general literature (Kagan, 1988), and it has been considered a problem in mindfulness research (Garland, et al., 2015a; Grossman, 2011b; Grossman & van Dam, 2011).

This thesis was motivated by the question “what is mindfulness?” Answering this question required an understanding of how mindfulness has been conceived across different traditions. In chapter 1, a traditional conceptualisation of mindfulness is advanced by which mindfulness is considered *constituted* by, or an *expression* of, relevant practices. By way of contrast, it is suggested that contemporary conceptualisations of mindfulness treat it as an *explanation* of practice. On this basis, it is suggested that an important shift has occurred in the conceptualisation of mindfulness; namely mindfulness *as* practice shifts to mindfulness *as a cause of* practice.

Chapter 2 introduces two contemporary psychometric representations of mindfulness, one of which corresponds to conceptualisation of mindfulness as an explanation or cause of practice (termed a *reflective factor model*). It is suggested that this statistical model implies a realist position with respect to the mindfulness variable, which facilitates the reification of this variable. Chapter 3 introduces a novel psychometric representation in which mindfulness is modelled as a phenomenon constituted by practices. This statistical model supports an alternative ontology for mindfulness; namely the traditional conceptualisation advanced in which mindfulness is interpreted as an expression of practice. Two cross-sectional studies are then proposed, and the tone of the thesis changes. It is suggested that a regular mindfulness (or related meditative) practice may lead to synergistic interactions developing among relevant practices, such that a dense network emerges. Differences in network density might hence be observed between practitioners and non-practitioners at the cross-sectional level. On this reasoning, the studies hypothesised that the networks of regular practitioners would be characterised by greater density than the networks of non-practising individuals.

Networks have both central and peripheral practices. Highly central practices have been suggested to be relatively more important to network dynamics relative to more peripheral practices. At the cross-sectional level, these differences may manifest in topological differences in network organisation. To this end, an exploratory analysis was conducted to determine the most prominent group level network differences. An introduction to the estimation of networks from self-report data is provided in chapter 4. The methodology of the two studies is detailed in chapter 5, and chapter 6 outlines the results and their interpretation. Chapter 7 constitutes a general discussion of the results and the limitations of the studies.

Chapter 1: Traditional and Contemporary Conceptualisations of Mindfulness

Mindfulness practice derives from Buddhism. Few researchers would contest the diversity of systems falling under the rubric *Buddhism*, although canonical assumptions and goals are still typically endorsed as they provide a useful starting point. To this end, an introduction is first outlined. A conceptualisation of mindfulness is then advanced which arguably captures elements of mindfulness associated with more traditional formulations. This traditional conceptualisation is then contrasted with a conceptualisation of contemporary mindfulness. It will be argued that the conceptualisation of mindfulness has shifted in an important way; namely, that *which was* practice appears to have become that *which stands apart* from practice; and ultimately, *explains* it.

1.1 Conceptualising Traditional and Contemporary Mindfulness

Buddhism is claimed, first and foremost, to be the story of Siddhartha Gautama (Buddha) and his path to liberation (Carrithers, 2001). Arguably, Buddhist practitioners aspire to emulate Buddha by following the path he used to achieve what is believed to be his *enlightenment* (Sanskrit: *Bodhi*). In effect, Buddha outlined this path in what is considered to be his first sermon following his enlightenment. Known as the sermon on the *Four Noble Truths* (Sanskrit: *catvāri āryasatyāni*), Buddha is believed to have articulated 1) that the human condition is marked by suffering (Sanskrit: *duḥkha*); 2) that suffering is caused by greed and desire, ignorance or delusion, hatred and destructive urges; 3) that one can liberate themselves from this suffering by *letting go* of desire and attachment; and 4), that the path to enlightenment and liberation is the Noble Eightfold Path (Sanskrit: *āryāṣṭāṅgamārga*; Tsering, 2005). The Noble Eightfold Path thus functions as Buddha’s conceptual prescription for the relief of suffering, and it is here that mindfulness is found, alongside other concentration practices (right effort and concentration), ethical practices (right speech, action and livelihood), and wisdom practices (right view and thought; Bodhi, 1994).

Meditative practices have generally been considered the most important path for developing mindfulness (Bishop et al., 2004; Kabat-Zinn, 1994; Griffiths, 1983), and this is especially true of modernist schools of Buddhism such as the *Vipassna* and *Zen* Buddhism (Sharf, 2015). Through practicing mindfulness, the practitioner is believed to encounter what Buddhism believes to be the true nature of mind and self; namely, its illusoriness and impermanent nature. Specifically, the practitioner may learn to recognise that "all temporal things, whether material or mental, are compounded objects in a continuous change of condition, subject to decline and destruction" (Rhys-David & Steed, 1921, p. 335). For Buddhist practitioners, it follows then that attachments to (or craving for) transitory phenomena may only invite loss, confusion and suffering.

In Buddhism, insights of this sort are not considered philosophical or articles of faith. Rather, they have been described as *experienced*, *embodied*, *enacted* or *embedded* understandings (Bronkhorst, 1993; Grossman, 2015; Kirmayer, 2015; Monteiro, Musten & Compson, 2015; Stanley, 2012; Thompson, 2017). Taken together, these perspectives variously afford the body (embodiment), physical environment (enactivist), and even social environment (embedded), constitutive roles in cognitive processing and knowledge formation. Mindfulness has hence been conceived of *emerging* through the activity of a subject engaging reciprocally with their environment[1] in specific ways, thus construing mindfulness as a relational phenomenon (Stanley, 2012; Thompson, 2017). In doing so, the researcher's attention is directed to investigating the dynamic and reciprocal interactions among relevant *components* of mindfulness which may be, for want of better words, internal

[1] Dewey (1916/2004b) notes that the term environment denotes something more than simply a subject's surroundings. Rather, environment denotes the *continuity* of surroundings with the subject's tendencies. This is because the environment provides reciprocal influence in that it strengthens some activity and weakens others. This gradually produces a system of behaviour.

and external to the subject[2]. In this way, conceptual aids which provide a model of the mind (and map out possible experiences), as with environmental elements such as calm and attentive spaces, come to be considered constitutive of mindfulness (Kirmayer, 2015).

Cognitive phenomena are not eschewed in these perspectives, but rather subordinated to activity. By this, it is meant that conceptual phenomena, where they arise, are considered only waypoints or phenomena before the facts. What counts is the practical activity of knowing, by which it is meant the verification of cognitive phenomena through active experimentation (Dewey, 1916/2004a). Conceptual knowledge thus becomes embodied or enacted knowledge once verified in practical activity. This is not to say that conceptual knowledge *sets in motion* verification activity; rather embodied and enactivist approaches would generally consider the two synonymous: knowledge does not stand apart from activity, rather *it is* activity. A formulation of this type is inferred in the earliest English translation of the term mindfulness (Sanskrit: *Smirti*); namely, a "calling to mind *and* taking up" (Mendis & Horner, 1993, p. 37, emphasis mine). It is also consistent with Michel Foucault's (1982/2005) conceptualisation of spiritual practices as *modes of experience*, by which *experience* in French has the dual meaning of *experience* and *experiment*[3].

Experimentation and verification happen in a social environment. A subject in a social environs cannot perform activities without taking others into account, for they are indispensable to the realization of his activities. As Dewey (1916/2004b) notes: "when he moves he stirs them and reciprocally" (p. 10). Experimentation and verification thus provide

[2] Within the field of philosophy of mind, the internal/external distinction specified is contentious. The location of the constituents of certain mental states and processes critically differentiate embodied, enactivist and embedded perspectives from cognitivist perspectives which tend to consider cognitive phenomena to be materially situated in the brain. The location of cognitive constituents also differentiates embodiment (a place for the body in constituting cognitive processes and mental states) from enactivist perspectives (the physical and social environment are partly constitutive) and embedded perspectives (mental states and processes reside beyond the subject; see Alessandroni, 2017; Clark & Chalmers, 1998; Glenberg, 2010; Ward, Silverman, & Villalobos, 2017).

[3] Interestingly, Raymond Williams (1976/1985) has suggested that this double meaning also existed in English at least until the end of the eighteenth century.

the practitioner the opportunity to contemplate behaviour ethically. Behavioural discernment of this type is important to traditional perspectives which speak of *right* and *wrong* mindfulness (Bodhi, 2011; Monteiro, Musten, & Compson, 2015) or *wholesome* and *unwholesome* activity (Harrington & Dunne, in press). Mindfulness has thus been described as a commitment to a certain noble or wholesome way of life, if not an *expression* of it (Panaioti, 2015). Traditional formulations may thus differentiate the practitioner from non-practitioner by way of the qualities or habits they practise. In the language of contemporary mindfulness, these may include habits of behavioural discernment, being open to the present, and practising non-judgment and/or compassion. In more traditional formulations of mindfulness, the mindful practitioner may be considered to enact habits which express the *three characteristics;* namely, everything is impermanent (Sanskrit: *anitya*); life is suffering (Sanskrit: *duḥkha*); there is no unchanging, self, soul or essence in living beings, (Sanskrit: *anātman*; Thera, 1973; Grabovac, Lau, & Willett, 2011). Regardless, the point to be made is that the very qualities which arise from a given mindfulness practice, constitute precisely those required to cultivate the practice in the first place. Put differently, the *ends* of mindfulness are simply the flourishing of its *means*. Mindfulness can thus be considered an *autotelic* practice or a practice which has purpose in and not apart from itself (see Keown, 1996; 2007 for discussion of Buddhism and autotelic practice). At face value, typical mindfulness instructions support this formulation: the practitioner is explicitly directed to the means of any given activity (in which mindfulness forms the prefix), to the exclusion of the ends. For example, the mindful walker is specifically directed to attend to the walking itself (means), and not the destination (ends). In summary, a traditional perspective may imply that the practitioner does not seek out an experience (ends) which exists independent of practice (means): they are one and the same.

1.2 Contemporary Mindfulness

Contemporary formulations of mindfulness differ from the traditional formulation advanced here in several important ways. Firstly, contemporary mindfulness tends to emphasise clear end goals such as self-efficacy, wellbeing, happiness or symptom alleviation (Shonin, Williams, Van Gordon & Griffiths, 2013), which might at best, be considered secondary to traditional aims (Buttle, 2015). Secondly, although such goals are prescriptive and value-laden in and of themselves, contemporary mindfulness has generally downplayed normative or ethical prescriptions associated with mindfulness or Buddhism, possibly as a consequence of advertising itself as a Western *value-neutral* scientific endeavour (e.g., Wilson, 2014; Shonin et al., 2013b; Sun, 2014). Thirdly, contemporary mindfulness has also tended to be reductive, marginalising intention (Bodhi, 2011; although see Shapiro, Carlson, Astin, & Freedman, 2006, for an important exception). Mechanisms of mindfulness are increasingly framed in neurological terms (e.g., Black & Slavich, 2016; Farb et al., 2007; Hölzel et al., 2007; Pascoe et al., 2017; Tang et al., 2007, 2009; Tomasino & Fabbro, 2016; Zeidan et al., 2015); and psychological mechanisms – at face value intentional (e.g., self-compassion, non-judgement, acceptance) – seem to be reduced to almost non-moral, non-evaluative properties[4]. Finally, by considering mindfulness discoverable, contemporary mindfulness conceptualises mindfulness as an entity standing prior to and apart from empirical procedures or enquiries. Importantly, these enquiries demand nothing of the researcher beyond rigor in their methodology, which when met, allow results to be credited (at a minimum) a *working* existence beyond the means by which they were obtained (i.e., they come to constitute scientific knowledge). This has implications for the wider system in

[4] It is noted that intentional and moral content, as well as challenging the idea of a value neutral science, are less amenable to being reduced to biology. This is because intentional states are likely to be multiply realisable; namely, their content may be realised (physical instantiated) in multiple ways within and between people (Fodor, 1974; Putnam, 1967; Pylyshyn, 1984; although see Bechtel & Mundale, 1999; Bickle, 2008; Gillet, 2003; Borsboom & Cramer, 2018 for a discussion of multiple realisability in the psychopathology networks).

which mindfulness has typically been considered embedded (i.e., the Eightfold Path): with the ends of mindfulness now fixed by science, large amounts of Buddhist doctrine and praxis may be written off as mere *means* to inculcate the now independently established ends. The mindfulness consumer, like the pharmaceutical consumer, need not understand the means by which their product was manufactured, or the mechanisms by which it achieves its (now pre-defined) ends. The ends can simply be achieved by following a prescription. In the case of mindfulness, what is prescribed are rapid, evidence-based skills, tools or techniques, narrowly defined and fit for purpose (Purser & Loy 2013; see Marcel 1950/2015 for further discussion of the differences between religious and technical practices). Far from mindfulness as active experimentation, or a *journey without a goal* (Buttle, 2015), the consumer is seemingly *shown the way* to predefined ends.

None of this is to undermine the gains demonstrated by such prescriptions, nor is it to suggest that contemporary practitioners may not expand their expectations from contemporary goals of symptom alleviation, to a greater interest in self-transformation (Shapiro, 1992; Shapiro et al., 2006). The aforementioned discussion serves only to highlight a shift that appears to have happened in the conceptualisation of mindfulness; namely, by severing the ends from the means, that which formerly *was* practice, now appears to stand apart from practice. Put differently, the distinction between means and ends, formerly only temporal (i.e., the ends are simply the means at a later point in time), now appears ontological. None of this occurred in a vacuum, however, and contextual considerations are discussed next.

1.4 Buddhist Modernism and Contemporary Mindfulness

Buddhist Modernism refers to a number of reforms developed in Buddhism in the 19th century (Gombrich & Obeyesekere, 1988; Lopez, 1995; McMahan, 2008; Sharf, 1995). These reforms drew heavily on Western movements such as Romanticism and

Transcendentalism which emphasised themes of interiority, self-reflexivity, and subjectivism as guarantors of true knowledge (McMahon, 2008; Sharf, 1995). In the religious context, this manifested in the pursuit of authentic intuitive religious experiences in defiance of doctrinal authoritative interpretations of religious scripture, and its prescriptive rituals and ethics.

Of particular interest to contemporary mindfulness is the modern Theravada Vipassna movement, and Japanese Zen Buddhism. The Vipassna movement emerged in colonial South East Asia, where an Asian Western educated middle class – prevented from ascending into colonial ranks, yet also alienated from their cultural roots – enacted a new identity in a series of reforms under the banner of Theravada Buddhism (Sharf, 1995). Likewise, Zen Buddhism emerged from the modernising reforms of Japanese intellectuals, facing internal suppression (Sharf, 1995). In both cases, forms of Buddhism emerged which often toned down elements of Buddhist ritual, cosmology, monasticism, clerical hierarchy and even core concepts such as karma (Jordt, 2007; Lopez, 1995; McMahon, 2008; Sharf, 2015). Rather, Buddhist Modernists emphasised other aspects, such as Romantic and Transcendentalist themes of interior exploration, self-reflexivity and satisfaction in one's current life.

Buddhist Modernists also reframed Buddhism as a mode of investigation or *inner science* (Lopez, 2008; MacMahan, 2008). Buddhism was argued to provide the means for investigating the contents of one's consciousness and the realm of *inner reality* (Harrington & Dunne, in press). Typical of perennialism in religious scholarship (i.e., the belief that a single trans-religious, trans-historical truth underlies all religious traditions), this inner reality transcended Buddhism. Buddhism hence become more than a localised religion, for it prescribed a universal ontology of the mind, discoverable through mindfulness meditation. The latter henceforth became core to Buddhist Modernist schools (McMahon, 2008; Sharf, 1995, 2015), and it was in this milieu that the technique of learning to focus attention on the breath while simply observing any sensations, thoughts, or feelings, was promoted

(Goldstein, 1976). Through mindfulness meditation, the practitioner was believed to achieve *bare attention*, by which it was meant the bare registering of perennial facts, observed without judgment or reflection (Thera, 2005). Taken together, these developments largely constitute the popular contemporary definition of mindfulness, namely, Kabat Zinn's (1994) definition of mindfulness as "paying attention in a particular way: on purpose, in the present moment, and nonjudgmentally" (p. 4).

The significance of these reforms were not lost on commentators. Buddhist Modernists were charged with distorting mindfulness in their emphasis on passive momentary states over long-term active transformation; inner stillness over critical engagement with the canon; and satisfaction in one's own life over ethical training (c.f., *meditation sickness*, Ahn, 2007; McMahon & Braun, 2017; Sharf, 2015). Of particular concern was the philosophical implications of the bare attention which contradicted traditional philosophical propositions (Bodhi, 2011; McMahon, 2008; Sharf, 2015; Bikkhu, 2010). Of note, these same concerns persist in relation to contemporary mindfulness (e.g. Grossman & Van Dam, 2011; Monteiro et al., 2015; Purser & Loy, 2013).

By privileging bare attention, the truth of Buddhism was fixed to experience, achievable first hand by lay meditators. In doing so, the authority of the clergy and monastic training was greatly diminished (hence Buddhist Modernism has also been termed *Protestant Buddhism*; Sharf, 1995). Readily accessible and hence imminently exportable, this formulation of mindfulness would eventually appeal to 1950's American *beat* intellectuals looking for a form of liberal spirituality as opposed to religiosity (Carrette & King, 2004). By the 1970's, this primarily intellectual movement had taken root in a number of established secular institutions across America, of which the Stress Reduction Clinic (later to be termed the Mindfulness-Based Stress Reduction clinic) would be particularly important. Established by John Kabat-Zinn in the University of Massachusetts teaching hospital, 1979, the Stress

Reduction Clinic offered eight week mindfulness courses which aimed to help people by transforming how they perceived their ailments (Kabat-Zinn, 2011).

The influence of Kabat-Zinn's theoretical and clinical work on contemporary mindfulness cannot be overstated. His definition of mindfulness largely informed Bishop and colleagues (2004) two-factor model of mindfulness, which in turn has informed subsequent measures and their interpretation[5]. Verbal definitions aside, Kabat-Zinn's (1982) Mindfulness Based Stress Reduction programme (MBSR) and derivatives (most obviously, Mindfulness Based Cognitive Therapy, MBCT; Segal, Williams & Teasdale, 2002) continue to function as the gold standard for mindfulness research. This is because participating in some form of a MBSR or MBCT continues to constitute the mindfulness condition in many experimental studies (Ostafin, Robinson & Meier, 2015).

In summary, traditional conceptualisations of mindfulness may differ from cotemporary conceptualisations by way of the ontology they prescribe for mindfulness. It was suggested that mindfulness is best considered an expression of ethical practice in the former, whilst the latter, drawing from Buddhist Modernist reforms which increasingly privileged experience, tends to conceptualise mindfulness as a discoverable *really existing* entity, standing apart from practice. The statistical representation of this conceptualisation is discussed in the next chapter.

[5] Bishop and colleagues' (2004) two factor model conceived of mindfulness involving components of regulated attention (i.e. sustained attention on the present moment) and an orientation to experience (an open, curious, non-judgmental attitude). This went on to inform the popular Philadelphia Mindfulness Scale (Cardaciotto, et al, 2008), and analogous conceptualisations have come to inform other two-factor measures (State Mindfulness Scale, SMS; Tanay & Bernstein, 2013; Toronto Mindfulness Scale, TMS; Lau et al., 2006). As a conceptual device, two-factor models have further informed interpretations of measures initially conceived as uni-dimensional or multifactorial (Kohls et al, 2009; Davis, Lau, & Cairns, 2009; Sauer, Walach, Offenbächer et al., 2011; Baer et al., 2008; Tran et al., 2013). Two-factor models have also informed subsequent definitions of mindfulness which have arguably, only expanded on the second "orientation to experience component" of Bishop and colleagues (2004) model (Bergomi, Tschacher, & Kupper, 2013). As such, the mindful orientation to experience has expanded to include a compassionate and openhearted attitude, non-identification and non-reactivity to experience, a decentred perspective, insightful understanding, and a "full participation" in the experience (Brown & Ryan, 2004; Kabat-Zinn, 1994, 2003; Lau et al., 2006; Marlatt & Kristeller, 1999; Robins, 2002; Teasdale et al., 2002; Walach et al., 2006).

Chapter 2: Psychometric Representations of Mindfulness and their Interpretation

In this chapter, psychometric theory and the development of mindfulness scales are discussed. It is suggested that contemporary techniques risk reifying mindfulness, creating an ontologically implausible entity.

2.1 Trait Mindfulness

Similar to Buddhist Modernist framings of mindfulness as an inner science, Kabat Zinn conceptualised mindfulness as a "universal" (Kabat-Zinn, 1990, p. 12) and "innate capacity" (Williams & Kabat-Zinn 2011, p.15). This meant that mindfulness, although developed within Buddhism, became non-proprietary to Buddhism (Lindahl, 2015; Gethin, 1992/2001). Universality also presupposed that mindfulness would be effective across all contexts; henceforth, it became accessible to individuals of different religious persuasions, as well as those who endorse secularism (Brown, 2014; Kabat-Zinn, 2011). Mindfulness also became highly accessible to psychological researchers of the *individual differences* tradition who concerned themselves with investigating traits.

Individual difference researchers have often thought about how different trait dimensions underlie consistencies in behaviour over time, and across context (McCrae and Costa, 1990). The nature of traits have been subjected to much academic enquiry in the field of personality research (e.g. Allport 1966; Cattell & Kline, 1977; Cervone, 2008; Eysenck, 1947; Fridhandler, 1986, McCrae & Costa, 1990; Mischel, 1968; Tellegen, 1988); however standard assumptions exist. Fajkowska and Kreitler (2018) outline four such assumptions; namely, 1) underlying traits can be inferred from observable data, 2) they constitute the structure of personality, 3) they account for intra- and inter-individual differences, and 4) they are measurable and relatively independent of each other (see also Allport 1966; Cattel, 1965; Eysenck, 1947; see Matthews, Deary, and Whiteman, 2009 for review). These assumptions support a view of traits as universal *common causes* for personality, often considered instantiated in biology and/or genetics (Allport, 1966; Eysenck, 1947). Thus McCrae and Costa (1995) note, “the causal argument is in principle clear: traits as underlying tendencies cause and thus explain (in general and in part) the consistent patterns of thoughts, feelings, and actions that one sees” (p. 236).

Although psychology has moved on from necessarily interpreting traits causally (e.g. *probabilistic descriptions*, Fleeson & Jayawickreme, 2015; *cybernetic theory*, DeYoung, 2015; see Matthews et al., 2009 for a review), the standard assumptions outlined underpin classical test theory (Lord, Novick & Birnbaum, 1968), reliability estimation (Nunnally, 1978), and factor analysis (Harman, 1960). As such, the concept of traits as common causes for behaviour remains ever-present in the psychometric methodologies which dominate psychological and mindfulness research.

2.2 Measuring Traits

Given that direct enquiries into trait levels are prone to idiosyncrasy, researchers have typically developed relevant sets of items which capture the trait in ordinary language (Baer, Baer, 2011; Clark & Watson, 1995). In the context of mindfulness, this means making enquiries into how often an individual may “…sense [their] body, whether eating, cooking, cleaning” (FMI) or use mindfulness to “realize that [their] thoughts are not facts” (AMPS).

Once a suitable set of items has been developed, the item set (now a measure) is then applied to a sample, following which statistical techniques known as principal component analysis (PCA) or factor analysis (FA) are typically performed on the data (or a correlation matrix of the item set). These statistical analyses will typically reveal an underlying factor or principal component (or several) which account for and explain a certain percentage of the (common) variance observed in (group level) item responses. These factors or components are then inferred to represent the attribute the researcher was interested in the first place. In the case of mindfulness, an important finding has been the discovery that two factors reliably account for a consistent percentage of covariance among questionnaire item responses in practitioners and non-practitioner samples. This two-factor model has also been revealed in purportedly unidimensional measures, and also at a higher order in multifactorial measures (Davis et al., 2009; Kohls, Sauer & Walach, 2009; Sauer, Walach, Offenbächer, Lynch, & Kohls, 2011; Tran, Gluck & Nadar, 2013). The two factors have been inferred to represent attributes of interest to mindfulness theory, such as Acceptance and Presence (e.g., Kohls et al., 2009; Ströhle, 2006), and the model has received some neuro-scientific support (e.g. Lutz et al., 2014).

The next step in developing a measure involves establishing the construct validity of the underlying factor or principal component. Typically, this will involve correlating the factors or principal components with other related constructs. To the extent to which these correlations are in the *right direction*, the construct is considered valid (Borsboom, Cramer, Kievit, Scholten & Franic, 2009; Borsboom et al., 2004). In the context of mindfulness, the right direction means that trait mindfulness should positively correlate with constructs such as emotional intelligence and self-compassion, but negatively with concepts such as thought suppression (the tendency to try to get rid of unwanted thoughts, see Baer et al., 2006). This is because mindfulness is believed to foster a compassionate and accepting attitude. Other procedures can also be advanced in establishing the case for construct validity. Researchers may further associate their constructs of interest with relevant outcomes, or other related measures. Finally, the *internal consistency* of a construct can also be estimated (i.e., how well items positively associated with the same construct positively correlate with one another; Bollen & Lenix 1991). This is because measurement requires a degree of coherence in the construct to be measured (Nunnally, 1978). Borsboom, and colleagues (2004) have argued that validation efforts rarely go beyond these procedures, and Rau and Williams (2016) have concluded this is true also for mindfulness research.

Measuring mindfulness at the level of self-report has hence come to involve the development of a sum-score or observed score of mindfulness which constitute the attribute's operationalisation. This is then submitted to various statistical tests (factor analysis or principal component analysis), and then (almost sleight of hand) the results applicable to the sum-score are generalised to the theoretical attribute itself. This represents the influence of operationalism, by which the construct is considered synonymous with the theoretical attribute. As Thompson (2004) citing Cronkhite and Liska (1980) note, the procedure has been fruitful:

> Apparently, it is so easy to find semantic scales which seem relevant to sources, so easy to name or describe potential/hypothetical sources, so easy to capture college students to use the scales to rate the sources, so easy to submit those rates to factor analysis, so much fun to name the factors when one's research assistant returns with the computer printout, and so rewarding to have a guaranteed publication with no fear of non-significant results that researchers, once exposed to the pleasures of the factor analytic approach, rapidly become addicted to it (p. 106).

By shifting the focus of construct validation to investigations of internal consistency and how a construct relates to other constructs (i.e, the nomological network), ontological considerations of the attribute are circumvented. Put differently, the researcher circumvents the issue of whether their attribute really exists independent of their model fitting exercises. Salzberger (2013) suggests that "designing measurement instruments without evidence of the existence of the attribute as a quantitative latent variable is like taking the second step before ever having taken the first" (p. 3). A first step is however implied in the methodologies of factor analysis and principal component analysis, although this is rarely made explicit.

In psychometrics, the proposition that an underlying psychological attribute exists and causes changes in observable variables is known as *Latent Variable Theory*. Latent Variable

Theory can be investigated with factor analysis when it is assumed that 1) that the latent variable is the only cause of covariance (i.e. the “common cause”), and 2) that there are no direct associations between items after controlling for the effects of the latent variable (termed *local independence*; Bartholomew, 1980; Markus & Borsboom, 2013).

Although the fit of the factor model does not prove Latent Variable Theory true, the model does formulate a casual latent variable as a hypothesis. As such, the fit of the model (i.e., when local independence is demonstrated) can be adduced as evidence for the hypothesis that the construct is causal and hence *really exists* (Arntzenius, 2010; Borsboom, et al., 2003, 2004)[6]. In the absence of local independence, a case can be made that the latent variable does not in fact account for all the covariance observed[7].

Several key implications follow. Firstly, causality is assumed to only travel from the latent variable to the items. This means that 1) changes in the latent variable must precede changes in the observable items; 2) that the omission or addition of observable items should not influence the latent variable; and 3), that associations between items should be considered spurious (as the latent variable is considered the only cause for covariance). Furthermore, items are considered equivalent representations of the latent variable, and are hence considered interchangeable.

Latent Variable Theory reflects an attempt to model psychological measurement by way of analogy to physical measurement (Borsboom et al., 2003, 2004), of which the physical example of room temperature is illustrative. Room temperature can be considered an unobservable (latent) construct measured by an array of thermometers (the observable

[6] Non-causal interpretation of latent variable models exist in the literature. For example, a latent variable model can be seen as an abstraction (Markus & Borsboom, 2013) or data reduction device (Bollen, 2002; Harman, 1960; Nunnally, 1978), or technique for discovering regularities in data (Myung, Navarro, & Pitt, 2006).
[7] Latent variables can also be considered a partial causes of covariance with remaining variance being accounted for by direct associations between items (Bringmann & Eronin, 2018). That said, Cramer, and colleagues (2012) have suggested that such models are less useful as increasingly incorporating direct connections increasingly renders the latent variable less explanatory. It also increasingly makes it difficult to identify the effects of the latent variable.

variables or items). As expected, changes in room temperature must precede changes observed in the thermometers, and likewise, the omission and addition of (equivalent) thermometers should have no influence on room temperature. Finally, the readings on one thermometer should not directly influence those of another.

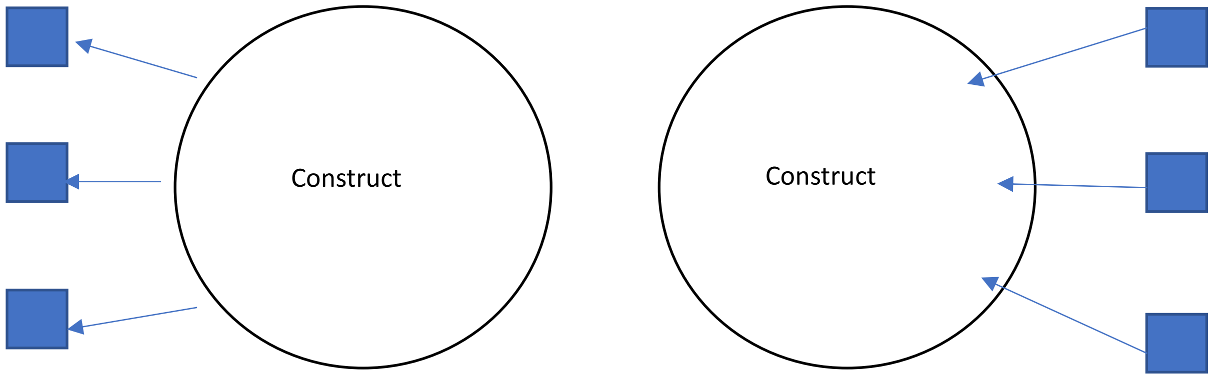


Figure 2. Reflective (left) and formative (right) models relating a construct to indicators (blue). Causality travels from the construct to indicators in the reflective model, and from the indicators to the construct in formative models.

Factor models interpreted this way are known as *reflective factor models* as the covariance in observable items reflects that of the latent variable (Figure 2; Bollen & Lennox, 1991; Edwards & Bargozzi, 2000). Reflective models are often contrasted with *formative factor models* in which causality is assumed to travel in the opposite way; namely, from the observable items to the latent construct (Bollen & Lennox, 1991). Formative models can be modelled with principal component analysis (Edwards, 2011), and the prototypical example is Socio-Economic Status (formed from indicators such as salary and home ownership, amongst others). Formative indexes of this type usefully predict all sorts of different outcomes which make them very useful instrumentally, but they are less suited to measurement. This is because they make only weak assumptions for causality (e.g., they do not require internal consistency), and the identity of the construct changes with the addition or omission of observable variables (Edwards, 2011; Edwards & Bagozzi, 2000; Guyon, 2018; Howell, Breivik, & Wilcox, 2007). For this reason, they are often best considered data-reduction devices (Edwards & Bagozzi, 2000). Ontologically, they are constructivist, for the latent variable (e.g., SES) is not assumed to exist as an independent entity (Borsboom et al., 2003).

2.3 Realism in Mindfulness Research

Although ontological considerations are rarely made explicit, the choice of statistical tests imply different ontologies. Mindfulness could be considered a causal function of practices sampled in the case of principal component analysis (i.e., people are mindful because they frequently "accept unpleasant experiences"; FMI, item 8), or a cause of practices in the case of factor analysis (i.e., people frequently "accept unpleasant experiences" because they are mindful). The latter invokes realism, and indeed, this ontological position has been argued to be the default position of practising and psychologists (Borsboom et al., 2004; Haig, 2014)[8], and scientists in general (Devitt, 1991).

Realism is apparent in casual euphemisms by which mindfulness has been described as *cultivating*, *fostering*, *enhancing*, *activating*, *yielding improved*, *determining*, and *leading to* various outcomes. Realism also justifies using different scales (irrespective of their heterogeneity) to measure the same trait (e.g., Monteiro et al., 2015). This is because the scales can be argued to be imperfect measures of the underlying trait, much like an array of imperfect thermometers. Finally, realism is implicit in biological (e.g., Black & Slavich, 2016; Pascoe et al, 2017), neurobiological (e.g., Holzel et al., 2011; Fox et al., 2014) and genetic investigations (Waszczuk et al., 2015) into mindfulness.

[8] Curiously, this position contradicts the idea of operationalising constructs, for an independent discoverable attribute is not consistent with it being synonymous with the statistical construct

2.4 The Plausibility of a Realist Interpretation of the Latent Construct.

Hypothesising trait mindfulness as causal requires, at a minimum, specifying a reflective model (Edwards & Bagozzi, 2000). This may not however be plausible for mindfulness. Firstly, many items in mindfulness scales conceivably cause changes in other items in non-spurious ways. For example, a correlation between practicing being “friendly to myself when things go wrong” (FMI, item 9) and being able to “accept unpleasant experiences” (FMI, item 8) may plausibly be explained by a psychological mechanism over and above that of the presence of a common underlying (trait mindfulness) cause (i.e. self-compassion may directly foster acceptance, or vice versa). The same appears true of many other items, and indeed, a causal structure among items can typically be hypothesised. Empirically demonstrated, such casual structures would render a casual latent mindfulness increasingly marginal to explanation, in turn, questioning its ontological status of *really existing*.

Secondly, it is plausible that responses to items, rather than originating from a common source, have different aetiologies and predict unique outcomes. Put differently, questionnaire items are not passive reflections of an underlying trait, but rather index unique and agentic phenomena. Support for this interpretation exists at the facet level in research with the FFMQ. For example, Cash and Whittingham (2010) found that the *Non-judgmental facet* of the FFMQ predicted lower levels of depression, anxiety, and stress-related symptomatology, whilst the *Acting with Awareness* facet predicted lower depressive symptomatology (See also Anicha et al., 2012; Baer et al., 2006; Bergman, Christopher, & Bowen, 2016; Boughner, Thornley, Kharlas & Frewen, 2016; Carmody & Baer, 2008; Didonna et al., 2018). Mindfulness facets have also been shown to develop differently in various subgroups of individuals, affording different profiles (Cebolla et al., 2017; Liljia, Lundh, Josefsson, & Falkenstrom, 2013). Taken together, FFMQ facets appear unique and agentic, rather that passive and reflective, and something similar might be assumed at the item level. In personality research, one of the most important aetiological questions is now whether traits correspond to latent common cause, or whether they emerge from more complex interactions among unique *basic components* (Baumert et al., 2017; Mottus, Kandler, Bleidorn, Riemann & McCrae, 201). This thesis extends that question to mindfulness.

Chapter 3: Network Models of Mindfulness

In this chapter the reader is introduced to a network model of mindfulness. The principles underpinning a network model are discussed, before briefly considering the wider literature in which the methodology has been applied. The chapter will conclude by formally outlining the main research question, relevant assumptions, and the relevance of the study to the field of mindfulness research.

3.1 Principles Underpinning a Network Model of Mindfulness

Recently, a novel psychometric model has emerged which bypasses some of the problematic issues involved in ascribing causal properties to a latent variable. Termed a *network perspective* (Schmittmann et al., 2013), psychological attributes are conceived of as emerging from a network of relevant causally interacting components. *Network psychometrics* (Epskamp, 2017) refers to the estimation of such networks, most often from self-report measures.

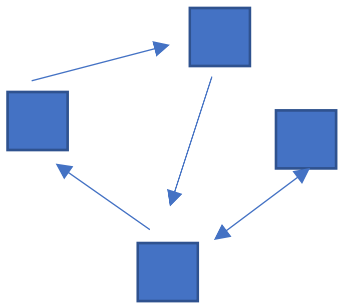


Figure 3. Network alternative to reflective and formative models. Items directly cause each other.

Networks consist of nodes and the edges which connect them (see Figure 3). At the level of self-report, questionnaire items can be modelled as nodes, and the statistical relations between them, edges. Applied to mindfulness, a network of this type could reconceptualise mindfulness as being constituted by practice (or an expression of practice) as opposed to a cause of practice.

Four axiomatic principles would characterise a mindfulness network of this type[9]. Principle 1 affirms that mindfulness is best characterised in terms of the interactions among relevant practices in a network (*complexity*). Principle 2 suggests that these practices correspond to those behaviours, cognitions and affects indexed by mindfulness questionnaire items (*item-practice correspondence*). Principle 3 states that the structure of mindfulness is generated from direct causal connections between practices (*direct casual connections*). Principle 4 states mindfulness networks have a non-random architecture: their configuration determines their behaviour (*mindfulness follows network structure*). These principles constitute the assumptions of network psychometrics, which will be dealt with in turn.

Item-practice correspondence is perhaps the most controversial of these assumptions, although this is not limited to network analyses. A mindfulness network model assumes that the items in a given measure correspond to relevant affective cognitive or behavioural practices (i.e. what people say they do, is what they do), yet this is not formally tested. Assuming direct casual connections is also contentious at the level of cross-sectional research as these designs only provide information on concurrent associations. To provide further support for causality, a timeline is required, as this allows the researcher to establish whether changes in one practice precede changes in another (Bos et al., 2018). Finally, associations need to be non-spurious (i.e., the association should not derive from a third variable).

Individual level analyses with temporal data can provide information on time order, although ultimately, experimental designs provide the most powerful design for testing causal hypotheses. This is because experimental designs allow the researcher to establish association (two comparison groups), time order (e.g., by controlling who is intervened on and when), and non-spuriousness (random assignment). In the network literature, cross-sectional networks using partial correlations (the unique variance predicted by one node on another,

[9] These principles derive from those outlined by Borsboom (2017a) in the context of psychopathology networks.

after controlling for all other nodes in the network) have been advanced as providing indirect support for causality. Partial correlations represent predicative associations and they go some way in removing spurious correlations. As such, partial correlations have been described as “potential causal relationships” (Epskamp et al., 2018, p. 419) or “clues about the causal skeleton of a network” (Borsboom & Cramer, 2013, p. 105; see chapter 4 for more detail on estimating partial correlation networks).

Assuming direct casual connections also assumes that items represent unique or independent practices. This is because cause and effect do not make sense when practices overlap in content (i.e., are the same; Borsboom et al., 2003, 2004). This assumption is considered plausible given that scale construction generally involves removing item redundancies, although it is noted that no formal analyses are proposed beyond this (for a more detailed discussion on the assumption of node independence see chapter 7).

The assumptions of complexity (principle 1) and non-random architecture (principle 4) are considered plausible in light of 1) the established literature on Dynamical Systems Theory, and 2) the limitations of a Latent Variable Theory interpretation. In Dynamical Systems Theory, networks move through a trajectory of different states (Schmittman et al., 2013) which can be explained in terms of entropy; namely, existing states remain stable until sufficient disorder (entropy) overwhelm their internal constraints. This then frees up the network to new forms of connectivity, which may eventually lead to new stable configurations (Heylighen 2002; Schneider & Sagan, 2005; for an accessible introduction to this concept of self-organisation; see Prigogine & Stengers, 1984). These stable configurations have often been considered *attractor states* in the literature (Newman, 2009), meaning states in which networks may repeatedly settle or converge into irrespective of their initial state (Schmittmann et al., 2013). A common example is the pendulum, by which the lowest point of the pendulum may be considered the attractor point or state. Irrespective of its initial state, a pendulum will eventually settle into this attractor point (due to gravity).

In a mindfulness network of positive connections, practices may settle into a relatively stable configuration by way of dependencies among practices (e.g., being "friendly to myself when things go wrong" may lead to being able to "accept unpleasant experiences", and so on). Actively configuring one's environment (e.g., seeking quiet spaces, using instructional aids) may further maintain such a configuration as it makes other possibilities less accessible (e.g. environments affording distraction). Mindfulness can thus come to be considered a relative equilibrium between the subject and their environment, analogous to an attractor state. This state would be considered stable so much as it is resilient to small disturbances. Thus, in the presence of a mindful attractor state, a practitioner will not always be mindful, yet *out of character* occurrences may become increasingly transient and rare.

In summary, the elaborated theories of Dynamical Systems Theory provide a way of explaining how items may activate one another if they are connected in the network architecture. In doing so, items will co-vary in specific (non-random) ways, which across time, may lead to stable trait-like states. From this perspective, trait mindfulness becomes not a cause of item covariance, but rather an expression of it. This explanation can be contrasted with Latent Variable Theory which attributes item covariance to the causal influence of a common cause. Exactly how this influence occurs (i.e., the nature or mechanisms underlying the arrows in a reflective model) is left unspecified, and the plausibility of items being simply passive reflections of a latent variable is questionable.

A network approach to mindfulness is not without precedent in the literature. Also citing concerns with reification, Garland and colleagues (2015b) have proposed that "it may be fruitful, for instance, to consider that there may be no actual entity called 'mindfulness', but rather a network of interacting cognitive and affective processes…that we, for scholarly convenience, label ‘mindfulness’” (p. 2). Likewise, van Dam and colleagues (2017) have called for mindfulness research to move from efforts to obtain single unitary measures to data-driven dynamic approaches, less constrained by researchers’ *a priori* theories. Chiesa (2013) has also recommended that a “new operational model of mindfulness…be developed and empirically tested while taking into account the components of mindfulness and their interactions”. Chiesa (2013) argued that such a network model was more consistent with traditional formulations which speak to synergy and mutually reinforcing inter-relationships between practices.

Extant network models also exist in the literature. Garland and colleagues (2009, 2010, 2015a) have proposed increasingly more integrated system theories of mindfulness in which various practices feedback into each other, fostering positive states of mind. A more neurobiological account is also found in Vago and Silbersweig’s (2012) influential systems-based model which conceives of mindfulness as a “multidimensional skill set” (p. 3) which, in interaction, reduces self-processing biases and fosters a healthy mind. The network model proposed here thus represents an attempt to address recommendations made in the literature at the level of self-report. This is believed to be the first study of its kind in the field of mindfulness; however, the theoretical rationale and empirical methodology derive from psychological network studies in other fields. These are reviewed next.

3.2 The Application of Psychological Networks in Psychology

In their aforementioned influential review, van Dam and colleagues (2017) suggested that mindfulness research needed to shift to a data-driven network solution similar to what occurred in intelligence research. That field had been dominated by a conceptualisation of intelligence as an underlying *g* factor which caused the changes in observable tests. A marked void existed in conceptualising exactly what *g* was, although references to “mental energy” (Spearman, 1927, p. 411) and a “biologically based variable” (Jenson 1998) were made in seminal texts. Although *g* has been shown to be heritable (see Plomin & Deary, 2015 for review), efforts to discover biological basis of this unitary entity remain unconvincing, possibly indicating the limitations of a realist interpretation of *g* (Gould, 1996).

Network Psychometrics also derives from intelligence research. In their pioneering simulation study, van Der Maas and colleagues (2006) demonstrated that item covariation formally attributed to the *g*, could also be generated by direct reciprocal *mutual* interactions among observable indicators. Their data-driven mutualist model of intelligence was dynamic in that the cognitive processes, initially un-correlated, came to be correlated over time through their mutual interactions.

Much as factor analysis generalised to common causes in personality through the work of Cattell and Kline (1977), so too did the mutualist model in the work of Cramer and colleagues (2012). These authors demonstrated that the covariance observed in personality tests could be explained by reference to direct mutual interactions between the variables measured through personality items. In this way, co-variation in items such as ‘‘I like to go to parties’’ and ‘‘I have many friends’’ were explained by direct causal sequences (i.e. going to parties increases the likelihood of meeting more people, and people with more friends get invited to more parties). This explanation contradicted causal accounts by which underlying traits such as *extraversion*, or other “raw material” (McCrae, Gaines, & Wellington, 2012, p. 75) were considered common causes (although see Ashton & Lee, 2005; DeYoung, 2015, Fleeson & Jayawickreme, 2015; Funder, 1991; Matthews, Deary, and Whiteman, 2009 for other conceptualisations). Recently, Mottus, Kandler, and colleagues (2017) have also shown that personality items uniquely predict different items, challenging the idea that they are equivalent. As such, Mottus, Bates, Condon, Mroczek and Revelle (2017) concluded that personality is best considered by reference to “specific aspects…rather than by a few ostensible underlying structures” (p.33).

The field in which network models have found most fruition is in psychopathology research. In psychopathology, symptoms have often been construed as indicators of underlying disease entities, a fact implicit in the definition of symptom itself. This common cause model proved powerful in medicine where it contributed to advancing the field from symptom treatment to identifying aetiological pathways to the common cause. This allowed for targeted treatments at this underlying level, with upstream effects on the symptom array (Clare, 1980). Unsurprisingly, psychiatry sought to emulate this method (Borsboom, 2017a). To this end, research has demonstrated biological correlates and implicated genes involved in psychopathology, yet like *g*, no compelling reductive account of mental disorders has been provided (Borsboom et al, 2018). Thus after "decades of work, the genetic, metabolic and cellular signatures of almost all mental syndromes remain largely a mystery" (Adam, 2013, p. 41; see also Deacon, 2013; Kapur, Phillip & Insel, 2012; Lacasse & Leo, 2005; Matins De-Souza, 2013). The network perspective on psychopathology circumvents these problems in its suggestion that mental disorders do not exist as underlying common causes. Rather, from a network perspective, mental disorders are said to arise from a network of interacting symptoms (Borsboom & Cramer, 2013; Cramer, Waldorp, van der Maas & Borsboom, 2010; Kendler, Zachar & Craver, 2011).

In the last few years, the plausibility of network conceptualisations for mental disorders have been established for Major Depressive Disorder (MDD; van Borkulo et al., 2015; (Fried, Epskamp, Nesse, Tuerlinckx, & Borsboom, 2016; Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015), Post Traumatic Stress Disorder and associated symptomology (Armour, Fried, Deserno, Tsai, & Pietrzak, 2017; Birkeland & Heir, 2017; McNally et al., 2015; McNally, Heeren & Robinaugh, 2017; Mitchell et al., 2017; Spiller et al., 2017; Vanzhula, Calebs, Fewell & Levinson, 2018) Obsessive-Compulsive Disorder (Carbonella, 2018; McNally, Mair, Mugno & Riemann, 2017), Psychosis and Schizophrenia

(Fonseca-Pedrero et al., 2018; van Rooijen et al., 2017; van Rooijen et al., 2018;), Social Anxiety Disorder (Heeren & McNally, 2016), Eating Disorders (Levinson et al., 2017; Forbush, Siew, & Vitevitch, 2016; Olatunji, Levinson, & Calebs, 2018; Smith et al., 2018) and Substance Abuse (Rhemtulla et al., 2016). Common to this field has been the identification of highly central symptoms, by which it is meant symptoms with large numbers of connections to other symptoms in the network. Highly central symptoms have been argued to be possible candidates for intervention, for changes in these symptoms should spread widely across a symptom network given their wide connectivity (see chapter 4 for a more detailed discussion of centrality and its caveats). Evidence in support for this was found by Boschloo, van Borkulo, Borsboom and Schoevers (2016), who showed that the most central depression symptoms in the baseline network of their sample were the most predictive of future Major Depressive Disorder onset six years later.

It was within the field of psychopathology that the notion of network density (the total level of connectivity of a network) came to the fore. Several network studies using different types of data suggested that greater connectivity may be associated with greater symptom severity (Cramer et al., 2016; Bringmann et al., 2015; van Borkulo et al., 2015; Wichers, Groot, & Psychosystems, ESM Group, EWS Group, 2016; Wigman et al., 2013). Especially relevant to the current theory was the pioneering study by van Borkulo and colleagues (2015) which compared the networks of remittent and persistent MDD patients in a prospective study. Using a newly developed Network Comparison Test (NCT; van Borkulo et al., 2017), they found that the symptom network of patients with persistent MDD were more densely connected at follow-up than that of the patients who recovered. This meant that that increased overall network connectivity predicted a worse prognosis, and this remained even when their groups were matched on depression severity sum-scores. This finding stimulated further theoretical and experimental work. Cramer and Borsboom (2015) proposed an “entirely new criterion for depression….namely, that a set of symptoms, experienced by a person, are part of a disordered system if and only if they stand in a certain configuration of causal relations with respect to one another" (p.8). In support of this, recent research has reported greater network connectivity (global density) in a sample of individuals with social anxiety disorder (Heeren & McNally, 2018) and comorbid Post Traumatic Stress Disorder-Eating Disorder (Vanzhula et al., 2018), compared with nonclinical samples. Interestingly, in both these studies, no changes were noted in the network structures (or architecture), suggesting that the difference between groups was a squarely a consequence of *how strongly* symptoms were connected, rather than *how* they were connected. Put differently, the potentially causal pathways did not change, but the strength of these pathways did.

Recent results now provide a more complicated picture. A replication study of von Borkulo's and colleagues (2015) study by Schweren and colleagues (2017) failed to find evidence of a significant difference in density between MDD treatment responders and non-responders (although it is noted that the effect was in the direction predicted by von Borkulo and colleagues, 2015). Likewise, van Loo and colleagues (2018) failed to find evidence of density differences in a retrospective study in which patients with MDD were divided into different subgroups[10]. In another cross-sectional study, the network structures of depression symptoms in healthy people were found to be more highly interconnected that those in a group with MDD (Fried et al., 2016; see also Fried, 2017). The density hypothesis thus remains an open question.

As the field has developed, technical critiques have emerged (Guloksuz, Pries & Van Os, 2017; Forbes, Wright, Markon & Krueger, 2017; Steinley, Hoffman, Brusco, & Sher), along with rejoinders (Borsboom et al., 2017; Epskamp et al., 2018) and refinements to

[10] The eight subgroups were: Family history (present or absent), polygenic risk score (low vs high), early vs. late age at onset, and severe adversity (present vs absent).

methodology (Bringmann & Eronen, 2018; Bringmann et al., 2018). Network psychometrics have extended into new areas (for example attitude structures, Dalege et al., 2016), and new network indices are regularly being proposed (e.g. "node predictability", Haslbeck & Fried, 2017). It is into this fertile field that the current study aims to situate mindfulness.

3.3 Study Aims

To the author's knowledge, the current study represents the first application of network psychometrics to mindfulness. The current study takes as its starting point the assumption that direct connections between practices evolve over time through a formal mindfulness practice. As such, practitioners' networks are hypothesised to evidence greater connectivity than non-practitioners.

Denser networks (characterised by positive connections) may facilitate greater feedback among nodes, which afford the network the ability to maintain a stable state within itself. Akin to closely spaced domino tiles falling, changes in one practice may quickly populate across the network, inducing changes in many other practices. On these grounds, it has been suggested that global levels of connectivity or network density might function analogously to attractor states (Borsboom, 2017a; Cramer et al., 2016; Dalege et al., 2016). By way of contrast, less dense networks may require continuous *external* influence to maintain the same state (Newman, 2009). To stay with the domino analogy, continuous influence would be required to collapse dominos spaced widely apart (i.e., each may have to be pushed over separately). Density in a network of positive connections also confers vulnerability, as decreases in one practice may also populate across the network rapidly (i.e., *vicious spirals*). Less dense networks hence convey more resilience to such decreases.

In this thesis, mindfulness will be considered an expression or emergent phenomenon of the activation of a network of relevant practices. In theory, a stable mindfulness (system state) can be achieved in a dense network of positive connections with minimal external influence, albeit such a system also conveys vulnerability. Such a network is assumed to come about through a regular practice, forming the basis of the main hypothesis[11].

3.3.1 Aim 1: To determine whether the practitioners' network is characterised by greater network density: A global test of strength invariance. The current research will investigate density differences in the mindfulness networks of practitioners and non-practitioners utilizing the Network Comparison Test (van Borkulo et al., 2017). The hypothesis is that: *the networks of regular practitioners will be characterised by greater overall connectivity (density) than the networks of non-practicing individuals.* It is noted that this analysis is not truly confirmatory, for no pre-registration of the hypothesis was made outside of the university (Wagenmakers, Wetzels, Borsboom, van der Maas & Kievit, 2012).

3.3.2 Aim 2: Investigating the architecture of mindfulness: A global test of network structure invariance and exploratory analysis of network structure. To investigate whether networks differ in *how they are connected* in addition to how strongly they are connected, structural differences will be tested for significance using the NCT. Unlike network density, it was unclear how well group level network structures may translate to the individual level where substantial heterogeneity in structures may exist. As such, no hypotheses were hence made in relation to structural differences.

3.3.2.1 Exploratory analysis of mindfulness networks. Bearing in mind possible heterogeneity, it was assumed that general or average features of a mindfulness architecture could be revealed through an exploratory analysis. For example, self-organisation theory suggests that paths may be broken, freeing up nodes to connect with new paths. This may

[11] A stable mindfulness system state can also be achieved in a weakly connected network, albeit it may require continuous influence of greater magnitude. A weakly connected system might also generate mindfulness following an especially powerful influence (akin to the lead domino being pushed with such force, it slides into the others). In reality, the dynamics of proposed mindfulness networks are much more complex. This is because different changes may occur across different timescales, and negative edges, if present, may correct for increases and decreases. Likewise, different practices may be central or peripheral to a network, which may determine their relative impact on a system state.

manifest in practices (nodes) becoming more central in a practitioners network as a consequence of their regular practice, relative to non-practitioners. In the absence of temporal and longitudinal data such dynamics remain hidden; however, at the cross sectional level, differences in practice centrality can be compared. Practice centrality will hence be investigated by comparing three well-known local node centrality measures: *strength*, *closeness*, and *betweenness* (Opsahl, Agneessens, & Skvoretz, 2010; see chapter 4 for a discussion of centrality and these metrics). Community structures will also be identified using the *Exploratory Graphical Analysis* (EGA; Golino & Epskamp, 2017), developed for use in network studies of the type proposed. The community structures provide information on how practices cluster in a network.

3.3.3 Measure Selection. Two mindfulness measures were selected to determine the relevant practices for network estimation. Study 1 used the Friedberg Mindfulness Inventory – Short Form (FMI-14; Walach et al., 2006) which is a well-established mindfulness measure in the literature, informed by Buddhist sources. The FMI has been validated using a number of different psychometric methods (see chapter 6 for a review of these studies) and most importantly, is one of the few measures validated on both practicing and non-practicing samples (Sauer, Walach, Offenbächer et al, 2011; Sauer, Lemke, Zinn, Buettner, & Kohls, 2015; Walach et al., 2006).

A second process measure was used to more accurately capture the idea of practices as processes. Study 2 uses the Applied Mindfulness Process Scale (AMPS; Li, Black & Garland, 2016) which is a brief process measure specifying the process required to achieve the various traits specified in popular measures (such as the FMI). The major limitation of this measure was its lack of validation beyond the original study and its adaption in this study to a population it was not designed for (i.e. non-practitioners). Thus, taken together, the two different measures represent the different sides of the trade-off between theoretical relevance and psychometric validation.

3.4 Relevance to the Literature

Maris and Kruis (2016) have recently demonstrated that *reflective*, *formative* and network models are mathematically equivalent (see also Molenaar, van Rijn, & Hamaker, 2007; Molenaar, 2010; Marsman et al., 2018). This does not entail, however, that the theories that drive these models are equivalent (Borsboom, 2017b). The network models proposed here seek to complement existing approaches in several ways. Firstly, in a very general sense, network models highlight unique covariance between pairs of variables which can complement extant latent variable approaches which focus on variance shared across all items (Costantini et al., 2015). Assuming item practice correspondence, the statistical relations in network models come from material referents in the real world (Fried & Cramer, 2017). Networks hence direct attention to casual mechanisms which appear more plausible than those specified in Latent Variable Theory. In the latter, the analogy reflective factor models make with physical systems of measurement break down when the nature of the causal paths is further examined. In the temperature example, the arrows from the latent variable to the indicators refer to a well-defined mechanism in which increases in ambient room temperature cause the temperature of mercury to increase, causing it to expand in the glass tube (Cramer et al., 2012). Nothing of this sort is offered in the psychological equivalent, and consequently; the descriptive aspect of trait theory (the pattern of behaviour from which the trait is inferred) remains disjointed from the explanatory aspect (mechanisms of structures which are the source of the pattern). The network models advanced suggest something different; namely, that the pattern of behaviour arises from direct causal interactions among the behaviours. In this way the distinction between description and explanation collapses, and so too the problem of reification.

Secondly, metrics and postulates difficult to conceive of in extant approaches are explored. For example, concepts of density and structure provide a different and perhaps complementary way of thinking about transformation. Extant mindfulness measures typically consider change in terms of accumulation (i.e., sum-totals indexing high frequencies of behaviour); however, network models view change structurally (indicated in the covariance matrix). Advanced practitioners might thus differ from novice and non-practitioners not by way of the (sum-total) strength of their practices, but rather in how those practices *work together*. Node centrality represents another novel metric that may provide information about the dynamics of a network. In general, it has been suggested that “as highly central nodes go, so should go the network” (Robinaugh, Millner & McNally, 2016, p. 748)[12], and thus highly central nodes have been advanced as possible targets for network interventions (Borsboom & Cramer, 2013; Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Newman, 2004). Exploring centrality may hence generate hypotheses for future experimental work[13]. Finally, these studies provide proof-of-principle for future research which may wish to incorporate a much wider range of nodes. In these networks, biological, psychological, social and environmental variables may be found to be deeply intertwined in feedback loops, potentially challenging a purely reductionist vision of mindfulness. The networks can hence be interpreted from embodied, enactivist and embedded perspectives.

[12] The situation is more complex when negative edges are present in a network because parts of a network might be suppressed by a highly central node, whilst other parts are activated (see Robinaugh, Millner & McNally, 2016 for further discussion of this point and a novel centrality metric to address it).

[13] Interestingly, the concept of node centrality may help understand research reporting similar increases in mindfulness across both intervention and active control conditions (Goyal et al., 2014; MacCoon et al., 2012; Goldberg et al., 2018). Items such as being “friendly to myself when things go wrong” (FMI, item 9) represent practices which are likely non-specific to mindfulness, meaning they are amenable to a wide range of interventions such as those included in an active control. If items of this sort were particularly important to a casual structure within a measure (i.e. changes in this item cause changes in a number of other items), it might be expected that mindfulness levels in both groups may increase. Some support for this idea comes from a recent meta-analysis on self-compassion (Wilson et al., 2018), of which the item being “friendly to myself when things go wrong” is indicative. The authors found specific self-compassion therapies to demonstrate no advantage over active controls in increasing self-compassion, which increased across both conditions.

Chapter 4: Network Psychometrics

In this chapter, the reader is introduced to Network Psychometrics. This chapter is included only due to the relative novelty of network psychometrics, especially in the field of mindfulness. Those familiar with this methodology may well wish to move on to chapter 5 where the method of the current studies is outlined.

4.1 Introduction to Psychological Networks

Network science has arguably transformed disciplines ranging from physics to sociology, such that a *network takeover* has been proposed (Barabasi, 2012). Whenever complex phenomena are modelled as networks, they converge on generic organizing principles suggesting common fundamental laws (Barabasi, 2016). Thus, despite each discipline bringing its own unique goals and technical challenges, they all share a common set of mathematical tools. This has led to a fertile cross-disciplinary science (Barabasi, 2016).

Psychology has recently joined this enterprise through the work of Borsboom and his colleagues at the theoretical (Borsboom & Cramer, 2013; Borsboom et al, 2011; Cramer, et al., , 2010; Schmittmann et al., 2013; Fried et al., 2016) and computational levels (Epskamp et al., 2012; von Borkulo et al., 2014, Epskamp, Borsboom & Fried, 2018). Although social network analyses are well established in psychology, the network analysis of psychological constructs measured with self-report questionnaires is new. These networks differ from social networks in important ways. In social networks, the nodes of the network are represented by people, and the edges represent the relationships between them. As such, these networks can be considered representations of the raw data (Bringmann et al., 2018). In psychological networks, edges cannot be observed directly, and are hence estimated. As such, the edges of psychological networks are statistical relations (Epskamp, Borsboom & Fried, 2018).

Several tutorials now exist to guide researchers lacking advanced statistical knowledge in network estimation (see for example, Constantini et al., 2015, 2017; Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Epskamp, Borsboom & Fried., 2018; Jones, Mair, & McNally, 2018). Networks are most easily interpreted when they are visualised. With a visual topology, the most central items and most important edges become readily apparent. Psychological networks endorse an interventionist theory of causation (Woodward, 2003) which suggests that experimental (or natural) interventions on one node will change the probability distribution of the other nodes. Networks are hence useful for generating hypotheses around removing or rewiring edges, or weakening or strengthening nodes, which can be experimentally tested later (Epskamp, 2017).

The following sections aim to introduce the reader to the field of Network Psychometrics. Methods commonly used to estimate psychological networks will be discussed first. Network interpretation will then be covered. Although far from an exhaustive review, it is anticipated that the material will provide the reader with the requisite knowledge for understanding the methodology, results and discussion of this study.

4.2 Network Estimation

Psychological networks can take many forms. They can consist of un-weighted edges which merely show that two variables are connected, or weighted edges which describe the magnitude of such associations. Psychological networks can also estimate directed edges (in which an arrow indicates the direction of predicted activation) with longitudinal data. This chapter will be limited to weighted undirected networks which are typical of the cross-sectional data (for further information about directed networks, see Bringmann et al., 2016). Figure 4 shows a simple weighted network consisting of three nodes and three edges. The two blue edges indicate positive associations between nodes 1 and 2, and 2 and 3. The single orange edge represents a negative association between nodes 1 and 3. The thickness of the edges represent the strength of the statistical relation.

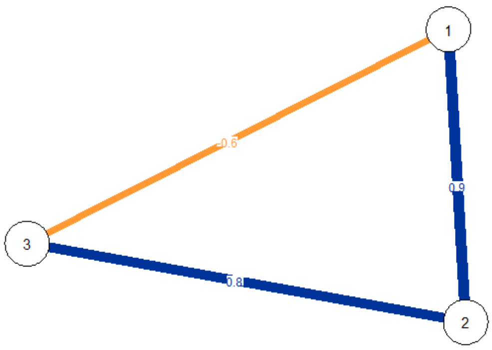


Figure 4. A three node undirected weighted network.

4.2.1 Partial correlation networks. Perhaps the most common type of cross-sectional network estimated are *partial correlation networks*. Partial correlations are useful because they can remove spurious associations in the data. To illustrate this, Constantini and colleagues (2015) provide the example of the strong association which may be found between ice-cream sales and drownings. This is a spurious association because the two cannot cause each other; rather the association is a function of a common cause; namely, summer.

Partial correlations usefully remove spurious associations by testing for direct effects (pairwise conditional dependence) between variables while controlling for all other variables included in the model. The unique association revealed is predictive, and hence considered potentially causal (Borsboom & Cramer, 2013; Epskamp, Borsboom & Fried, 2018).

The partial correlation network is directly encoded through the inverse covariance matrix in the Gaussian Graphical Model (GGM; Constantini et al., 2015; Lauritzen, 1996). In the GGM, partial correlation coefficients edge weights range from -1 to 1. Edge weights of zero are particularly interesting to researchers, because they represent conditional independencies in the data (Epskamp, Borsboom & Fried, 2018)[14]. This means that the two variables could not have caused each other (Pearl, 2000).

[14] This interpretation assumes multivariate normality which may not be satisfied in most psychological datasets. The influence of deviations in normality on network structure remains unresolved in the literature.

Conditional independence is unlikely to be found in real data due to background noise ("everything correlates to some extent with everything else"; Meehl, 1990, p. 204). Thus, to create more interpretable networks, very small associations are removed. Each correlation could be tested for statistical significance; however, this increases the likelihood of false positives (false edges being estimated due to multiple testing), which if corrected for (such as through the common Bonferroni correction) reduces the power of a study. Network modelling has hence turned to a different technique, known as regularisation (although see Williams, Rhemtulla, Wysocki, & Rast 2018, for non-regularized methods).

4.2.2 Regularised Networks. Regularisation essentially involves shrinking all the partial correlation coefficients of a network such that arbitrary small edges reduce to zero (Epskamp, Borsboom & Fried, 2018; Epskamp, Kruis & Marsman, 2016). It employs machine learning algorithms such as the *Least Absolute Shrinkage and Selection Operator* (LASSO; Tibshirani, 1996), of which a popular variant in the network literature has been the graphical LASSO (Friedman et al., 2008; henceforth referred to as 'glasso').

The degree (or severity) of regularisation is controlled with a tuning parameter λ (lambda) set between 0 and 1. Lower values prioritise sensitivity over specificity. This means that fewer connections are removed, but at the cost of leaving too many potentially spurious connections (i.e. they increase the likelihood of false positives). Higher values are more liberal in their pruning, but increase the likelihood of removing too many potentially real connections (i.e. they increase the likelihood of false negatives).

The task of selecting the optimal balance has usually been resolved by employing a data-driven procedure known as the *minimizing the Extended Bayesian Information Criterion* (EBIC; Chen & Chen, 2008). Optimal sparsity is achieved by generating a range of networks across the λ (lambda) parameter range, and then calculating the EBIC value for each (Epskamp, Borsboom & Fried, 2018). In effect, the EBIC penalises models which have too many parameters to reduce *over-fitting*[15]. Simulation studies have shown that selecting λ models with the lowest EBIC value is effective in retrieving the true network structure provided it is a sparse network (Foygel & Drton, 2010; van Borkulo et al., 2014; Epskamp, 2017; for limitations of the glasso/EBIC procedure in dense networks, or networks with high sample sizes, see Williams & Rast, 2018). The use of the EBIC does not completely absolve the researcher of the responsibility of choosing the optimal network, for the EBIC uses another γ (gamma) hyper-parameter to determine the level of sparsity. This is typically set between 0 and 0.5 and reflects the same trade-off between sensitivity and specificity discussed in relation to the λ tuning parameter. None-the-less, the literature has suggested using a γ value of 0.5 given that it has performed well in retrieving a true model in simulation studies (Epskamp & Fried, 2018).

4.3 Network Inference

Network inference involves asking questions about the 'local' and 'global' properties of networks. Investigating local properties involves the identification of edges and nodes which are most important to a network, and how they cluster. This information can inform possible network interventions (Valente, 2012). Investigating global properties involves asking questions about the overall strength of a network's connectivity, or its structure. This area is a recent field of investigation in which the statistical analyses are still being worked out.

4.3.1 Local inference. Important edges are those with large edge weights. Nodes connected with strong edges are those able to influence each other more quickly than those connected by weak edges. One way to think about strong edges is to consider the distance between two people trying to communicate with each other. Communication is easiest with

[15] Over-fitting is a problem in machine learning, because it leads to models which do not generalise beyond the data the machine learning algorithm was trained on.

shorter distances, and this can be represented by inversing edge weights. As such, edge weights can loosely convey information about how quickly activation may travel between nodes (Borgatti, 2005)[16]. That said, statistical analyses on data collected over time would be required to provide information about how long particular causal processes may take to operate.

Edge strengths go on to inform centrality metrics. These metrics attempt to capture how important a node is in a network. Network science has developed a number of quantitative measures of centrality, the most common being *strength*, *closeness*, and *betweenness centrality* (Opsahl et al., 2010). Node *strength centrality* reflects the degree to which a given node is involved in the network. This is calculated by simply summing the edges between the focal node and the other nodes in the network. In a cross-sectional (undirected) network, a node with a high strength centrality value is one which has either a large influence on a networks activation (common cause) or is influenced greatly by a network's activation (common effect). In cross-sectional psychological networks, both may be true as psychological processes are likely reciprocal (Constantini et al., 2015).

The utility of strength centrality in terms of a networks overall activation can be overstated, for the index only takes into account the focal node and its neighbours. It has been argued that a more global index is required which can take into account the edge structures of the whole network (Scott, 2017). *Closeness centrality* achieves this by measuring the mean shortest paths between a given node and all other nodes in the network. Closeness centrality can thus provide an understanding of how quickly influence may travel between a node and the rest of the network (although again, formal analyses on data collected over time are

[16] Note that with partial correlation networks, negative edges can be retrieved. Since distances cannot be negative, absolute values are used when computing centrality indices.

required to provide information of the actual time-scale in which causal processes may unfold).

Betweenness centrality is another global index which measures how often a node lies on the shortest path between every combination of two other nodes. A betweenness value of one means that the node lies on the connecting edge between at least two other nodes. If it lies on the connecting edge of two further nodes, then it will have a value of two (and so forth…; Constantini et al., 2015). Nodes with high betweenness centrality are important because they mediate or facilitate the influence of activation between two nodes. Moreover, they act as bridges between *communities* of nodes. If a node with high betweenness (but perhaps low strength) is removed, we might expect the distances amongst other nodes or communities to increase (Barrat, Barthélemy, Pastor-Satorras & Vespignani, 2004).

Of these measures, strength centrality has been considered the most useful centrality metric for interpretation (Bringmann et al., 2018). This is because global measures of closeness and betweenness make assumptions on the overall network which are difficult to meet. Specifically, they assume that effects always travel the shortest path (Borgatti, 2005; Fornito, Zalesky & Bullmore, 2016). This implies that node *knows* the shortest paths in advance (Borgatti, 2005). This may be problematic in a psychological context, especially in the absence of any knowledge about the dynamics of a system (see Bringmann et al., 2018 for further discussion of the assumptions of centrality).

As noted, nodes in networks often cluster forming communities. Under certain conditions, these communities have been shown to be mathematically equivalent to factors (Golino & Epskamp, 2017), although they afford different theoretical interpretations. One technique developed for network analysis is Exploratory Graph Analysis (EGA; Golino & Epskamp, 2017). The EGA first estimates a regularised network and then applies a *walktrap* algorithm (Pons & Latapy, 2005) to detect clusters of nodes. The walktrap algorithm is premised on the idea that random walkers on a network tend to get trapped in densely connected parts of the network, corresponding to communities (Pons & Lapperty, 2005). Simulation and real-world research has shown that the EGA accurately identifies communities in data comparable or better than other methods (Golino & Epskamp, 2017).

4.3.2 Global inferences. Psychological research often involves comparing two groups on some measure. From a network perspective, this involves comparing two network models. Recently, von Borkulo and colleagues (2017) developed a permutation test called the Network Comparison Test (NCT) which investigates the difference between two networks. The NCT works on the assumption that two networks differ to the extent that their architectures (or data-generating mechanisms) differ (von Borkulo et al., 2017). These differences may be in global strength (*S*, the absolute sum all the edge weights in a network) or structure (*L*, the degree of difference in the edge that changes the most from one network to the other). The NCT works on the following premise: *If* only one network architecture is responsible for generating all the data observed for both groups (the null hypothesis), then reshuffling participants between groups (for example, 10,000 times) should not substantially alter global strength or structure. The NCT tests this proposition by first estimating the difference between the original networks (in either strength or structure), and then repeatedly calculates this difference in sets of randomly regrouped individuals (the permuted networks).

This permutation procedure results in a reference distribution of values of strength or structure differences. These values can be compared with the values observed in the original networks. If the observed result is found to fall in the tails of the reference distribution, then the two groups are considered significantly different (the reader is referred to the paper by von Borkulo and colleagues, 2017 for more information around the NCT).

Chapter 5: Method

5.1 Participants and Procedures

Participants consisted of 654 registered users of Amazon Mechanical Turk (MTurk). MTurk is a crowd-sourcing Internet marketplace where a pool of potential participants accept studies put up by researchers. Participants completed the study via a single online questionnaire using the TurkPrime interface (Litman, Robinson & Abberbock, 2017). TurkPrime provides a simple interface for researchers, and tools for controlling aspects of their studies such as remuneration and selection.

A recent demographic survey of the MTurk population found that US workers comprised 75% of respondents, followed by Indian (16%) and Canadian respondents (1.1%; Difallah, Filatova, & Ipeirotis, 2018). The current studies restricted respondents to US workers, which has been recommended for clinical research (Chandler & Shapiro, 2016; although see Milland, 2017 for a critique). This is because US worker data has consistently been shown to be of better quality than data collected from Indian workers (Kazai et al. 2012, Khanna et al. 2010, Shaw et al. 2011), possibly due to language difficulties (Litman, Robinson, & Rosenzweig, 2015). US worker data has also been shown to be less biased by financial compensation compared to non-US worker data (Litman et al., 2015). The demographic characteristics of US workers are also better understood. Demographic research has shown that MTurk users in the United States are representative of the general population (Berinsky, Huber, & Lenz, 2012; Huff & Tingley, 2015), and more representative of the general population than traditional university subject pools (Paolacci, 2010).

Participants also had to be over the age of 18 and have a study approval rate of greater than 95%. This means that a participant must have adequately completed 95% or more of the previous studies/tasks to the standards of the requester. Setting the approval rate at 95% helps ensure high quality participants (i.e. those who tend to complete studies) and is typical in the literature (Litman, et al., 2017). In this study, all participants could receive remuneration without having to answer any questions.

At the time of writing, mindfulness research using MTurk was limited. No studies recruiting only mindfulness practitioners was identified, although one study had recruited a sample of 130 mindfulness practitioners and practitioners of a related contemplative practice (Hanley, Warner & Garland, 2014). The current study aimed to recruit at least as many participants as the number of parameters required for network estimation (120 parameters), but ideally three times that (it has been suggested that network studies recruit a minimum of three persons per parameter; Epskamp, Borsboom & Fried, 2018). Recruitment hence aimed for 360 mindfulness practitioners and non-practitioners (see Section 5.3 for details on sample size estimation). Given the uncertainty around how many mindfulness practitioners existed in the MTurk population, the criteria for selection was expanded to include practitioners of mindfulness and those of a related meditative practice.

The MTurk platform allowed participants to select a study based on a study’s listed title and a short description of the study. To maximise the likelihood of attracting mindfulness practitioners, two separate studies were listed with the first directly appealing to mindfulness practitioners in the title and description (See Table 1). A second study was then listed to target non-practitioners. Practitioners and non-practitioners could complete either survey, but not both. This discrimination was achieved using a restriction tool in the Turkprime toolbox.

Table 1

Mechanical Turk Study Titles and Descriptions for Each Group

	Practitioner Group	Non-Practitioner Group
Title	Do you regularly practice Mindfulness or a related meditative practice?	Lifestyle/Mindfulness survey

Description	2 surveys for people who regularly (at least weekly) practice mindfulness or a related meditation	2 brief surveys for people who are not involved in mindfulness or any other related meditative practice

Upon selecting a study, all participants were provided with a title page (Appendix A) with the following description regarding Mindfulness:

> Mindfulness is a popular meditation practice that has often been defined as ‘paying attention in a particular way; on purpose, in the present moment, and nonjudgmentally‘, although many people have their own understanding. It often involves certain meditations and practices that are common to other contemplative traditions (such as vipassana, zen, transcendental meditation, amongst others). Typically, mindfulness practices involve sitting and walking meditations, mindful yoga, body-scans, mantras or contemplative prayers, loving-kindness or compassion meditations, amongst others.

Participants were then presented with a drop-down item with the following options: “I regularly practise mindfulness or a related meditation (at least weekly)”, “I do not practise mindfulness or a related meditation or contemplative practice” or, “I infrequently practise mindfulness or a related meditation”. Participants indicating infrequent practice were further provided a free response space to describe the frequency of their practice.

All participants were compensated US $0.80 after completing a single online survey session which included two mindfulness measures. This compensation was consistent with typical remuneration of $US 0.10 a minute for studies using the Mechanical Turk platform (Buhrmester, Kwang, & Gosling, 2011). The average session lasted approximately 8.6 minutes, with the median time being 6.6 minutes. After removing missing data (section 5.4), there was 654 respondents, of which 364 identified as frequent practitioners (weekly), 224 as non-practitioners, and 59 as practicing infrequently. The socio-demographic information for all groups is provided in Table 2. Overall, the sample was primarily Caucasian, (76%), aged between 25-35 years (49%), with either a four-year college degree (35%) or some college education (28%). Respondents most frequently reported having no religious affiliation (52%), with the second largest group being protestant Christian (24%). There were slightly more males (54%) than females (46%) in the total sample. These differences generally characterised all three groups.

Table 2

Demographics and Characteristics

	Practice (n = 364)	Controls (n = 224)	Irregular (n = 59)	Total (n = 654)
Age, *n (%)*				
15-24	66 (18)	27 (12)	10 (17)	103 (16)
25-34	188 (52)	95 (43)	29 (50)	312 (48)
35-44	62 (17)	66 (30)	11 (19)	139 (22)
45-54	29 (8)	21 (10)	4 (7)	54 (8)
55 -64	17 (4)	11 (5)	3 (5)	30 (5)
65 plus	3 (1)	2 (1)	2 (3)	7 (1)
Education, *n (%)*				
Less than high school	1 (0)	0 (0)	0 (0)	1 (0)
High School	37 (10)	35 (16)	5 (9)	77 (12)
Some College	102 (28)	62 (28)	19 (32)	183 (28)
2-year College Degree	58 (16)	23 (10)	5 (9)	86 (13)
4-year College Degree	130 (36)	74 (33)	19 (32)	223 (35)
Master’s Degree	31 (9)	21 (10)	8 (14)	60 (9)
Doctoral Degree	2 (1)	4 (2)	2 (3)	8 (1)
Professional Degree	3 (1)	3 (1)	1 (2)	7 (1)
Gender, *n (%)*				
Male	201 (54)	119 (54)	30 (51)	350 (54
Female	163 (45)	103 (46)	29 (49)	295 (46)

Race, *n (%)*				
White/Caucasian	265 (73)	174 (79)	49 (83)	488 (76)
African American	32 (9)	20 (9)	2 (3)	54 (8)
Hispanic	2 (6)	9 (4)	1 (2)	30 (5)
Asian	39 (11)	16 (7)	7 (12)	62 (10)
Native American	3 (1)	0	0	3 (1)
Other	5 (1)	3 (1)	0	8 (1)
Religious Affiliation, *n (%)*				
None	182 (50)	129 (58)	30 (51)	341 (53)
Protestant Christian	88 (24)	57 (26)	14 (24)	156 (24)
Roman Catholic	33 (9)	22 (10)	10 (17)	65 (10)
Buddhist	20 (6)	0 (0)	2 (3)	22 (3)
Other	44 (12)	14 (6)	3 (5)	61 (10)

Researchers have often used attention checks such as trick questions to improve data quality. These can then be used to screen out inattentive participants prior to analysis (Oppenheimer, Meyvis, & Davidenko, 2009). An attention check may involve a nonsensical question such as “Have you ever, while watching TV, had a fatal heart attack” which inattentive respondents might affirm (Paolacci et al., 2010). Alternatively, a question such as “which sports do you like?” may be preceded with a lengthy block of text containing information to disregard the question. Several reviewers have suggested attention checks are less useful for MTurk research (Chandelr & Shapiro, 2016; Hauser & Schwarz 2015; Peer, Vosgerau & Acquisti, 2014; Vannette, 2017). Firstly, removing respondents who fail attention checks may introduce a demographic bias. This is because inattentive responders may not represent a random subset of the population (Berinsky, Margolis, and Sances 2014; Vanette, 2017). Secondly, attention checks may have other consequences, such as inducing Hawthorne effects (motivating self-censorship or desirable responding; Clifford and Jerit 2015; Vannette 2017). For these reasons, attention checks were not included in the studies.

That said, research with MTurk has shown that restrictions on approval rate (such as used in the current studies) is effective in discriminating attentive from inattentive participants (Peer et al. 2014).

5.2 Mindfulness Measures

5.2.1 Friedberg Mindfulness Inventory – Short Form (FMI-14). The FMI, in its short form, is a 14-item scale designed to measure mindfulness as a stable trait (Appendix B). It has been shown to be useful in distinguishing between participants with and without meditation experience (Sauer, Walach, Offenbächer et al., 2011; Sauer et al., 2015; Walach et al., 2006).

The FMI-14 was constructed to reflect mindfulness from the perspective of Buddhist Psychology (Wallach et al., 2006). The scale was initially developed as a unidimensional scale; however, research also supports a two-factor solution of *Presence* and *Acceptance* (albeit different studies have attributed different items to these factors; see for example, Kohls et al., 2009; Ströhle, 2006). Presence is generally thought to reflect the awareness of stimuli in the subjective now (Sauer et al., 2012), and Acceptance, “a non-judgmental stance toward all kinds of experience” (Kohls et al., 2009). The FMI utilises 4-point rating scale (“rarely”, “occasionally”, “fairly often” and “almost always”). The 14 items are listed in Table 3.

Table 3

Friedberg Mindfulness Inventory (FMI) Items

Item	Item Description
FMI 1	I am open to the experience of the present moment
FMI 2	I sense my body, whether eating, cooking, cleaning or talking
FMI 3	When I notice an absence of mind, I gently return to the experience of the here and now

FMI 4	I am able to appreciate myself
FMI 5	I pay attention to what's behind my actions
FMI 6	I see my mistakes and difficulties without judging them
FMI 7	I feel connected to my experience in the here-and-now
FMI 8	I accept unpleasant experiences
FMI 9	I am friendly to myself when things go wrong
FMI 10	I watch my feelings without getting lost in them
FMI 11	In difficult situations, I can pause without immediately Reacting
FMI 12	I experience moments of inner peace and ease, even when things get hectic and stressful
FMI 13	I am impatient with myself and with others
FMI 14	I am able to smile when I notice how I sometimes make life difficult

Note. Item 13 is reverse coded.

The FMI has been validated using a number of different psychometric methods. In the original study (Walach et al., 2006), a principal component analysis suggested one common component, and good internal consistency was achieved in lay, meditating and clinical participants (Cronbach's alpha = .86). Correlations with other relevant constructs (self-awareness, dissociation, global severity index, meditation experience in years) were significant in the medium to low range. In a subsequent analysis, Ströhle (2006) reported evidence for a two-factor solution comprised of two inter-correlated sub-factors (Presence and Acceptance). In a confirmatory factor analysis, Kohls and colleagues (2009) reported good internal consistency for both the one factor model ($\alpha = 0.83$) and two factor models (Presence, $\alpha = 0.69$, items 1, 2, 3, 5, 7, 10; Acceptance $\alpha = 0.77$, items 4, 6, 8, 9, 11, 12, 14), but found both models to have suboptimal fit indices. A subsequent exploratory analysis revealed an 8-item solution which demonstrated an improved fit. FMI-14 scores were associated with substantively lower anxiety and depression scores, which was largely accounted for by the Acceptance factor. In a non-clinical sample, Sauer, Walach, Schmidt and collegues (2011) found further support for differential factor functioning in support of their broad proposition that Acceptance is probably involved in regulation of emotions, and Presence, attentional regulation.

Using an Item Response Theory methodology (Rasch Analysis), Sauer, Walach, Offenbächer and colleagues, (2011) investigated the psychometric properties of the FMI in a clinical sample (patients with psychosomatic conditions). The analysis did not support a uni-dimensional model, and item 13 did not fit the Rasch model. They found good support for a 13-item two-factor solution (Acceptance and Presence) in which the negatively worded item (item 13) was removed. A Rasch analysis can identify whether items are equally difficult for different groups such as practitioners and non-practitioners. Lack of this property is called Differential Item Functioning (DIF). The authors found no evidence of Differential Item Functioning between mindfulness practitioners, non-practitioners and practitioners of other spiritual practices (such as prayer or meditation in general). Strong floor and ceiling effects were reported which they suggested may limit the discriminative capabilities of the instrument. The two factors (Acceptance and Presence) exhibited good adherence to the Rasch model, although reliability could be improved. A difference in the difficulty of items was also reported, such that the Presence items were found to be substantially easier to interpret than Acceptance items. They suggested that this may support Kohls and colleagues (2009) assertion that the ability to be present is established before the ability to accept things.

In a qualitative study, Belzer and colleagues (2013) found evidence that many of the items may be subject to differential interpretations by practitioners and non-practitioners. Contrary to the findings of Sauer, Walach, Offenbächer and colleagues (2011), they found that Presence items were the most difficult to understand for persons without mindfulness experience. Those with mindfulness experience comprehended all the items of the FMI-14 as they were intended, somewhat homogenously (Belzer et al., 2013).

The FMI has also been validated with a novel statistical method derived from machine learning. Sauer and colleagues (2015) used a *Random Forest* algorithm to generate a set of decision trees for the purpose of ascertaining the predictive accuracy of FMI items in correctly classifying whether an individual was a practitioner or non-practitioner (see Strobl, Malley & Tutz, 2009 for a detailed discussion of Random Forest in psychological research). The researchers used two samples to allow for the replication of results. The samples also allowed them to assess the influence of data quality. What they designated as their *high quality* sample consisted of 38 expert mindfulness practitioners with at least five years of regular practice, age and gender matched with a group of 28 non-practitioners (see Sauer et al., 2012 for further details of this group). Their *low quality* sample consisted of 72 regular practitioners (mindfulness training included Buddhist meditation, Thai Chi, or Yoga exercises) and 129 non-practitioners recruited online. The authors found that the FMI-14 was capable of distinguishing practitioners from non-practitioners across both samples, but that many individual items were unable to reliably predict class membership. This was especially true for the low quality sample, raising issues of sensitivity (only item 2 could accurately discern the groups). Consistent with previous findings (Sauer, Walach, Offenbächer et al., 2011), item 13 made no contribution to predictive accuracy in either of their samples.

5.2.2 Applied Mindfulness Process Scale (adapted). The Applied Mindfulness Process Scale (AMPS; Li et al., 2016) is a recent mindfulness scale designed to measure the frequency with which people use various mindfulness skills to cope with daily stressful events (Appendix C). The AMPS is a 15-item scale where each item reflects a different mindfulness skill, as well as the processes required for achieving the specific trait mindfulness characteristics previously described in trait scales (Li et al., 2016).

In the AMPS, respondents are asked to indicate how often they have used mindfulness to cope in a variety of ways for the period of the past seven days (see Table 5 for a list of items). A 5-point rating scale is employed with response options ranging from 0 (“Never”) to 4 (“Almost always”). Higher scores indicate the more frequent use of each mindfulness process, and these can be summed to create a total process score. In its original publication, a potential three factor solution was identified by a visual analysis of scree plots. The subscales were labelled *decentering* (items, 1, 3, 12, 13, 15), *positive emotion regulation* (items 5, 9, 11, 14) and *negative emotion regulation* (items 2, 5, 6, 8, 10). This three-factor model was then subjected to a confirmatory factor analysis where it achieved good internal consistency (Cronbach's $\alpha = 0.91$), but only borderline acceptable fit. In the original study, the AMPS total score was positively correlated with a number of measures, including the FMI ($r = .52$), and partial correlations revealed it to demonstrate incremental validity over the FMI (Li et al., 2016). In this study, the AMPS was adapted for use with non-meditating populations by making a simple change to the preliminary instructions (Table 4). No changes were made to item content.

Table 4

Preliminary AMPS Instructions Provided to Each Group

	Practitioners	Non-practitioners
Instruction	Everyone gets confronted with negative or stressful events in daily life, and people who practice mindfulness experience these events in different ways. Please indicate how often you have used mindfulness in each of the following ways for the period of the last week	Everyone gets confronted with negative or stressful events in daily life, and people experience these events in different ways. Please indicate how often you may have done each of the following for the period of the last week.

The AMPS is a novel measure in the literature in that it incorporates mindfulness practices which the authors believe promote well-being and eudemonia. The *Mindfulness to Meaning Theory* advanced by Garland and colleagues (2015a) attempts to explicate this. Briefly, the MMT suggests that in a single iterative step, mindfulness facilitates de-centering from stress into a non-evaluative, metacognitive state of mindfulness. This leads to a broadening of awareness to encompass previously unattended information. In turn, this broader awareness allows for increased flexibility and ultimately, a basic re-appraisal of the stressor. This basic re-appraisal is then proposed to lead to more durable positive emotional regulation processes such as positive reappraisal (seeing the positive side of a stressor), and hedonic and implicational savouring. These terms informed the labelling of AMPS nodes (see *node descriptions*, Table 5) which were used for the sake of brevity when presenting results.

Table 4

Applied Mindfulness Process Scale (AMPS) Items and Node descriptions

Item	Item description	Node description
AMPS 1	observe my thoughts in a non-attached manner	De-centered Observation
AMPS 2	relax my body when I was tense	Relaxation
AMPS 3	see that my thoughts were not necessarily true	Metacognitive Perception.
AMPS 4	enjoy the little things in life more fully	Hedonic Savouring
AMPS 5	calm my emotions when I was upset	Emotional Calming.
AMPS 6	stop reacting to my negative impulses	Non-reactivity to Impulses
AMPS 7	see the positive side of difficult circumstances	Positive Re-appraisal
AMPS 8	reduce tension when I was stressed	Reduce Tension
AMPS 9	realize that I can grow stronger from difficult circumstances	Implicational Savouring
AMPS 10	stop my unhelpful reactions to situations	Non-reactivity to Situations

AMPS 11	be aware of and appreciating pleasant events	Awareness and Appreciation
AMPS 12	let go of unpleasant thoughts and feelings	Letting Go
AMPS 13	realize that my thoughts were not facts	Meta-cognitive Realization.
AMPS 14	notice pleasant things in the face of difficult circumstances	Broadening Attention
AMPS 15	see alternate views of a situation	Flexibility

The AMPS was designed to measure mindfulness in populations participating in a mindfulness intervention. An important consideration in these studies was the use of the AMPS for populations it was not designed for or validated on; namely, regular practitioners (versus participants in a formal intervention) and more importantly, non-practitioners.

5.3 Sample Size Determination

Determining an adequate sample size is often referred to as power analysis (Cohen, 1977) in the literature. To conduct a power analysis, an expectation of the effect size is required. The network equivalent is an expected (weighted) network structure (Epskamp, Borsboom & Fried, 2018); however, as the first study of this type, no previous mindfulness networks had been estimated. Sample size was hence determined from a general *rule of thumb* suggested in the literature; namely, three individuals per parameter (Epskamp, Borsboom & Fried, 2018). Allowing for the possibility of fully connected networks (whereby all nodes share paths with all other nodes), the 15 node AMPS network would require a maximum of 120 parameters whilst the 14 node FMI network would involve 105 parameters[17]. This means that the two studies needed group sizes of 360 and 315 participants to meet the "rule of thumb" respectively. These numbers were also considered adequate given that simulation studies have suggested that a sample size of 250 is generally sufficient for networks with around 25 nodes, based on continuous data (Epskamp, 2017). These numbers

[17] The number of parameters were calculated as follows: 15 item AMPs: 15 + 15*14/2 = 120; 14 item FMI: 14 + 14*13/2 = 105.

were achieved for the practitioners' group (*n* = 371) but were not met for the non-practicing group (*n* = 224). Given that regularised networks remove some edges, a slightly smaller sample size may suffice. Nonetheless, it was unclear whether regularisation was sufficient to achieve an optimal sample size for the non-practitioner group.

5.4 Missing Data

Participant compensation was granted when participants opened the survey and was not conditional on answering the survey questions. In 23 cases, participants did not answer any of the survey questions and were excluded from analysis. In four cases, participants completed a survey twice. This led to two entries in the dataset from the same subject. In all four cases, the first entry was incomplete, but the second entry complete. The second entry was used, and the first entry excluded from analysis.

In three cases, participants completed the entire AMPS but not the FMI. Likewise, in six cases, participants completed the entire FMI, but not the AMPS. Only the completed measures were used in the analysis. In one case, two of the 15 items of the AMPS were missing. For this case, the average item score was calculated, and this value was used as a replacement for the missing values.

5.5. R Code and Materials Sharing

All R code and the dataset are available on the Open Science Framework for reproduction and replication purposes (https://osf.io/vr3aj/). All identifying information has been removed.

5.6 Analysis Plan

All analyses were conducted using the R statistical software, version 3.5.3 (R Core Team, 2019). Networks were estimated with using the R package *qgraph*, version 1.5 (Epskamp, Cramer, Waldorp, Schmittmann, Borsboom, 2012). Formal tests of network density and network structure were performed using the R package *NetworkComparisonTest* version 2.0.1 (Van Borkulo et al., 2017). Community structures were estimated using the *Exploratory Graphical Analysis* R package, version 0.4 (Golino & Epskamp, 2017).

5.6.1 Aim 1: To determine whether the practitioners' network is characterised by greater network density: A global test of strength invariance. Network connectivity (density) was calculated with a global strength test statistic *S*, which is the absolute sum of all connections in a network (Barrat et al., 2016; von Borkulo et al., 2017). To determine how commonplace any given group difference in *S* might be, a 2-tailed non-parametric permutation test (NCT; von Borkulo et al., 2017) was performed. This generated an external standard by which any difference in *S* could be tested for significance. 500 permutations were selected (for further detail on the NCT, see chapter 5).

The NCT requires equal sample sizes across groups as the EBIC penalises networks more severely as sample size decreases, leading to sparser networks (Rhemtulla et al., 2016). As such, unequal samples can confound network comparisons. Although cases could have been dropped from the practitioners sample to achieve a comparable sample size with non-practitioners, this would sacrifice power. Low power reduces ability of the NCT to detect differences, and hence an alternative procedure was used to maximise the power of the study. This involved two steps. First, the smaller irregular and non-practitioner samples were combined to increase the sample size of the non-practicing group. Visual inspection and an analysis of path weights and centrality indices revealed this to be a viable strategy for both the FMI and AMPS comparisons (see Appendix D and Appendix E). The second step used a bootstrap procedure to create equal groups, similar to that used by Rhemtulla and colleagues (2016). This involved drawing 500 resamples of n = 325 (with replacement) from each group (the sample size of 325 was chosen because it was the average of the two samples combined). NCTs were then performed on each resample, such that a range of 500 results were generated. Given the likelihood of outliers and a strong skew in p value sampling distributions for significant results, the median of this distribution was chosen as the best statistic to represent the central tendency of the data. To maximise the sensitivity of the NCT to detect differences (von Borkulo et al., 2017), a gamma value of 0 was used. The trade-off for lower gamma values is the possibility of increased false positive rates, although research has suggested that with large samples, a gamma of 0 reveals error rates close to the nominal level ($\alpha = .05$; von Borkulo et al., 2017). When the central tendency of the data suggested a significant difference, the same procedure was repeated at the higher gamma levels of 0.25 and 0.5 to assess the potential stability of this difference.

Terluin, de Boer and de Vet (2016) have shown that network correlation coefficients can be biased if the variance of one or both items is restricted (see also, Goodwin & Leech, 2006). If an item shows a floor effect, it will often have small variance, which in turn means that the variable cannot correlate strongly with other variables. This poses problems for comparing networks as differences in connectivity may be solely due to differences in item variances. To address this concern, the centrality and standard deviation of each item was correlated. In the case of a high correlation, differential variability of the nodes in the network may drive the centrality of the nodes, and hence network structure. Floor and ceiling effects were also visually investigated by inspecting the item score distributions in density plots (Appendix F). Finally, the centrality and mean of each item were correlated to check whether centrality may have been driven by mean scores.

5.6.2 Aim 2: Investigating the architecture of mindfulness: a global test of network structure invariance and exploratory analysis of network structure. NCT tests of structural invariance were conducted using the aforementioned procedure. The NCT *Structural Invariance Test* calculates the maximum absolute difference in edge weight between two networks, represented in the test statistic *L*. Put differently, *L* represents the degree of difference in the edge that changes the most from one network to the other (von

Borkulo et al., 2016). Because networks have only to differ in one edge to be deemed different in the NCT, the edge lists of the exploratory networks were correlated to provide another difference measure known as the *coefficient of similarity* (Borsboom et al., 2017; Fried et al., 2018; Rhemtulla et al., 2016). A correlation of 1 implies that the networks are the same (perfectly linearly related), and a value of zero indicates no detectable (linear) correspondence. A value of minus one would suggest that the networks are opposites (Borsboom et al., 2017).

5.6.2.1 Exploratory Network Estimation. Network estimation for the exploratory analysis involved estimating undirected partial correlation networks (also called Gaussian Graphical Models; Costantini et al., 2015; Epskamp & Fried, 2018; Lauritzen, 1996) for practitioners and non-practitioners, with and without regularisation.

Psychological data rarely meet the assumption of normality; however, this assumption can be relaxed if it is assumed that the observed data is a transformation of a latent normally distributed score (Liu et al., 2009). With ordinal data, a threshold function known as a polychoric correlation has become the standard transforming function in the network literature (Epskamp & Fried, 2018). Polychoric correlations have been shown to be generally robust to moderately skewed data (Flora & Curran, 2004; Quiroga, 1992), and they have been shown to perform well in recovering the true network in a simulation study with moderately skewed data (Epskamp & Fried, 2018). Polychoric correlations were calculated using the *corauto* function in the *qgraph* package (Epskamp et al., 2017), which outputs a covariance matrix.

Polychoric correlations can become unstable whenever the pairwise cross-tabulations of items contain zeros or show only a few cases (i.e. below 10; Olsson 1979). Following the recommendations of Epskamp and Fried (2018), the estimated networks were compared with networks estimated with Spearman's correlations to check for their stability. Cross-tables were also inspected.

Regularization of the partial correlation networks were conducted using the graphical LASSO in combination with Extended Bayesian Information Criterion (EBIC) model selection (Foygel and Orton, 2010). This was implemented in the *qgraph* package (Epskamp et al., 2017). The tuning parameter was left at the default value of 0.5, which has been shown to yield accurate network estimations (Epskamp & Fried, 2018). In visualising the networks, the Fruchterman–Reingold algorithm (Fruchterman & Reingold, 1991) was used. This algorithm tends to migrate the most central nodes to the centre of the graph.

5.6.2.2 Exploratory Network Analysis. The NCT and coefficient of similarity can indicate whether differences exist between networks, but not what these are. The exploratory analysis sought to reveal differences by visualising the networks. Further to this, community structures were estimated, and centrality indices calculated.

Community structure was estimated using the *Exploratory Graphical Analysis* R package (EGA, Epskamp & Golino, 2017). The EGA uses a walk-trap algorithm to find communities of items in a network. In effect, the walk-trap algorithm simulates random walks through a networks structure, such that random walkers spend a long time (become "trapped") in dense areas (i.e., areas of the network with lots of edges among nodes). It is important to note that an item can only be part of one community using this procedure.

Strength, closeness and betweenness centrality were calculated using the *centralityPlot* function, implemented in *qgraph* (Epskamp et al., 2017). Briefly, strength centrality provides a measure of the likelihood that activation of a given node will be followed by activation of other nodes. Closeness centrality indexes the topological distance between two nodes, and hence provides an implication of how fast information might travel. Betweenness centrality provides an indication of how important a given node is in mediating influence between two other nodes. The main analyses explored the differences in centrality using Z-scores. A given Z score represent the difference between a nodes centrality value and the mean centrality value of the sample, divided by the standard deviation of the node centrality value. This allows a common standard to be set for both practitioners and non-practitioners (i.e., a mean of 0 and a standard deviation of 1). Raw score equivalents can be found in Appendix G.

5.6.2.3 Accuracy and Stability Estimation. Networks must be accurate and stable if they are to be plausibly interpreted. Accurate and stable networks are those which are robust to sampling variation and their interpretation remains similar across sample sizes. Edge weight stability was determined for the exploratory networks by using a bootstrap procedure to construct 95% confidence intervals around each edge in the networks. Bootstrapping involved simulating numerous data sets (set at default = 1000), and then repeatedly estimating edge weights in these. This creates a distribution for each edge, allowing for a confidence interval to be calculated. Data was simulated using a non-parametric method, which involved randomly resampling the original data with replacement. This meant that in the first bootstrap, subject A may be there three times, but not subject B. In the second bootstrap, subject B may be there twice, but subject A may be absent. The *non-parametric bootstrap* function is implemented in the R package *bootnet*, version 1.2 (Epskamp, Borsboom & Fried, 2018).

Bootstrap procedures have not proved reliable for complex statistics such as centrality (Epskamp, Borsboom & Fried, 2018). Instead, Epskamp and Fried (2018) have suggested determining the stability of the centrality estimates with another method. This involves creating subsets of the original network by progressively dropping nodes or people from the network. Centrality metrics of the original (full) data set are repeatedly correlated with those calculated from subsamples in which increasing percentages of people are dropped. If the correlation changes considerably as persons are dropped, then the centrality estimate may be problematic.

Epskamp, Borsboom and Fried (2018) have also developed an index to quantify the effects of this person-dropping procedure. For each subset level, an interval can be constructed of the correlation coefficient. Epskamp, Borsboom and Fried (2018) have suggested that this interval should entirely be above 0.7. This value was chosen given that it typically represents a large effect in the behavioural sciences (Cohen, 1977). The *Correlation Stability* coefficient (*CS)* thus represents "the maximum proportion of participants that can be dropped while maintaining 95% probability that the correlation between centrality metrics from the full data set and the subset data are at least 0.7 or higher" (Epskamp, Borsboom & Fried, 2018; p. 200). The *CS* ranges from 0 (no linear correspondence) to 1 (a perfect linear correspondence), and simulation research has shown that centrality indices generally do not differ when the *CS* falls below 0.25. A cut-off value of 0.5 has hence been recommended (Epskamp, Borsboom & Fried, 2018). Finally, bootstrapped significant difference tests were performed for centrality and edge weights. These tests determine the difference between the bootstrap values of two edges or centrality estimates, and then constructs a bootstraped Confidence Interval around the difference scores (Epskamp, Borsboom & Fried, 2018). The presence of zero in the bootstrap CI can be interpreted as indicating that the difference is not statistically significant (Chernick & LaBudde, 2011)[18]. It is important to mention that no corrections for multiple testing were involved in these tests (see Epskamp, Borsboom & Fried, 2018, for details on the problems of correcting for multiple testing in the network context). The person drop bootstraps, *CS* coefficients and bootstrap significance tests were all

[18] Epskamp, Borsboom & Fried (2018) have stressed that it is important that bootstrapped results should not be used to test for the significance of an edge being different from zero in regularized networks. This is due to the nature of regularisation which by its nature, produces sparser networks with more missing edges.

conducted using functions in the R package *bootnet*, version 1.2 (Epskamp, Borsboom & Fried, 2018).

5.7 Nomenclature.

The network model of mindfulness proposed here conceptualise mindfulness as emerging from relevant practices which are causally interconnected. Questionnaire items are considered to represent the relevant practices and these constitute the nodes of the network. The term *path* has been used to represent network edges as this term better conveys the idea of activation travelling along a causal pathway between practices. That said, the edges estimated in the studies networks are only statistical relations. The use of flow metaphors such as "travelling activation" thus represent conceptual devices beyond the data. Another important note relates to the qualitative descriptors used in network interpretation. Descriptive terms used to characterise paths strengths (i.e., a strong, moderate, or weak path) reflect arbitrary interpretations of the thickness and saturation of paths as they are visualised in the networks. They do not correspond to established standards such as Cohen's (1977) rule of thumb (i.e., an *r* of .1 represents a *small* effect size, .3 a *medium* effect and .5 a *large* effect).

5.8 Ethics.

The methods used in this research were considered low risk in consultation with supervising staff and by reference to the Massey Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants (Massey University, 2015). A low risk notification was reported to the Massey University Human Ethics Committee (Human Ethics Notification Number 4000015652).

Chapter 6: Results and Discussion

This chapter outlines the results of the two studies and their interpretation. A general discussion of the results and study limitations are detailed in chapter 7.

6.1 Study 1: Network Analysis of the FMI

6.1.1 General differences. After removing missing data, a total of 651 participants were involved in the Network Comparison Tests (NCT) of the Friedburg MindfuIness Inventory (FMI). The exploratory analysis involved 592 participants (irregular practitioners were excluded). A one-way ANOVA was conducted to compare the self-attributed total FMI Mindfulness scores across the three groups. There was a significant difference in total mindfulness levels across the groups ($F(2, 648) = 57.24$, $p < .001$). Post hoc comparisons using the Tukey HSD test indicated that the mean score for practitioners ($M = 40.35$, $SD = 7.10$) was significantly different ($p < .001$) to the mean score of non-practitioners ($M = 34.19$, $SD = 7.68$) and irregular practitioners ($M = 37.64$, $SD = 7.98$. No significant differences were observed between irregular practitioners and non-practitioners.

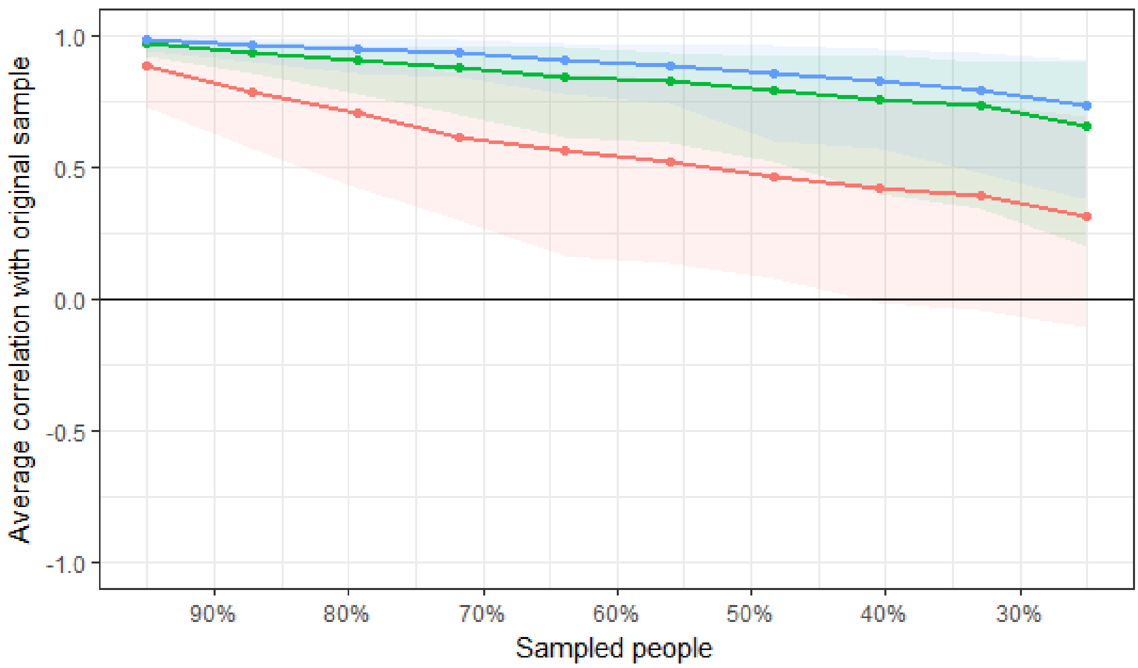
6.1.2 Aim 1: To determine whether the practitioners' network is characterised by greater network density: A global test of strength invariance. The Network Comparison Test (NCT; von Borkulo et al., 2016) was used to test the hypothesis that the practitioners' FMI mindfulness networks would be characterised by greater connectivity (density) than the non-practitioners' networks. Only 15% of the 500 resampled networks achieved significant p-values ($p < .05$) at the gamma level of 0 (median $S = .76$, median $p = .33$). As such, the null hypothesis could not be rejected: when networks were adjusted for sample size, it appears that networks of practitioners and non-practitioners were similar in overall connectivity (density).

6.1.3 Aim 2: Investigating the architecture of mindfulness: A global test of network structure invariance and exploratory analysis of network structure. The second aim of the study was to explore the structural profiles of practitioners' and non-practitioners' mindfulness networks. To this end, the NCT was first used to test whether the groups significantly differed in network structure. Across 500 resamples, 62% achieved significant *p* values ($p < .05$) at the gamma level of 0 (median $L = .24$, median $p = .03$). NCTs were then performed at higher gamma levels of .25 and .5 to check for the stability of this difference. At higher gamma levels of .25 (median $L = .23$, median $p = .04$) and .5 (median $L = .23$, median $p = .04$), significant *p* values ($p < .05$) were only observed in 58% and 54% of the resamples respectively.

Item variance (standard deviation) and practice strength centrality were moderately correlated in the non-practitioners' sample ($r_S = .45$), but not in practitioners ($r_S = -.08$). Visual analysis of item distributions (Appendix F) did not reveal substantive differences in item distributions, and floor and ceiling effects were not considered a concern. Mean levels of items did not appear to drive strength centrality in either sample (practitioners' $r_S = -.06$ non-practitioners' $r_S = -.24$).

6.1.3.1 Network stability and accuracy of exploratory networks. Network stability must be inspected before interpreting networks because networks with low path weight accuracy and unstable centrality indices are prone to error and cannot be meaningfully interpreted. As such, these results are reported before the exploratory analysis.

The accuracy of the order of centrality was explored using the subset person-drop procedure recommended by Epskamp, Borsboom and Fried (2018). Figure 5 shows the average correlations between centrality indices of networks sampled with persons dropped, and the centrality indices of the original sample. It depicts the maximum proportion of the original sample that can be dropped (X axis) while confidently retaining a correlation above .7 with the centrality indices in the original (full) sample (Y axis). Figure 5 shows that strength and closeness appeared relatively stable up to around the 70% mark in both groups in the glasso networks. This means that when (close to) 30% of the people were dropped from the FMI networks, the order of the practice strength and closeness centrality remained relatively stable. The results for betweenness centrality were mixed: betweenness centrality appeared stable in the non-practitioners' networks but declined steadily in the practitioners' networks. The regularized networks substantially outperformed the partial correlation networks where centrality indices dropped substantially in subsets in which persons were dropped (Appendix H, Figure 23). Analysis was hence limited to glasso networks.



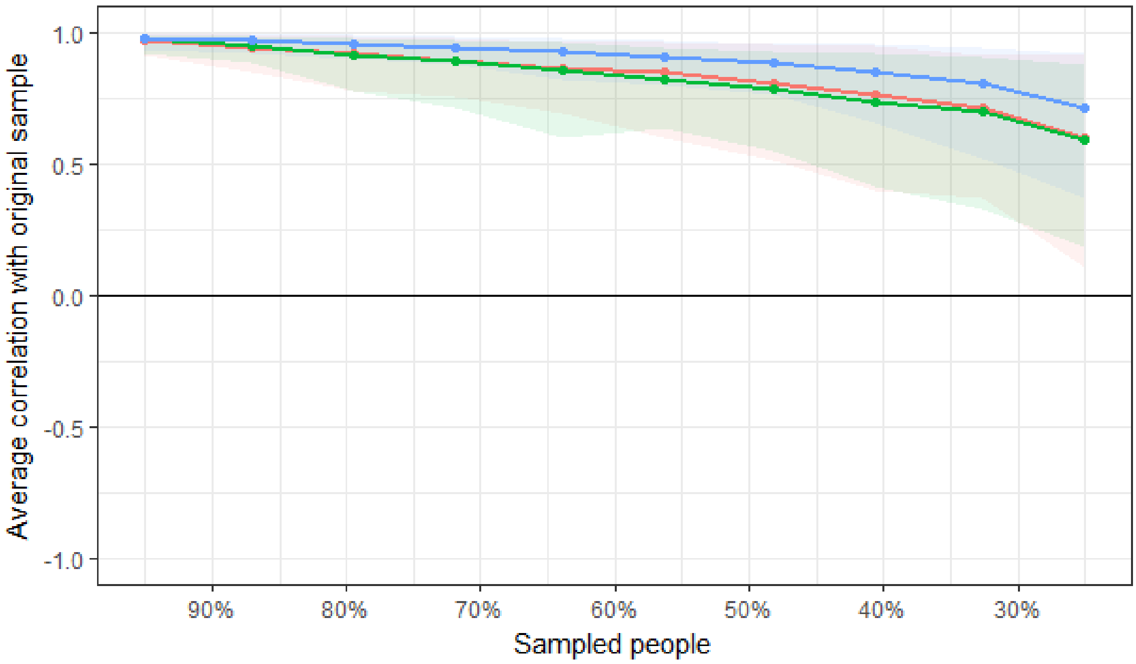
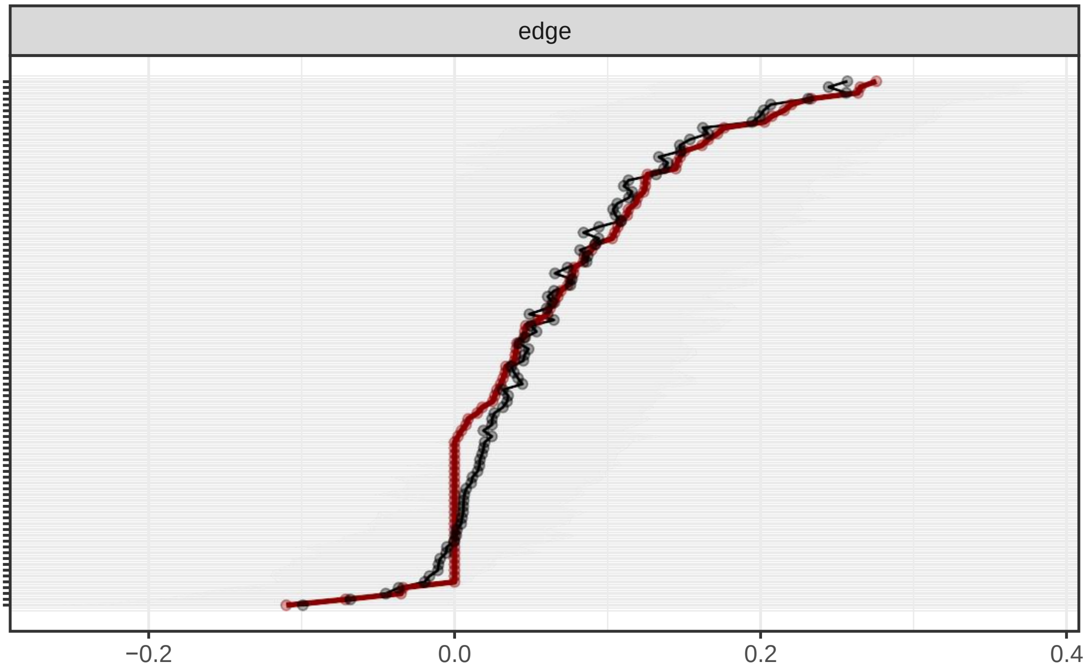


Figure 5. Average correlations between centrality indices of (glasso) networks sampled with persons dropped, and the centrality indices of the original sample for practitioners (top) and non-practitioners (bottom). Legend: blue = strength, green = closeness, red = betweenness.

To provide a quantitative measure of stability, centrality stability coefficients (*CS*) were calculated. Epskamp, Borsboom and Fried (2018) suggest that the stability coefficients should be between .25 and .5 to be meaningfully interpreted. Analysis of the *CS*-coefficients suggested that only practice strength could be interpreted with some confidence for both practitioners (*CS* = .43) and non-practitioners (*CS* = .36). CS-coefficients suggested that comparisons between closeness would need to be interpreted with care (practitioners' *CS* = .29, non-practitioners' *CS* = .28). Betweenness was interpretable for practitioners (*CS* = .36), but not for non-practitioners (*CS* = .07). On the basis of these results, centrality analysis was limited to strength centrality given its relative robustness. Strength centrality also benefits from less problematic assumptions (see chapter 4).

To assess the path weight stability of the exploratory networks, 95% confidence intervals (CIs) were obtained for each path via a non-parametric bootstrap method (Epskamp, Borsboom & Fried, 2018). Figure 6 shows the results of the bootstrap procedures for the glasso networks of both groups. Substantial 95% CI ranges were obtained for most of the paths across both networks suggesting that the models were only moderately accurately estimated. This meant that only the strongest paths differed from the weakest, and this was confirmed in by bootstrap significant difference tests (Appendix I, Figure 24). For both groups, dense networks were selected which meant that the smallest edges need to be interpreted with care (Williams & Rast, 2018).



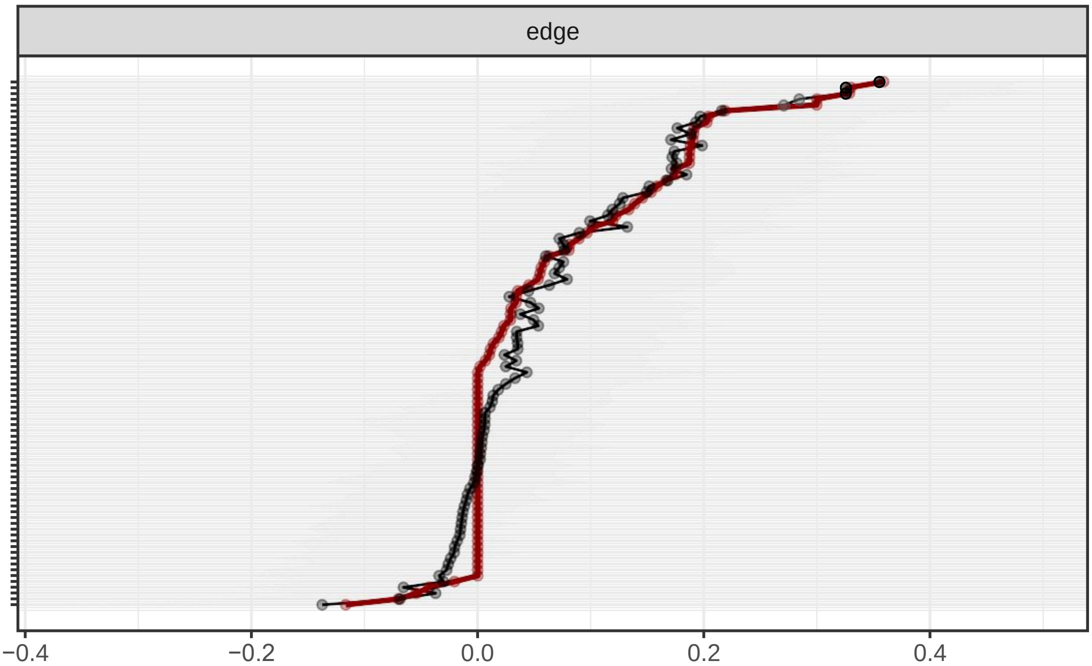


Figure 6. Bootstrapped confidence intervals (CIs) of estimated pathway weights for the estimated practitioners' (top) and non-practitioners' (bottom) regularised FMI mindfulness networks. The red line indicates the sample values, and the black line, bootstrapped mean levels. The grey area indicates the bootstrapped CIs. Each horizontal line represents one pathway in the network, ordered from strongest to weakest. Y-axis labels have been removed to avoid cluttering.

6.1.3.2 Exploratory analysis of network structures. An exploratory analysis was conducted to determine how the two networks may differ. To this end, community structures, centrality indices and discriminating topological features were compared. The exploratory networks were estimated with polychoric correlations and subjected to regularisation using a tuning (gamma) value of 0.5. Polychoric correlations are widely used in estimating psychological networks in the literature given that they are generally considered most appropriate for ordinal data and have been shown to be robust to moderately skewed data. The NCT however is currently limited to comparing networks estimated with Pearson's correlations. Because of this, the exploratory networks (estimated with polychoric correlations) were compared to networks estimated with Pearson’s correlations to determine how comparable they were. Centrality indices and edge weights were strongly correlated between Pearson’s and polychoric networks for both groups (see Appendix D). These results suggested that the networks were broadly comparable.

Figure 7 shows practitioner and non-practitioner FMI regularized (glasso) networks. The corresponding items, descriptions, abbreviations, sample means, and standard deviations for each network are presented in Table 6. The results of the centrality analysis are shown in Figure 8.

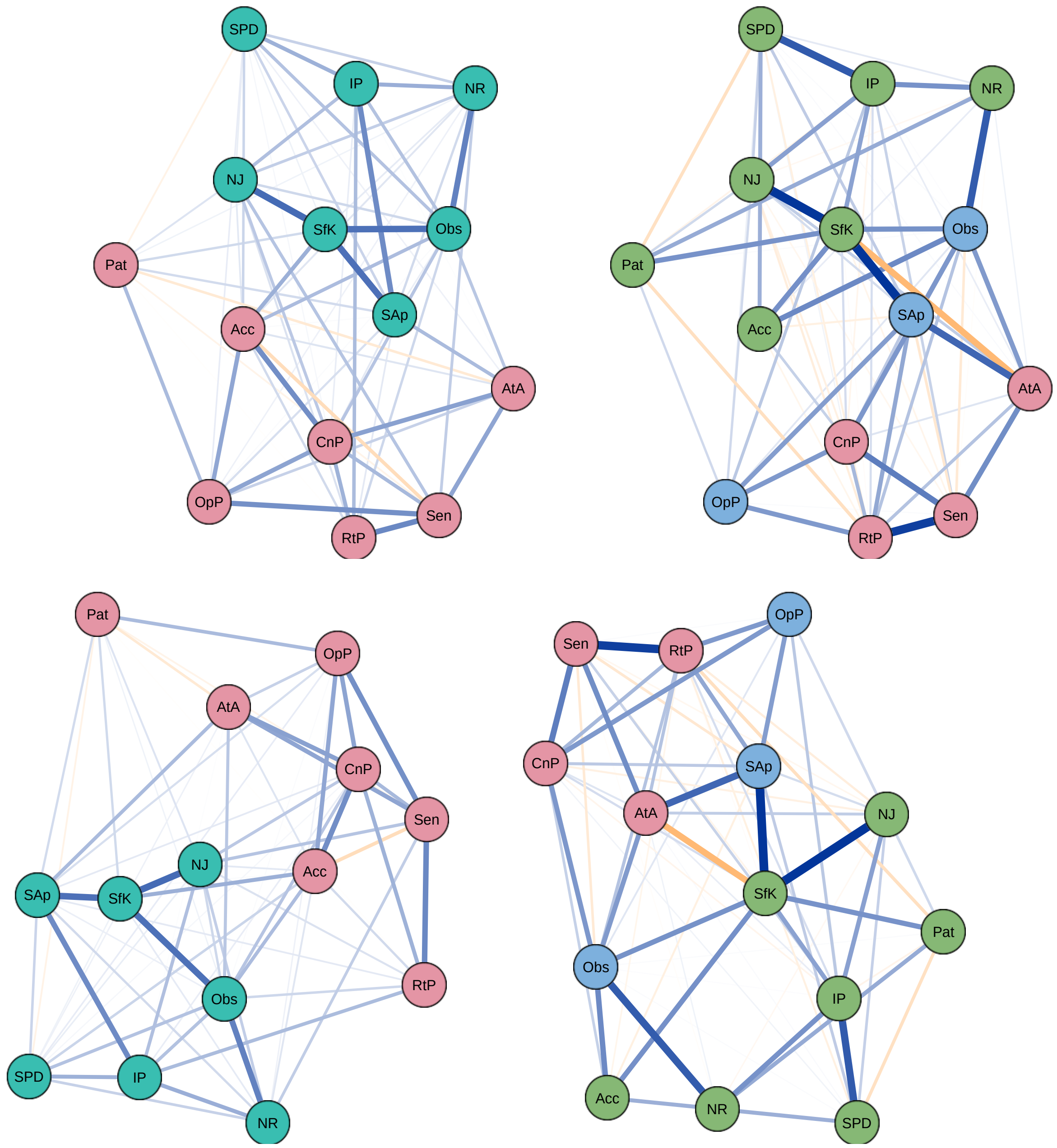


Figure 7. Glasso FMI mindfulness networks for practitioners (left) and non-practitioners (right). Each node represents a questionnaire item (abbreviated; see table 6). Each pathway represents the regularized covariance between two components. Thicker pathways signify stronger associations. Blue denotes a positive association and orange denotes a negative association. To assist comparisons, identical positioning (layout) of practices was imposed in the top networks. This involved taking the mean of the individual layouts represented in bottom figures. Minimum path weight for inclusion was set at 0 for both networks, and the maximum 0.38 (the maximum path value found across the networks). The gamma value used

was 0.5. Graphs depict communities detected using the *Exploratory Graphical Analysis* package (EGA, Golino & Epskamp, 2017). The Fruchterman-Reingold algorithm (FR, Fruchterman & Reingold, 1991) was used to layout all graphs. This algorithm tends to cause the most central nodes to migrate to the centre.

Table 5

FMI items, content, abbreviations, means, and standard deviations.

Item	Item content	Abbreviations	Practitioners (*n* =368) *M* (*SD*)	Non-practitioners (*n* = 224) *M* (*SD*)
FMI1	I am open to the experience of the present moment	*Openness to Present (OpP)*	3.11 (0.68)	2.80 (0.77)
FMI2	I sense my body, whether eating, cooking, cleaning or talking	*Sensing the Body (Sen)*	2.86 (0.81)	2..29 (0.96)
FMI3	When I notice an absence of mind, I gently return to the experience of the here and now	*Returning to the Present (RtP)*	2.80 (0.77)	2.20 (0.95)
FMI4	I am able to appreciate myself	*Self-Appreciation (SAp)*	3.05 (0.81)	2.64 (0.93)
FMI5	I pay attention to what's behind my actions	*Attending to actions (AtA)*	3.10 (0.75)	2.67 (0.87)
FMI6	I see my mistakes and difficulties without judging them	*Being Non-Judgemental (NJ)*	2.67 (0.81)	2.15 (0.92)
FMI7	I feel connected to my experience in the here-and-now	*Connected to the Present (CnP)*	3.00 (0.73)	2.54 (0.82)
FMI8	I accept unpleasant experiences	*Acceptance (Acc)*	2.80 (0.83)	2.48 (0.87)

FMI9	I am friendly to myself when things go wrong	*Self-Kindness (SfK)*	2.67 (.90)	2.36 (0.95)
FMI10	I watch my feelings without getting lost in them	*De-centered Observation (Obs)*	2.84 (0.80)	2.39 (0.96)
FMI11	"In difficult situations, I can pause without immediately Reacting"	*Non-Reactivity (NR)*	2.86 (0.80)	2.51 (0.88)
FMI12	"I experience moments of inner peace and ease, even when things get hectic and stressful"	*Experiencing Inner Peace (IP)*	2.76 (0.84)	2.09 (0.87)
*FMI13	"I am impatient with myself and with others"	*Patience (Pat)*	3.03 (0.88)	2.95 (0.90)
FMI14	"I am able to smile when I notice how I sometimes make life difficult"	*Smiling at personal difficulties (SPD)*	2.69 (0.83)	2.12 (0.88)

** Item 13 is reverse coded*

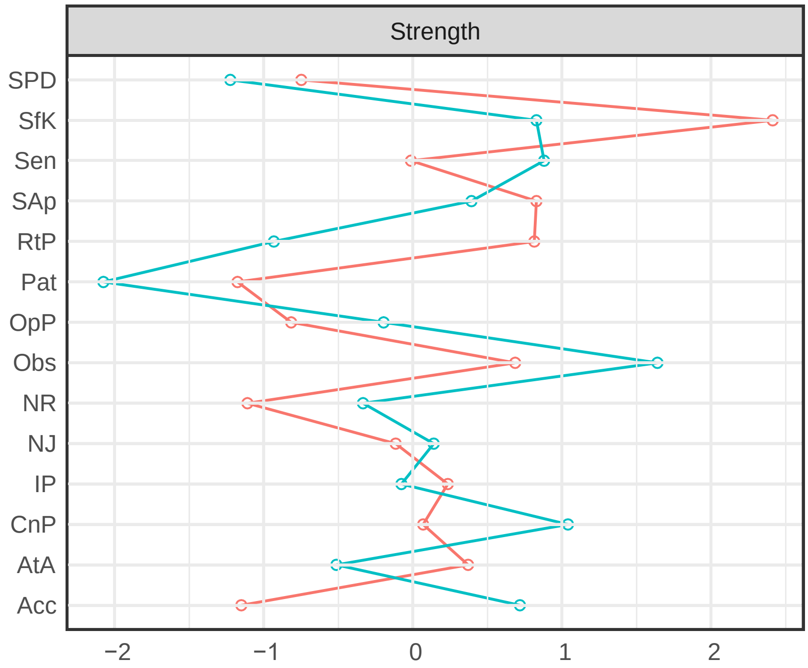


Figure 8. Standardized strength centrality values for practitioners' (blue) and non-practitioners' (red) 14 item FMI mindfulness network. Z-scores are shown on x-axis rather than raw centrality indices to allow for comparison.

The exploratory networks shared a similar number of paths (practitioners = 69 paths; non-practitioners = 67 paths). Interestingly, a visual inspection suggested that many of the paths in the non-practitioners tended to be stronger than those in their practicing counterparts. Broad similarities were observed as evident in the strong correlation between the path weights of the practitioner's and non-practitioners networks (co-efficient of similarity r_s = .51), and moderate correlation of strength centrality indices (r_s = 0.36; n.b., strong correlations were found for closeness centrality r_s = 0.55 and betweenness centrality r_s = 0.64). The community detection algorithm (EGA; Golino & Epskamp, 2017) revealed two communities of items in the practitioner sample, and the practices of each closely resembled the items attributed to previous two-factor (Presence and Acceptance) models recovered in the FMI factor analysis literature. Those naming conventions were used accordingly. Three communities of items were recovered in the non-practitioners' network. Communities of items resembling the Presence and Acceptance communities were identified in the practitioners' network, although both these communities lost items to a third community which now mediated their influence on each other. This community was termed a *brokering* community given its relative autonomy, yet mediating function[19].

The community level differences were borne out in differences in centrality and path structure. In the practitioners' sample, a number of highly central practices (*Decentred*

[19] In the wider network literature, Csermely (2008) has suggested that nodes which functionally perform a partially random sampling of the whole network, whilst connecting distant modules might be considered "active centres" or "creative elements". Csermely (2008) suggests that the relative autonomy of these "creative elements" afford greater flexibility to networks experiencing atypical situations. This is because they switch communities, allowing a network to adapt and re-organise into new stable states.

Observing, followed by *Connected to the present*, *Sensing*, *Self-Kindness* and *Acceptance*) were identified. Bootstrapped statistical difference tests revealed no significant differences between the strength centrality values of these practices (no correction for multiple testing; see Appendix J, Figure 27). By way of contrast, the non-practitioners' network was dominated by the highly strength central practice of *Self-Kindness*, which statistically differed from all other practices in that network (no correction for multiple testing; Appendix J, Figure 27).

The exploratory analysis focused on those practices which evidenced the greatest differences in centrality across networks. It was thought that these differences might imply structural changes associated with a regular practice. Figure 8 shows that the most prominent differences in centrality were observed in the three practices of *Returning to the Present, Self-kindness,* and *Acceptance*. To a lesser extent, differences were also observed in *De-centered Observation, Sensing, Connected to the Present, Patience* and *Attending to Actions*.

Returning to the present was found to both much more peripheral to the practitioners relative to non-practitioners. *Self-kindness* was a highly central practice for practitioners, yet remained substantially less central to their network relative to its position in the non-practitioners' network. The practice of *Acceptance,* peripheral to non-practitioners, was found to be substantially more central to practitioners. These practices formed the focus of further visual (topological) analysis.

Across both networks, *Returning to the present* shared prominent paths with the practices of *Sensing* and *Connected to the present*, the former stronger in the non-practitioners network (practitioners: *RtP-Sens M* = .22, 95% CI [.11, .33]; *RtP-CnP* = .15, [.01, .28]; non-practitioners: *RtP-Sens* = .33, [.18, .47]; *RtP-CnP* = 0.15, [-.01, .31]. In the non-practitioners network, additional prominent paths were shared with *Openness to the Present* (*RtP-OpP* = .18, [.04, .31]) and *Self-Appreciation* (*RtP-SAp* .10, [-.05, .25]). In the practitioners network, the former path was missing (*RtP-OpP* = 0, [-.07, .07]) and the latter, attenuated (*RtP-Sap* = .04, [-.06, .14]).

Self-kindness shared several common paths across both networks. The most obvious paths were with the practices of *De-centered Observation, Non-Judgmental, Acceptance,* and *Self-appreciation*. These paths tended to be stronger in the non-practitioners' network with the exception of *Decentred Observation* (practitioners: *Sfk-Obs* = .26, [.14, .39]; *SfK-NJ* = .28, [.15, .40]; *SfK-Acc* = .15, [.02, .27]; *SfK- SAp* = .27, [.14, .40]; non-practitioners: *SfK-Obs* = .19, [.06, .32]; *SfK-NJ* = .36, [.23, .49]; *Sfk-Acc* = .19, [.06, .32]; *SfK-SAp* = .33, [.17, .49]. In the non-practitioners' network, *Self-kindness* shared unique paths to *Inner Peac*e (*SfK-IP* = .16, [.02, .30]) and *Attending to Actions* (*SfK-AtA* = -.12, [-0.31, .08]) which were absent in the practitioners network (*SfK-IP* = 0, [-.7, .7]; *SfK-AtA* = 0, [-.05, .5]).

The topology of *Acceptance* differed in important ways. Falling in the Presence community in practitioners, *Acceptance* shared prominent paths with the affiliated Presence practices of *Openness to the present* (*Acc-OpP* = .16, [.02, .30]), *Connected to the present* (*Acc-CnP* = .18, [.04, .31]), and a uniquely negative path with *Sensing* (*Acc-Sens* = -.11, [-.26, .04]). These paths were either missing or much attenuated in the non-practitioners' network (*Acc-OpP* = 0, [-.06, .06]; *Acc-CnP* = .06, [-.07, .20]; *Acc-Sens* = 0, [-.07, .07]). Instead, *Acceptance* fell in the Acceptance community in the non-practitioners' network. Here, it shared its most prominent paths with *Self-Kindness* (*Acc-SfK* = .20, [.06, .32]), *Smiling in Difficulty* (*Acc-SPD* = .13, [-.01, .28]), and the brokering practice of *De-centered Observation* (Acc-Obs = .20, [.06, .34]). All these paths were attenuated in the practitioners' network (*Acc-SfK* = .15, [.02, .27]; *Acc-SPD* =.08, [-.03, .18]; *Acc-Obs* = .12, [.01, .26]).

The stability of negative paths was investigated by comparing the networks with networks estimated with Spearman's correlations (Appendix K). Comparisons between the exploratory networks and Spearman's networks suggested that the path between *Self-kindness* and *Attending to Actions* was likely a stable network feature, but that the path between *Acceptance* and *Sensing* should be interpreted more cautiously (this path was missing in the Spearman's network). The negative paths between *Patience* and both *Returning to the Present* and *Smiling at Personal Difficulties* in the non-practitioners' network (*Pat-RtP* = .07 [-.64, .64]; *Pat-SMD* = -.04 [-.02, .09]) were also maintained in the corresponding Spearman's network.

Cross-tables were also explored to ascertain whether adequate sampling had occurred. Olsson (1979) has recommended that cells should have at least 10 cases for stable polychoric correlations. Inspecting the cross-tables for all four negative paths revealed that no cells had 0 cases; however, for all four paths, seven of the 16 cells had less than 10 cases. Taken together, these results suggest some caution in interpreting the negative paths, especially that between *Acceptance* and *Sensing* in the practitioners' network.

6.1.4 Discussion of the FMI results. As a general point, the estimated networks revealed the plausibility of a network conceptualisation of mindfulness: plausible bi-directional paths (predictive associations) were revealed among most, if not all the items. Negative paths and missing paths were revealed which are more difficult to reconcile with a latent variable approach, as a common factor model would imply a fully connected network of positive edges (Marsman et al., 2018). That said, the effects of regularisation cannot be discounted as it by design, retrieves a sparser network.

6.1.4.1 Network comparison tests. It was proposed that network density may distinguish practitioners from non-practitioners. The evidence favoured the null hypothesis: the majority of practitioners' and non-practitioners' resampled networks did not statistically differ in global strength. Support was found for a significant difference in network structure (62% of 500 networks), albeit this attenuated as the networks become more similar (i.e., the networks increased in sensitivity).

The failure to reject the null hypothesis is not inconsistent with the mixed findings in psychopathology studies which have investigated group level density differences between symptomatic and asymptomatic participants (e.g., Fried et al., 2016; Schweren et al., 2017; van Loo et al., 2018). Although the results can be taken as evidence against the main hypothesis, the absence of a statistical difference does not necessarily mean the two groups did not differ (i.e. an absence of evidence is not evidence of an absence). Rather, methodological and statistical considerations need to be taken into account (Lesaffre, 2008). To this end, it is noted that the study may have been underpowered. The NCT requires a lot of power to detect differences (Fried, 2017), and although the current study came close to achieving a recommended sample size (three persons per parameter), the networks were only moderately accurate in their estimation. This is suggestive of insufficient sampling which may have reduced the power of the NCT to detect network differences.

The quality of sampling may also have contributed to reduced sensitivity. In a previous study, Sauer and colleagues (2015) found that only one FMI item (item 2, *Sensing*) had acceptable discriminative properties for differentiating practitioners from non-practitioners in a study using online recruitment. By way of contrast, many more items were found to be discriminative in a second high-quality sample in which practitioners represented subjects with at least five years of daily meditation practice[20]. Future research may wish to sample different populations (e.g., university practitioners), although it is noted that the results of the current study were found to better resemble those obtained from Sauer and colleagues (2015) high-quality sample (this is discussed further in a later section).

Two further points bear mention. Firstly, a visual inspection of the two networks appears to suggest that a larger number of relatively weaker interconnections characterised

[20] The high quality sample consisted of 38 expert mindfulness practitioners with at least five years of regular practice, age and gender matched with a group of 28 non-practitioners. See Sauer, Lemke, et al. (2012) for details.

the practitioner's network, relative to fewer, but stronger paths in the non-practitioners' network. Summing the interconnections would lead to comparable density scores which obscures the possibility of different underlying developmental processes (i.e., the development of *more* associations between practices versus the development of *stronger* associations). The concept of density may thus require further theoretical refinement.

Secondly, evidence of range restriction was found in the non-practitioners' sample (variation was moderately correlated with practice strength). A visual analysis of floor and ceiling effects suggested that this was unlikely to have biased network structure, but it may however, limit the generalizability of results. This is because observed differences may not remain in other populations in which item variance differs (for example, samples in which variability may be found to be comparable across all items).

6.1.4.2 Community analyses. The exploratory analyses ascertained *how* the networks may have differed across groups. At the community level, greater differentiation was observed in the practitioners' network relative to the non-practitioners' network (manifest as strong intra-community paths, but weaker inter-community paths). This is interesting in light of factor research which has suggested that factorial differentiation may reflect the development of an attribute (see General Discussion, chapter 7 for further consideration).

6.1.4.3 Centrality analysis. The centrality analysis revealed a number of Presence community practices (*Decentred Observing*, *Connected to the present*, *Sensing*, *Acceptance*) to be highly central for practitioners relative to non-practitioners (with the exception of *Self-kindness*). Of these, *De-centered Observation* ("I watch my feelings without getting lost in them") was the most strength central, but this did not statistically differ from other Presence practices. This means its prominence may not generalise beyond the sample. For non-practitioners, *Self-kindness* ("…friendly to myself when things go wrong") dominated the network, statistically differing from all other practices.

In interpreting centrality, it must be remembered that relatively higher strength centrality does not infer relatively higher mean levels of a practice, for mean levels are not taken into account in estimating the covariance matrix. Nonetheless, generally higher strength centrality may index a greater degree of development of a practice given that connectivity, summed to provide the strength centrality index, was theorised to increase across the development of a mindfulness practice[21]. Some evidence in support of this may be found in research investigating the FFMQ *observing* facet (attending to internal and external experience)s, of which the Presence practices are considered representative. FFMQ research has shown that *observing* is a key facet of mindfulness, but only once a certain level of meditation practice has been established (Baer et al., 2008; see also, Camody & Baer, 2008; Lilja, Lundh, Josefsson, & Falkenström, 2013; Williams, Dalgleish, Karl, & Kuyken, 2014). The current study thus compliments factor research by suggesting that high item centrality may offer an additional way of indexing development, beyond the summation of mean levels of item endorsement.

The high centrality of *Self-kindness* across both groups could be considered consistent with research which has established the importance of self-kindness (Manavipour & Saeedian, 2016; Stallman, Ohan & Chiera, 2017) and self-compassion (of which self-kindness is a considered a facet; Neff, 2003) to mindfulness (Hollis-Walker & Colosimo, 2011; MacBeth & Gumley, 2012; Marsh, Chan, & MacBeth, 2018; Shapiro et al., 2005; van Dam, Sheppard, Forsyth & Earleywine, 2011; Zessin et al. 2015). The broader concept of self-compassion has been shown to increase with mindfulness instruction (Shapiro et al., 2005), better predict health outcomes than mindfulness (van Dam et al., 2011) and mediate the association between mindfulness and positive outcomes (Hollis-Walker & Colosimo,

[21] It is again worth mentioning that connectivity could represent a few very strong paths, or many, relatively weaker paths.

2011). A number of meta-analyses have also associated higher levels of self-compassion with lower levels of mental health symptoms (MacBeth & Gumley, 2012; Marsh, Chan, & MacBeth, 2018), as well as greater overall psychological well-being (Zessin et al. 2015).

In undirected networks, it is unknown whether highly strength central practices are common causes (by which the direction of causality travels from the focal node to other nodes in the network), common effects (in which causality travels to the focal node from other nodes in the network), or both. When it is assumed that highly strength central practices are common causes, these practices have been considered candidate practices for network interventions (Borsboom & Cramer, 2013; Borsboom et al., 2011; Newman, 2004). This is because changes in these practices may propagate across the network. In the absence of information on directionality, the results of this study generate a hypothesis that targeting *De-centered Observation* may be an important practice for *galvanising* (or maintaining) mindfulness in regular practitioners. Prima face, targeting *Self-kindness* may be important for galvanising mindfulness in non-practitioners[22].

6.1.4.4 Network differences. The most apparent differences in centrality were found in the practices of *Self-kindness*, *Returning to the Present* (relatively more central to non-practitioners), and *Acceptance* (relatively more central to practitioners'). A prominent negative path between *Self-kindness* and *Attending to Actions* was also found to be unique to the non-practitioners' network. This will be discussed first.

The unique negative path helps account for the high centrality of *Self-kindness* in non-practitioners, for it is taken as an absolute value in centrality calculation. Although speculative, the negative path can be interpreted in two ways: either being "…friendly to myself when things go wrong" (*Self-kindness*) predicts less "…attention to what's behind my

[22] A caveat on this recommendation is the suggestion in the literature that self-compassion may arise after mindfulness (Neff, 2003; Birnie, Speca, & Carlson, 2010; Bergen-Cico & Cheon, 2014). This interpretation is more consistent with a common effect interpretation, making the practice less suited to intervention.

actions" (*Attending to Actions*) in non-practitioners only (i.e., a *letting one off the hook* explanation); or alternatively, regularly attending to what's behind one's actions predicts less self-kindness in non-practitioners only. An obvious interpretation is that *Attending to Actions* may index a more critical or judgmental process in non-practitioners, relative to practitioners. This interpretation is broadly consistent with the results of a qualitative study of the FMI (Belzer et al., 2013 in which non-practitioners were found to interpret *Attending to Actions* in the context of a moral evaluation of pro's and con's. By way of contrast, practitioners interpreted the item (more homogenously) in the context of "continuous action monitoring" (p. 40) or the "mere registration of impulses, emotions, behaviours of the self in the present moment" (p. 40)[23].

The *letting one off the hook* interpretation has received little consideration beyond popular commentary (Neff, 2012); however, the judgmental or *critical processing* interpretation, taken together with the absence of this path in the practitioners' network, is consistent with a large body of work associating mindfulness with reduced self-criticism and rumination (e.g., Teadale, Segel & Williams, 1995; van der Velden et al., 2015). Plausibly, *critical processing* may have been ameliorated or impeded by a regular mindfulness (or related meditative) practice, accounting for its absence in the practitioners' network. Presuming that the practitioners' network resembles a network architecture conducive to the capacity to be mindful, the results suggest that interventions targeting this negative path may facilitate a network more conducive to mindfulness. Certainly, the centrality of *Self-kindness* would become more comparable, for beyond the negative path, the topology of the practice is markedly similar across groups. It might also be predicted that *Acceptance* may become more central, for this is almost an antonym for critical processing,

[23] Perhaps consistent with this, a relatively stronger path was seen between *Attending to Actions* and *Connected to the Present* ("I feel connected to my experience in the here-and-now") in the practitioners' network.

The convergence between network topology and qualitative results makes it difficult to distinguish whether a regular mindfulness practice may attenuate the negative path between the practices (presumed invariant across the groups), or lead to a practice being interpreted differently, or both. This has implications for investigations into network dynamics and intervention recommendations, for these presume measurement invariance (i.e., that the nodes/practices themselves do not change across time or represent different things to different groups). It thus remains unclear whether the practice of *Attending to Actions* (interpreted as a judgmental/critical process) is the appropriate target, or whether the path it shares with *Self-kindness* is the preferred target. In theory, the latter intervention would not change the nodes *per se*, for it only targets the mechanisms underpinning the (presumed) causal association. In practice, this issue is likely less of a concern as psychological interventions are typically *fat-handed,* by which it is meant that a number of variables are typically influenced (Bringmann et al., 2018).

Determining whether practices are variant, or invariant is further complicated when it is recognised that any given practice may evidence both differences and similarities in topology (suggesting practice variance and invariance respectively). To suggest that *Attending to Actions* refers categorically to *critical processing* in non-practitioners will thus only create flow on problems in interpreting other paths. For example, one is left theorising why critical processing shares positive paths with *Self-Appreciation*, *De-centered Observation*, *Connected to the Present* and *Sensing*. A more plausible explanation may be that a degree of heterogeneity underlies the non-practitioner’s sample, such that different sub-groups exist; one of which is characterised by high levels of self-critical processing. *Person-orientated* approaches such as *cluster analysis* (e.g., Lilja et al., 2013) and *Latent Class Analysis* (e.g., Pearson, Brown, Bravo, & Witkiewitz, 2015) may be suited to elucidating such subgroups, albeit they invoke different interpretations to network analysis.

In lieu of these considerations, the results are considered best interpreted as supporting the more general recommendation for interventions aimed at critical processing. This is considered consistent with the literature which has identified reductions in rumination as a mechanism of change in mindfulness (van der Velden et al., 2015). Future experimental and temporal research may help elucidate the effects of such interventions on network architecture and dynamics.

Belzer and colleagues' (2013) study provides further insight into the topological differences in the other two practices in which the most pronounced differences in centrality were observed. In practitioners, *Acceptance* fell in the Presence community, consistent with Belzer and colleague's (2013) findings that practitioners tended to stress the *present moment* aspect of the *Acceptance* practice in their interpretation of the item. By way of contrast, Belzer and colleagues (2013) found that non-practitioners tended to interpret the item as a statement about past experiences. Correspondence is less clear; however, the prominent path with *Smiling at Personal Difficulties* ("I am able to smile when I notice how I sometimes make life difficult") might be considered consistent with this, given that the item content can imply a past tense.

This present moment/statement of past experiences distinction also bears some resemblance to Grabovac, Lau and Willett's (2011) distinction between awareness based and cognitive acceptance. Awareness based acceptance refers to *awareness without judgment* which was considered to develop with mindfulness practice. This was differentiated from cognitive forms of acceptance, which the authors associated with activity such as thinking accepting thoughts about one's self or others. Although speculative, the paths with Presence practices in the practitioners' network may thus be indicative of a more insight-based acceptance developed through a regular practice, whilst the paths *Acceptance* shared with *Self-kindness* and *Smiling at Personal Difficulties* in the non-practitioners' network might be considered more consistent with a cognitive practice (that said, the third prominent path with *De-centered Observation* could be considered inconsistent with this).

Convergence between topology and observed comprehension differences may also inform the interpretation of *Returning to the Present* ("When I notice an absence of mind, I gently return to the experience of the here and now"). In the practitioners' network, this practice featured prominent paths with practices indexing mindfulness skills such as *Connected to the present* ("I feel connected to my experience in the here-and-now") and *Sensing* ("I sense my body, whether eating, cooking, cleaning or talking"). This was considered broadly consistent with Belzer and colleagues (2013) finding of the practice being interpreted as the prototypical mindfulness skill ("this describes exactly mindfulness meditation"; p. 39) in their practicing sample. Correspondence was less clear for non-practitioners, as the paths with *Self- appreciation* ("I am able to appreciate myself") and *Openness to the present* did not obviously correspond to Belzer and colleagues (2013) findings of non-practitioners interpreting the item in the context of returning to everyday tasks after distraction (i.e., "waking up", p. 39). This lack of correspondence might be taken to support the previous suggestion of possible heterogeneity underpinning the non-practitioner's sample.

The final features warranting further discussion were the brokering practices (*Self-appreciation*, *Openness to the Present* and *De-centered Observation*). Given that *Openness to the Present* and *De-centered Observation* have already been interpreted in the discussion of centrality differences, only *Self-appreciation* is analysed.

Across both groups, *Self-appreciation* shared a common strong path with the only other positively worded introspective item; namely *Self-kindness* ("I am friendly to myself when things go wrong"). This is considered consistent with observations that semantically similar items may tend to cluster in semantic fluency research (e.g., Zemler & Austerweil, 2018). Beyond this, the topologies differed markedly between groups[24]. In practitioners, *Self-appreciation* shared one especially prominent path with the only truly experiential practice in the FMI; namely, *Inner Peace* ("I experience moments of inner peace and ease, even when things get hectic and stressful"). For non-practitioners, *Self-Appreciation* shared a number of prominent paths with the practices which appeared more performative; namely, *Attending to Actions, Returning to the Present* and *Openness to the present*[25]. Although purely speculative, this difference might be interpreted in lieu of the prominent conceptualisation of mindfulness as a practice which shifts practitioners from *doing* (in which awareness is dominated by relatively impersonal goal-oriented strategies) to *being* (in which awareness is dominated by a non-evaluative awareness of present subjective-self-experience; Barnard & Teasdale, 1991). Accordingly, the path between *Self-appreciation* and *Inner Peace* may be indicative of being, whilst the broader connectivity with a number of performative practices evident in the non-practitioners' network may be indicative of doing. In support of this interpretation, Belzer and colleagues (2013) reported *Self-Appreciation* to have been interpreted in the context of meditation experience for practitioners, but personal performance in non-practitioners.

Several other findings bear mention. Firstly, the identification of two communities in the practitioners' network support the results found in factor analyses of the FMI, albeit with a different method. This is consistent with research suggesting that communities recovered in network analyses, under certain conditions, are mathematically equivalent to factors (Golino & Epskamp, 2017). Of course, the two models offer very different interpretations of the data:

[24] It is worth noting that *Self-Appreciation* is similar in its relative centrality across both groups, despite being organised quite differently. A focus on centrality values alone can thus miss important topological differences.

[25] Although the path shared with *Openness to the Present* might be considered contrary to this, Belzer and colleagues '(2013) findings suggest that this item may been interpreted more performatively in non-practitioners'; namely, as an attitude "openness", rather than an experience.

community structures are assumed to represent interrelations forming among practices whilst factors represent underlying causes.

Secondly, the practices which demonstrated the most discrepant centrality (*Self-Kindness*, *Returning to the present*, *Acceptance,* and to a lesser extent *Decentred Observing*, *Connection to the present*, *Sensing* and *Attending to Actions*) have also been identified as usefully discriminative in previous research. Using machine learning methodologies, Sauer and colleagues (2015) found all these practices (in addition to the practices of *Self-Appreciation* and *Inner Peace*) to be those which best predicted group membership (practitioner or non-practitioner) in their high-quality sample. When both the high- and low-quality samples were combined in a second study, a more limited selection of the same practices was also found to demonstrate high predictive accuracy using a different algorithm (Sauer et al, 2018)[26]. This convergence between the current study and a previous study using a high-quality sample may be taken as evidence in support of the sampling quality of the study, and the feasibility of using MTurk for mindfulness research.

In summary, several conclusions follow. Firstly, the plausibility of a network explanation for the covariance observed in the FMI was established. The estimated paths were plausible and connectivity differences could meaningfully be interpreted in the wider literature. Secondly, convergence between topological interpretations and previous qualitative research brought into question the nature of the networks estimated. Comparative network studies have typically assumed that items index the same sampled behaviours across groups, and this was inferred in the hypothesis and rationale of this study (i.e., comparing density and centrality; postulating differential organisation and brokering practices). Contrary to this, evidence of convergence between practice topologies and comprehension differences

[26] Using the most accurate algorithm (of ten), the five items with the highest predictive importance were *Returning to the Present, Sensing, De-centered Observation, Inner Peace* and *Acceptance*. That said, across all ten algorithms, the items that separated the mindfulness practitioners most strongly from the non-practitioners were the items *Returning to the Present*, *Attending to Actions* and *Smiling at Personal Difficulties.*

suggested that some practices may have been interpreted differently by the groups. It also brought into question whether the main hypothesis was not so much unsupported, as untested (i.e., one cannot meaningfully compare density when networks sample different behaviours).

In theory, future experimental research in which specific practices are subjected to manipulation may help discern whether practices are invariant across networks or not. This is because networks typically presume that their structures are potentially causal, which means that one can predict what should happen when practices or paths are manipulated experimentally. If experiments and longitudinal manipulations result in changes consistent with those predicted in both networks, it might be inferred that the practices are invariant. In the absence of this, it might be inferred that practices index different behaviours. Unfortunately, experimental research of this type may be less feasible in practice. This is because psychological interventions are typically fat-handed, such that number of practices and paths may be influenced.

In this study, the negative path between *Self-kindness* and *Attending to Actions* in the non-practitioners' network was an obvious target for future experimental research. This was interpreted as supporting a more general recommendation for interventions directed at critical processing. To this end, it is noted that self-compassion has been shown to mediate the relationship between depression and anxiety (Raes, 2010), with evidence suggesting that this may be achieved in part by reducing negative processes such as rumination (Krieger, Altenstein, Baettig, Doerig & Holtforth, 2013; Svendsen, Kvernenes, Wiker, & Dundas, 2017). Self-compassion interventions (e.g., techniques such as self-compassionate meditation, imagery, therapeutic letter writing, dialogic role-play, Gilbert 2009; or compassionate audio recordings, Arch et al., 2014) might thus be candidate techniques for targeting either the negative path between *Attending to Action* and *Self-kindness*, or the practice of *Attending to Actions* (interpreted as critical processing) itself[27].

A final point concerns the nature of the networks themselves. It was only assumed that the networks sample behaviour (i.e., the assumption of item-practice correspondence) and it is perfectly possible that the networks were purely semantic. In a semantic network, paths may represent logical and semantic relations as opposed to potentially causal behavioural paths. Future experimental research may contribute to this vexing question as effects consistent with predicted effects may be taken as evidence for paths being behavioural.

6.2 Study 2: A Network Analysis of the Applied Mindfulness Process Scale (adapted).

6.2.1 General Differences. After removing missing data, a total of 648 participants were involved in the NCT analysis of the (adapted) Applied Mindfulness Process Scale (367 practitioners, 222 non-practitioner and 59 irregular practitioners). The exploratory analysis involved a total of 589 participants (367 practitioners and 222 non-practitioners). A one-way ANOVA revealed a significant difference in (self-attributed) total AMPS Mindfulness scores across the three groups ($F(2, 645) = 71.50$, $p < .001$). Post hoc comparisons using the Turkey HSD test indicated that the mean score for practitioners ($M = 54.89$, $SD = 9.9$) was significantly different ($p < .001$) to the mean score of non-practitioners ($M = 44.70$, $SD = 10.49$, $p < .001$) and irregular practitioners ($M = 48.17$, $SD = 10.67$). No significant differences were observed between irregular practitioners and non-practitioners.

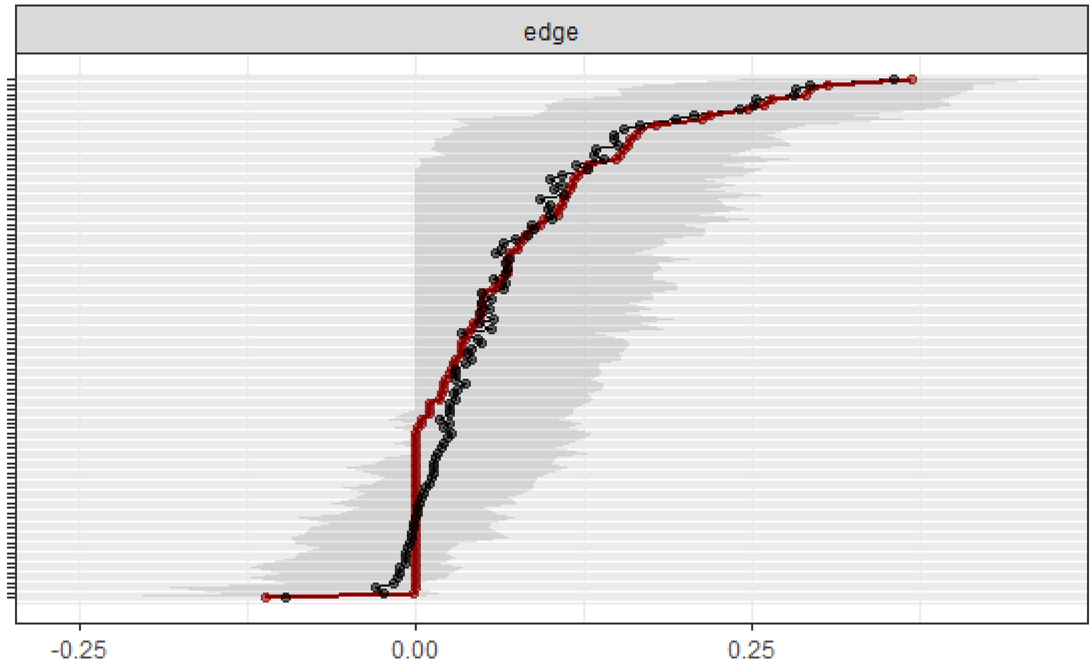
6.2.2 Aim 1: To determine whether the practitioners' network is characterised by greater network density: A global test of strength invariance. Consistent with findings in Study 1, the NCT results failed to reject the null hypothesis: Across the 500 resamples,

[27] It is noted that many techniques will influence self-compassion, beyond those in name. In a recent review Wilson, and colleagues (2018) concluded that "we should…be cautious about claiming that it is possible to 'target' self-compassion in therapy. Instead, it would seem that self-compassion is one of the many psychological characteristics that are modifiable during the course of a range of therapies" (p. 12).

there was no evidence for a difference in global strength between the groups AMPS networks (median *S* = 0.80, median *p* = 0.20). Only 25% of the 500 resamples significantly differed in global strength at $p < .05$.

6.2.3 Aim 2: Investigating the architecture of mindfulness: A global test of network structure invariance and exploratory analysis of network structure. Support for structural differences in the AMPS networks was found: 79% of the 500 resamples (median *L* = 0.28, median *p* = .02) were significantly different in network structure ($p < .05$), and this difference persisted at higher gamma levels of 0.25 (76% of samples significantly differed; median *L* = 0.27, median *p* = .01) and 0.5 (75% of samples significantly differed; median *L* = 0.27, median *p* = .02). To check for the influence of range restriction on structural differences, practice strength centrality was correlated with item variance and means. For practitioners, practice strength centrality appeared unrelated to item variability (r_s = -.01) but was moderately correlated with mean item levels (r_s = .35). For non-practitioners practice strength centrality was unrelated to item variability (r_s = -.11) or mean levels (r_s = .05).

6.2.3.1 Network stability and accuracy of exploratory networks. The results of the path weight bootstrap revealed substantial 95% CIs for most of the paths, limiting accurate comparisons beyond comparing the strongest from the weakest practices (Figure 9). This was confirmed by Bootstrapped significance tests (see Appendix I, Figure 25). The glasso selected a dense network for both groups which meant that the smallest edges of both networks required interpretation with care (Williams et al., 2018). The person-drop bootstraps confirmed the superiority of regularized (glasso) networks over their un-regularised counterparts in terms of the stability of centrality indices (Appendix H, Figure 24). Analyses were hence limited to regularized networks (Figure 10).



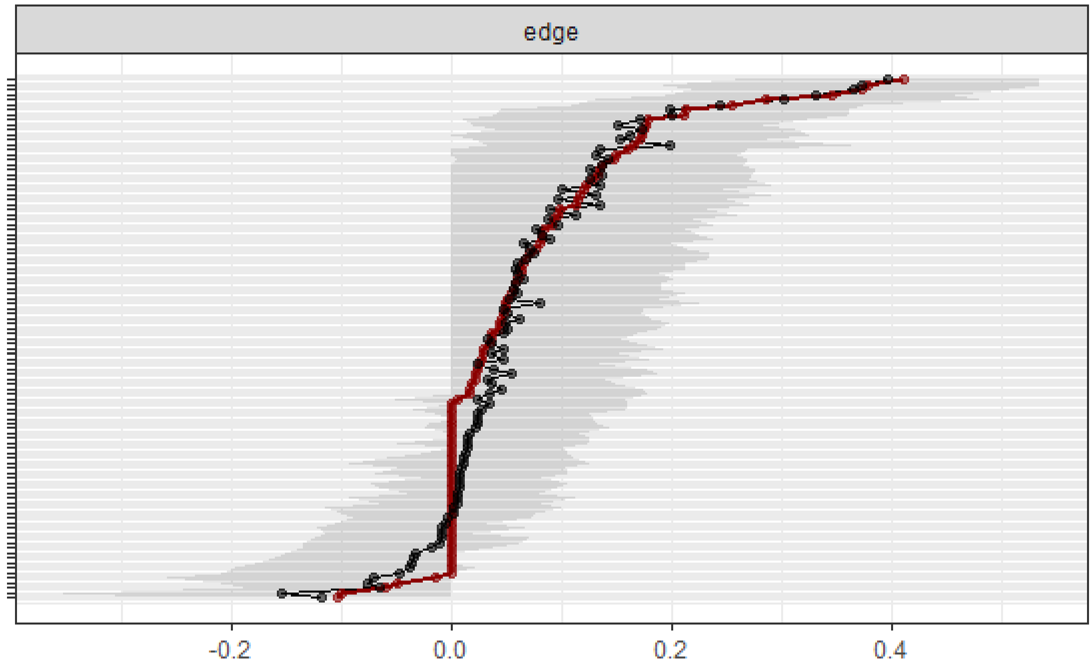
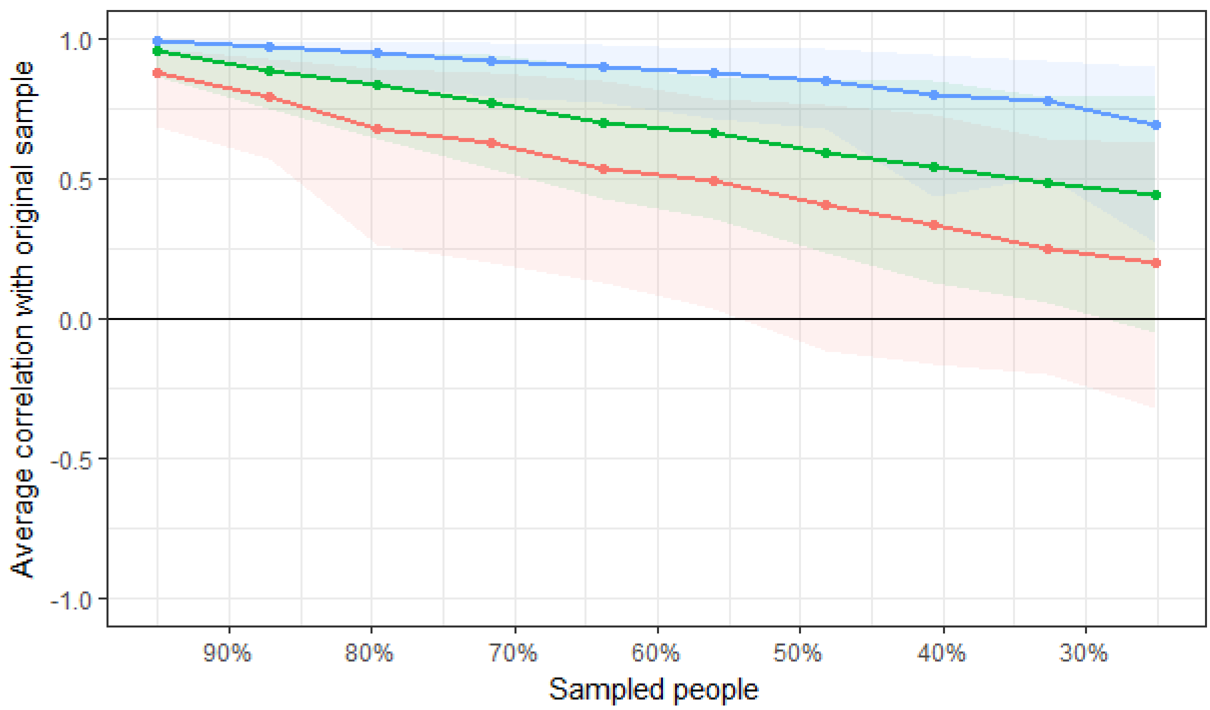


Figure 9. Bootstrapped confidence intervals (CIs) of estimated pathway weights for the estimated practitioners' (top) and non-practitioners' (bottom) regularised AMPS mindfulness networks.

Figure 10 shows the results of the subset (person-drop) bootstrap. Only strength centrality in the practitioners' network appeared stable, and this was confirmed by the *CS*-coefficients calculated: the *CS*-coefficient for strength centrality in the practitioners' network was above the recommended level of .5 (*CS* = .52), but closeness and betweenness fell below the recommended minimum level of .25 (Closeness *CS* = .13, Betweenness *CS* = .05). CS-coefficients in the non-practitioners' network were all below the minimum recommended for meaningful interpretation (strength *CS* = .13, closeness *CS* = .13, betweenness *CS* = .05). As such, the non-practitioners' network was not considered robust, rendering centrality comparisons speculative and less meaningful beyond the sample. Bootstrapped significance difference tests revealed significant differences only between the most central and least central practices in the practitioners' network (see Appendix J, Figure 28). This meant that the most central practices could not be distinguished from each other. Essentially none of the practices significantly differed in centrality in the non-practitioners network (see Appendix J, Figure 28).



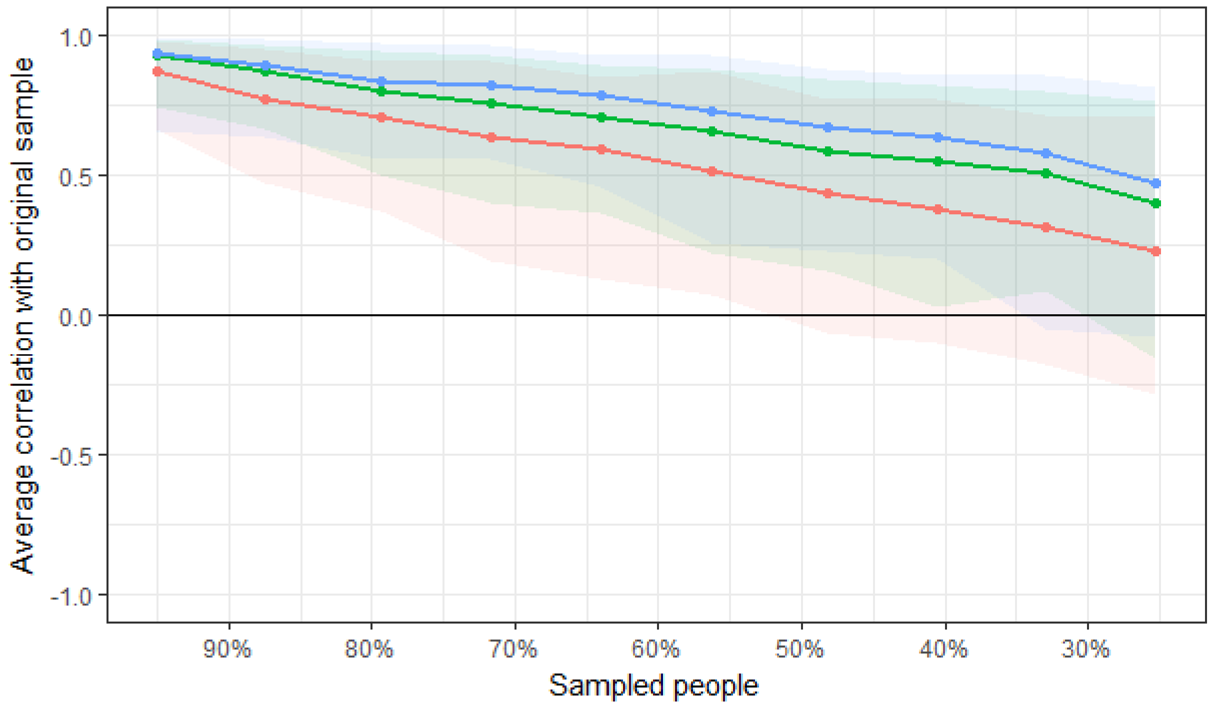
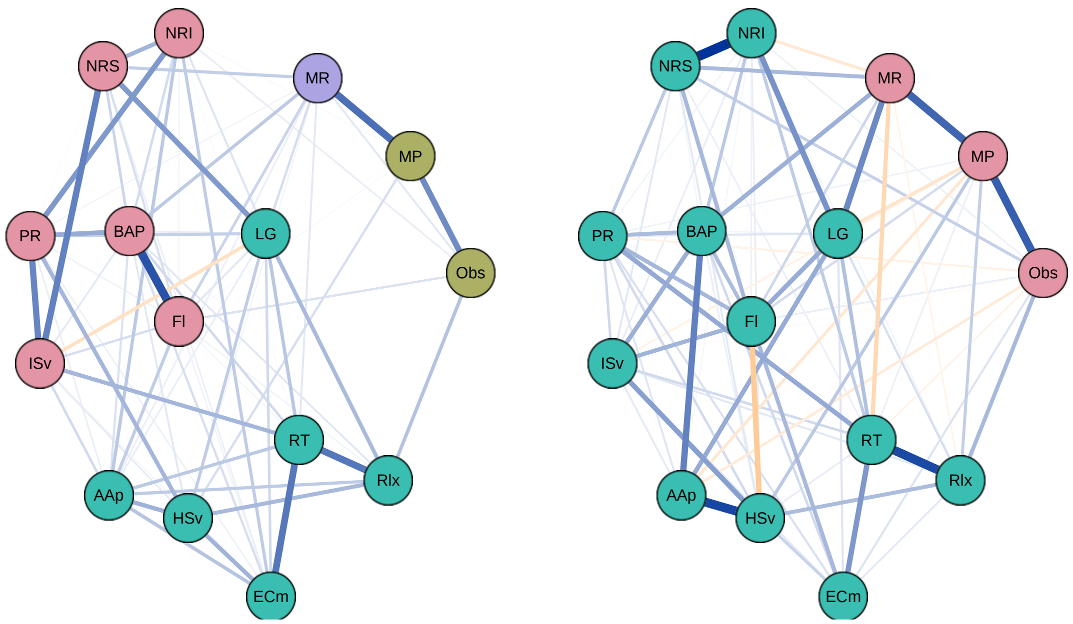


Figure 10. Average correlations between AMPS centrality indices of networks sampled with persons dropped and the original sample using the glasso networks for practitioners (top) and non-practitioners (bottom). Legend: blue = strength, green = closeness, red = red = betweenness.

6.2.3.2 Exploratory analysis of network structures. A graphical depiction of the practitioners' and non-practitioners' AMPS networks is presented in Figure 11 with centrality estimates shown in Figure 12. Table 7 contains items, corresponding item descriptions, abbreviations, sample means, and standard deviations of the network of 15 items of the AMPS.

An analysis of paths revealed that the practitioners' network had 74 paths and the non-practitioners' network, 79 paths. Visual inspection revealed substantial structural differences, borne out in weak correlations across all centrality indices (strength r_S = .16, betweenness r_S = .01 and closeness r_S = -.16). None-the-less, a moderate coefficient of similarity was obtained (r_S = .48). No substantial differences in centrality or edge weights were found between networks estimated with Pearson's correlations (used in the NCT) and the exploratory networks (practitioners: strength r_s = .78, closeness r_s = .81, betweenness r_s = .92; co-efficient of similarity r_s = .96; non-practitioners: strength r_s = 0.85, closeness r_s = .67, betweenness r_s = .78, co-efficient of similarity r_s = .90). As such, the NCT and exploratory networks were considered comparable.

The exploratory analysis focused on differences in community structure, borne out in differences of centrality and topology. The *Exploratory Graphical Analysis* (Golino & Epskamp, 2017) found four communities in the practitioners' sample and two communities in the non-practitioners' sample. Specifically, the practitioners' network was characterised by two major communities and a peripheral cluster of three practices which constituted a further two communities (although it may be a misnomer to speak of a single practice as a community). By way of contrast, the non-practitioners' network was characterised by one large community, with the same peripheral cluster of three practices forming a second community.



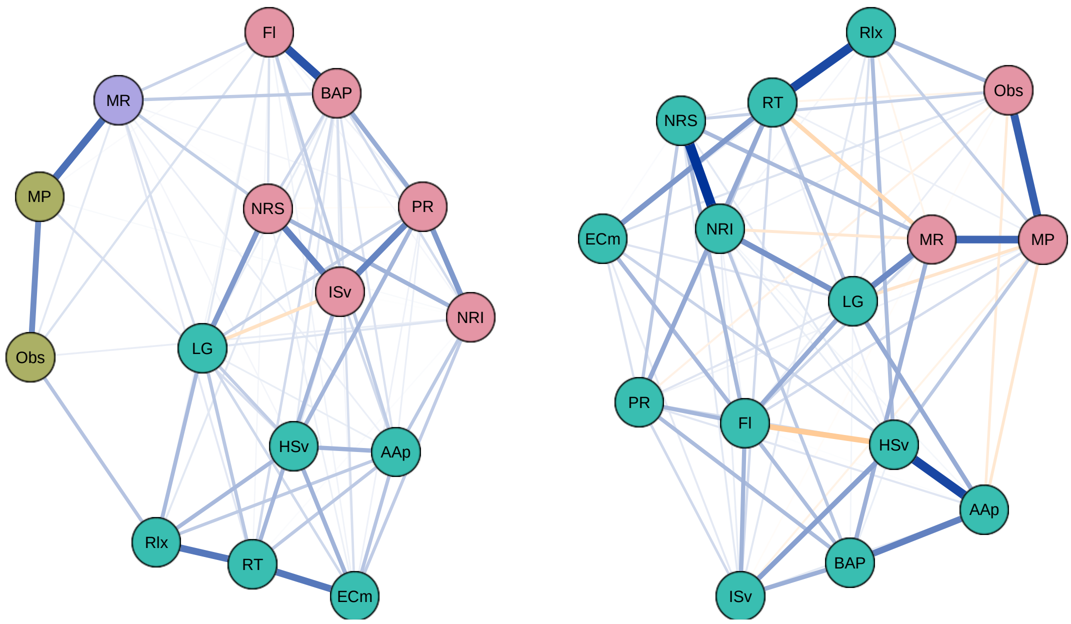


Figure 11. Glasso AMPS mindfulness networks for practitioners (left) and non-practitioners (right). Minimum path weight was set at 0, and the maximum 0.44. Gamma = 0.5. Graphs depict communities detected using the *Exploratory Graphical Analysis* package (EGA, Golino & Epskamp, 2017). The Fruchterman-Reingold algorithm (FR, Fruchterman & Reingold, 1991) was used to layout all graphs. To assist comparisons, identical positioning (layout) of practices was imposed on the top networks.

Table 6

Items, Content, Abbreviations, Means, and Standard Deviations for 15 AMPS Items.

Item	Item content	Abbreviation	Practitioners (*n* =368) *M (SD)*	Controls (*n* = 224) *M (SD)*
AMPS 1	observe my thoughts in a non-attached manner	*De-centered Observation (Obs)*	3.32 (0.93)	2..23 (0.95)
AMPS 2	relax my body when I was tense	*Relaxation (Rlx)*	3.81 (0.89)	2.75 (0.91)
AMPS 3	see that my thoughts were not necessarily true	*Metacognitive Perception (MP)*	3.38 (0.98)	2.42 (0.98)
AMPS 4	enjoy the little things in life more fully	*Hedonic Savouring (HSv)*	3.77 (0.95)	3.11 (1.05)
AMPS 5	calm my emotions when I was upset	*Emotional Calming (ECm)*	3.82 (0.92)	3.18 (1.01)
AMPS 6	stop reacting to my negative impulses	*Non-reactivity to Impulses (NRI)*	3.56 (0.91)	2.95 (0.97)
AMPS 7	see the positive side of difficult circumstances	*Positive Reappraisal (PR).*	3.71 (0.97)	3.16 (1.01)
AMPS 8	reduce tension when I was stressed	*Reduce Tension (RT)*	3.75 (.95)	3.02 (0.95)
AMPS 9	.realize that I can grow stronger from difficult circumstances	*Implicational Savouring (ISv)*	3.75 (0.99	3.16 (1.12)
AMPS 10	stop my unhelpful reactions to situations	*Non-reactivity to Situations (NRS)*	3.58 (0.91)	2.94 (1.01)
AMPS 11	be aware of and appreciating pleasant events	*Awareness and Appreciation (AAp)*	3.81 (0.84)	3.50 (1.07)
AMPS 12	let go of unpleasant thoughts and feelings	*Letting Go (LG).*	3.69 (0.89)	2.99 (0.96)
AMPS 13	realize that my thoughts were not facts	*Metacognitive Realization (MR)*	3.54 (1.03)	2.88 (1.06)
AMPS 14	notice pleasant things in the face of difficult circumstances	*Broadening Attention (BAP)*	3.59 (0.98)	3.00 (1.04)
AMPS 15	see alternate views of a situation	*Flexibility (Fl)*	3.81 (0.89)	3.41 0.97)

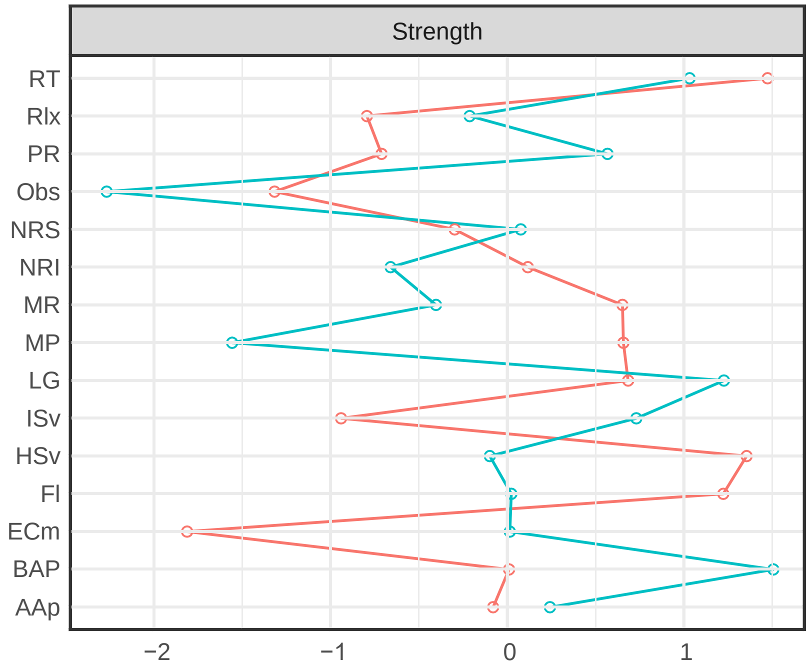


Figure 12. Strength centrality measures for practitioners (blue) and non-practitioners (red) for the 15 item regularised AMPS mindfulness networks.

Those practices most strength central to practitioners were *Broadening Attention*, followed by *Letting Go* and *Reducing Tension*. Those practices most strength central to the non-practitioners' network were *Reducing Tension*, *Hedonic Savouring* and *Flexibility*.

Substantive group level differences in centrality were found in a large number of practices. The practitioners' network was revealed to be one in which *Positive Re-appraisal*, *Implicational Savouring*, *Emotional Calming*, and *Broadening Attention* were highly central relative to their position in the non-practitioners' network. The two *Meta-cognitive* practices (*Perception and Realisation)*, *Hedonic Savouring*, and *Flexibility* were found to be much more peripheral to the practitioners' network, relative to their position in the non-practitioners network. The non-practitioners' network was one in which the practices of *Returning to the Present*, *Hedonic Savouring* and *Flexibility* were highly central, but *Emotional Calming* and *De-centered Observation*, peripheral. The sheer magnitude of network differences precluded further full topological analyses; however, the significant topological differences in the practices of *Positive Reappraisal*, *Letting Go* and *Flexibility* are noted.

The presence and absence of negative paths also constituted important differences. A large number of negative paths were revealed between the De-centering practices (*Meta-cognitive Perception, Meta-cognitive Realisation* and *De-centered Observation)* and other practices in the network in the non-practitioners network. Of these, the negative paths between *De-centered Observation* and *Awareness and Appreciation* (*Obs-AAp M* = -.06, 95% CI [-.17, -.05]), and *Reducing Tension* and *Metacognitive Realization* (*RT-MR* = -.1 [-.25, .4]) were maintained in the Spearman's network (Appendix K; n.b., practitioners: *Obs-AAp* = .00, [-.06, .06]; *RT-MR* = .05, [-.04, .14]). Another prominent negative path was revealed between *Hedonic Savouring* and *Flexibility* which was maintained in the Spearman's network (*HSv – Fl* = -.1 [-.29, .09]; absent in practitioners, *HSv – Fl* = 0, [-.03, .03]). In the practitioners, the negative path *Letting Go* and *Implicational Savouring* was maintained in Spearman's network (*ISv-LG* = -.11 [-.27, .04]; absent in non-practitioners: *ISv-LG* = .00, [-.07, .07]). An inspection of cross-tables (Table 8) suggested that insufficient sampling belied many of the negative paths, suggesting caution in their interpretation.

Table 7

Cross-Table Frequencies for Negative Paths

Path	Frequency of n = 0	Frequency of n <10
Non-Practitioners		
Obs-AAp	5	16
RT-MR	0	13
HSv-Fl	3	19
Practitioners		
LG-ISv	3	14

Note. Total number of cells = 25.

6.2.4 Discussion of AMPS results. The estimated AMPS graphs again demonstrated the feasibility of explaining the covariance observed in items by recourse to a network model. Mirroring the results of Study 1, the NCT provided support for the null hypothesis; namely, no differences in density were observed between practitioners and non-practitioners. Support for a significant difference in network structure was found. This was supported by the differences revealed in exploratory analysis; namely, the different community structures, weak associations between the centrality indices of the two groups, and the moderate difference in the path weight co-efficient of similarity.

The scale of structural differences and the poor estimation of the non-practitioners' network made interpretation more difficult, warranting attention. The decision to adapt the AMPS for non-practitioners reflected a prioritisation of theory over psychometric validation. The results of this study do not support this decision, and future research would benefit from investigating how psychometric properties translate to network estimation. The AMPS was also selected on the belief that its less technical wording of items may increase the likelihood of items being interpreted more homogenously across groups. Contrary to this, the large structural differences suggest that the more general wording of items allowed for much greater heterogeneity in item comprehension[28].

Another limitation of the measure relates to distinctiveness of items. Many of the items appeared to have over-lapping content and/or strong logical connections, manifesting in strong paths between items, common to both networks. For example, it is difficult to see how *Metacognitive perception* ("see that my thoughts were not necessarily true") could not lead to *Metacognitive realization* ("realize that my thoughts were not facts"), making the path un-falsifiable and arguably, pseudo-empirical (Smedslund, 2016). The same appears true also for the path between *Reducing Tension* ("reduce tension when I was stressed") and *Relaxation* ("relax my body when I was tense"), and perhaps also, the path between *Reducing Tension* and *Emotional Calming* ("calm my emotions when I was upset").

By inducing stronger paths, strong logical connections and/or overlapping item content inflate centrality scores, rendering comparisons less meaningful. Interpretation is also less meaningful, for it makes little sense to speak of potentially casual pathways in practices which index the same behaviour (Bringmann & Eronin, 2018; Fried et al., 2016; Fried & Cramer, 2017). Likewise, strong logical connections are less informative as the path *could only have been*. More informative are paths *which could have been otherwise*, for this affords the possibility of structural variation, perhaps brought about by a regular practice[29].

Bearing in mind these limitations, several findings warrant mention. Firstly, greater differentiation was found in the community structure of the practitioners' network, manifest in more distinct communities. This will be discussed in further detail in the General

[28] Of the communities, only the De-centering community corresponded to that identified in the original (and only) validation study of the AMPS (Li et al., 2016). Interestingly, these items appeared the most technically worded items.
[29] The challenge in developing items is to thus allow for structural differences, yet word items in a way which both groups comprehend them similarly (practice invariance). More general wording brings the risk of greater subjectivity or heterogeneity in comprehension, yet too specific wording raises the risk of items being interpreted differently as a function of meditation experience.

Discussion (chapter 7). A second interesting finding relates to the type of practices in which substantial differences in centrality were observed, and their position in the Mindfulness to Meaning Theory (Garland et al., 2015a) from which the AMPS was derived. To recap, the Mindfulness to Meaning Theory grants De-centering community practices a foundational role in mindfulness, from which increasingly higher order eudemonic (meaning-based happiness) practices develop. Central to the theory is *Positive reappraisal* which involves *Broadening* (the scope of) *Attention* to “appreciate that even aversive experiences are potential vehicles for personal transformation and growth” (Garland et al., 2015a, pg. 295). These eudemonic processes in turn, have adaptive benefits such as alleviating negative emotions (Teasdale, 1993). In this way, meaning-making (eudemonic) practices are theorised to become increasingly important as a practice develops.

Broadly consistent with this, the foundational De-centering community practices (*Meta-cognitive Realizatio*n, *Meta-cognitive Perception* and to a lesser extent, *Flexibility*) tended to be those most central to non-practitioners relative to their position in the practitioner’s network (save *Hedonic Savouring*[30]). By way of contrast, more eudemonic practices tended to be those most central to practitioners (*Positive Re-appraisal* , *Broadening Attention*, *Implicational Savouring*), relative to their position in the non-practitioners’ network. Of these, *Positive Re-appraisal* appeared particularly important in maintaining its associated community. Taken together, these results suggest that meaning-making practices may become increasingly important in galvanizing or maintaining mindfulness (relative to other practices) as a formal regular practice develops. Future temporal and longitudinal research might further investigate this hypothesis.

[30] One cannot rule out the likelihood of this practice sampling quite different behaviours across groups given the substantial difference in centrality and topology observed.

A third interesting finding related to the high strength centrality of *Letting Go* across both networks. A practice of this type features in Buddhist theory (i.e., the third Noble Truth claims that one can liberate oneself from this suffering by *letting go* of desire and attachment), but also, in the literature. For example, Frewen, Dozois, Joanisse and Neufeld (2008) suggested that an individual's capacity to let go of negative automatic thoughts may promote cognitive flexibility, thereby increasing their potential range of responses to a given situation. Consistent with this, *Letting Go* featured a strong path with *Flexibility* in the non-practitioners' network, and more generally, mediated the influence of De-centering practices on purportedly upstream practices.

Finally, the many negative paths revealed between De-centering community practices and other practices, unique to non-practitioners' network, were interesting. Two of these negative paths were maintained in the networks estimated with Spearman's correlations, of which the negative path between *Metacognitive Realization* and *Reducing Tension* may be illustrative. This path may suggest that realising that one's thoughts are not facts may predict increased tension in non-practitioners only (or at least a subset of non-practitioners). Alternatively, it suggests that *Reducing Tension* may inhibit *Metacognitive Realization.*

The possibility of *Metacognitive Realization* predicting increased tension has some precedent in the literature (see Lindhal, Fisher, Cooper, Rosen & Britton, 2017 for review), and deleterious effects have been suggested to be especially likely in the preliminary stages of a practice (Epstein & Lieff, 1981). Plausibly, realizing that one's *thoughts are not facts* could invoke feelings of invalidation as beliefs lose their credibility and generate anxiety in the resulting uncertainty. Bearing in mind the limitations of inferring from group level data; the results might thus suggest that a regular mindfulness (or related meditative) practice may buffer individuals from such negative effects. Although speculative, two possibilities are considered. Firstly, it may be that *Metacognitive Realisation* is being practiced in the absence of a developed sense of acceptance. A challenge of mindfulness involves combining high levels of self-observation with a high level of a self-acceptance (Grabovic et al., 2011; Lilja et al., 2013) which may have been absent in non-practitioners. In support of this, *Acceptance* was observed to be much more central to the practitioners' network relative to the non-practitioners network in study 1, suggested to be indicative of its greater level of development in the former. By way of contrast, it was suggested that the non-practitioners' network evidenced practices of (self) critical processing. In addition, (or alternatively), it may be that a regular mindfulness or related meditative practice provides the appropriate conceptual or interpretive aids which help assimilate or mediate the consequences of the De-centering practices. This might be considered consistent with Wildman's (2011) observation that "the intense experiences of nonreligious people are sometimes difficult to assimilate for the lack of any conceptual framework or social context for making sense of them" (p. 97, as cited in Lindhal et al., 2017).

Interpreting *Metacognitive Realization* in the context of anxiety may also inform the interpretation of the alternative possibility; namely, *Reducing Tension* impeding *Metacognitive Realization*. If *Metacognitive Realization* was to index anxiety, and *Reducing Tension*, relaxation; a negative path might be expected between the two given that relaxation has frequently been shown to reduce anxiety (e.g. Eppley, Abrams, & Shear, 1989; Manzoni, Pagnini, Castelnuovo, & Molinari, 2008).

The other prominent negative paths also bear brief mention if only because they may challenge a core contention of the *Mindfulness to Meaning Theory*; namely, that mindfulness and reappraisal are not contradictory psychological operations. For example, the negative path between *De-centered Observation* ("observe my thoughts in a non-attached manner") and *Awareness and Appreciation* ("be aware of and appreciating pleasant events") in the non-practitioners sample could be explained by the incompatibility of being both attached (appreciative) and detached (de-centered). A similar dynamic might account for the other negative paths between *Flexibility* (detached) and *Hedonic Savouring* (attached), and *Letting Go* (detached) and *Implicational Savouring* (attached).

In summary, the AMPS study revealed greater differentiation in practitioners' networks relative to non-practitioners, in which more eudemonic practices tended to be more central, and more foundational mindfulness practices less central. The study also suggesting psychometric considerations be prioritised over theoretical considerations, and that greater consideration may be required in identifying appropriate nodes for a network when using extant scales. Finally, it highlighted possible deleterious effects of practicing De-centering community practices in isolation of a formal regular mindfulness or related meditative practice.

Chapter 7 General Discussion

The two studies hypothesised that a regular mindfulness (or related meditative) practice would lead to greater correlations among practices relative to a non-practicing sample. At the cross-sectional level, this would manifest in a density difference. Across both studies, evidence was found in support of the null hypothesis. Future research examining network dynamics in the context of regular mindfulness practice is hence required to investigate the hypothesis outlined.

The second aim of this study was an exploration of network structures. Network structure has long been associated with network dynamics in the broader literature (i.e. Kolaczyk, 2009; Scheffer et al., 2012; Watts, 2002), and it was suggested that practices may re-organise differently across a regular mindfulness or related meditative practice. This may manifest in non-random structural differences at the cross-sectional level. Support was found for a significant difference in network structure across both studies. This was most obvious for the AMPS, but evidence was more tentative for the FMI (only 62% of 500 resampled networks significantly differed, and this reduced as gamma values increased).

The results of Study 1 rendered it unclear whether structural differences represented the re-organisation of the same practices, or whether the networks represented the organisation of different practices (sharing the same name). In the case of the latter, the same networks may not have been compared, rendering the main hypothesis and centrality comparison less meaningful. Future research is hence required to establish the nature of network differences observed, and novel scales suited to network analysis may be required.

Comparisons could not be made between the two scales as they indexed different practices. As such, future research would also benefit from comparing network structures across more comparable mindfulness measures. Bearing this in mind, one common finding was revealed across both measures; namely, the greater level of differentiation observed in practitioners' networks. This manifested in practitioners evidencing distinct communities characterised by relatively stronger intra-community paths, and relatively weaker inter-community paths.

The factor analytic literature on factorial variance may shed some light on this common result. Factorial variance refers to shifting factor structures across groups or time points. In the mindfulness literature, factorial variance has been demonstrated across samples of meditators and non-meditators (i.e. Baer et al., 2008; Christopher, Charoensuk, Gilbert, Neary & Pearce, 2009; Van Dam, Earleywine & Danoff-Burg, 2009; Williams et al., 2014), and across time points (before and after mindfulness training; Grossman, 2008; Gu et al., 2016). Factorial variance has often been considered a problem in the literature as it suggests that two groups are not being compared on the same latent construct/s (Grossman, 2008; Van Dam et al., 2009; Williams et al., 2014). Explanations advanced have been differential item responding or comprehension (Belzer et al., 2013; Grossman, 2008), and response shift (i.e., a subject's *frame of reference* changing as their practice develops; Grossman, 2008; Gu et al., 2016; Krägeloh, Bergomi, Siegert & Medvedev, 2017; see Güthlin, 2004 for further discussion of response shift).

Comprehension differences (across subjects or within subjects over time) are interesting as perceptual shifts might be expected in a highly introspective practice measured by self-report (Davidson & Kaszniak, 2015; Grossman, 2008; Shapiro et al., 2006; Shonin, et al., 2013). To this end, Bucheld, Grossman & Walach (2001) suggested that the shifting factor structure they observed in their study may reflect "a meta-level shift in conception of the self and the nature of experience" (p.26). Differences in community structures may thus index something important to mindfulness, and it would be interesting to associate community differentiation with relevant outcome measures.

Alternatively, when practice invariance is assumed (i.e., practices refer to the same thing in both groups' networks), the greater differentiation in the practitioners' network could be considered consistent with developmental interpretations in the wider factorial literature (e.g., Bridges, 1932; Coan, 1966; Garret, 1938, 1946; Nesselroade, 1983; Piaget, 1947; Werner, 1956). For example, Nesselroade (1983) has suggested that "structural change is a prominent thread in the fabric of developmental theory and, to the extent that it is meaningfully represented as changes in factor-loading patterns, its appearance should not be summarily precluded'' (p.63). More generally, Werner (1956) has proposed an "othogenetic principle"; namely, "wherever development occurs, it proceeds from a state of…lack of differentiation to a state of increasing differentiation, articulation and hierarchic integration" (p. 126). A developmental interpretation of this sort was suggested in Baer's (2008) interpretation of shifting factor structures in their FFMQ study. Baer suggested that the *Observing* facet of the FFMQ may have been sensitive to changes in meditation, such that it's associations with the other facets became stronger as a practice unfolded (see also, Camody & Baer, 2008; Lilja et al., 2013)[31]. In a different line of FFMQ research, Eisenlohr-Moul, Walsh, Baer, and Lynam (2012) used statistical interaction terms to show how the effects of one aspect of mindfulness, varied as a function of another aspect. They found that these interaction terms demonstrated incremental validity in predicting positive outcomes (see also Desrosiers, Vine, Curtiss, & Klemanski, 2013; Peters, Eisenlohr-Moul, Upton, & Baer, 2013). Taken together, these studies could be considered consistent with a developmental interpretation of greater differentiation forming across time, affording the possibility for interactions (i.e., hierarchic integration). The results of study 1 were considered consistent with this in that the Presence community practices (which closely resemble FFMQ *Observing*

[31] This is considered consistent with van De Maas and colleagues' (2006) mutualist theory, by which uncorrelated components come to be increasingly correlated through mutual interactions across time

items) were found to be much more central to the practitioners' network relative to their non-practicing counterparts. These are precisely the practices a formal mindfulness practice is suggested to target or influence (Lilja et al., 2013).

Another possible explanation for differences observed in differentiation may be differences in sample heterogeneity. It may be that non-practitioners are more alike as practices increase and decrease more randomly due to external life influences. This could lead to a degree of homogeneity in item endorsement patterns (e.g. 222222) which would manifest in a more uniform community structure. By way of contrast, a regular mindfulness (or related meditative) practice may lead to practices beginning to influence each other in different patterns leading to different subgroups. Strong item endorsement patterns may hence emerge (e.g. 24314), manifesting in greater community differentiation. Put very crudely, all non-practitioners are alike, but all mindful people (practitioners) are mindful in their own way[32]. In support of this, latent class analyses and cluster analyses with the FFMQ have demonstrated distinct mindfulness sub-groups, suggested to have come by way of different learning trajectories (Lilja et al., 2013; Pearson et al., 2015). To this end, it must also be noted that different meditative practices might also plausibly lead to different item endorsement patterns. Although group level research may elucidate general tendencies, the presence of subgroups may require greater consideration in network analyses. Future research might also consider attempting to limit recruitment to practitioners of mindfulness, but not other related contemplative practices.

A final point relates to the ontology of mindfulness in the network models proposed. The breakthrough of network models is their ability to examine and explain psychological data without having to resort to essentialism and *biological realism* (Lloyd, 2010). The

[32] This interpretation is indebted to Denny Borsboom's social media commentary on differing dimensionality in the network psychopathology (Borsboom, 2019).

networks modelled could hence conceptualise mindfulness *as* practice, and not something *standing apart* from, and *caused by* practice. This is consistent with the idea of practices being autotelic, by which it is meant that practices are performed for their own sake, and not for the purpose of leading to something that exists independently or beyond them. From this perspective, it follows that a practitioner does not practice *in order to become* mindful, for no independent state exists beyond what they are doing. An idea (or narrative) of what mindfulness is does however exist, and this may form an exemplar. Formulated from an embodied or enactive practice, the practitioner might thus be said to practice not in order to become mindful; but rather, simply *as if* they were mindful. Sharf (2005) suggests much the same in his research in Zen Buddhism; namely, the practitioner practices seated meditation (zazen) "not in order to become an enlightened Buddha, but simply *as if* one were an enlightened Buddha" (Sharf, 2005 p. 256). For this reason, Sharf (2005) considers Zen Buddhism as *ritual play*: much as the child plays with a stick *as if* it were a horse, the practitioner engages in ritual *as if* they are a Buddha. Put differently, Zen training may be said to represent the ritual expression, embodiment, or *enactment* of Buddhahood. This thesis has argued that contemporary mindfulness may represent a reversal of this situation. It was suggested that contemporary conceptualisations framed mindfulness as a stand-alone, universal (trans-historical) experience (represented statistically in the reflective factor model). André van der Braak (2015) makes a similar point when he notes:

> Many Western zazen practitioners do not realize that zazen is conceived in Japan and China as the ritual embodiment of Buddhahood. They do not feel they are engaging in ritual play when they practice zazen. In terms of the Zen tradition: they do not sit *as* a Buddha, but *in order to become* a Buddha (p. 165, emphasis mine).

To practice or play *as if* a state of mindfulness exists might be considered a sham, but this discounts several important points. Firstly, play *does* something very important by way of removing the subject from instrumental activity[33]. Secondly, playing *as if* things were true is consonant with the canonical Buddhist truth of impermanence; namely, it appreciates the intrinsic emptiness of all dependently arisen things. Finally, play reorients the subject to the object, a process commonly ascribed to mindfulness.

At the most basic level, the networks modelled predict group level associations among practices. Given that autotelic intention was in theory crucial for distinguishing mindfulness from instrumental activity[34], the absence of this information in the networks may cause pause in considering them *network models of mindfulness*. To stay with the play analogy, modelling predictive associations among practices to explore mindfulness may be akin to modelling predictive associations among objects to explore play. Play, like mindfulness does not reside in objects. To use terms common to mindfulness, play seems more about *being* than *doing*[35], and in this way, it is intentional. That said, a network model in which objects (termed toys when played with) formed the nodes could tell us something very useful about which objects were central to developing a system of activity, which through reciprocal predicative associations, may become self-sustaining and potentially stable across time. It may go beyond the data to suggest that this is *play*, but something is happening, and perhaps this is enough to inform decisions on, for example, which objects might be purchased for a waiting room. Put differently, the networks may still be useful if we proceed *as if* objects were toys, and this logic is extended to the mindfulness networks. The studies hence proceeded *as if* the practices were carried out with autotelic intention which may constitute a limitation[36].

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[33] André van de Braak (2015) cites the twentieth-century Zen master, Kōdō Sawaki (1880-1965), who makes a similar point of zazen; namely, it requires "leaving behind a means-end rationality" (p.160).

[34] Intention also was suggested here to differentiate contemporary and traditional formulations. This parallels a similar conclusion reached by Shonin and colleagues (2013) who suggested that intention "happens to be one of the principal factors that differentiates mindfulness as taught in MBIs from its Buddhist construal" (p. 2).

[35] It is interesting to reformulate Teasdale's (1993) distinction between *doing* and *being* as *doing* and *playing*.

[36] Whether or how intention can be ascertained is beyond the scope of this thesis, although it is noted that Shapiro and colleagues (1992) have investigated motivations for mindfulness with open questions, and Grossman (2011) has suggested that researchers measure not only the frequencies of given practices, but also how much respondents personally value such practices. Questions might also be worded to better capture the

Other important limitations need mention. Firstly, cross-sectional generalisations may not correspond to causal mechanisms that characterise the development of mindfulness within persons (see Bos & de Jonge, 2014; Bos & Wanders, 2016; van Borkulo, Borsboom, & Schoevers, 2016 for further discussion of this point). Cross-sectional networks can thus only provide a starting point to investigate how mindfulness practices relate to each other on average. Future ideographic research is needed to investigate the substantial heterogeneity which likely exists at the individual level.

Another important limitation relates to assumptions underpinning the network density hypothesis and centrality estimates; namely, that all the relevant nodes in a network are present. The common factor model circumvents this problem by considering items interchangeable indicators of an underlying latent variable; however, the addition and omission of nodes in a network model changes the identity of the emergent construct (Fried & Cramer, 2017; Marius & Kruis, 2016). The failure to incorporate all nodes can thus misrepresent the network structure, and in theory, the assumption can never be met in a network study. Although more nodes might be considered superior to fewer, much larger samples are required to maintain adequate power (Fried & Cramer, 2017). The current studies were thus limited to choosing relatively prescribed measures (14-15 item measures), and future research may benefit from more using larger sample sizes with more comprehensive measures (e.g., the FFMQ). Future research may also benefit from focusing attention away from global network characteristics to examining specific paths between nodes.

The centrality interpretation used in these studies also made further assumptions. Firstly, negative edges were treated as absolute values which is routine but somewhat arbitrary. One might just as easily take centrality at its real value leading to reductions with

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intention by which a practice is carried out. As noted previously, mindfulness instructions also go some way to ensuring autotelic practice by directing attention exclusively to the means of any given activity.

negative edges. The presence of negative edges also brings into the question the utility of targeting central nodes. When negative edges are present, changes may populate across a network, but reciprocal feedback could make the change short-lived (Fried et al., 2018; Smith et al., 2018). For this reason, it has been suggested that network interventions might better focus on clusters or chains of practices in which central items are embedded (Letina, Blanken, Deserno, & Borsboom, 2018; Smith et al., 2018).

Bringmann and colleagues (2018) have also challenged the use of flow processes to describe how influence travels down paths without further conceptual analysis (e.g., whether flow may be serial or parallel, across what timescales etc.). The authors also raise the issue of node distinctiveness which appeared a real concern in study 2. Currently, there are no established recommendations for determining node redundancy (Zhang & Horvath, 2005), although recent papers have advanced novel statistical solutions to help researchers identify relevant practices for a network (e.g., Bulteel, Tuerlinckx, Brose, & Ceulemans, 2016; see also R package *NetworkTool*s, Jone, 2017). It also bears mention again that due to the cross-sectional nature of the studies, it cannot be determined whether central practices with high centrality influence other practices, are the end result of other causal practice chains, or both. The current findings would ideally be replicated with designs using temporal data to uncover whether changes in one practice precede changes in another. Finally, Bringmann and colleagues (2018) note that centrality assumes that the practices are exchangeable much as latent variable theory does. This is inferred in calculating centrality by summing paths. This assumption is unwarranted as different practices may well turn out to be more important than others in terms of outcomes predicted. Taken together, Bringmann and colleagues (2018) thus suggest that "it is not enough to state that one wants to measure how central a node is, but one has to make explicit what is meant with being a central or important node, and what assumptions the centrality measure of choice entails" (p. 20-21). Future research would benefit from heeding these recommendations.

Another limitation relates to the power of the study to detect differences. Firstly, the sample sizes involved in these studies may have been insufficient. A rule of thumb exists suggesting three subjects per parameter, yet this appeared insufficient in the current studies as wide confidence intervals were still obtained for edges. This lack of precision reduces the chances of detecting network differences. Future studies would benefit from larger sample sizes to increase power and sensitivity. That said, determining appropriate sample sizes has proved problematic in the network literature. Epskamp and Fried (2018) have recommended a simulation approach for gaining insight into adequate sample sizes, although this requires an idea of an expected network structure, unavailable to the present research. Plausibly the current networks might be helpful for future studies using this approach.

The quality of the online sample may have limited the sensitivity of the study to detect group level network differences. Limited sample quality can attenuate existing associations and hence the power of statistical tests such as the Network Comparison Test. Data quality was only ascertained by the restrictions on approval rate (implemented in Turkprime) and future studies may wish to use other measures such as attention checks (albeit these have limitations). Future research might also benefit from recruiting from more traditional sources or using established open source data. It is further noted that the use of regularization can also erode sensitivity given that it prioritises specificity (not detecting false edges). The evidence for structural differences observed only in the most sensitive FMI networks (gamma = 0) is illustrative. Williams and colleagues (2018) have suggested non-regularised approaches which future research may consider.

Limitations also exist in relation to the measures used in these studies. The two studies used two quite different measures which represented different trade-offs. The FMI was psychometrically validated but employed quite technical language. The AMPS used more general language and was more theoretically coherent (it specified actual practices required to achieve the trait designation); however, it lacked strong psychometric support. Although it remains unknown how certain psychometric properties affect accuracy of network estimation, the lack of stability of the AMPS in non-practitioners may suggest that psychometric properties be prioritised over theory. Ultimately, network studies into mindfulness may require novel measures. Factor analysis measures are designed to maximise common variance pertaining to a pre-conceived mindfulness construct, but this common variance is excluded in a network analysis. A measure designed specifically for a network study might be advantageous by maximising unique variance. This requires a variety of relevant, but quite distinct items (cite; Mõttus et al., 2017). Given that extant ordinal scales may have issues with range restriction (causing correlations to be underestimated), it may be also be useful to use scales with a wider ordinal range. It has also been suggested that networks consider including parcels (i.e. querying participants using multiple questions) of items given that single items are subject to measurement error (Epskamp et al., 2016). Future research might also wish to combine network models with latent models to help reduce measurement error (Cramer et al., 2016; Epskamp, Maris, et al., in press; Fried & Cramer, 2017; Markus, 2010). It has also been suggested that outcomes, if employed, match the breadth of predictors (whether items, parcels of mixed models; Mõttus et al., 2017). This means that in networks of items, more specific outcomes should be employed.

Another limitation relates to the use of self-report data. Self-report data can rarely be independently verified meaning that item-practice correspondence can only be assumed (i.e., it is assumed that what people say is actually what they do; see Stone, Bachrach, Jobe, Kurtzman, & Cain, 1999, for a general review of self-report data and its limitations). This means that it is difficult to determine whether networks are behavioural or semantic in nature (i.e., they map only semantic or logical associations). In turn, this determines the relevance of recommendations for network manipulations which presume paths index behavioural processes.

Beyond this, issues of response shift and differential item responding suggest that item variance is a real concern in self-report mindfulness measures. Social desirability issues have also been noted in the literature (Brown and Ryan 2003; Cardaciotto et al. 2008). These issues have frequently been raised in the mindfulness literature (e.g. Bergomi et al., 2012), of which it is typically concluded that either better measures are required, or that self-report measures may be unable to capture mindfulness (e.g., Grossman, 2008). To this end it is noted that more objective measures of purported physical correlates of mindfulness have been developed such as breath counting; however, where such studies have occurred, results have been mixed (see for example, Frewen, Lundberg, MacKinley & Wrath, 2011; Levinson, Stoll, Kindy, Merry & Davidson, 2014; see also Ring, Brener, Knapp & Mailloux, 2015 for potential problems with breath counting).

A final point relates to the *Exploratory Graphical Analysis* used to identify community structures. The EGA has performed well on simulated and real data (Golino & Demetriou, 2017; Golino & Epskamp, 2017; Golino et al., 2018), but the technique is still new to the field. Future research should compare the EGA results with other community detection algorithms (Golino & Epskamp, 2017).

7.1 Conclusion

This is the first study to investigate the network structure of mindfulness at the level of self-report. Using tools unique to network analysis, networks were estimated on two mindfulness measures for practitioners and non-practitioners.

The main hypothesis that practitioners' networks would be characterised by greater density than their non-practicing counterparts was not supported. Evidence suggested that the two groups were unlikely to significantly differ in network density. Support for a significant difference in network structure was found for both measures, albeit this was limited to only the most sensitive networks for the FMI.

The exploratory analysis revealed more differentiated community structures for practitioners across both measures which may reflect behavioural re-organisation as a function of regular practice. Several important differentiating features were identified.

In Study 1, the practice of *Acceptance* was found to be relatively more central to practitioners, compared to its position in the non-practitioners' network. By way of contrast, *Returning to the Present* was much more peripheral to practitioners, relative to non-practitioners. A negative path between *Self-kindness* and *Attending to Actions* was also identified, unique to the non-practitioners' network. This was considered a possible target for future network interventions. Study 2 revealed the practitioners' network to be characterised by greater centrality in eudemonic practices relative to non-practitioners. In the latter, more foundational De-centering community practices were substantially more central.

Further recommendations were advanced. Firstly, it was suggested that novel measures be constructed to advance the field of network studies of mindfulness. Secondly, it was suggested that future research involve outcome measures to determine the relevance of topological differences. Thirdly, the failure to find density differences indicated that further research is needed to understand network dynamics in the context of regular mindfulness practice. Finally, it was suggested that the issue of intention may need to be considered more thoroughly with respect to mindfulness.

In summary, these studies suggest that mindfulness research should continue to employ data-driven predictive models as used here. Such models are arguably more consistent with traditional formulations of the construct, counteract tendencies for reification, and re-direct attention to observable behaviours and their interactions. This allows researchers to empirically investigate more complex theories and models, and potentially provide insight into the dynamics of mindfulness.

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Appendix A: Information Sheet for Practitioners

MASSEY UNIVERSITY
Ψ School of PSYCHOLOGY

MASSEY UNIVERSITY
COLLEGE OF HUMANITIES
AND SOCIAL SCIENCES
TE KURA PŪKENGA TANGATA

'Mindfulness' Survey

'Mindfulness' is a popular meditation practice that has often been defined as "paying attention in a particular way; on purpose, in the present moment, and nonjudgmentally", although many people have their own understanding. It often involves certain meditations and practices that are common to other contemplative traditions (such as , vipassana, zen, transcendental meditation, amongst others). Typically mindfulness practices involve sitting and walking meditations, mindful yoga, body-scans, mantras or contemplative prayers, loving-kindness or compassion meditations, amongst others.

As noted this study is wanting to recruit participants who engage in a regular mindfulness practice (at least weekly). If you do not practice mindfulness or a related tradition, you can still complete this survey. Please be aware that will not be able to complete a related survey especially directed to non-practitioners if you complete this survey.

You are under no obligation to accept this invitation. If you decide to participate, you have the right to:

- Ask any questions about the study at any time.
- Provide information on the understanding that your name will not be used.
- Be given access to a summary of the project findings when it is concluded
- Decline to answer any particular question.

Many thanks,
Joseph Smith

Contact information

If you have any questions or queries regarding this project, please don't hesitate to contact the following:

Principle Researcher
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This project has been evaluated by peer review and judged to be low risk. Consequently it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named in this document are responsible for the ethical conduct of this research.
If you have any concerns about the conduct of this research that you want to raise with someone other than the researcher(s), please contact Dr Brian Finch, Director (Research Ethics), email humanethics@massey.ac.nz.

MASSEY UNIVERSITY

Appendix B: FMI Survey Measure

Freiburg Mindfulness Inventory

Description:

The FMI is a useful, valid and reliable questionnaire for measuring mindfulness. It is most suitable in generalized contexts, where knowledge of the Buddhist background of mindfulness cannot be expected. The 14 items cover all aspects of mindfulness.

The purpose of this inventory is to characterize your experience of mindfulness. Please use the last ___ days as the time-frame to consider each item. Provide an answer the for every statement as best you can. Please answer as honestly and spontaneously as possible. There are neither ‘right’ nor ‘wrong’ answers, nor ‘good’ or ‘bad’ responses. What is important to us is your own personal experience.

1	2	3	4
Rarely	Occasionally	Fairly often	Almost always

I am open to the experience of the present moment.	1	2	3	4
I sense my body, whether eating, cooking, cleaning or talking.	1	2	3	4
When I notice an absence of mind, I gently return to the experience of the here and now.	1	2	3	4
I am able to appreciate myself.	1	2	3	4
I pay attention to what’s behind my actions.	1	2	3	4
I see my mistakes and difficulties without judging them.	1	2	3	4
I feel connected to my experience in the here-and-now.	1	2	3	4
I accept unpleasant experiences.	1	2	3	4
I am friendly to myself when things go wrong.	1	2	3	4
I watch my feelings without getting lost in them.	1	2	3	4
In difficult situations, I can pause without immediately reacting.	1	2	3	4
I experience moments of inner peace and ease, even	1	2	3	4

when things get hectic and stressful.

I am impatient with myself and with others.	1	2	3	4
I am able to smile when I notice how I sometimes make life difficult.	1	2	3	4

Scoring Information:

Add up all items to get one summary score. When scoring, please observe that there are a couple of reversed items. For these you need to reverse the scoring, preferably by a recode command that recodes 1 into 4, 2 into 3, 3 into 2 and 4 into 1.

The item to be recoded is "I am impatient with myself and with others."

At the moment, we do not recommend to use separate factor-scale scores. If you wish to do so, we recommend that you analyze your own data set and extract 4 to 6 factors according to the data structure you find and then proceed accordingly, adding up item scores per scale.

Reference:

Walach, H., Buchheld, N., Buttenmuller, V., Kleinknecht, N., Schmidt, S. (2006). Measuring Mindfulness--The Freiburg Mindfulness Inventory (FMI). *Personality and Individual Differences, 40*, 1543-1555.

Appendix C: AMPS Survey Measure

Applied Mindfulness Process Scale (AMPS)

Dear Colleague:

The Applied Mindfulness Process Scale (AMPS) is public domain and does not require special permission for use in research or clinical work. The AMPS measures the application of mindfulness practices in daily life among persons participating in mindfulness-based interventions (MBIs). This *process measure* has been validated for use among adult mindfulness practitioners and college students enrolled in a MBI (Li, Black, & Garland, 2016). A detailed description of AMPS, the AMPS instrument itself, and instructions for use and scoring are available on the following pages.

Please e-mail us with any questions about the interpretation or use of the AMPS. We also appreciate your sharing any new research or clinical findings when using this scale.

Regards,

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Applied Mindfulness Process Scale (AMPS)

Description of the scale:

The Applied Mindfulness Process Scale (AMPS) is a process measure used to quantify how participants in mindfulness-based interventions (MBIs) use mindfulness practice when facing challenges in daily life. Development and validation of the AMPS yielded 15 items representing three domains of applied mindfulness processes: (a) decentering (items 1, 3, 12, 13, 15), (b) positive emotional regulation (items 4, 7, 9, 11, 14), and (c) negative emotional regulation (items 2, 5, 6, 8, 10).

The AMPS has has demonstrated strong internal consistency (Cronbach's α) ranging between 0.91-0.94, as well as adequate nomological validity with related constructs (e.g., stress, depression, trait mindfulness, anxiety, and general well-being). As a process measure, the AMPS can be used as a standalone measure or alongside established measures of mindfulness as a *construct*. The AMPS is intended for use among current mindfulness practitioners or MBI participants. Completion of the AMPS questionnaire should take approximately 5 minutes.

AMPS norms to date:

	n	Mean	SD	Score Range
Adult meditation practitioners	134			
AMPS total		39.87	8.66	(0-60)
Decentering		13.62	3.09	(0-20)
Positive emotional regulation		13.26	3.42	(0-20)
Negative emotional regulation		12.94	3.19	(0-20)
College students	180			
AMPS total		40.55	9.49	(0-60)
Decentering		13.27	3.34	(0-20)
Positive emotional regulation		13.85	3.75	(0-20)
Negative emotional regulation		13.42	3.37	(0-20)

Instructions for administration: We suggest that the AMPS process measure be administered one or more times during the course of the intervention when the participant has become familiar with the practice (for example, at a program mid-point and conclusion). Increases over time in AMPS scores suggest greater application of the use of mindfulness skills in daily life coinciding with mindfulness practice.

Instructions for scoring: (1) Sum each factor individually to obtain a score ranging from 0-20, and/or (2) sum all 15 items to obtain a score ranging from 0-60.

Please use the following reference to cite this scale:

Li, M. J., Black, D. S., Garland, E. L. (2016). The Applied Mindfulness Process Scale (AMPS): A process measure for evaluating mindfulness-based interventions. *Personality and Individual Differences*, 93,6-15.
https://www.ncbi.nlm.nih.gov/pubmed/26858469

Instructions: Everyone gets confronted with negative or stressful events in daily life, and people who practice mindfulness experience these events in different ways. Please indicate how often you have used mindfulness in each of the following ways for the period of the **last week (past 7 days)**.

I used mindfulness practice to…	Never	Rarely	Sometimes	Often	Almost Always
1. Observe my thoughts in a detached manner	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
2. Relax my body when I am tense	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
3. See that my thoughts are not necessarily true	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
4. Enjoy the little things in life more fully	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
5. Calm my emotions when I am upset	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
6. Stop reacting to my negative impulses	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
7. See the positive side of difficult circumstances	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
8. Reduce tension when I am stressed	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
9. Realize that I can grow stronger from difficult circumstances	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
10. Stop my unhelpful reactions to situations	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
11. Be aware of and appreciate pleasant events	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
12. Let go of unpleasant thoughts and feelings	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
13. Realize that my thoughts are not facts	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
14. Notice pleasant things in the face of difficult circumstances	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
15. See alternate views of a situation	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐

Appendix D: FMI NCT Preparation and Exploratory Network Comparisons.

In preparing the data for the NCT, non-practitioners and practitioners were collapsed into one group to help balance the sample size difference. Figure 13 shows the non-practitioner and newly combined non-practitioner and irregular practitioners' networks. Figure 14 shows the centrality estimates for the respective networks. Visual analysis reveals no substantive differences in estimated networks and centrality. This was confirmed by the strong correlations in centrality (strength $r_s = .90$, closeness $r_s = .74$, betweenness $r_s = .90$) and edge weights (*co-efficient of similarity* $r_s = .96$) between the two networks.

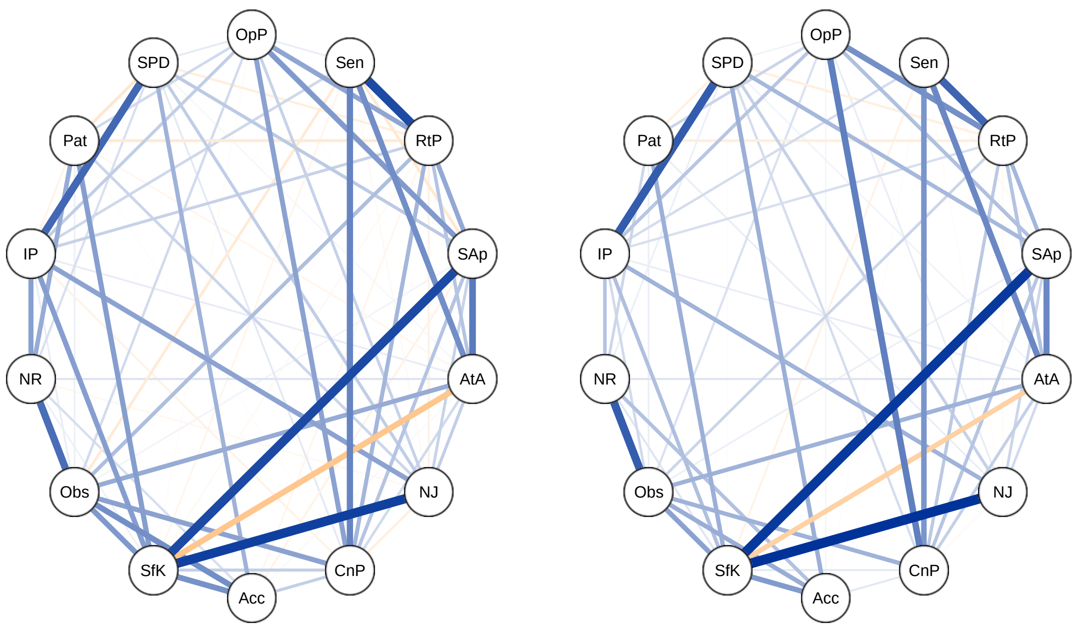


Figure 13. FMI Networks estimated for non-practitioners (left) and a combined non-practitioner and irregular practitioner sample (right). Maximum edge weight = .37. All networks estimated with Pearson's correlations and a gamma tuning value of 0.

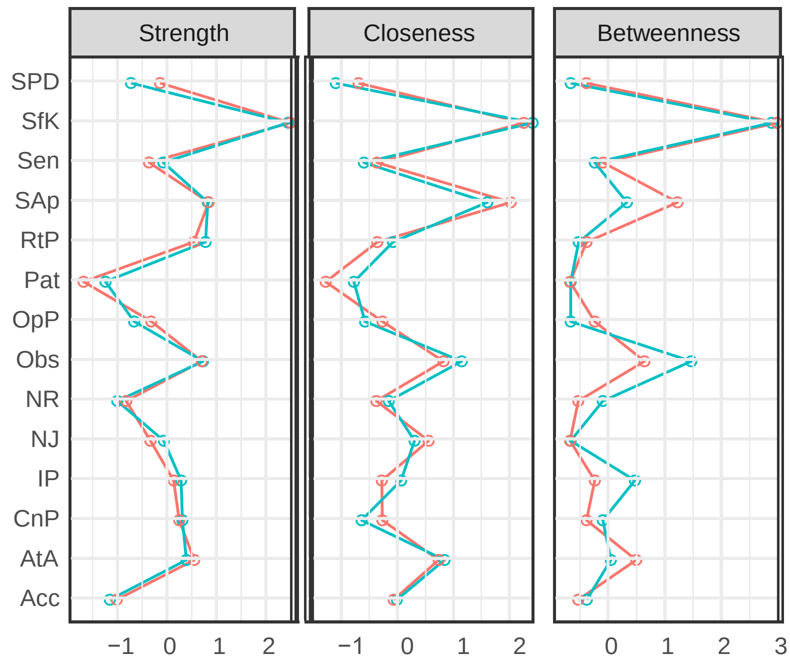


Figure 14. Centrality metrics for non-practitioners (blue) and the combined sample (red).

The resampling procedure used to correct for sample sizes makes it unfeasible to compare networks estimated in the exploratory analyses (using polychoric correlations) and those used in the NCT. None-the-less some assessment of comparability was required. This was achieved by estimating a network with Pearson's correlations and comparing it to its exploratory counterpart (Figure 15). The gamma value was set to 0 for both networks.

Figure 16 shows the centrality indices superimposed for both groups. Visual analysis suggested that the only substantive deviation was in the strength centrality of *Sensing* in the practitioners' networks, which was higher in the exploratory networks than in those that may have been estimated in the NCT. Regardless, the practitioners' exploratory network was considered to adequately characterise that which may have been estimated in the course of the NCT, as evident in the strong (Spearman's) correlations between the centrality indices (strength r_s = .87, closeness r_s = .89, betweenness r_s = .98) and edge weights matrix (*co-efficient of* *similarity* r_s = .98). No significant deviations are observed between the non-practitioners networks suggestive of their comparability (strength r_s = .87, closeness r_s = .82, betweenness r_s = .78, *co-efficient of similarity* r_s = .92). The same was true also of comparisons made at the higher gamma value of .5 (practitioners strength r_s = .87, closeness r_s = .95, betweenness r_s = .88, *co-efficient of similarity* r_s = .97; non-practitioners strength r_s = .93, closeness r_s = .70, betweenness r_s = .76, *co-efficient of similarity* r_s = .94).

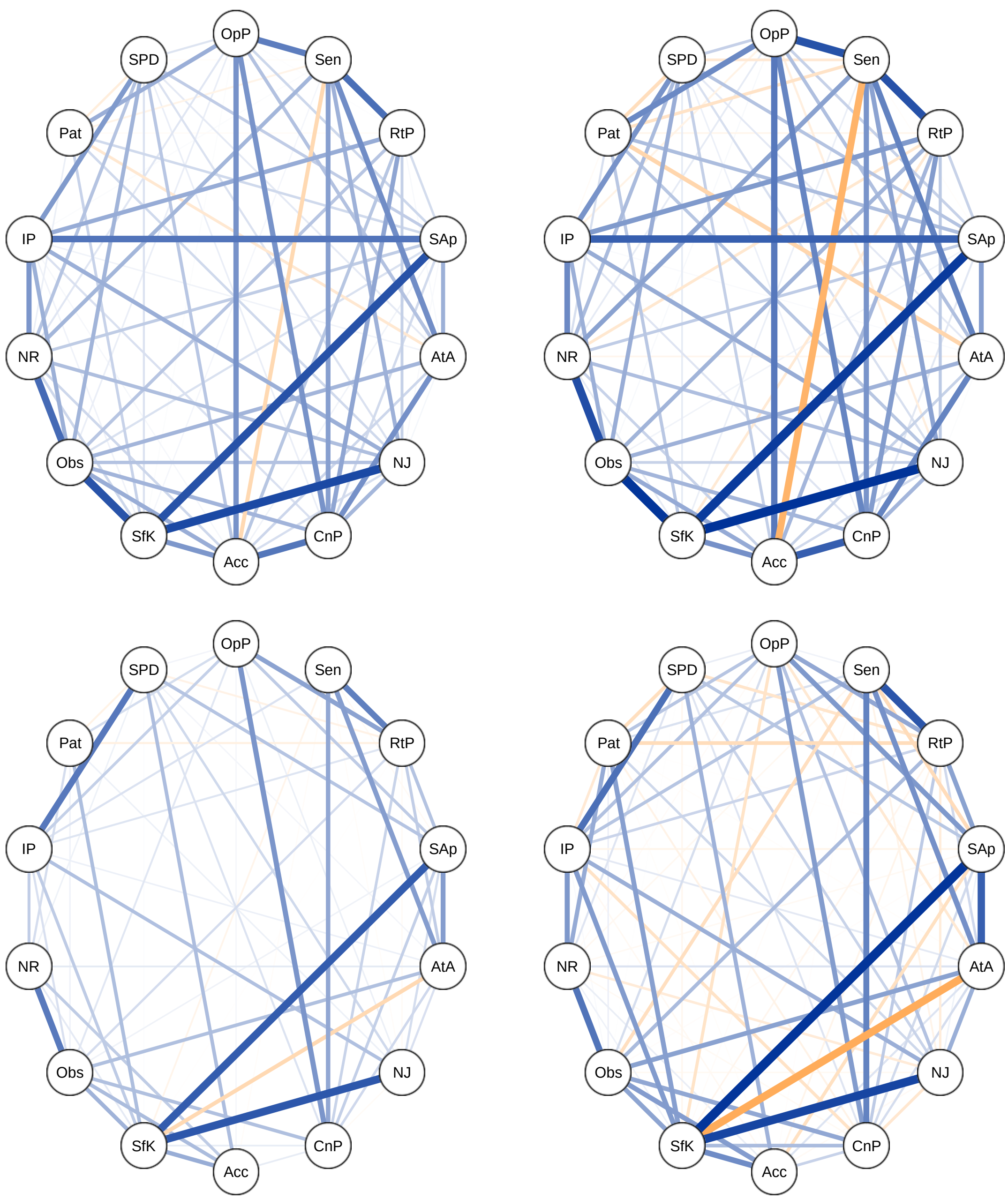
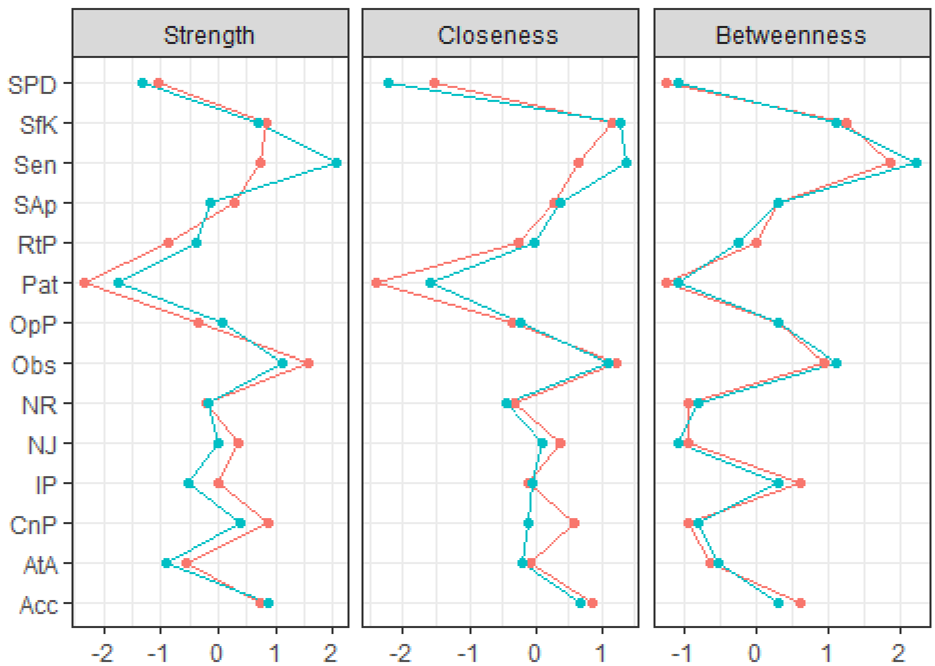


Figure 15. Networks estimated with Pearson's correlations (left) and polychrolic correlations (right). The practitioners' networks (top) have a maximum edge weight of .28. Combined non-practitioners and irregular practitioners Person network (bottom left) and non-practitioners polychoric network (bottom right) have a maximum edge weight of .45. Networks estimated with gamma tuning value of 0.



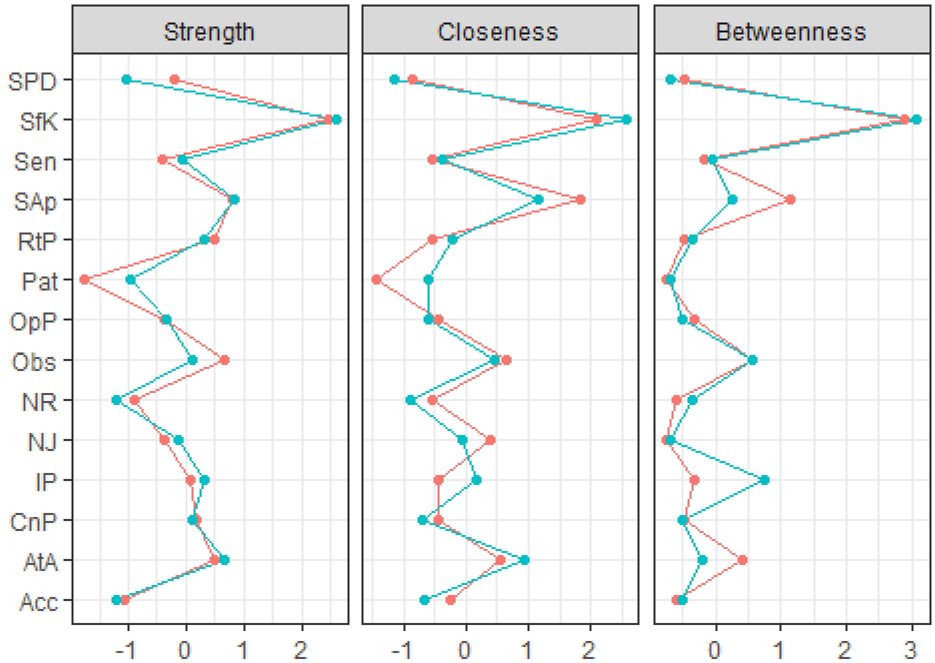


Figure 16. Three centrality metrics. Top: practitioners' Pearson network (red) and practitioners' polychoric network (blue). Bottom: combined non-practitioners and irregular practitioners' Pearson's network (red) and non-practitioners polychoric network (blue). Z scores are used on the x axis to aid comparison. A gamma value of 0 was used in the networks estimated.

Appendix E: AMPS NCT Preparation and Exploratory Network Comparisons.

To investigate the feasibility of combining non-practitioners and irregular practitioners, networks were estimated (Figure 17) and centrality calculated (Figure 18). The networks were highly similar and this was corroborated by strong correlations in centrality (strength r_s = .90, closeness r_s = .84, betweenness r_s = .67) and edge weights (*co-efficient of similarity* r_s = .92). Limiting the analysis to strength centrality, the most obvious differences were in the practices *Flexibility* (more pronounced in combined group) and *Letting Go* (more attenuated in the combined group).

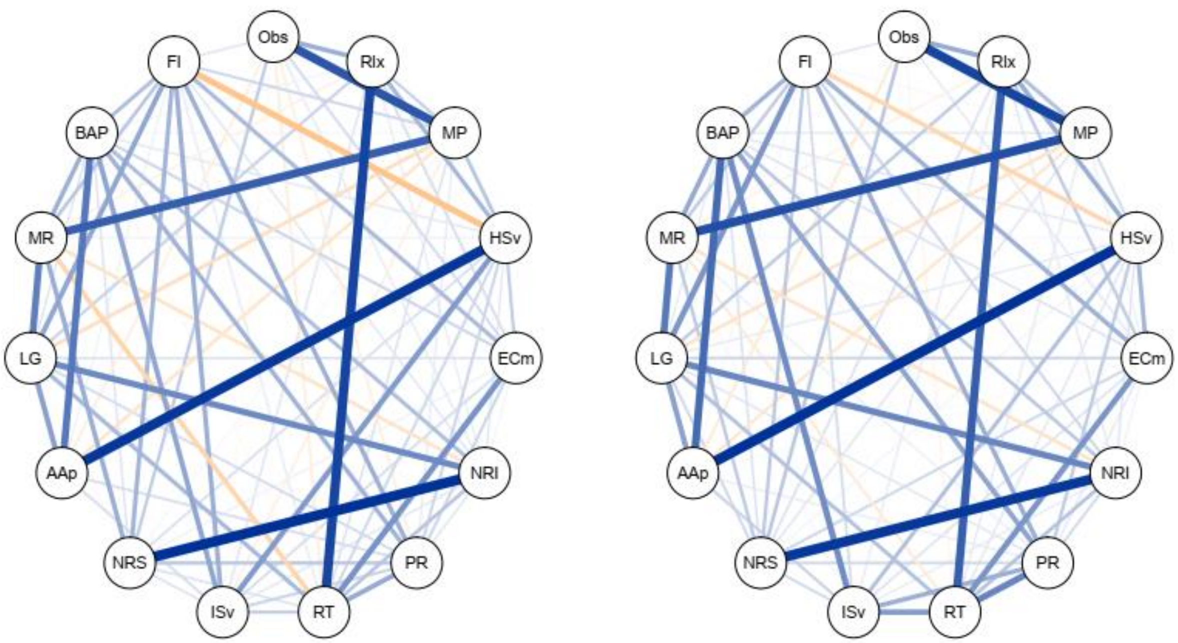


Figure 17. AMPS Networks estimated for non-practitioners (left) and a combined non-practitioner and irregular practitioner sample (right). Maximum edge weight = .38. All networks estimated with Pearson's correlations and a gamma tuning value of 0.

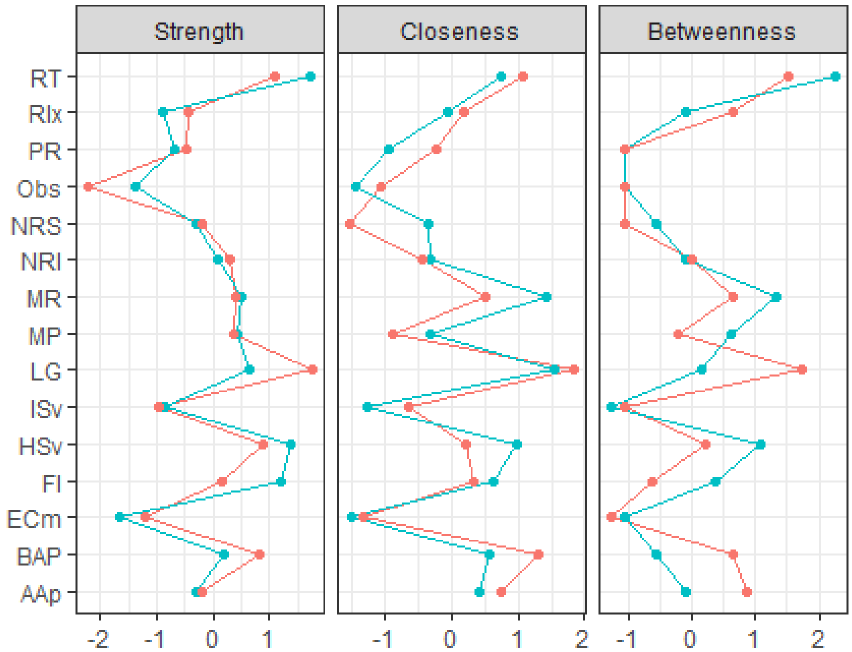


Figure 18. Associated centrality metrics for non-practitioners (blue) and the combined sample (red).

To ascertain how comparable exploratory networks were with those which may have been estimated in the NCT, networks estimated with Pearson's correlations were compared with those estimated with polychoric correlations for both groups (Figure 19). Visual inspections of networks and centrality (Figure 20) suggested broadly similar networks, albeit differences were apparent in some practices. Strong correlations were found between all centrality indices for practitioners (strength r_s = .78, closeness r_s = .91, betweenness r_s = .81) and non-practitioners (strength r_s = .84, closeness $\mathrm{r_s}$ = .78, betweenness r_s = .67). Likewise for edge weights (practitioner *co-efficient of similarity* r_s = .96; non-practitioner *co-efficient of similarity* r_s = .90).. Taken together, exploratory networks appeared fair representations of NCT networks at the gamma value of 0. This remained true at the higher gamma value of .5 (practitioners strength r_s =

.99, closeness $r_s = .99$, betweenness $r_s = .84$, *co-efficient of similarity* $r_s = .98$; non-practitioners strength $r_s = .64$, closeness $r_s = .90$, betweenness $r_s = .70$, *co-efficient of similarity* $r_s = .91$).

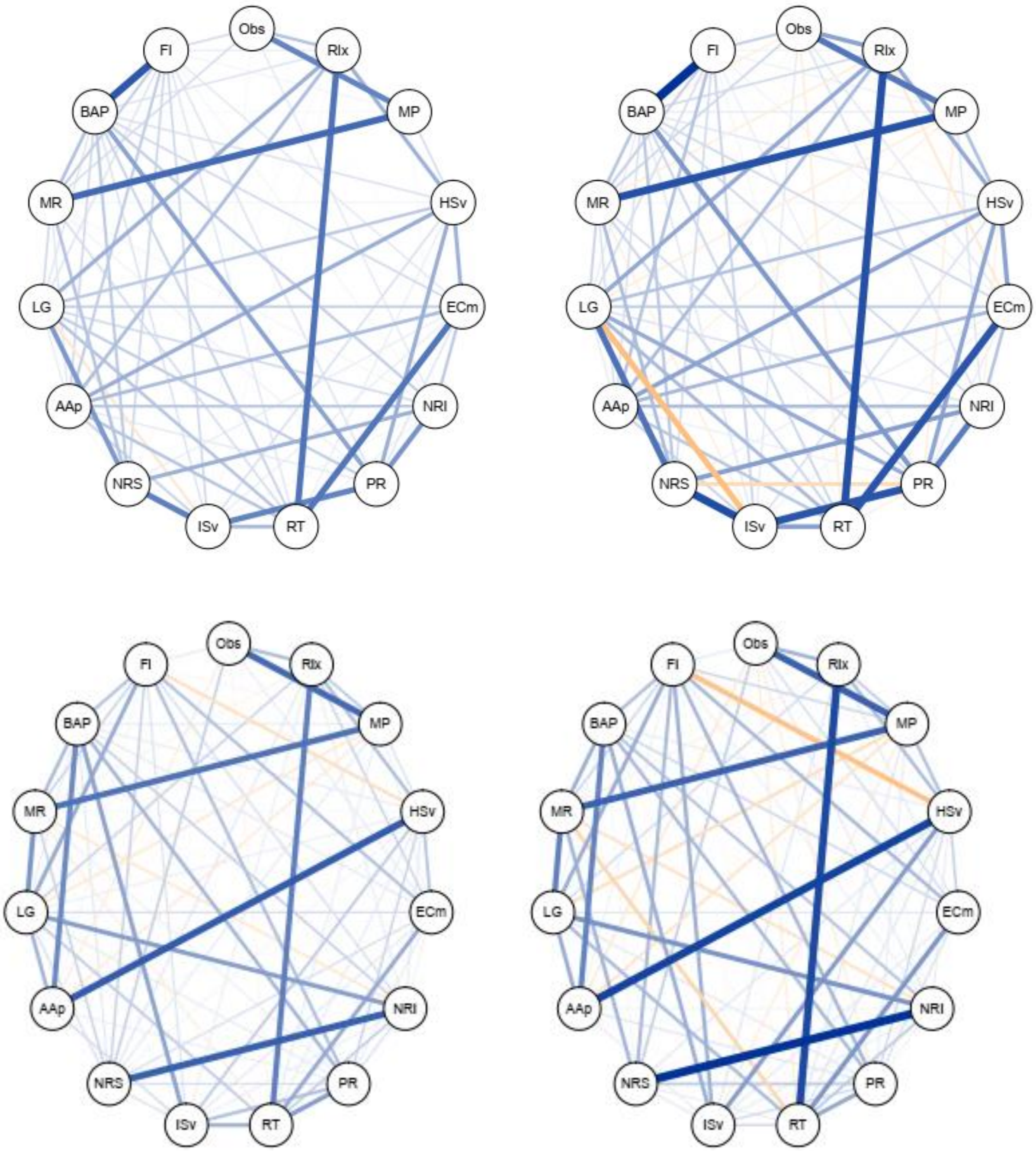
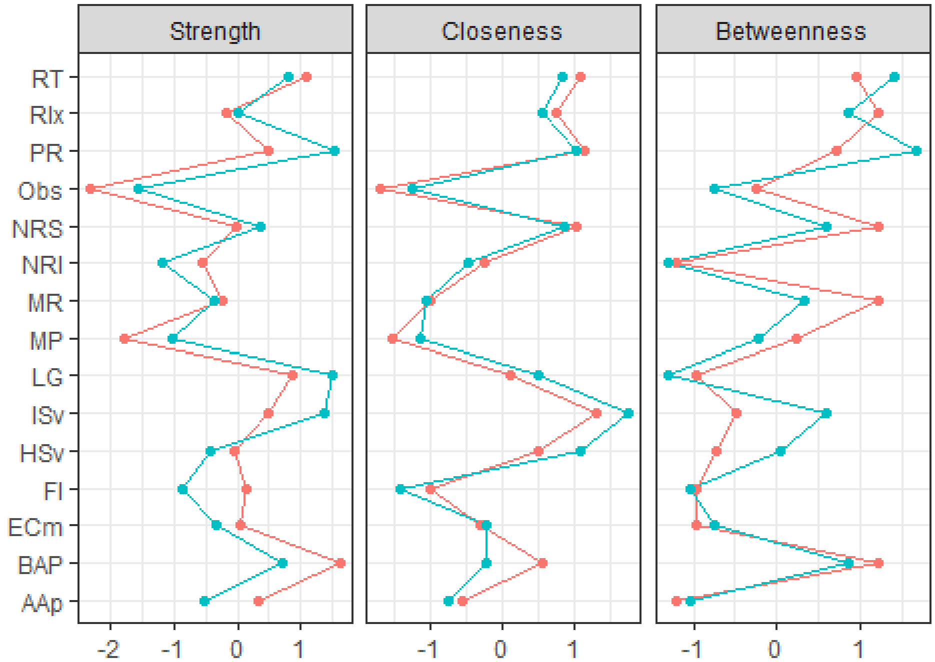


Figure 19. Top: Practitioners' networks estimated with Pearson's correlations (left) and polychrolic correlations (right). Maximum edge weight of .38. Bottom: combined non-practitioners and irregular practitioners' Pearson's network (left) and non-practitioners

polychoric network (right). Maximum edge weight of .44. All networks estimated with a gamma value of 0.



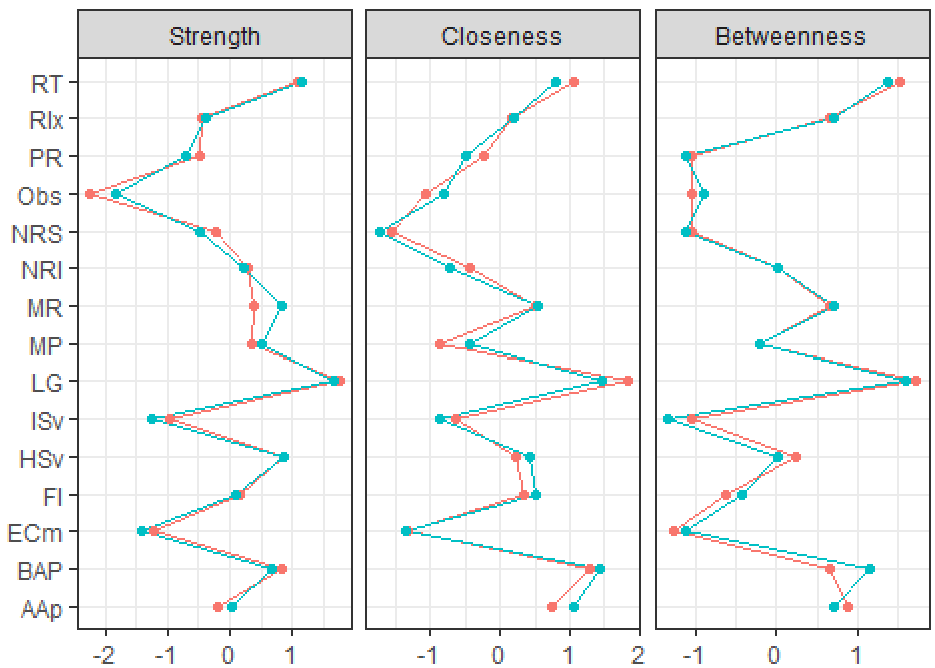
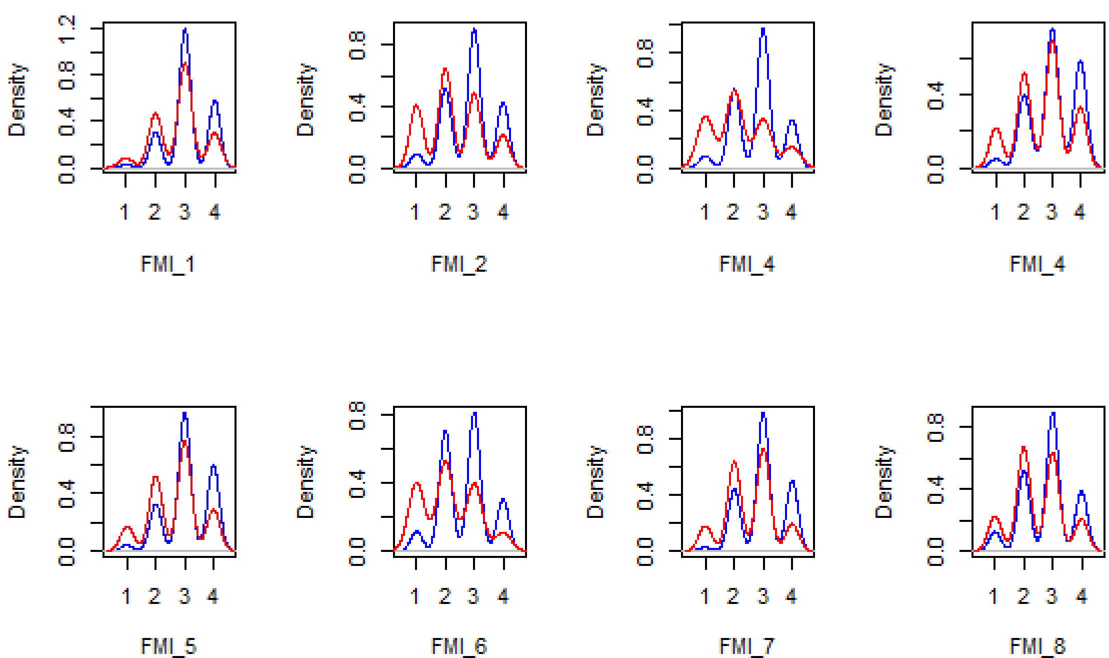


Figure 20. Three centrality metrics for networks estimated with Pearson's (red) and polychoric correlations (blue) for practitioners (top). Bottom: Pearson' combined non-practitioners/irregular practitioners (red) and non-practitioners (blue). Z scores are used on the x axis to aid comparison.

Appendix F: Exploring Floor and Ceiling Effects.

Differences in item variance can meaningfully effect network comparisons when floor and ceiling effects occur (van Borkulo et al, 2015; Terluin et al., 2016)). These occur when large proportions of the study subjects have the minimum or maximum score on an observed variable, causing a restriction in range. This in turn influences network connectivity of the observed variable Range restriction was investigated by inspecting item score distributions in density plots. As shown in Figure 21 and Figure 22, item distributions appear similar across groups and approximate normal distributions. Taken together, it is unlikely that range restriction would create differences in network connectivity.



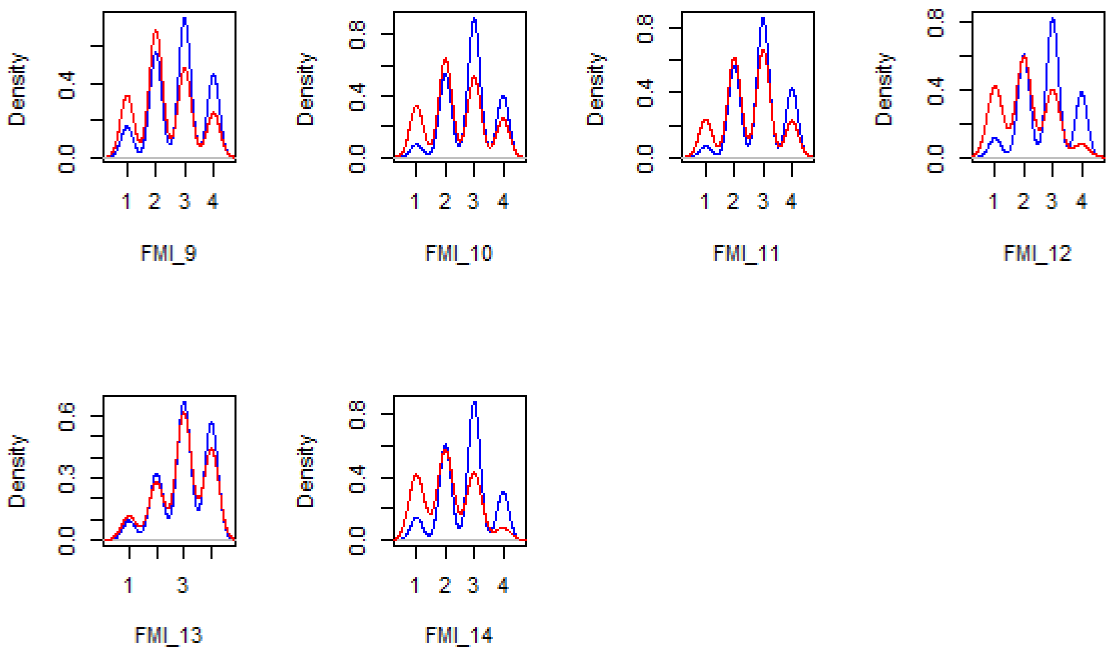
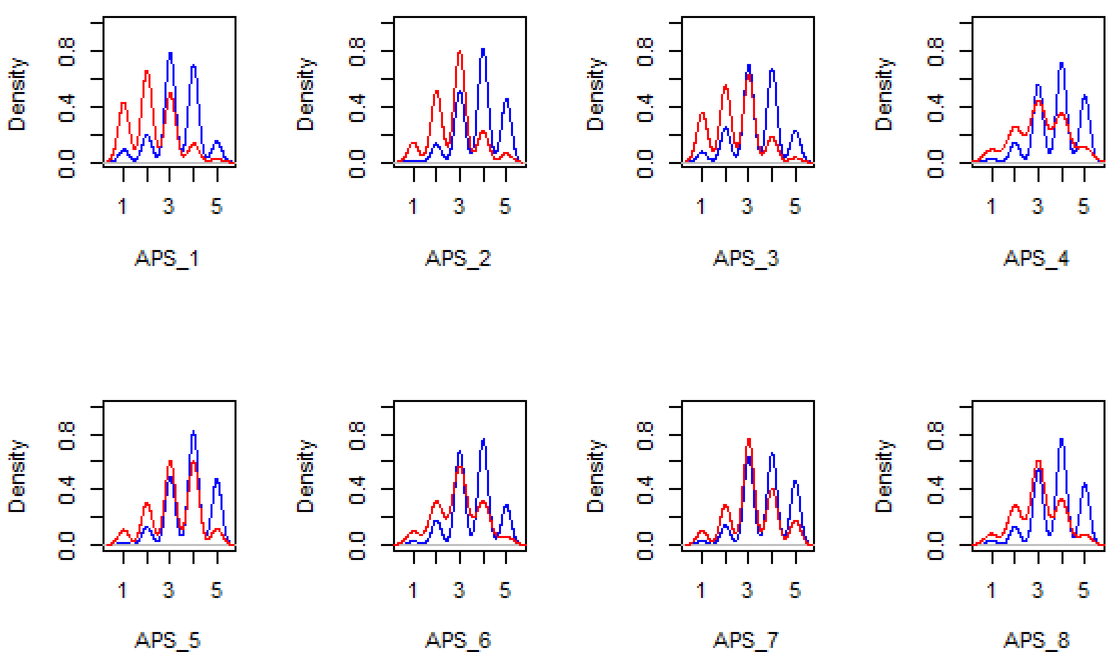


Figure 21. Density plots of FMI Mindfulness practice scores for mindfulness practitioners (red) and non-practitioners (blue).



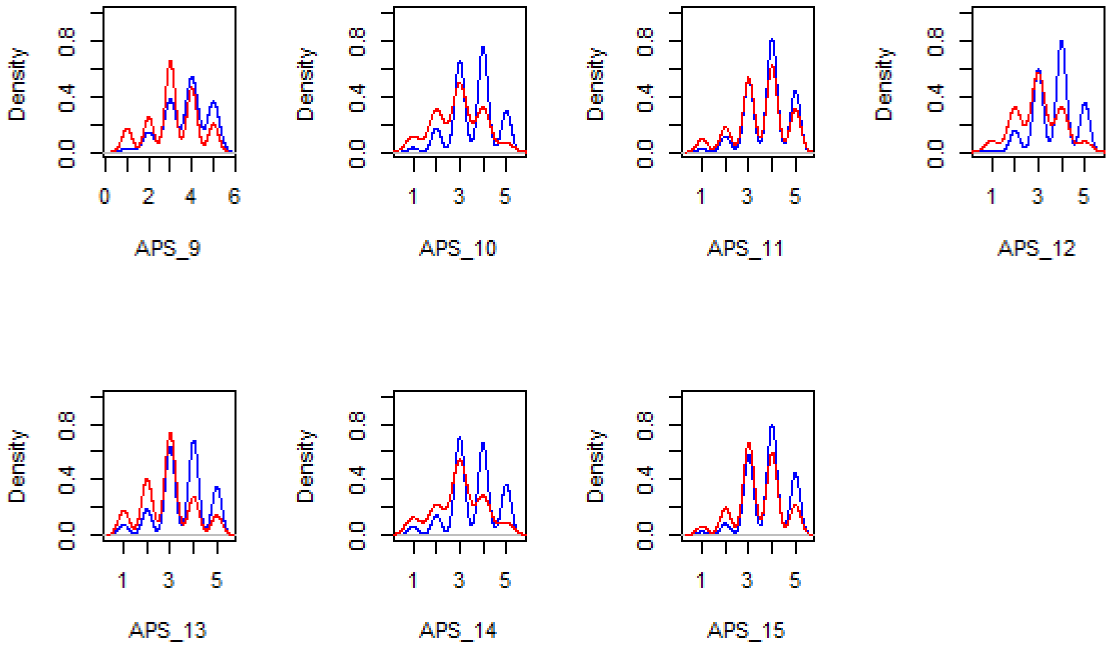


Figure 22. Density plots of AMPS Mindfulness Component scores for mindfulness practitioners (red) and non-practitioners (blue).

Appendix G: Raw Centrality Scores

Centrality comparisons made in the main text were based on z-scores. The raw score equivalents are provided below.

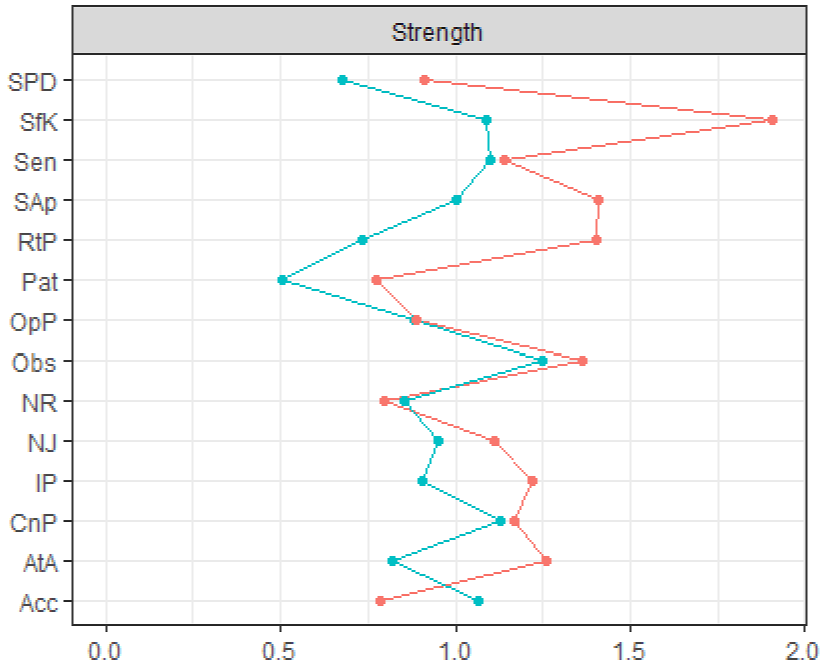


Figure 23. Raw scores for FMI strength centrality for non-practitioners (blue) and the combined sample (red). O included on the X axis.

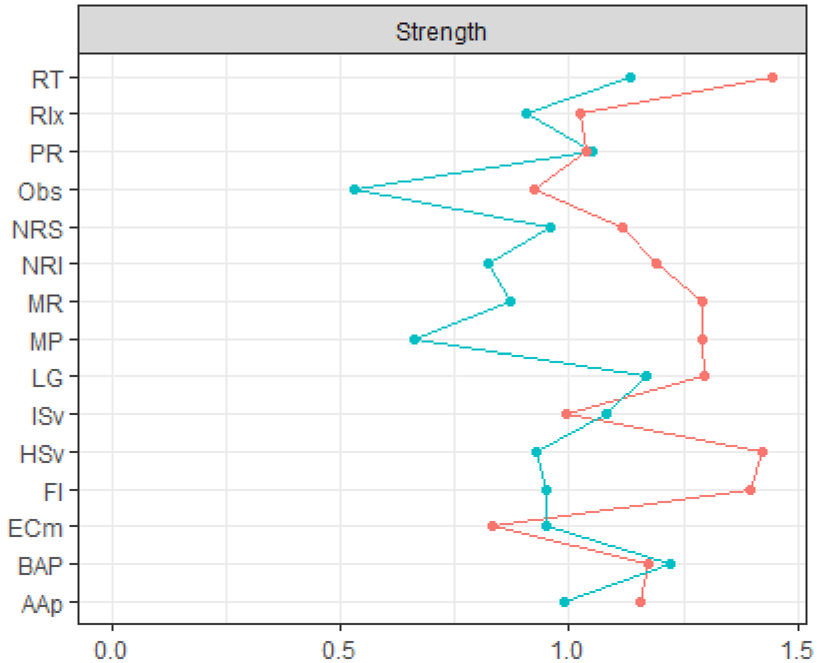


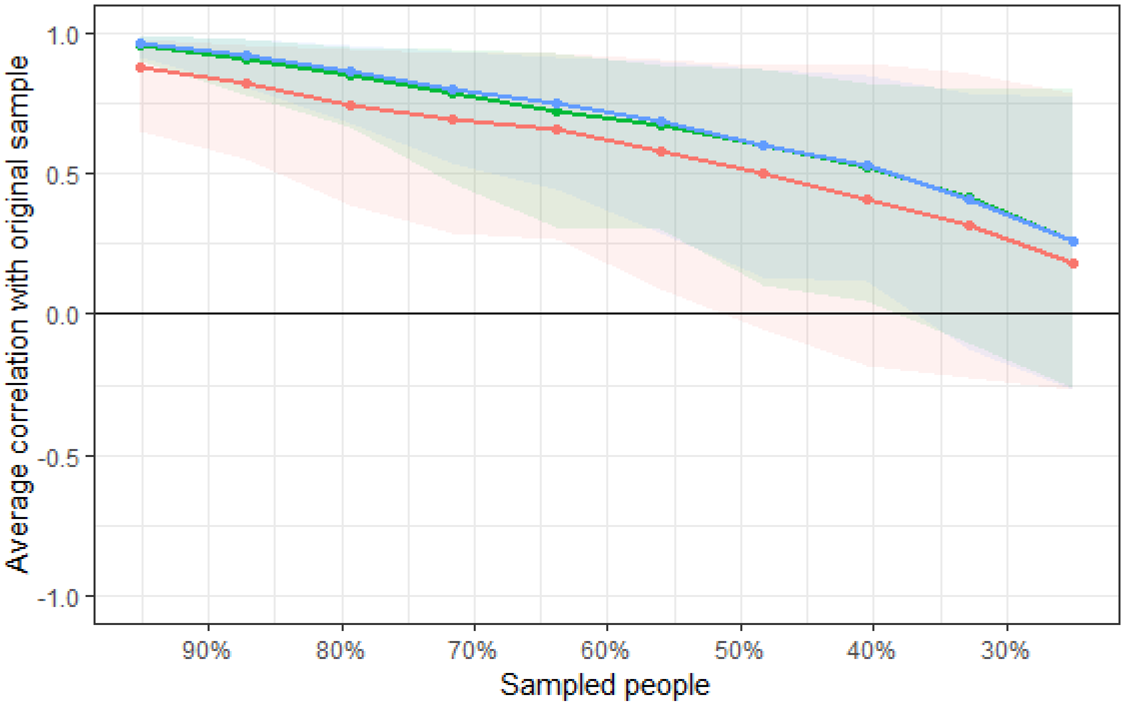
Figure 24. Raw scores for AMPS strength centrality metrics for non-practitioners (blue) and the combined sample (red). O included on the X axis.

Appendix H: Person Drop Bootstrap for Unregularised Networks

Estimated Networks must be accurate and stable for results to generalise. Epskamp, Borsboom and Fried, (2018) have recommended using a person drop bootstrap to determine the stability of the order of centrality. They also developed a centrality stability (CS) coefficient to this end (see Section 5.5.2.3 *Accuracy and Stability Estimation* for further details of this procedure). The stability of the order of centrality was analysed for unregularised partial correlation networks and the glasso networks (for both groups) to determine which networks were most suitable for the exploratory analysis.

Figure 23 shows that all centrality indices drop substantially in FMI partial correlation (un-regularised) networks. This can be contrasted with the glasso networks in the main wherein strength and closeness appeared relatively stable up to around the 70% mark for both groups. The regularised networks were hence selected for the exploratory analysis. For completion, *CS* co-efficients were calculated for the partial correlation (un-regularised) networks. Epskamp, Borsboom and Fried (2018) have recommended only interpreting the order of centrality when *CS* coefficients exceed .5. A *CS* value of .25 was suggested as the minimum value for meaningful interpretation.

CS coefficients for the un-regularised networks confirmed that the order of centrality was unstable for practitioners (betweenness *CS* = .05, closeness *CS* = .13, strength *CS* = .21), but that strength centrality might be interpreted with caution for non-practitioners (strength *CS* = .28, betweenness *CS* = .21, closeness *CS* = .21). CS coefficients for the regularised network can be found in the main analysis (Section 6.1.3.1)



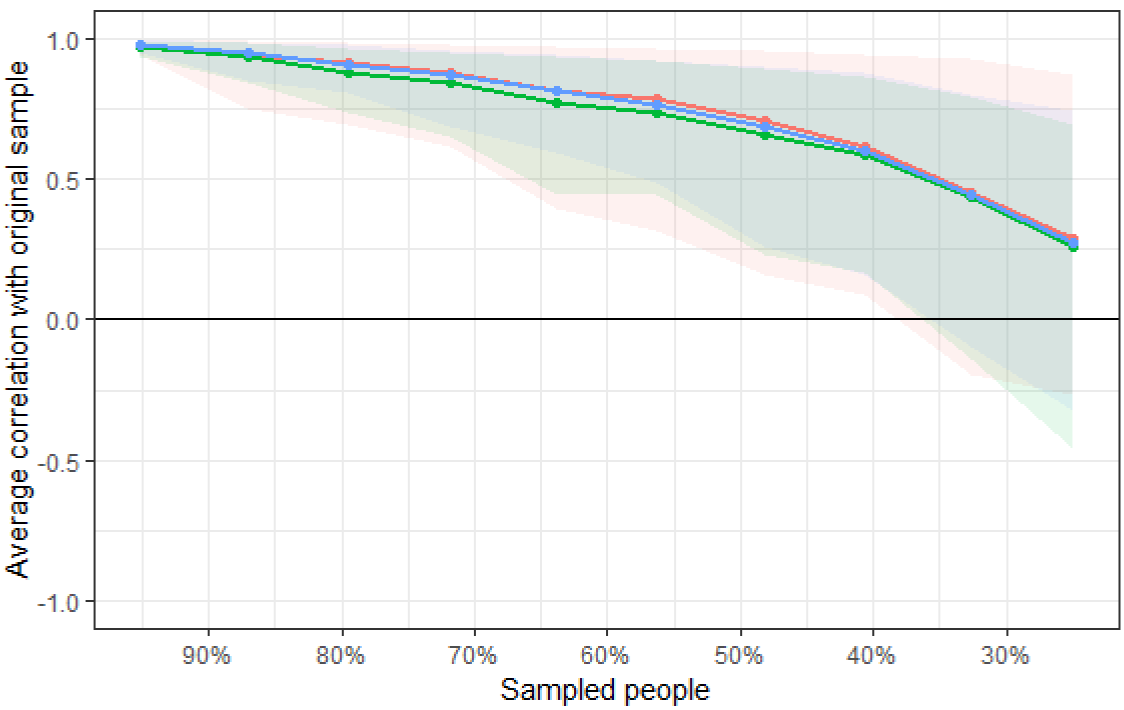
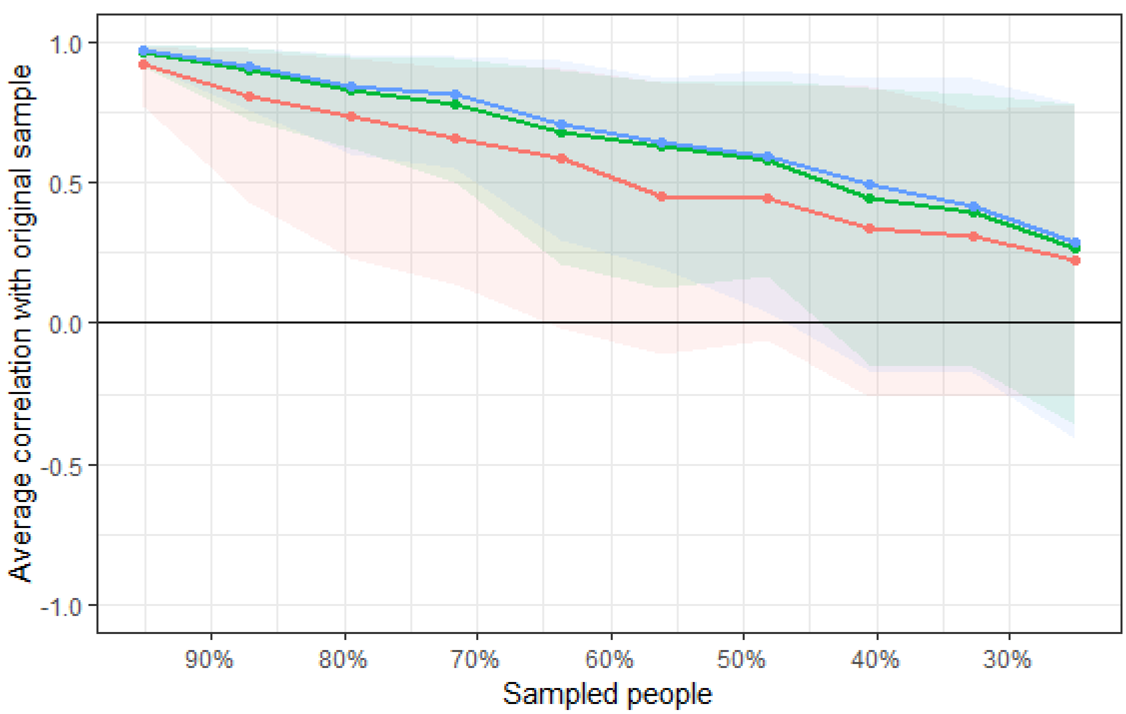


Figure 25. Average correlations between centrality indices of subsamples (networks sampled with persons dropped) and the original sample in an un-regularised FMI network for

practitioners (top) and non-practitioners (bottom). Red = betweeness; Green = closeness; Blue = strength.

Figure 24 pertains to the stability analyse performed on the AMPS networks. Figure 24 shows that correlations between centrality indices of subsamples (networks sampled with persons dropped) and the original sample using un-regularised partial correlation networks. The order of centrality metrics were not considered stable. This was confirmed by *CS* coefficients for practitioners (Strength *CS* = .13; betweenness *CS* = .05; Closeness *CS* = .13) and non-practitioners (Strength *CS* = .13; betweenness *CS* = 0.05; Closeness *CS* = .05). Regularised networks were hence selected for the exploratory analyses. The stability analyses for the regularised networks are reported in the main analysis (Section 6.2.3.1).



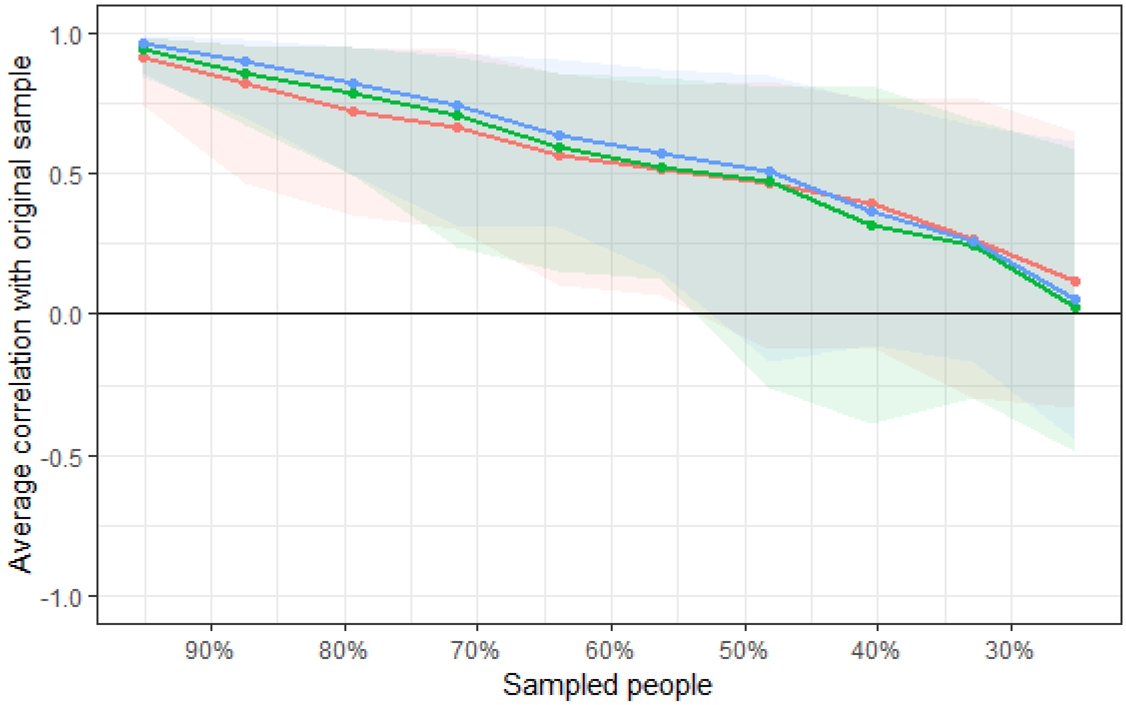
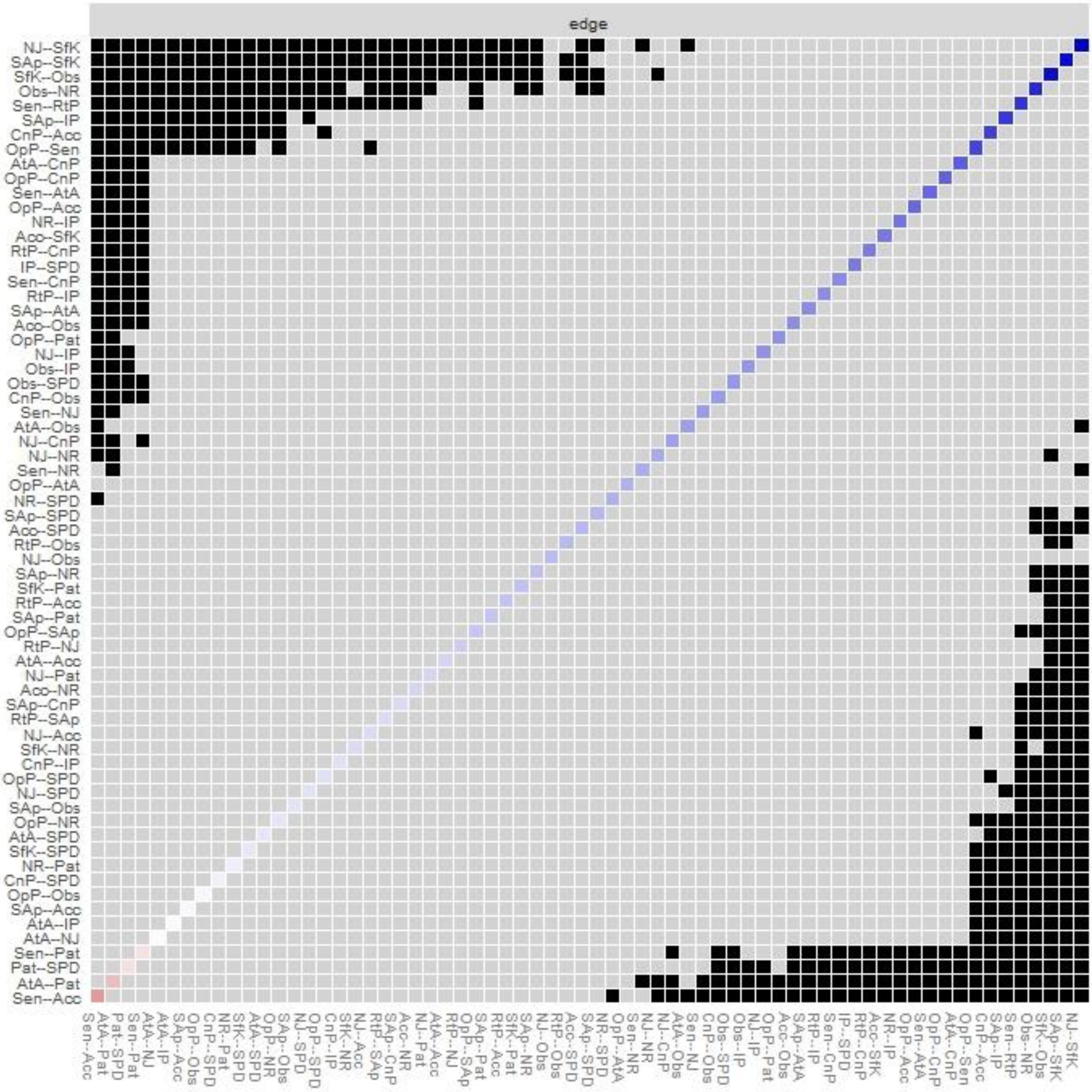


Figure 26. Average correlations between centrality indices of networks sampled with persons dropped) and the original sample in un-regularised AMPS networks for practitioners (top) and non-practitioners (bottom). Red = betweeness; Green = closeness; Blue = strength.

Appendix I: Testing for Significant Differences in Network Edges.

Bootstrapped difference tests can be used to determine significant differences between different network edges. This test involves taking the difference between the bootstrap values of one edge weight, and constructing a bootstrapped CI around the difference scores. The null hypothesis can then be tested by checking if zero is in the bootstrapped CI. This can be taken as evidence that the edges may differ. No correction is made for multiple testing (see Epskamp, Borsboom & Fried, 2018 for further details on this test, and the issue of multiple testing). In this analysis, all edges were compared to inform the interpretation of network accuracy (see Sections 6.1.3.1 and 6.2.3.1, *Network Stability and Accuracy of Exploratory Networks*). As evident in Figures 25 and 26, only the strongest edges differed from the weakest suggesting that the networks were only moderately accurately estimated.


edge
NJ--SfK
SAp--SfK
SfK--Obs
Obs--NR
Sen--RtP
SAp--IP
CnP--Acc
OpP--Sen
AtA--CnP
OpP--CnP
Sen--AtA
OpP--Acc
NR--IP
Acc--SfK
RtP--CnP
IP--SPD
Sen--CnP
RtP--IP
SAp--AtA
Acc--Obs
OpP--Pat
NJ--IP
Obs--IP
Obs--SPD
CnP--Obs
Sen--NJ
AtA--Obs
NJ--CnP
NJ--NR
Sen--NR
OpP--AtA
NR--SPD
SAp--SPD
Acc--SPD
RtP--Obs
NJ--Obs
SAp--NR
SfK--Pat
RtP--Acc
SAp--Pat
OpP--SAp
RtP--NJ
AtA--Acc
NJ--Pat
Acc--NR
SAp--CnP
RtP--SAp
NJ--Acc
SfK--NR
CnP--IP
OpP--SPD
NJ--SPD
SAp--Obs
OpP--NR
AtA--SPD
SfK--SPD
NR--Pat
CnP--SPD
OpP--Obs
SAp--Acc
AtA--IP
AtA--NJ
Sen--Pat
Pat--SPD
AtA--Pat
Sen--Acc
Sen--Acc
AtA--Pat
Pat--SPD
Sen--Pat
AtA--NJ
AtA--IP
SAp--Acc
OpP--Obs
CnP--SPD
NR--Pat
SfK--SPD
AtA--SPD
OpP--NR
SAp--Obs
NJ--SPD
OpP--SPD
CnP--IP
SfK--NR
NJ--Acc
RtP--SAp
SAp--CnP
Acc--NR
NJ--Pat
AtA--Acc
RtP--NJ
OpP--SAp
SAp--Pat
RtP--Acc
SfK--Pat
SAp--NR
NJ--Obs
RtP--Obs
Acc--SPD
SAp--SPD
NR--SPD
OpP--AtA
Sen--NR
NJ--NR
NJ--CnP
AtA--Obs
Sen--NJ
CnP--Obs
Obs--SPD
Obs--IP
NJ--IP
OpP--Pat
Acc--Obs
SAp--AtA
RtP--IP
Sen--CnP
IP--SPD
RtP--CnP
Acc--SfK
NR--IP
OpP--Acc
Sen--AtA
OpP--CnP
AtA--CnP
OpP--Sen
CnP--Acc
SAp--IP
Sen--RtP
Obs--NR
SfK--Obs
SAp--SfK
NJ--SfK

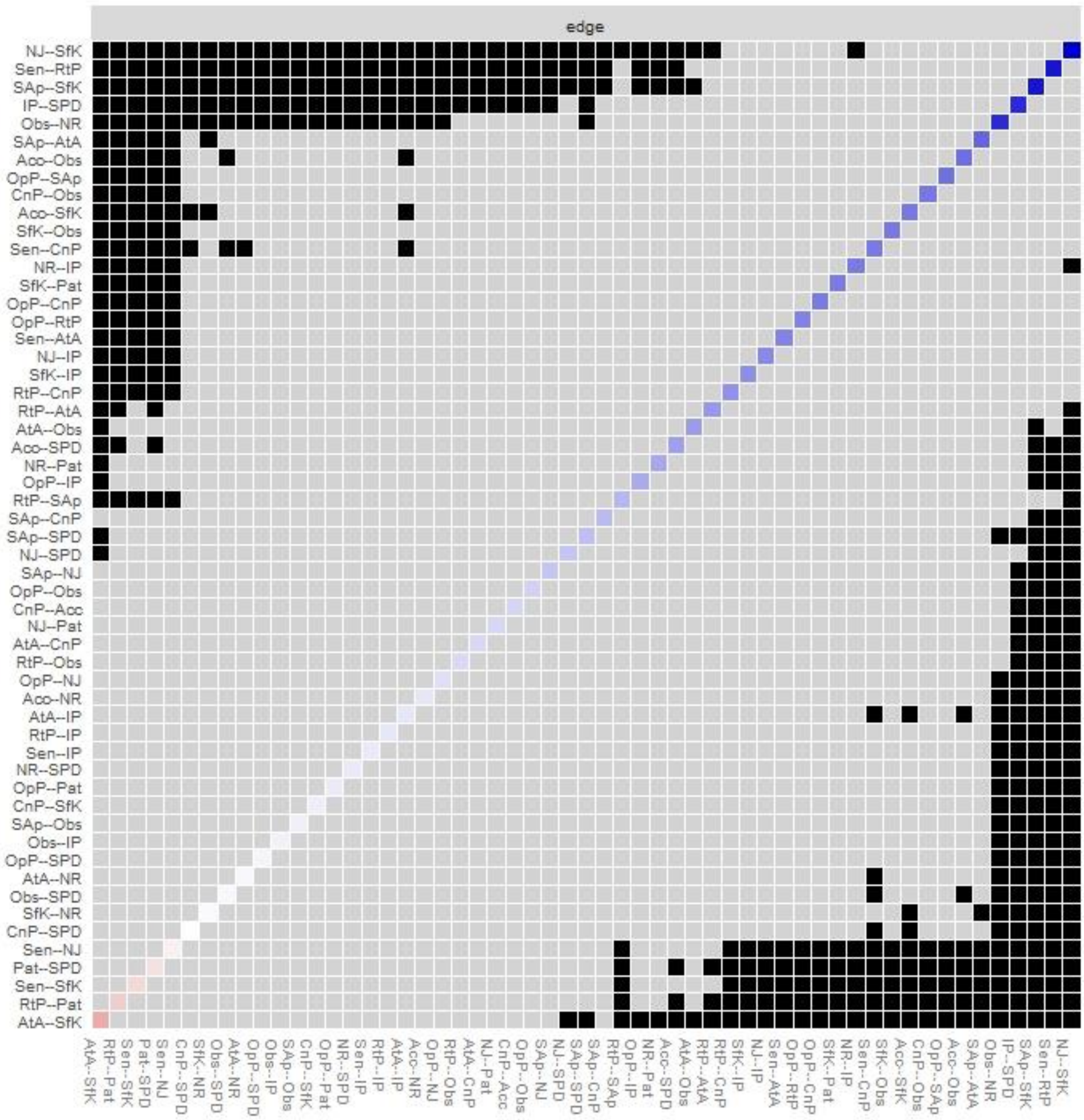
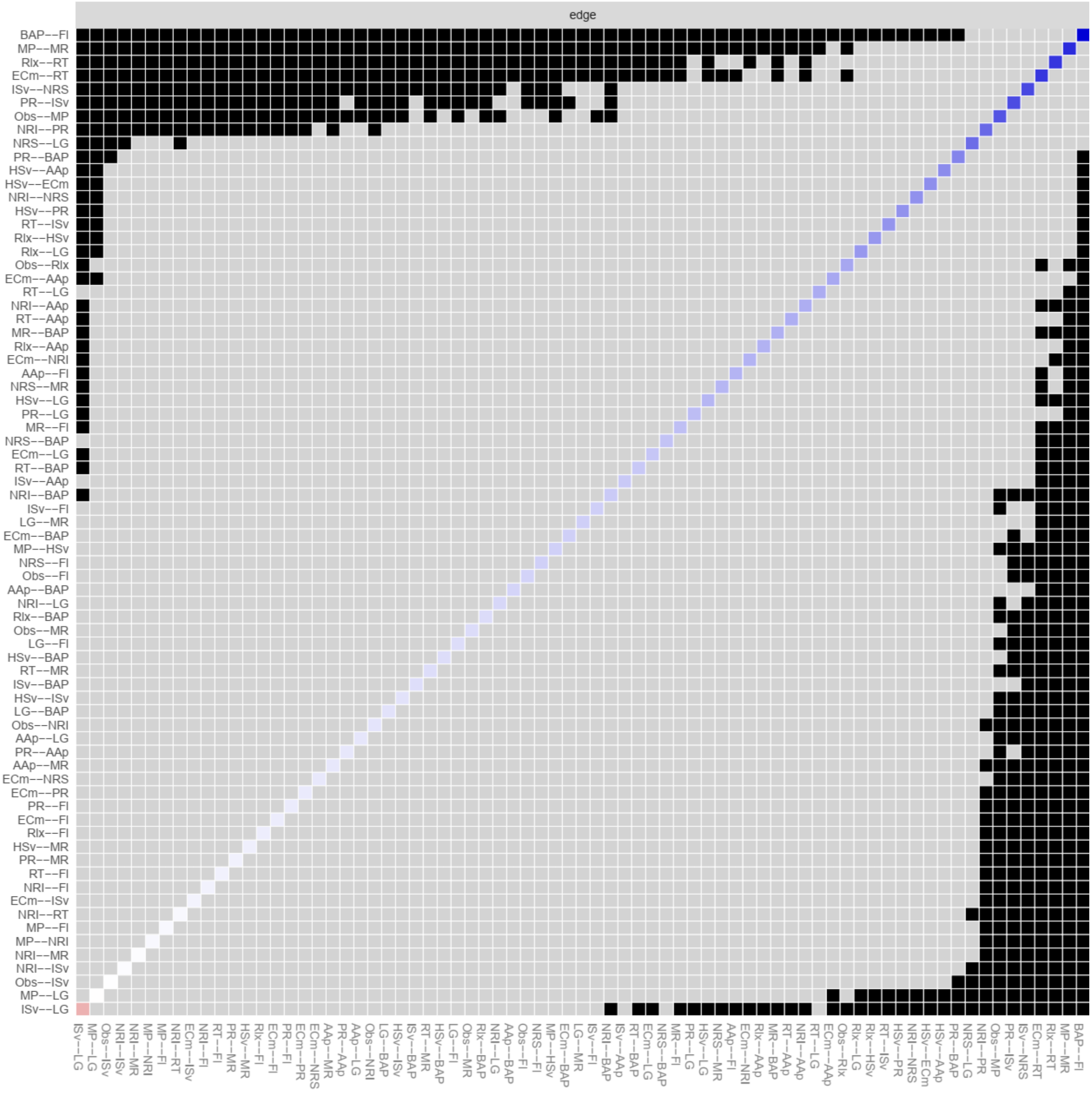


Figure 27. Bootstrapped difference tests (alpha = .05) between pathway-weights that were non-zero in the estimated practitioners' (top) and non-practitioners' (bottom) FMI mindfulness networks. Grey boxes indicate pathways that do not differ significantly from one another and black boxes represent pathways that significantly differ. Diagonal indexes path strength ranging from the strongest negative path (bottom left) to strongest positive paths (top right). Saturation reflects strength of correlation from positive (blue) to negative (red). No corrections made for multiple testing.


edge
BAP--FI
MP--MR
Rlx--RT
ECm--RT
ISv--NRS
PR--ISv
Obs--MP
NRI--PR
NRS--LG
PR--BAP
HSv--AAp
HSv--ECm
NRI--NRS
HSv--PR
RT--ISv
Rlx--HSv
Rlx--LG
Obs--Rlx
ECm--AAp
RT--LG
NRI--AAp
RT--AAp
MR--BAP
Rlx--AAp
ECm--NRI
AAp--FI
NRS--MR
HSv--LG
PR--LG
MR--FI
NRS--BAP
ECm--LG
RT--BAP
ISv--AAp
NRI--BAP
ISv--FI
LG--MR
ECm--BAP
MP--HSv
NRS--FI
Obs--FI
AAp--BAP
NRI--LG
Rlx--BAP
Obs--MR
LG--FI
HSv--BAP
RT--MR
ISv--BAP
HSv--ISv
LG--BAP
Obs--NRI
AAp--LG
PR--AAp
AAp--MR
ECm--NRS
ECm--PR
PR--FI
ECm--FI
Rlx--FI
HSv--MR
PR--MR
RT--FI
NRI--FI
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MP--FI
MP--NRI
NRI--MR
NRI--ISv
Obs--ISv
MP--LG
ISv--LG

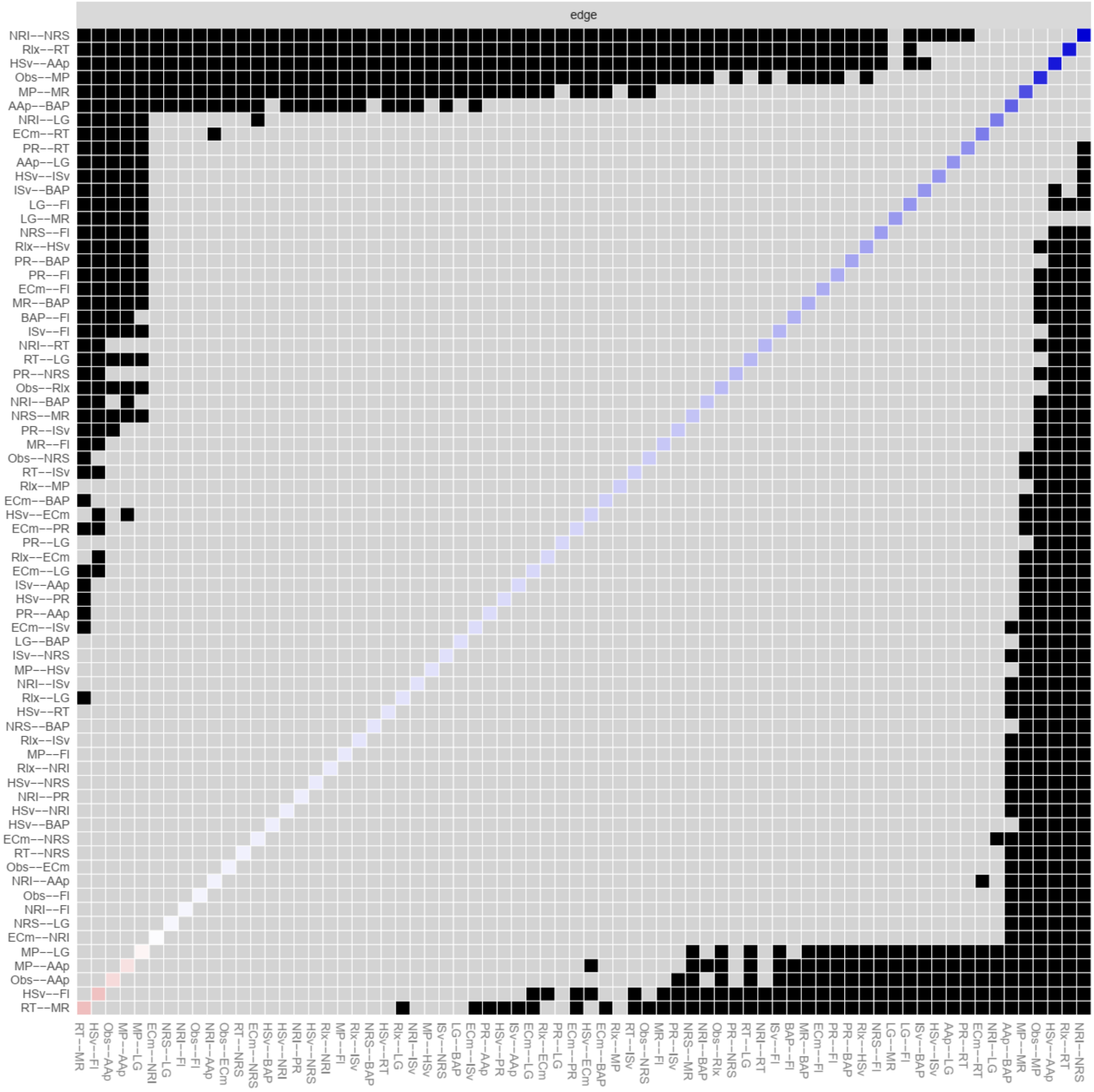
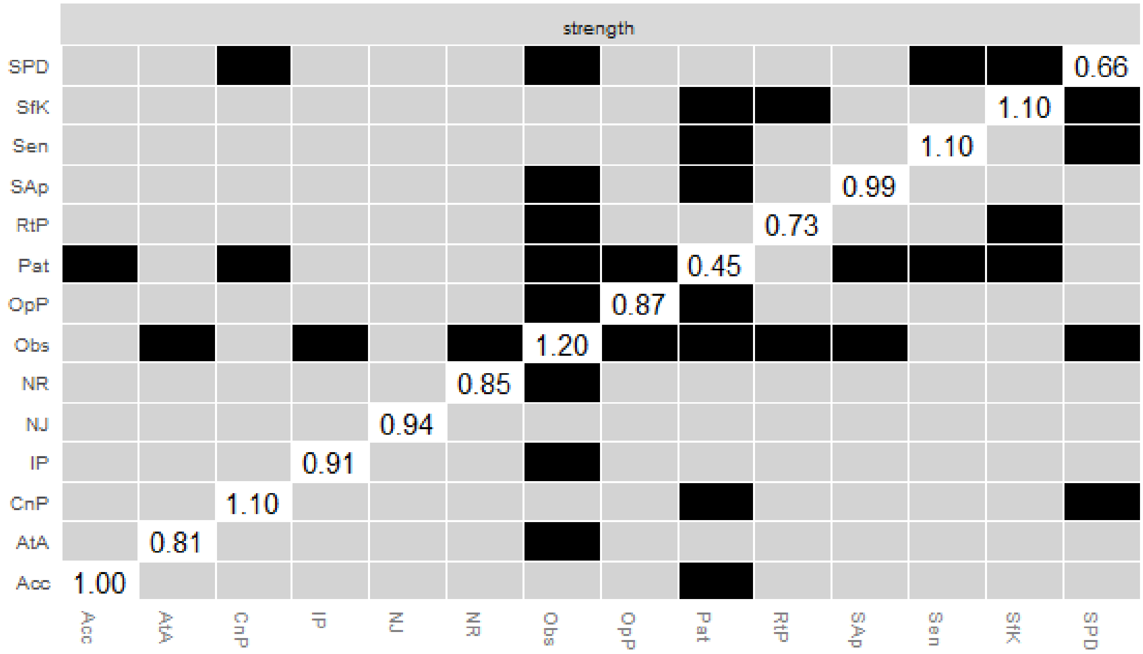


Figure 28. Bootstrapped difference tests in the estimated practitioners (top) and non-practitioners (bottom) AMPS mindfulness network. Grey boxes indicate pathways that do not differ significantly from one-another and black boxes represent pathways that significantly differ. Diagonal indexes path strength ranging from the strongest negative path (bottom left) to strongest positive paths (top right). Saturation reflects strength of correlation from positive (blue) to negative (red). No corrections made for multiple testing.

Appendix J: Testing for Significant Differences in Network Strength Centrality

Bootstrapped values were used to test the null hypothesis that two different practice centralities did not differ. Practices were compared to help inform centrality interpretation. Of particular interest was whether the most strength central practices differed significantly from each other. See chapter 6 for discussion of these results.



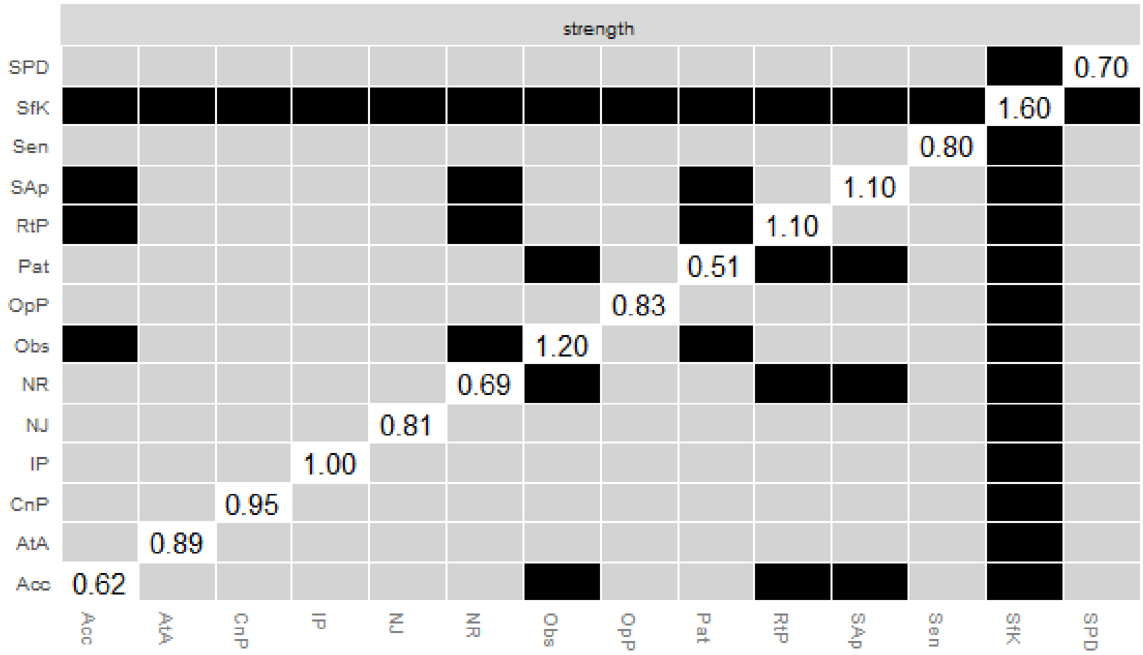


Figure 29. Bootstrapped difference test results for estimated centrality values for practitioners' (top) and non-practitioners' (bottom) FMI mindfulness networks. Raw scores are listed in the diagonal (white boxes) and significant differences between practices are indicated by boxes filled black. No correction for multiple testing has been applied.

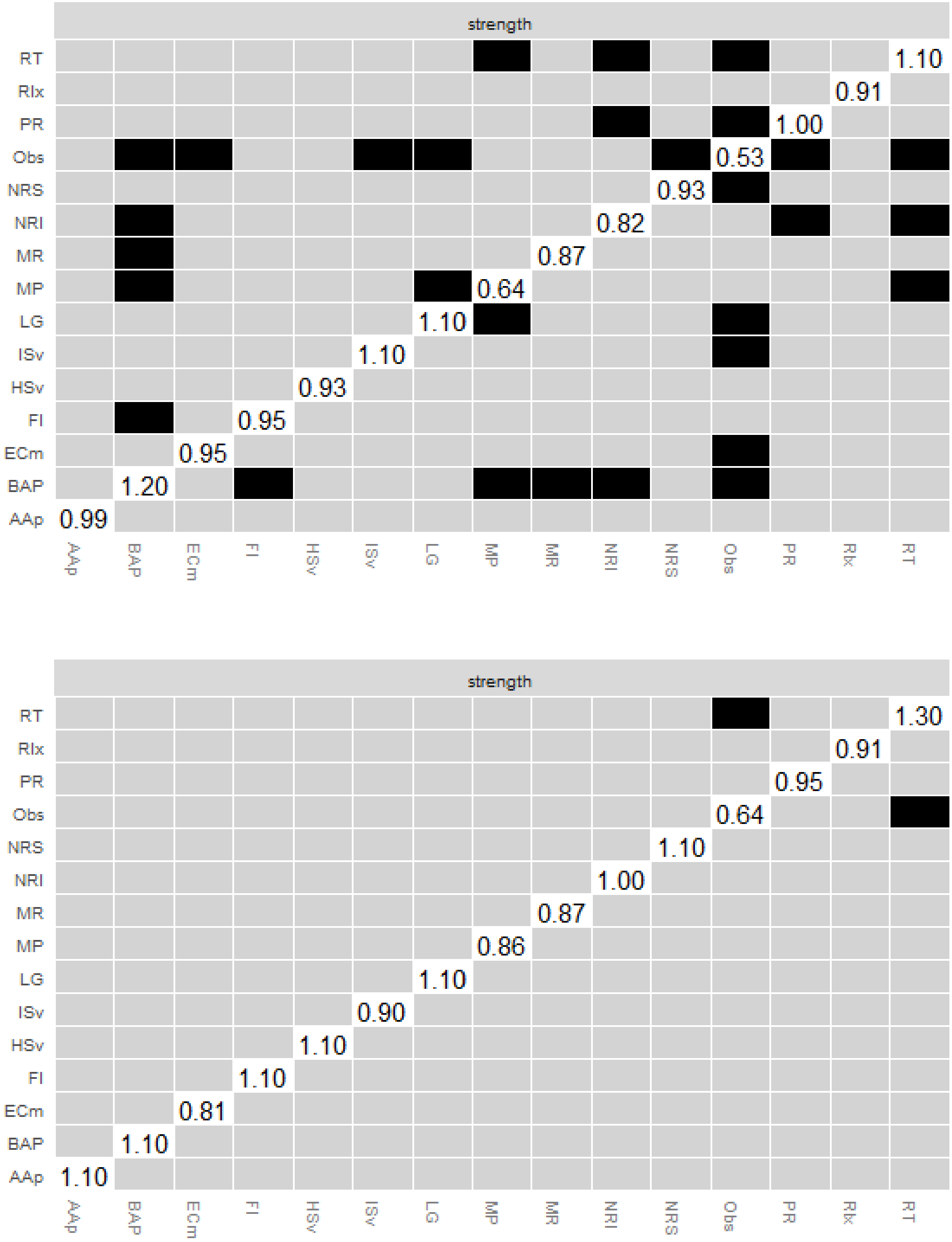


Figure 30. Bootstrapped difference test results for estimated centrality values for practitioners’ (top) and non-practitioners' (bottom) AMPS mindfulness networks. Raw scores are listed in the diagonal (white boxes) and significant differences between practices are indicated by boxes filled black. No correction for multiple testing has been applied.

Appendix K: Comparing Regularised Spearman and Polychoric Networks

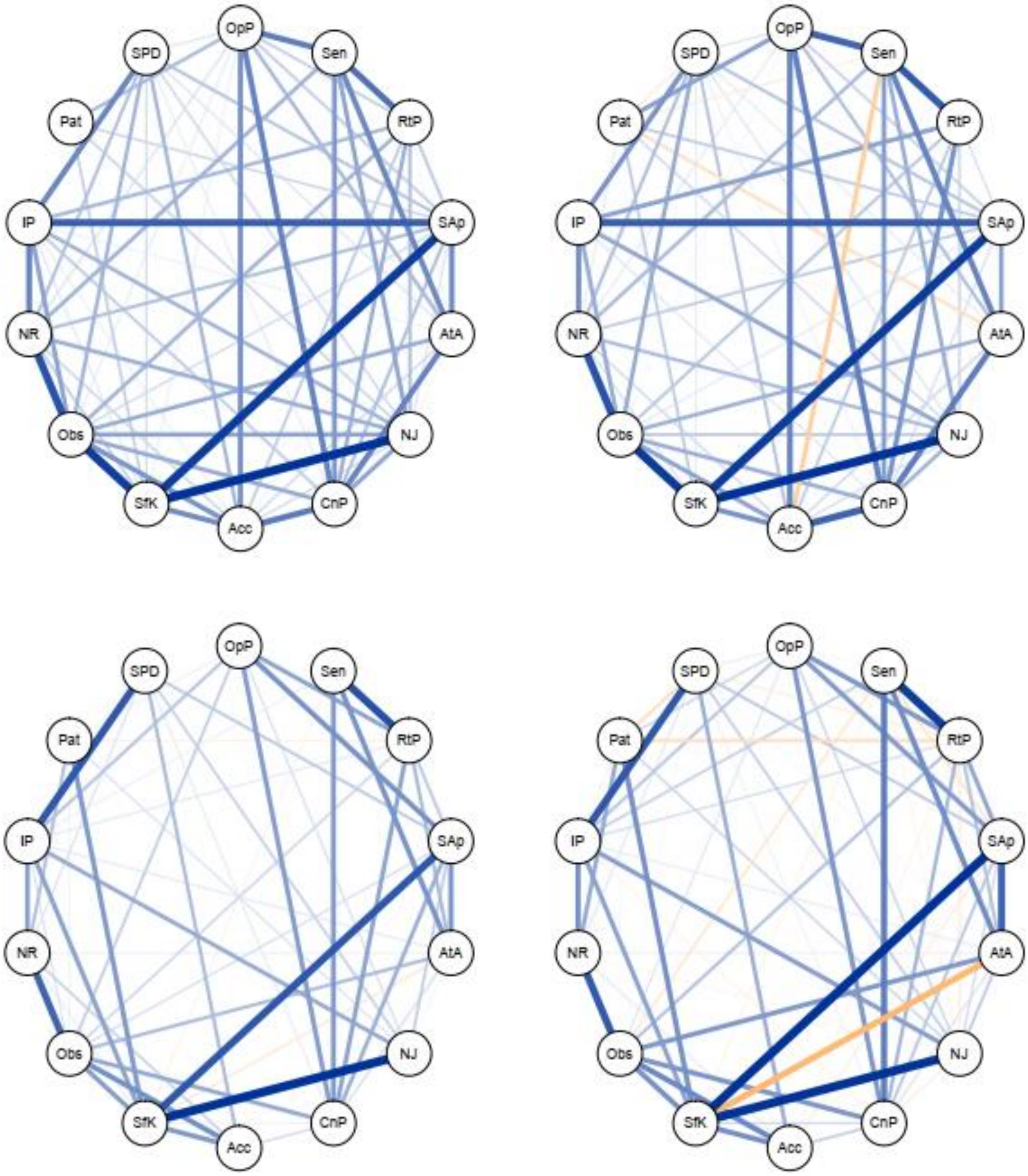


Figure 31. Networks estimated with Spearman's correlations (left) and polychoric correlations (right), for practitioners (top) and non-practitioners (bottom). Maximum Edge weights: practitioners' Spearman (.24), practitioners' polychoric (.35); non-practitioners' Spearman (.38), non-practitioners polychoric (.44). All networks estimated with gamma tuning value of .5.

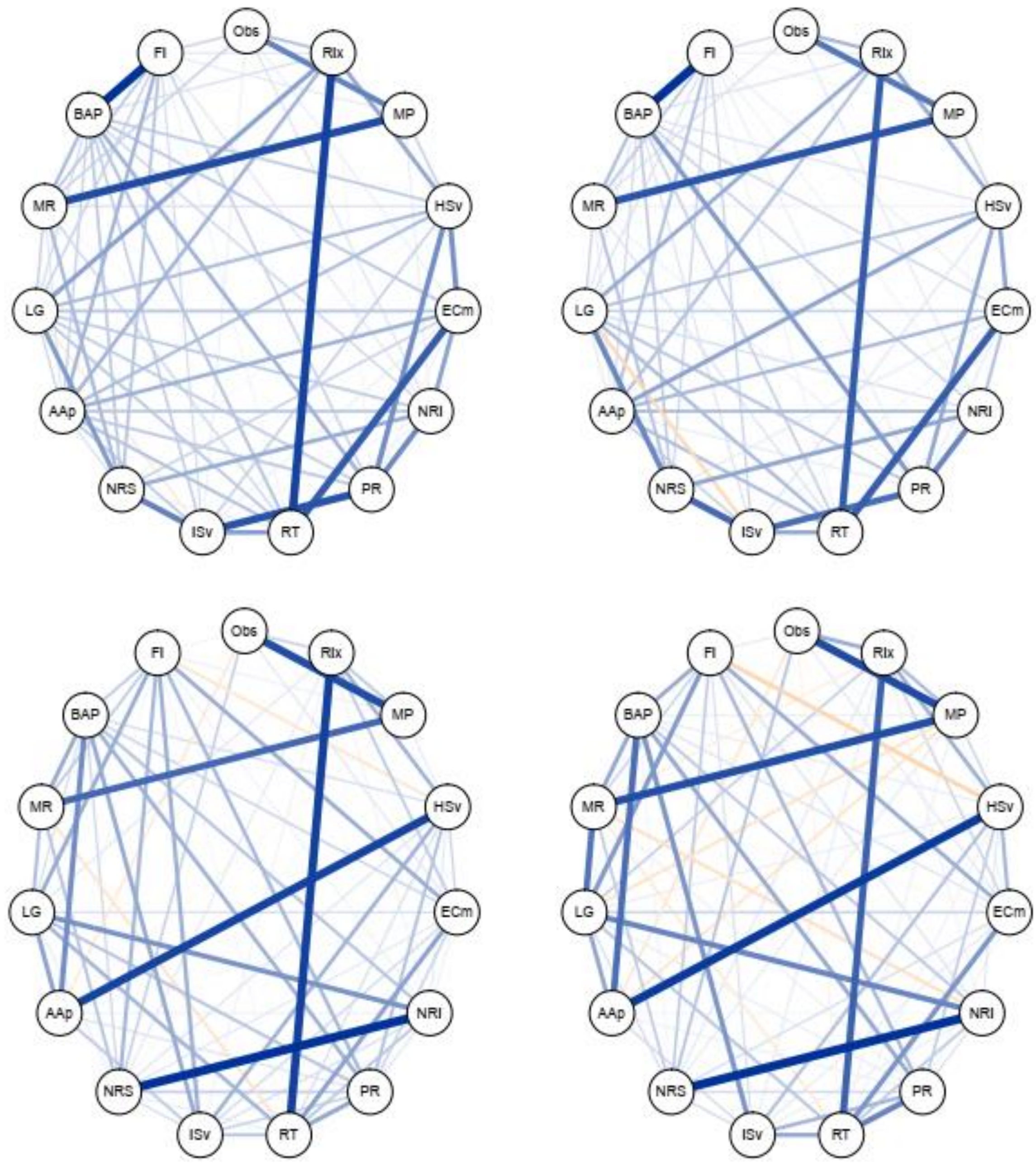


Figure 32. Networks estimated with Spearman's correlations (left) and polychoric correlations (right), for practitioners (top) and non-practitioners (bottom). Maximum Edge weights: practitioners' Spearman (.32), practitioners' polychoric (.37); non-practitioners' Spearman (.37), non-practitioners polychoric (.44). All networks estimated with gamma tuning value of .5.

Appendix L: Case Study

As part of the requirements of this degree, a case study was required related to the thesis. The following represents a positioning essay developed early in the piece. The essay hence represents a characterisation of the research at a certain point in time. This case study has already been examined as part of the clinical component of my Doctorate of Clinical Psychology degree. It need not be further examined.

Massey University

CASE STUDY 2 – Research Paper

Implications of a Network Approach to Mindfulness

Candidate: Joseph Smith

Clinical Psychology Programme Massey University

Student ID: [redacted]

Setting: Massey University

Supervisor: Dr Heather Buttle

This case was completed during the Massey internship year in 2017 and represents the work of the candidate

Student

Joseph Smith

Intern Psychologist

Date:

Implications of a Network Approach to Mindfulness

This essay aims to briefly explore the advantages of using a network perspective in the study of mindfulness. It is suggested that existing methodologies are susceptible to reifying the construct of mindfulness, which can render it too static. It is suggested that a network methodology provides another fruitful way to measure mindfulness which can achieve consilience with broader social theory.

Conceptualising mindfulness

Mindfulness has proven hard to define, although typically, contemporary definitions have emphasised practices most closely associated with the Buddhist Modernist revisions in the early 20th century; namely, focused attention in a non-judgmental or compassionate way (Baer, 2003; Bishop et al., 2004; Brantley, 2003; Germer et al., 2005; Kabat-Zinn, 1994; Salzberg & Goldstein, 2001). Further definitions in the literature may largely be said to have expanded on the second component to further incorporate aspects such as non-reactivity, full participation and other associated qualities (Begomi, Tschacher & Kupper, 2012).

Buddhist Modernism is credited with emphasising the role of meditation to the relative exclusion of traditional Buddhist doctrines, ritual and liturgical practice (Sharf, 2015; Stanley, 2013). The focus of meditation itself was also adapted in emphasising the concept of *sati* or *bare attention*. Meditation now came to be increasingly framed as an activity of focusing on whatever sensory objects arose in the moment-to-moment flow of consciousness (Sharf, 2015; Stanley, 2013). In this way, mindfulness became a practice more easily accommodated by the layperson, and contemporary (Western) definitions of mindfulness might be said to have further marginalised Buddhist soteriology to make the practices more palatable to a western audience (Purser & Milillo, 2015). Taken together, these revisions presented Buddhism as a rational, empirical tradition which can be studied in its own right, independent of the rest of the tradition.

Through this dialogue, mindfulness has come to be viewed as a universal capacity or *internal resource* which can be cultivated by anyone willing to engage in specific, intentional mindfulness instruction. This conceptualisation was immediately translatable to research psychologists long accustomed to the concept of internal resources, known otherwise as *traits* in the individual differences literature. It is the terms trait or *dispositional* mindfulness which now populate the literature, and to a lesser extent the concept of *state* mindfulness (referring to an individual's immediate experience). A number of self-report questionnaires have emerged to measure these concepts, by which the answers to items are believed to reflect the relative strength of the underlying concept.

Empirically, these questionaries' have most often been developed and analysed using a statistical technique known as factor analysis - a technique considered "the heart of the measurement of psychological constructs" (Nunnally, 1978, pp. 112-113). One of two factor analytic models are typically employed which, although differing in theory, tend to be interpreted in the same way in practice (Bollen 2002; Borsboom, Mellenbergh, & van Heerden, 2004). In *reflective factor models*, questionnaire items (or indicators) are believed to reflect the operations of the underlying *latent* or unobservable phenomenon. These are causal models which borrow their theory of measurement from the physical sciences (Borsboom, Mellenbergh, & van Heerden, 2003). The causal theory in reflective models can easily be illustrated by the idea of a number of different thermometers all *reflecting* the underlying construct of room temperature. As the latent construct of room temperature varies, so too will the readings of the observed indicators (i.e. thermometer readings will co-vary). Importantly, the observed indicators cannot be said to influence each other (i.e. the reading of one thermometer should not directly or causally influence the reading of another).

The latent construct of *formative models* can be contrasted with those in reflective models, as they do not cause, but rather are constituted (or *formed*) by the measured items.

Those items are often quite disparate, as exemplified by the prototypical formative construct, Socio Economic Status, which is composed of indicators of education, occupational prestige, income, and neighbourhood. Unlike in reflective models, changes in the items of formative models change the construct itself, which can lead to a plethora of constructs bearing the same name. Because the arrows of causality travel from the indicators to the construct, formative models are not well suited to the classical idea of measurement, by which one measures something that *actually exists*.

Although theoretically distinct, formative models are often treated as analogous with reflective models in psychological investigation: to the extent to which the researcher is concerned with investigating something that really exists, they tend to view the covariance observed in their indicators as caused by changes in the unobservable latent construct. Put differently, irrespective of the models employed, the latent constructs in factor analytic studies are often interpreted as the *common cause* of change in the observed items (Pearl, 2000). Of course, unlike in the physical sciences from which the common cause model is borrowed, any understanding of the actual mechanism or physical chain by which a latent psychological construct actually causes the changes in questionnaire items, remains outstanding. This can easily be contrasted to the physical sciences analogy; for example, in the example of temperature, the latent construct can be said to cause the change in the thermometer indicators by recourse to principles of thermal expansion, by which mercury expands, causing it to rise up the thin thermometer column.

In mindfulness research, the trait often appears to stand in for the common cause of the changes in observations in the questionnaire items. In making this analogy with the physical sciences, the latent construct – itself bearing no direct reference to a real entity (the arrows in the models only travel from the latent construct to the indicators) – gains substance. This is termed *reification* in the literature, and it is a very natural step to make for a researcher interested in *measuring*: something has to exist to be measured, and something has to exist to cause change in something else (Borsboom, Mellenbergh, & van Heerden, 2003). Common parlance further consolidates this interpretation in that we might say John is considered more mindful than Sarah, *because* he is *more* equanimeous and compassionate than her. The next natural step is to seek the neurobiological correlates of this substantive entity, and appropriate technologies come to be employed for this purpose. As a result of this process, mindfulness comes to reside in the brain. This process has been well established in other areas in the psychological literature where latent constructs have been interpreted this way. In psychopathology, mental illness is diagnosed by its symptoms, and a disease process is believed to underpin this (indeed, the word symptom itself, by definition invokes a latent construct). Likewise, a similar idea has been advanced in personality research, whereby traits such as *neuroticism* are believed to cause certain behaviour (McCrae and Costa, 1995). In both cases, bio-markers in the brain have been sought, although this endeavour appears unrewarding to date (Deacon, 2013; Kapur, Phillip & Insel, 2012; Lacasse & Leo, 2005; Matins De-Souza, 2013). Plausibly, a similar situation may well emerge in the contemplative sciences.

If we accept the argument that latent psychological constructs have no casual properties, the question remains as to what causes the observed covariance in indicators. In the case of psychopathology, covariance has been explained by plausible causal links between the symptoms themselves. For example, in Major Depression, one can easily imagine causal links between the core symptoms of insomnia, fatigue, a loss of concentration, worry and low mood (Borsboom & Cramer, 2013; Fried & Cramer, 2017). Such direct symptom-by-symptom interactions can explain the phenomenon of depression without invoking a causal disease entity *depression*. Likewise, in personality we can imagine causal connections between the items indicating *people who like to go to parties* and other items around *having more friends*. An underlying extraversion trait is not needed to explain this: people, who like parties, meet more people, which results in more friends. As a result, they get invited to more parties, and so on (Cramer et al., 2012). The current research project extends this logic to the items of mindfulness questionnaires. We need not invoke a substantive mindfulness entity to explain the covariance we might find on the measures.

Network models of mindfulness

Garland, Farb, Goldin and Fredrickson (2015) have called for a de-reification of constructs in mindfulness research in order to advance the field of contemplative science. They suggest that "it may be fruitful, for instance, to consider that there may be no actual entity called "mindfulness," but rather a network of interacting cognitive and affective processes…that we, for scholarly convenience, label "mindfulness" (p. 2). Recently, a novel statistical methodology has arisen which can model this intuition at the level of self-report questionnaires. Provided the items chosen for a questionnaire represent distinct or unique information (as they should to avoid content overlap and multi-collinearity), they can be represented as nodes in a network. The links that connect these nodes to form a network, are the correlations or partial correlations between them. In creating a mindfulness network, research can than draw on existing analyses unique to network science, such as global properties of network density (the sum of all connections) and local properties such as centrality (the relative importance of a given node in the network).

The current project was a cross-sectional study, but it suggested that a mindfulness network will form when initially uncorrelated nodes, existing in the general population, come to be corralled together through intentional mindfulness practices. At a critical point, this network may become self-sustaining when the nodes come to feedback upon themselves. When this happens a stable state occurs, and mindfulness might be said to *emerge* from the system. To the extent that this system entertains novel properties (i.e. new causal properties which cannot be reduced to the respective components alone), this stable state can be considered a *real* entity given its casual properties. Taken together, this developmental model can be considered a *mutualist model* (van der Maas et al., 2006), and it informs the major hypothesis that networks of mindfulness practitioners should be characterised by greater global density than those of non-practitioners i.e. they should have more connections of greater strength).

The ontology of constructs in networks

As noted, the ontology of a network construct might be considered real when it demonstrates properties irreducible and unpredictable from its components. In the absence of this, an emergent variable might better be considered a social or pragmatic construction which summarises the system (Kukla, 2001; Zachar & Kendler, 2007). In Network Science, an *emergent* state with novel causal properties has been termed an *attractor state* (Barrett, 2011; Maul, 2013), and networks shift into these states in what is known as a *phase shift*.

An attractor state is in equilibrium, and a state of equilibrium always exists within an environment (Cramer et al., 2012). In their network studies of personality, Cramer and colleagues (2012) viewed personality traits as states of equilibrium, noting that it was the environment which helped determine, or at least maintain, the relatively fixed behavioural repertoires humans seem to settle into (see also Kendler, Gardner & Prescott, 2003 for an interactional theory of personality). In interaction with each other and the environment, cognitions, affects and behaviours come to be either reinforced or inhibited (for example, it becomes difficult to both love parties and dislike being around people at the same time). As such, constellations emerge as these cognitions, affects and behaviours come to flock together.

These models mirror that advanced by John Dewey (1916/2004) in the early twentieth century. Dewey conceived of people as simply the *unification* of their habits. In this way, there was *nothing outside the flux*, which became the maxim of a school of philosophy known as Pragmatism. Like Cramer and colleagues' (2012) conceptualisation, Dewey noted that habits form because they are effective in enabling the person to find equilibrium within the surrounding environment. He suggested that to change a habit, a person might intentionally alter their environment, yet reliable change ultimately required acquiring new habits through practice. In acquiring new habits, Dewey believed that the system of existing habits comes to be disrupted as certain habits are reinforced, whilst others wane or are never eventuated. As such, habit acquisition involved fundamental change to the person's subjectivity. This could be conceived an ethical endeavour, to the extent to which a person may wish to better themselves. The question left begging is hence, which types of ethical practices might be most disruptive to an existing system of habits?

Mindfulness as ethical practice

Michel Foucault (1988) suggested that the prevalent idea that there is something hidden in ourselves was illusionary (see also Rose, 1998), and in this way, he mirrored the Pragmatist belief that there was no *soul* or *self* which directed a person's activity. In his late work, Foucault started to study the ethical practices of antiquity which he saw as a means to alter one's subjectivity. Foucault termed these *self-care* practices, and he went so far as to say that the ancient Socratic injunction to *know thyself* was actually subordinate to an injunction to *take care of oneself*. Self-care practices were conducted in the service of preparing the self for knowledge, which Foucault (1982/2005) contrasted with philosophy, which concerned knowledge itself:

> We will call "philosophy" the form of thought that asks what it is that enables the subject to have access to the truth and which attempts to determine the conditions and limits of the subject's access to the truth. If we call this "philosophy," then I think we could call "spirituality" the search, practice, and experience through which the subject

> carries out the necessary transformations on himself in order to have access to the truth. We will call "spirituality" then the set of these researches, practices, and experiences, which may be purifications, ascetic exercises, renunciations, conversions of looking, modifications of existence, etc, which are, not for knowledge but for the subject, for the subject's very being, the price to be paid for access to the truth (p. 15).

Foucault's work referenced a number of practices (many of which bear resemblance to current activities under the umbrella of mindfulness) which were crucially similar in one way: their intention was not for knowledge, but the subject.

Autotelic activities and eudemonia

Autotelic activities are activities conducted for them-selves. Put differently, the *means* are the *ends* in autotelic activity – the difference only being a passage of time. Autotelic activity is central to Virtue Ethics, a branch of western ethics closely resembling Buddhist thought. Virtue Ethics is closely associated itself with Aristotle, who believed that every action aims at some good. In doing an action well, the good of that act becomes manifest and the individual was said to achieve *eudemonia*. Eudemonia can be translated as both *flourishing* and *happiness*, but at core, the term captures the notion that the *ends* of a virtuous practice is simply the flourishing of the *means*.

The concept of eudemonia is evident in the mindfulness literature both implicitly and explicitly. Garland and colleagues (2015) explicitly talk of eudemonia as being important for mindfulness, and have attempted to capture it through self-report. More subtly, Grossman and van Dam (2011) suggest something akin to eudemonia in their recommendations that mindfulness questionnaires measure not simply how skilled individuals are in various practices, but also the extent to which they value those characteristics. The idea is also synonymous with the notion of *acceptance* or *allowing* which is widespread in the mindfulness literature (see for example *being* versus *doing* in Segal, Teasdale & Williams, 2012). In allowing something to play out, we let it flourish (and perhaps achieve its *internal good)*.

Mindfulness has always been interesting in that its operational definitions, for example "paying attention in a particular way: on purpose, in the present moment, and non-judgmentally" (Kabat-Zinn, 1994, p. 4) resembles the typical instruction which might be directed to a novice practitioner. When applied to various activities, it becomes even more apparent that typical instruction is precisely that to focus on the *means* for itself, as opposed to the ends (for example, it is certainly not the ends celebrated in mindful walking!). In this way, mindfulness is a set of techniques to facilitate autotelic activity and experience. To the extent to which a person wishes to move out of their familiar repertoire of cognition, affect and behaviour, they will need to disrupt the equilibrium they currently exist within. Such equilibrium might be said to represent a *cooperative contingency* in that it is stability depends on the cooperation of relevant personal and environmental factors (i.e., it is *contingent* on this). Mindfulness, and the self-care practices that precede it, are prototypical *non-contingent* activities (they have no ends), and are hence aptly suited to disrupting a cooperative contingency. By repeatedly acting non-contingently, the person exposes themselves again and again to potential *new beginnings*. In doing so, they transform themselves.

Autotelic practices have little informational value, which is to say that these practices – if interpreted literally – are red herrings for a researcher interested in their truth. Bruno Latour (2005) is a social anthropologist who has applied network thinking to his field of anthropology. Latour (2005) suggests that to understand the truth of an autotelic ethical practice, we must focus on what it *does*, not what it says. Latour (2005) was particularly interested in religion – whose truth value remains contentious in contemporary society. Through an analogy with *love talk*, Latour (2005) notes that "In religious speech as in love talk, what attests to the truth of an utterance is not its correspondence to some putatively objective reality but its renewal of speakers' and hearers' confidence in the reality of something vital: a sense of closeness; a promise of futurity" (Latour, 2005, p. 31). He goes on to say that that the truth value of love talk depends squarely on the ability of the lovers to re-enact the injunction to love again "in the minute they are reaching for one another" (p. 45) Indeed: "the great mistake of the lover whom when asked "do you love me?" answered, "I have already told you so many years ago, why do you ask again?" Why? Because it is no use having told me so in the past, if you cannot tell me again, now, and make me alive to you again, close and present anew (p. 46)".

To understand religion and love talk, the researcher needs to understand what these things *do*, for their truth lies in their transformative power, not their content. Religious talk and love talk are not easy; they are crafts which require practice, but crucially also, the right intention – the intention to bring a person right to the immediate present for purposes of renewing a relationship. The content of the means by which this is achieved is superfluous, for they must be judged by the intention in which they are performed – the extent to which they generally aspire to be a loving or religious performance. The ends of love and religion, is simply the flourishing of the means. The same too has been argued of mindfulness: it requires intention and skill, and its efficacy depends on the ability of these two factors to be employed. To some extent, the rest might be said to be secondary.

Consilience between practice theories and a network perspective: Implications for research.

In developing an understanding of *what is mindfulness?* – a question which has perplexed many, we have come to perhaps an unsatisfying conclusion that it is exactly what is says it is, for example, "paying attention in a particular way: on purpose, in the present moment, and non-judgmentally (Kabat-Zinn, 1994)". There is no deeper essence beyond this, no deep truth to be found in neurobiology. Evan Thompson (2014) suggested that saying mindfulness resides in the brain is akin to saying flight resides in the wings: Mindfulness is enabled, but it certainly does not *cause* anything as a factor analytic model might suggest. Given the intentional element of mindfulness, the mindfulness networks of this project sought to analyse mindfulness at the level of self-report. The networks of practitioners were hypothesised to be denser than their non-practitioner counterparts on the mutualism assumption that uncorrelated practices relevant to mindfulness will become increasingly correlated as they are repeatedly enacted. Density is reflected in more and stronger connections between practices, and in this way can be said to index the *unification* of which Dewey (1916/2004) talks about. In this way, density index's subjectivity and hence a network model accommodates a notion of transformation much better than any approach relying on sum scores alone. Networks are created from covariance, not sum scores, and hence a network approach raises the quite intriguing prospect that two individuals with the same sum-score, might have vastly different networks (see van Borkulo et al., 2015 for a paper in which this situation occurred in psychopathology networks). In such a situation, the researcher may be misled should they be evaluating the effectiveness of an intervention on sum-score alone.

Mindfulness has been argued to be a set of techniques to direct a person to the means of activity rather than the ends. Done well, the activity, and the autotelic experience it fosters, will flourish. A network approach again accommodates this conceptualisation well as density simply reflects the flourishing of a networks operation: the ends of a mindfulness network is simply the flourishing functioning of its means. Mindfulness, as with any non-contingent (or autotelic) activity has been argued to be precisely what is required to disrupt a system in equilibrium (i.e., cooperative contingency). Future research might investigate how such systems (for example a psychopathology system) are disrupted - possibility in *real-time* if experience sampling methods are used. A network approach is suited to this as it allows for the modelling of the waxing and strengthening of connections, and they are limited only by their choice of nodes. The network approach also affords statistical techniques which are hard to envisage within a factor analytic approach. Networks are architectures with central and peripheral nodes. Network researchers have often suggested that central nodes might constitute important intervention targets, for when change occurs in them, it will rapidly spread throughout the rest of the system. The network models in this project offer the promise of identifying those most central mindful practices, which might provide useful starting points for interventions (e.g., Boschloo et al., 2016; Fried et al., 2016)

In summary, this essay has sought to demonstrate how existing factor analytic approaches to mindfulness reify the construct such that it becomes *a thing*. In contrast, mindfulness has been argued to be a dynamic equilibrium state. A network methodology was advanced as the most appropriate way of capturing this conceptualisation, and links were made between network theory and other social and philosophical theory. This is important, because in drawing social theory with empirical research, the network approach arguably does a better job in capturing the ethical, intentional and embodied aspects of mindfulness, which reified factor analytic constructs cannot accommodate.

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