UNIVERSITY OF SOUTHERN QUEENSLAND

In The Mood: Online Mood Profiling, Mood Response Clusters, and Mood-Performance Relationships in High-Risk Vocations

Renée L. Parsons-Smith BSc Hons (Psych)

Being a report of an investigation submitted as a full requirement

for the award of Doctor of Philosophy, at the

University of Southern Queensland

2015

Abstract

The relationship between mood and performance has long attracted the attention of researchers. Typically, research on the mood construct has had a strong focus on psychometric tests that assess transient emotions (e.g., Profile of Mood States [POMS]; McNair, Lorr, & Dropplemann, 1971, 1992; Terry, Lane, Lane, & Keohane, 1999). Commonly referred to as mood profiling, many inventories have originated using limited normative data (Terry et al., 1999), and cannot be generalised beyond the original population of interest. With brevity being an important factor when assessing mood, Terry et al. (1999) developed a 24-item version of the POMS, now known as the Brunel Mood Scale (BRUMS). Including six subscales (i.e., tension, depression, anger, vigour, fatigue, and confusion), the BRUMS has undergone rigorous validity testing (Terry, Lane, & Fogarty, 2003) making it an appropriate measure in several performance environments. Mood profiling is used extensively for diverse purposes around the world, although Internet-delivered interventions have only recently been made available, being in conjunction with the proliferation of the World Wide Web. Developed by Lim and Terry in 2011, the *In The Mood* website (http://www.moodprofiling.com) is a web-based mood profiling measure based on the BRUMS and guided by the mood-performance conceptual framework of Lane and Terry (2000). The focus of the website is to facilitate a prompt calculation and interpretation of individual responses to a brief mood scale, and link idiosyncratic feeling states to specific mood regulation strategies with the aim of facilitating improved performance. Although mood profiling has been a popular clinical technique since the 1970s, currently there are no published investigations of whether distinct mood profiles can be identified among the general population. Given this, the underlying aim of the present research was to investigate clusters of mood profiles. The mood responses (*N* = 2,364) from the *In The Mood* website were analysed using agglomerative, hierarchical cluster analysis which distinguished six distinct and theoretically meaningful profiles. K-means clustering with a prescribed six-cluster solution was used to further refine the final parameter solution. The mood profiles identified were termed the iceberg, inverse iceberg, inverse Everest, shark fin, surface, and submerged profiles. A multivariate analysis of variance (MANOVA) showed significant differences between clusters on each dimension of mood, and a series of chi-square tests of goodness-of-fit indicated that gender, age, and education were unequally distributed. Further, a simultaneous multiple discriminant function analysis (DFA) showed that cluster membership could be correctly classified with a high degree of accuracy. Following this, a second (*N* = 2,303) and third (*N* = 1,865) sample each replicated the results. Given that certain vocations are by nature riskier than others (Khanzode, Maiti, & Ray, 2011) highlighting the importance of performance in the workplace, the present research aimed to further generalise the BRUMS to high-risk industries using a web-based delivery method. Participants from the construction and mining industries were targeted, and the relationship between mood and performance in the context of safety was investigated, together with associated moderating variables (i.e., gender, age, education, occupation, roster, ethnicity, and location).

Certification of Dissertation

This report contains no material offered for the award of any other degree or diploma, or material previously published, except where due reference is made in the text. This report is presented in American Psychological Association (APA) 6th Edition formatting.

______________________	October 21, 2015
Signature of Candidate	Date

ENDORSEMENT

______________________	October 21, 2015
Signature of Supervisor	Date

Acknowledgements

My sincere gratitude goes to my primary supervisor Professor Peter Terry, who has been a steadfast presence throughout my learning journey. Thank you for providing the knowledge to scaffold independence; the encouragement to maintain confidence; and the optimism to achieve success.

Thank you to my secondary supervisor Professor Tony Machin, who has been both dependable and professionally supportive during my candidature.

My deepest heartfelt thanks go to my *“best friend”*—Clint Smith, who has supported the pursuit of my academic dreams with strength and love. To my beloved daughters Rhiannon and Imogen, I hope that I have been the role model that each of you deserves, and that one day you too will share my passion for learning.

A special mention goes to Tanya Machin for *traversing the doctoral terrain* with me. You have been a precious source of social support... Additional special mentions go to Jan Davies, Terri Bates, Sonya Errington, Sonya Digby, Trish Evers, Tracy McLean, Tanja Hirvonen, Liz Blight, Kassandra Kanagaratnam, and Bronwyn Lester for each being treasured friends. One last special mention goes to Dr Mark Perissinotto, who is considered a cherished friend by every member of our family...

Further, I would like to acknowledge the unending love and encouragement from my parents Darryl Parsons and Robyne Page-Faull, and my sister Tahnee Parsons.

Finally, I would also like to acknowledge the contribution of Associate Professor Graeme Senior and Dr Rachel King in providing statistical support for the cluster analytic methodology; Dr Julian Lim in utilising his computer-based expertise to implement revisions to the *In The Mood* website; and Professor Peter Terry for his editing efforts in the final draft of this dissertation.

Table of Contents

List of Figures

List of Tables

List of Appendices

“I have seen the sea when it is stormy and wild;

when it is quiet and serene; when it is dark and moody;

and in all its moods, I see myself...”

— *Martin Buxbaum* —

CHAPTER 1:
Introduction

Despite more than 120 years of research, science has so far failed to clearly delineate the ethereal concept known as emotion (Ketai, 1975; Reisenzein, 2007). Although there is general agreement on the existence of transcultural rudimentary emotions, as well as complex higher-level feeling states (Oatley & Johnson-Laird, 1987; Plutchik, 1980), theorists disagree over the imperative features necessary for systematic classification (Ekman, 1994; Lazarus, 1984; Levenson, 2011). Meliorating this issue now appears to be a categorical imperative, a sentiment seemingly shared by Scherer (2005); “without consensual conceptualisation... of exactly what phenomenon is to be studied, progress in theory and research is difficult to achieve and fruitless debates are likely to proliferate” (p. 695).

In a similar vein, there remains no commonly accepted, nor applied, defining criteria for the mood construct (Terry & Lane, 2011), as evidenced by Lazarus’ (1984) assertion that “moods usually refer to sustained general states, such as sadness and contentment that may or may not be considered emotions depending on theoretical and definitional conventions” (p. 125). To complicate matters further, mood and emotion share an interrelated framework (Lane & Terry, 2000; Reed, 2005). Additionally, some researchers suggest that the affect construct is inextricably linked to both mood and emotion. In all but abandoning single-system and dichotomous models, a cadre of theorists continue to work towards conceptual clarity for the multidimensional sensations of mood and emotion (see Batson, Shaw, Oleson, & Clark, 1992; Ketai, 1975).

From a functional perspective, mood operates as a nonmonotonic feeling state which serves to mediate psychological resources, goal-directed behaviour, and environmental demands (Morris, 1992). Mood encompasses both essential and fundamental cognitive architectures (Sizer, 2000) which influence a range of cognitive processes. For example, creative thinking (see Baas, De Dreu, & Nijstad, 2008; Greene & Noice, 1988), problem solving (Nadler, Rabi, & Minda, 2010), motivation (George & Brief, 1996), decision-making (Herr, Page, Pfeiffer, & Davis, 2012), and evaluation processes may all be biased by transient feelings (Yuen & Lee, 2003).

Interestingly, numerous synergistic and interrelated systems underlie mood (Newman, Perkins, & Wheeler, 1930; Schachter & Singer, 1962; Thayer, 1989, 2001). Psychoneuro-immunological literature is replete with evidence highlighting the integral role of feelings in optimal health and psychological well-being. Indeed, mood has the capacity to influence the endocrine system (Houser, 2004; Nelson, 2005; Suchy, 2011; Wieck, 1996) as well as the autonomic and central nervous systems (i.e., levels of arousal; Dalgleish, 2004; LeDoux, 1992, Thayer, 2001). More specifically, psychosocial mediated immune variations have also been identified (see Maier, Watkins, & Fleshner, 1994; Valdimarsdottir & Bovbjerg, 1997). Findings such as these are perhaps not surprising, given the well-characterised transactional and homeostatic nature of many biological relationships (see Gold, MacLeod, Deary, & Frier, 1995).

In addition to biophysiological influences, mood may also positively or negatively impact upon dietary patterns (Christensen & Brooks, 2006; De Castro, 1987; Polivy & Herman, 1985) and overt health-related behaviours. In fact, physical activity has been acknowledged as a primary technique to regulate hedonic tone (Lane, Crone-Grant, Lane, 2002; Mohammadi-Nezhad, 2011; North, McCullagh, & Tran, 1990; Tsang, 2011). Music has also been recognised for its positive effects on psychological states (Terry, Karageorghis, Saha, & D' Auria, 2012; Terry et al., 1999). Indisputably, there exists a myriad of cognitive-behavioural mood-regulation strategies (see Fordyce, 1977, 1983; Lane, Davis, & Devonport, 2011; Parkinson & Totterdell, 1999; Solanki & Lane, 2010; Terry & Lane, 2011). Within the realm of sport and exercise, athletes have been shown to engage in multiple strategies to regulate differential mood dimensions (Terry, Dinsdale, Karageorghis, & Lane, 2006). However, mood regulation in this context usually aims to improve performance, rather than increase positive affect *per se*.

The fundamental role of mood in predicting performance has attracted great attention within the domain of sport, which has subsequently transpired into a considerable body of knowledge (Beedie, Terry, & Lane, 2000; Lane, Thelwell, & Devonport, 2009). A multitude of interactional mood-performance relationships have been proposed (Lane & Terry, 2000) between and within emotional dimensions, as well as across numerous contexts. Given this, it seems commonsensical to quantify and examine potential associations using mood dimensions (i.e., tension, depression, anger, vigour, fatigue, and confusion) as opposed to overarching categorisations (i.e., positive and negative affect). Seemingly substantiating this claim, mood-performance scientists suggest that high vigour often evokes greater effort towards performance goals, while confusion, depression, and fatigue have been consistently associated with performance decrements (Lane & Terry, 2000). Findings related to the mood dimensions of anger and tension suggest that each can either debilitate or facilitate performance, depending on the co-existence or absence of depressed mood (Lane & Terry, 2000).

Much of the aforementioned research has had a strong focus on single-adjective checklists (e.g., the POMS; McNair et al., 1971; Terry, Lane et al., 2003;

Terry et al., 1999). Nevertheless, many of these self-report inventories have not been supported by an expansive range of normative data. Breaking this trend, the BRUMS is one of the few variations of the POMS that has been validated via multi-sample confirmatory factor analysis for each subscale (i.e., anger, confusion, depression, fatigue, tension, and vigour), using four different samples. Additionally, the BRUMS has demonstrated high internal consistency, as well as appropriate test-retest reliability coefficients for a measure of temporary emotional states (Terry et al., 1999). Concurrent validity of the measure has also been supported, in that all correlations were in line with theoretical predictions (Terry, Lane et al., 2003). Conceivably, the psychometric robustness of the BRUMS makes it a particularly appropriate measure in several performance environments and its brevity readily lends itself to web-based mood profiling.

Recently developed, web-based mood profiling is currently used throughout the world for diverse purposes. Indeed, the *In The Mood* website (see http://www.moodprofiling.com; Lim & Terry, 2011) is but one exemplar. The newly constructed website was guided by the theoretical framework of Lane and Terry's (2000) conceptual model of performance, and designed according to a user-centred approach. The focus of *In The Mood* is to facilitate a prompt calculation and interpretation of individual responses to an online version of the BRUMS, and link specific mood profiles with evidence-based mood regulation strategies corresponding with each mood dimension (Lim & Terry, 2011). Raw and standard scores, as well as a graphical representation of the mood profile are also presented.

Being an artefact of the popularity of mood profiling (especially within athletic communities), three distinct mood profiles have previously been identified. Termed the iceberg (Morgan, 1980), Everest (Terry, 1995), and inverse iceberg profiles (Terry, 1995); each distinctive combination of the six mood dimensions appear to have a well-enunciated positive or negative impact on performance (see Terry & Lane, 2011). Although individual dispositions and mood fluctuations exist (Cowdry, Gardner, O'Leary, Leibenluft, & Rubinnow, 1991; Penner, Shiffman, Paty, & Fritzsche, 1994), it remains unknown if relatively consistent mood patterning can be found within the general population. It is for this reason that the primary aim of the present research was to investigate whether distinct clusters of mood responses can be identified within the general population.

Due to burgeoning interest, the Internet now plays a pivotal role in delivering mental health interventions and resources (Fotheringham, Owies, Leslie, & Owen, 2000; Griffiths, Lindenmeyer, Powell, Lowe, & Thorogood, 2006). With an ability to transcend multiple barriers, the *In The Mood* website has utility for mood profiling in performance environments not previously considered. Unfortunately, the potential for injury and mortality are significantly greater in some workplace environments, making crucial the identification of factors that influence accidents (Abbe, Harvey, Ikuma, & Aghazadeh, 2011) and mediate occupational stressors (Lingard, Cooke, & Blismas, 2010). Given this, and with an aim to further generalise the scale, the current study will also investigate mood responses of individuals employed in high-risk vocations.

More specifically, the present research includes cluster analysis of three independent datasets collected via the *In The Mood* website. Additionally, the *In The Mood* website will be revised and improved according to Lim's (2011) recommendations and the User Experience Survey. Following this, mood and safety performance will be explored using a sample of respondents from the construction and mining industries. Variables that moderate the mood-performance relationship in the context of safety will also be investigated. To further generalise the scale, population-specific normative data for each of the two populations of interest will be developed where necessary.

The thesis is divided into eight chapters. Chapter 2 begins with an historical overview of emotion. An introduction on the nature of mood follows, and conceptual issues are addressed (e.g., the distinction between mood and emotion, and the impact of mood on performance). Additionally, mood regulation strategies, mood assessment issues as well as mood assessment measures are described, and Internet-delivered interventions are explored. The chapter concludes with an overview of the *In The Mood* website, followed by research aims. Chapters 3 and 4 together form Study 1. Chapter 3 begins with a brief introduction to cluster analysis. The existing Lim (2011) data are examined using a two-step clustering procedure, and a second sample is investigated (Chapter 4) to replicate the findings. Chapters 5 and 6 together form Study 2. Chapter 5 involves the implementation of revisions for the *In The Mood* website, and a third sample of BRUMS respondents is investigated (Chapter 6) to replicate the findings from Study 1. Chapter 7 outlines Study 3. It provides a brief review on mood and safety performance in high-risk vocations. The dataset is analysed to identify mood-performance relationships and moderating variables. Lastly, Chapter 8 provides an overview of results, discussion of main findings, strengths and limitations, implications and future directions, as well as conclusions.

CHAPTER 2:
Literature Review

2.1 Historical Overview of Emotion

Emotions are manifest expressions of underlying affective states. The study of emotion is a popular field of research, involving core theoretical debates that cross sub-disciplines (Levenson, 2011; Panksepp & Watt, 2011; Salas, Radovic, & Turnbull, 2011). However, various terms to conceptualise mood, sentiments, emotions, and emotional reactions have typically been used interchangeably. From a theoretical perspective, these practices have created concern among the scientific community (see Ketai, 1975, Lazarus, 1984; Ortony & Clore, 1981; Terry & Lane, 2011), highlighting a need for differentiating criteria (Beedie, Terry, & Lane, 2005).

Emotions are subjective conscious experiences, with some aspects considered universal, while others vary according to culture and gender (Westen, Burton, & Kowalski, 2006). According to Lazarus, Kanner, and Folkman (1980), emotions are complex organised psychophysiological reactions (i.e., cognitive appraisals, action impulses, and patterned somatic reactions) operating collectively in response to stimuli. Over the past 30 years, scientists have attempted to identify a finite list of pancultural *basic emotions* using facial recognition, standardised measures, induction procedures, and data analytic techniques (Coan & Allen, 2007; Ekman, 1992; Salas et al., 2011). Otherwise known as *fundamental* or *primary* emotions, discrete emotion theorists posit that basic emotions are a subset of innate affective states associated with survival-critical functions, which evolved from an ancestral past (Darwin, 1872/1965; Ekman, 1972, 1994; Levenson, 2011).

Basic emotions share key features of separateness (i.e., clear boundaries), singularity (i.e., cannot be reproduced via blending), and demonstrate continuity across species/time/place (Ekman, 1994; Levenson, 2011). Additionally, basic emotions display distinct physiological and neural profiles (Vytal & Hamann, 2010). However, theorists often disagree on a list of hallmark features, which are necessary requisites for developing a taxonomy (Ekman, 1994; Lazarus, 1984; Levenson, 2011). For example, Ekman (1994) outlined eight defining characteristics including a universal signal, automatic appraisal, commonalities in antecedent events, presence in other primates (refer to Figure 2.1 for an illustration), quick onset, brief duration, unbidden occurrence, and distinctive physiology (with tripartite groupings of distinctness, continuity, and structure/function). Conversely, Levenson (2011) proposed three criteria involving distinctness, hard-wiredness, and functionality.

Figure 2.1. Illustrations and a photograph used by Darwin (1872/1965) to demonstrate cross-species similarities in anger/aggression (taken from Dalgleish, 2004).

Paradoxically, which criteria are used ultimately affects which emotions are labelled *basic emotions* (see Ekman & Cordaro, 2011; Izard, 2011; Levenson, 2011; Panksepp & Watt, 2011). This is evident in that some theorists propose as few as two basic emotions (Mowrer, 1960), while others have identified as many as 18 (Frijda, 1986; Ortony & Turner, 1990). Alternatively, *complex emotions* are considered combinations of conceptually defined basic emotions (Oatley & Johnson-Laird, 1987; Plutchik, 1980), while the term *affect* (i.e., feeling state or tone; Larsen,

2000) remains vague and undifferentiated (Lane & Terry, 2000). Perplexingly, Cacioppo and Berntson (2007) suggest affect may be “simply a form of cognition” (p. 1,348).

Following a review of the fields most prominent researchers (i.e., Ekman & Cordaro, 2011; Izard, 2011; Levenson, 2011; Panksepp & Watt, 2011), four central tenets were identified across four empirically tested theoretical models (Tracy & Randles, 2011). According to Tracy and Randles (2011), the scientists demonstrated considerable agreement on a defining criteria (i.e., discreteness, fixedness of neural and bodily expressed components, and fixedness of feeling/motivational components), as well as conformity that basic emotions are “primitive” in nature (p. 398). Additionally, there was consensus that cross-species generalisation (Ekman, 1994), and distinct neurobiology (Vytal & Hamann, 2010), were both verification of a basic emotion (Tracy & Randles, 2011). Table 2.1 lists the currently known basic emotions according to the four-abovementioned frameworks.

Table 2.1

Basic Emotions According to Four Theoretical Models (taken from Tracy & Randles, 2011)

Izard (2011)	Panksepp & Watt (2011)	Levenson (2011)	Ekman & Cordaro (2011)
Happiness	Play	Enjoyment	Happiness
Sadness	Panic/Grief	Sadness	Sadness
Fear	Fear	Fear	Fear
Anger	Rage	Anger	Anger
Disgust		Disgust	Disgust
Interest	Seeking	Interest	
Contempt			Contempt
	Lust	Love	
	Care	Relief	Surprise

Since the late 1800's, there have been numerous conceptualisations of emotion proposed. Such premises range from phylogenetic theories bound by limited physiological and neuroscientific knowledge (see Bard, 1929; Cannon, 1927, 1931; Newman et al., 1930), to more recent investigations involving detailed neuroanatomic and neurophysiologic hypotheses (see Hallaq, 1969; Northoff, 2012; Stephens, Christie, & Friedman, 2010). It has been over a century since the introduction of the James-Lange theory, which subsequently guided generations of research (Lang, 1994). Developed independently by both William James in 1884 and Carl Lange in 1885 (Newman et al., 1930), this influential model fixated on physical experience (Westen et al., 2006). For example, the hypothesis proposed that emotions are the subjective consequences of peripheral nervous system responses following interpretation by the central nervous system, a concept otherwise known as the *body loop* (Damasio, 1994; Westen et al., 2006). According to this person-environment relationship, emotions are the experiential component of physiological changes (i.e., visceral reactions and voluntary behaviours) in response to external stimuli (Newman et al., 1930).

Whereas James (1884) described various somatic and autonomic responses, Lange (1885/1912) observed a relationship between feeling states and the vasoconstriction or vasodilatation of blood vessels (Wassmann, 2010). Therefore, Lange asserted that the circulatory system, rather than the peripheral nervous system, was of greater significance in emotion generation (Westen et al., 2006). From this standpoint, emotion was a cardiovascular event effectuated by the vasomotor centre, being a neuroanatomical structure located in the lower brain stem (Lange, 1994; Wassmann, 2010). It should be noted that many rudimentary neurobiological models assumed that one specialised neural system was etiologically related to the generation of affective states (MacLean, 1949, 1952). Lange was likely the first affective scientist to use an illustration of the brain to explicate emotion (see Figure 2.2; Wassman, 2010).

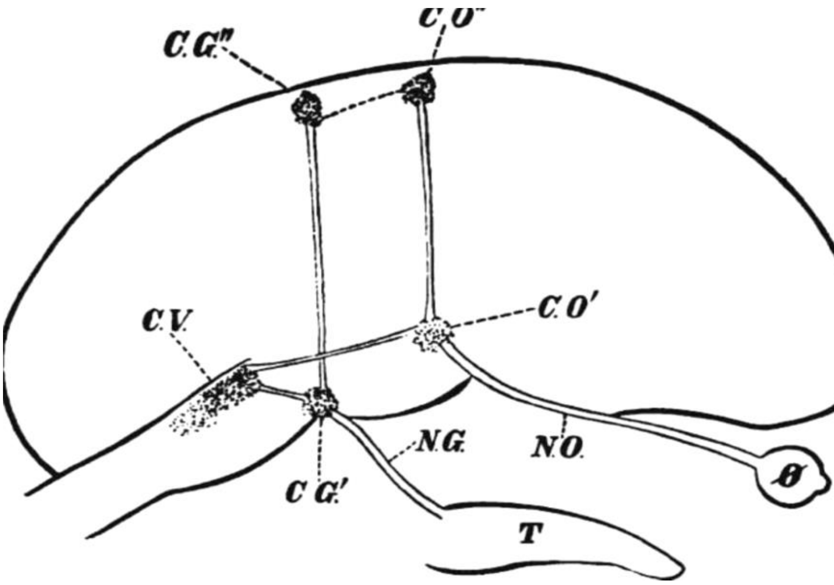


Figure 2.2. The first illustration of the brain by Lange (1885/1912). Lange (1885/1912) proposed that pathways for visual and gustatory impressions involved sensory information from the eye (Ø) that travel through the optical nerve (N.O.) to the *central organ of seeing* (C. O′), where it became a sensation. A nervous fibre tract from C. O′ to the *vasomotor centre* (C.V.) would transfer the visual information to the C.V. and trigger vasoconstriction/vasodilatation of blood vessels and other emotion-related changes. Visual information would be transferred at the same time from C. O′ to the *cortical centre of vision* (C O″), where the image came into conscious awareness. Similarly, gustatory information would be transferred from the *tongue* (T) via the *gustatory nerve* (N.G.) to the *central organ of taste* (C G.′) and a nervous fibre tract to the C.V. would trigger an emotional reaction (taken from Wassman, 2010).

Although James' (1884) and Lange's (1885/1912) views differed slightly, each shared the belief that physical and behavioural responses (associated with specific emotions) preceded the conscious emotional experience (refer to Figure 2.3; Lang, 1994). Unfortunately, the James-Lange theory was met with reservation from colleagues, and James' famous declaration that "we feel sorry because we cry, angry because we strike, and afraid because we tremble" (as cited in Palencik, 2007, p. 770) drew immediate criticism.

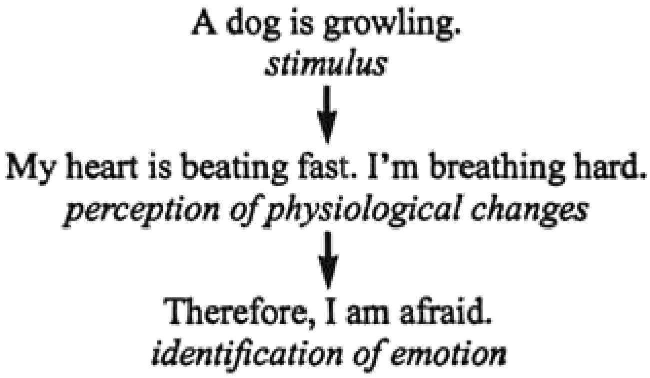


Figure 2.3. A flowchart highlighting the process underlying the James-Lange theory (taken from Almoite & Norasakkunkit, 2012).

Walter Cannon and Philip Bard were two of the many researchers (see Dana, 1921; Irons, 1894; Worcester, 1893; Wundt, 1891) who challenged the plausibility of the James-Lange theory (Palencik, 2007). Cannon (1927, 1931) argued that delays in visceral changes could not account for the immediacy of feelings, and artificially produced visceral changes did not induce emotion (Fehr & Stern, 1970). Further, according to Cannon and Bard (1929) the viscera were "insensitive structures" (as cited in Fehr & Stern, 1970, p. 411), and any changes were described as having a universal impact (Friedman, 2009). Moreover, Cannon asserted that emotional behaviour was not influenced by interruptions of the body loop (via afferent feedback from the peripheral nervous system; Fehr & Stern, 1970).

Cannon (1927, 1931) and Bard (1929) concluded that autonomic responses occurred an estimated 1 to 2 seconds following the presentation of a stimulus, while emotional responses could be described as immediate (Westen et al., 2006).

Furthermore, feelings often preceded autonomic reactions and behaviours (Westen et al., 2006), as well as shared highly similar visceral responses (Friedman, 2009). Therefore, the Cannon-Bard theory (otherwise known as the emergency theory) maintains that external stimuli elicit both conscious emotional experience and physical responses independently and simultaneously (Friedman, 2009; Westen et al., 2006). According to this view, emotion originates in the thalamus (Cannon, 1931) which relays relevant information bilaterally to the central and peripheral nervous systems, thereby initiating physiological arousal and motor movement (e.g., a *fight or flight* response; Westen et al., 2006). Additionally, activation of the cerebral cortex stimulates a cognitive interpretation of the situation (Ledoux, 1992). Refer to Figure 2.4 for an example of the Cannon-Bard theory.

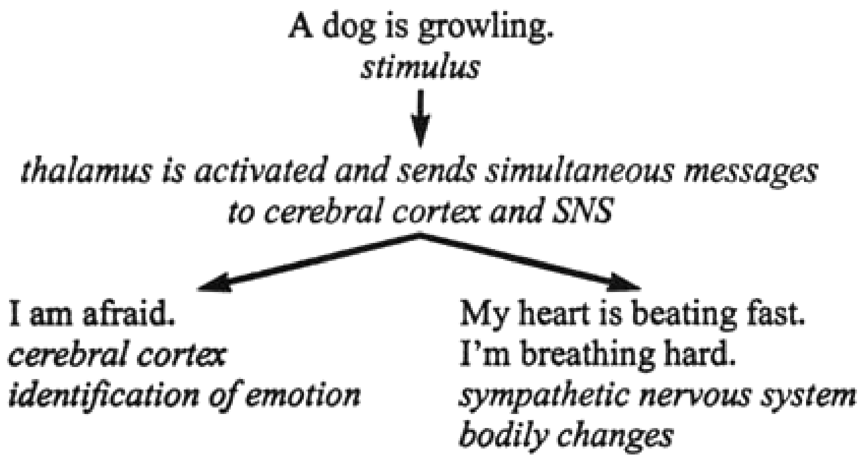


Figure 2.4. An example of the Cannon-Bard theory highlighting cognitive appraisal, in terms of the concurrence of conscious affective experience and physiological responses (taken from the CliffsNotes website, *nd*).

Ruckmick (1936), Hunt, Cole, and Reis (1958), and Schachter and Singer (1962) all posited that cognitive factors are important determinants of emotional states. Following experimental work, Schachter and Singer (1962) put forward an alternative model of emotion which suggested that physiological responses play a causal role in emotion generation, in support of the Jamesian position (Friedman, 2009). However, these findings failed to identify distinct autonomic patterns, which was consistent with Cannon's (1927, 1931) view. Indeed, the same physiological arousal patterns could be labelled "joy or fury or jealously, or any of a great diversity of emotional labels..." (Schachter & Singer, 1962, p. 398). Given this, Schachter and Singer proposed that individuals rely on environmental cues to determine subjective states in the absence of obvious causes. In such cases, a label is assigned to the emotion upon a cognitive appraisal of the environment. Additionally, by manipulating cognitions, the subjective experience could subsequently be altered. This position is otherwise known as Schachter-Singer's two-factor theory of emotion.

In contrast with the notion that feelings are discrete, Wilhelm Wundt (1902) was the first to formulate a dimensional theory of emotion. He suggested that all affective epiphenomenon could be identified as combinations of the pleasant-unpleasant, tense-relaxed, and excitement-depression dimensions; and could be located on continuous dimensions within a two-dimensional space (Wundt, 1902). While early models proposed three dimensions (see Engen, Levy, & Schlosberg, 1958), Russell (1980) proclaimed that pleasantness versus unpleasantness, and activation/arousal feeling combinations could be arranged around the perimeter of a circle. That is, four bipolar dimensions spaced 45 degrees apart defined an affect circumplex (refer to Figure 2.5 for example emotions according to a two-dimensional valence-arousal model, as well as a mixed model of valence). Described as the *pièce de résistance* for explicating affective states as bipolar (Green, Goldman, & Salovey, 1993); conceptualising potential parameters and systematically arranging mood descriptors was considered a major contribution to the extant literature, and provided a valuable impetus for future research (Watson, Wiese, Vaidya, & Tellegen, 1999).

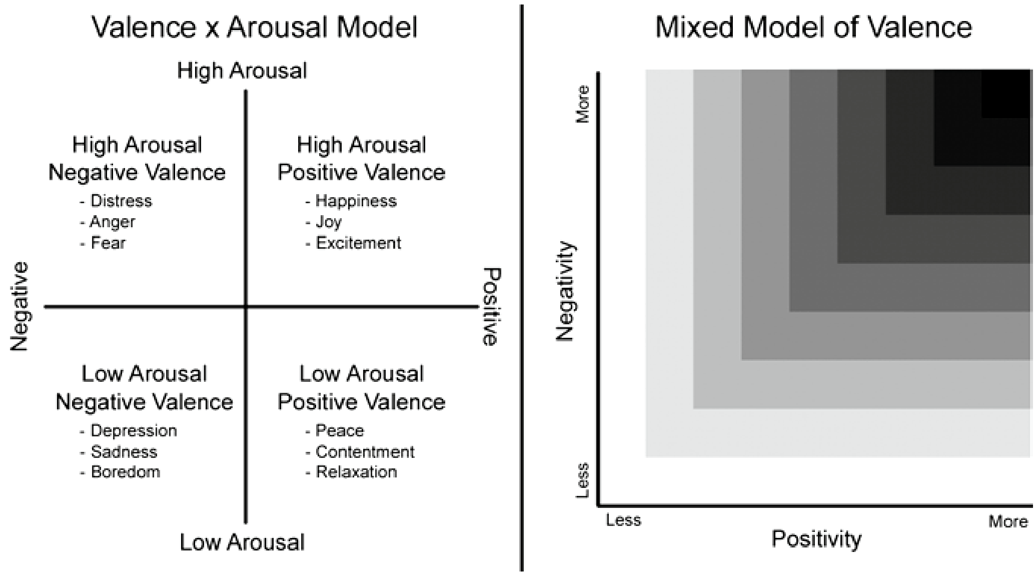


Figure 2.5. Schematic illustrations of two circumplex models of emotion. The *left panel* shows a diagram of two-dimensional affective (valence x arousal) space: the circumplex model. Example emotions are noted in each quadrant. The *right panel* shows a model of mixed valence. Pure positive and negative responses lie along the axes in white. Darker shades of grey represent greater mixed feelings, which have shared positive and negative activation to varying degrees (taken from Hunter & Schellenberg, 2010).

Such taxonomies were developed via the study of similarities and differences in visual facial stimuli and word recognition (Barrett & Russell, 1998; Larsen, Kasimatis, & Frey, 1992; Russell, 1980; Watson et al., 1999). Visual stimuli designed to represent and evoke emotions (e.g., International Affective Picture System, Self-Assessment Manikin, and Semantic Differential Scale; Bradley & Lang, 1994; Mehrabian & Russell, 1974) have also provided support for two-dimensional models (Hunter & Schellenberg, 2010). Emotional dimensions can also be identified through factor analysis and/or unidimensional scaling, whereby statistical analyses are applied to word sets that quantitatively vary (e.g., good versus bad, happy versus sad, pleasant versus unpleasant; see Terry, Lane et al., 2003).

According to data on orthogonal emotions, pleasant-unpleasant (i.e., valence) was identified as the most important dimension in numerous studies, followed by level of arousal (Osgood, Suci, & Tannenbaum, 1957; Russell & Mehrabian, 1977; Titchner, 1910; Wundt, 1902). More recently, however, there have been a number of alternative models of emotion devised (see Gross & Muñoz, 1995; Gross & Thompson, 2007; Levenson, 1994). Some examples include the general model of emotion (Gross & Muñoz, 1995), cognitive-motivational-relational theory of emotion (Lazarus, 1991), fuzzy logic adaptive model (FLAME; El-Nasr, Yen, & Ioerger, 2000), and the facial feedback hypothesis (Buck, 1980). Additionally, peripheral physiological emotion specificity concepts have also been proposed (Heller, 1993; Stemmler, 1992).

Improvements in brain science including high spatial resolution imaging methods and group-averaged activation patterns further assist the consideration of neural architecture (Sloman, 2004). Recent meta-analyses of neuroimaging data suggest that different feelings engage clear patterns of cortical and subcortical structures (refer to Figure 2.6), as opposed to stimulating single-system mechanisms (see Murphy, Nimmo-Smith, & Lawrence, 2003; Vytal & Hamann, 2010). Such findings could be considered evidence that discrete emotions differ in core relational themes (Lazarus & Cohen-Charash, 2001) and levels of arousal (Barrett & Russell, 1998; Shockley, Ispas, Rossi, & Levine, 2012). Although some emotions engage similar regions of the brain, specific neural circuits (e.g., networks monitoring and/or modulating others according to chemical mechanisms) remain largely unknown (Sloman, 2004; Tettamanti et al., 2012; Vytal & Hamann, 2010). Akin with Sloman’s (2004) nascent conviction, perhaps inter- and cross-disciplinary collaboration may accelerate the development of a finer-grained ontology.

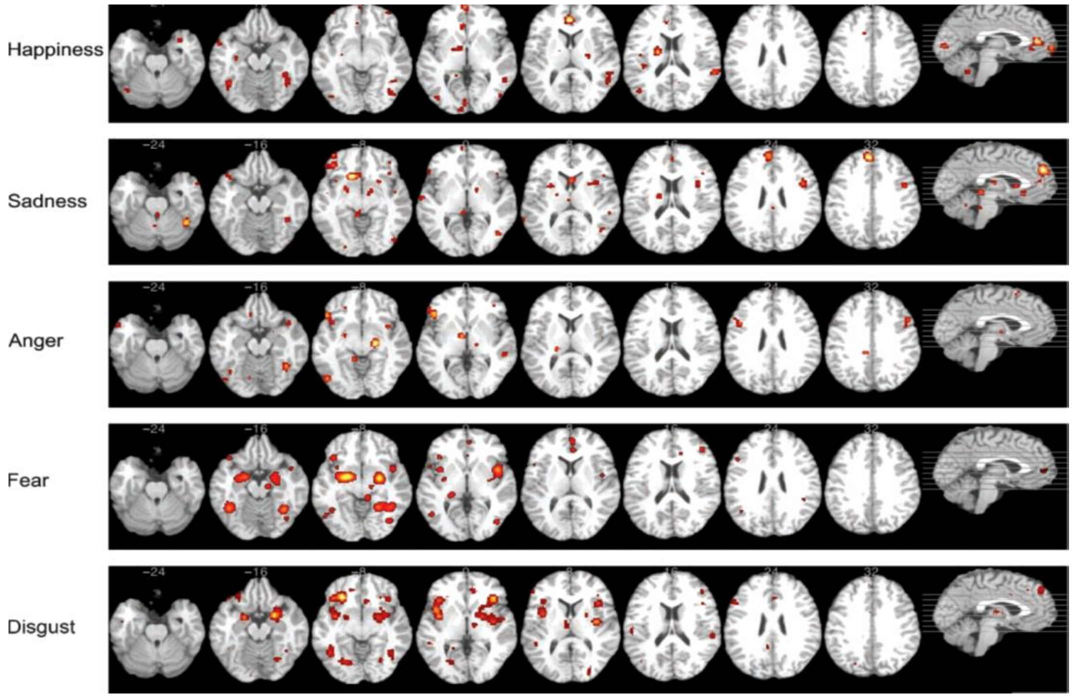


Figure 2.6. Activation maps consistently associated with five basic emotions (taken from Vytal & Hamann, 2010).

From an epistemological perspective, the plethora of research on emotion has generated innumerable theoretical debates, as well as subjected the construct to increasingly powerful critiques (see Darwin, 1872/1965; Ekman, 1972; Salas et al., 2011; Scarantino & Griffiths, 2011; Vytal & Hamann, 2010; Zajonc, 1984). Emotion is considered a profound and pervasive characteristic of human experience, meaning that with such hedonistic appeal this doctrine of psychology is likely to continue to attract attention and mature. While some scientists attempt to determine a conceptual taxonomy (Levenson, 2011; Panksepp & Watt, 2011), dimensional theorists focus on neural mechanisms involving dual- and multisystem models (Green & Salovey, 1999; Murphy et al., 2003; Russell & Barrett, 1999; Vytal & Hamann, 2010; Watson et al., 1999). In any case, both historically and currently, the bifurcated study of emotion involves a combination of differing paradigms (e.g., conceptual, biological, computational, and physiological; El-Nasr et al., 2000; Scarantino & Griffiths, 2011) and trajectories (Gross & Thompson, 2007).

2.2 The Nature of Mood

In what may be considered an enigmatic affect barometer, mood can assimilate and communicate the emotional equilibrium. According to Lane and Terry (2000), mood can be described as “a set of feelings, ephemeral in nature, varying in intensity and duration, and usually involving more than one emotion” (p. 17). Additionally, mood may be considered ubiquitous, although the strength and extent of conscious feelings often vary. It is important to note that key to this definition, mood and emotion each play a contributing role to the experiential sensation (Lane & Terry, 2000; Suchy, 2011).

Historically, the mood construct has lacked a clear conceptualisation, and despite the vast amount of literature, researchers have so far failed to agree on a definition (Augustine & Hemenover, 2009; Batson et al., 1992; Lane & Terry, 2000). For example, Frijda (1986) asserted that mood “can be described as experiences of situational meaning structure with the characteristic of globality: Everything seems open and attainable, or nothing is attractive, or nearly everything is irritating” (p. 252). Alternatively, Griffiths (1989, 1997) suggested that mood involves higher order functional states, comprising of lower order functional states. This pre-scientific and hierarchically structured conception of the mind comprised both a psychological and physiological component. A similar physiological view was proposed by Sizer (2000) in that moods were characterised as “biases in operations at the level of our functional architecture” (p. 759). The theory of mood as a global mental state, as opposed to an evaluative or cognitive state, has received at least some agreement between theorists (de Sousa, 1987; DeLancey, 2006; Griffiths, 1989, 1997; Tye, 1995).

Although mood has typically been treated as ancillary to emotion (DeLancey, 2006), a few supplementary theories have been proposed. For example, mood-emotion identity theory, activation theory, and Lormand's (1985) *M*-state theory. In applying mood-emotion identity theory, DeLancey (2006) instantiated that some basic moods are in fact low intensity basic emotions (i.e., bad moods are anger, good moods are joy, etc.) which prime higher intensity emotions. Alternatively, according to activation theory as interpreted by Lindsley (1951) and Woodworth and Schlosberg (1958); feeling states lie on one end of a continuum of activation that is defined according to degree of autonomic arousal. Conversely, Lormand's *M*-state theory suggests that moods are cognition-assessing variations, with the functional component of the mind (i.e., *M*) affecting a range of cognitive states (DeLancey, 2006). According to this theory, particular states of *M* correlate with specific moods.

Given the paradigmatic differences underlying each theory, it becomes intuitively obvious that the mood construct still requires adequate delineation. The value of an agreed upon definition was plainly outlined by Lane and Terry (2000) in that a consensus among researchers is necessary to minimise inconsistent conclusions due to inconsistent conceptualisations. Lane and Terry posited that mood entails two components: evaluation and arousal. The arousal component refers to the degree of activity physiologically experienced (discussed in further detail later), while the evaluative component involves judgement of feelings on a pleasant-unpleasant continuum. While arousal and pleasantness-unpleasantness are each considered unrotated dimensions of mood, two varimax-rotated factors have been investigated more extensively (Watson, Clark, & Tellegen, 1988).

Two distinct affective processes have been identified via factor-analytic research (Tellegen, Tuma, & Maser, 1985; Tellegen, Watson, & Clark, 1999). Positive affect (PA) reflects underlying positive feeling states on a continuum ranging from enthusiasm, alertness, joy, and determination at the upper end; to lethargy at the lower end (Murray, Allen, & Trinder, 2002; Suchy, 2011). Similarly, negative affect (NA) reflects negative feeling states such as anger, fear, sadness, and guilt; to calm and relaxation (refer to Table 2.2 for associated PA and NA states and traits; Murray et al., 2002; Suchy, 2011). Considered mutually orthogonal (Steer, Clark, Kumar, & Beck, 2008; Tellegen et al., 1999; Watson, 1988a), these two dissimilar dimensions subsuming polar opposites have been validated across a variety of methods and populations.

Table 2.2

States and Traits Associated with PA and NA Profiles (taken from Suchy, 2011)

	Positive Affect	
Negative Affect	High	Low
High	High engagement	Unpleasantness
	High arousal	Sadness
	Astonishment	Distress
Low	Pleasantness	Disengagement
	Happiness	Sluggishness
	Contentment	Anhedonia

A number of classification systems have been developed in order to categorise both the number and underlying nature of the mood construct (Lane & Terry, 2000; Thayer, 2001). Although different researchers propose different techniques, a common approach to determine moods/groupings and distinguish how moods relate to one another traditionally involves the use of psychometric adjective checklists (i.e., self-report measures). Pioneering this methodology, Nowlis (1965) identified 12 separate dimensions of mood: aggression, anxiety, surgeoncy, elation, concentration, fatigue, social affection, sadness, scepticism, egotism, vigour, and nonchalance. The development of the popular POMS (discussed in Section 2.7.2; McNair et al., 1971, 1992)—whereby individuals rate their current mood according to descriptive terms—was built from this foundation (Thayer, 2001). However, alternative indirect and objective measurements are also often utilised (i.e., physiological measures, brain activity measures, and behavioural measures; Jacobs, Fehres, & Campbell, 2012; refer to Table 2.3 for an overview of measures).

Table 2.3

An Overview of Mood/Emotion Measures (taken from Jacobs et al., 2012)

Category	What is measured?	What can be inferred?	Time dimension
Physiological measures	Autonomic nervous system, e.g., • heart rate • skin conductivity	• valance • arousal	• current emotional states • emotional dispositions
Brain activity measures	Brain activity, e.g., • electromagnetic field • oxygen in blood	• approach and avoidance tendencies	• current emotional states • emotional dispositions
Behavioural measures	Behaviours, e.g., • facial expressions • vocal features • whole body postures	• valance • arousal	• current emotional states • emotional dispositions
Self-report measures	Experiences	• valance • arousal • specific discrete emotions	• current emotional states • remembered emotional states • anticipated emotional states • emotional dispositions

Although Thayer (2001) took into account the checklist approach to grouping incorporeal feelings, the anatomical foundation underpinning mood dominated his theory development. More specifically, factor analytic techniques were used with a focus on physiological variables such as biological rhythms (relating to alertness and tiredness) and the effects of exercise, food, and stress. Two biopsychological dimensions of mood were identified: energetic arousal and tense arousal (i.e., energy and tension, respectively). According to Thayer, *good moods* comprise of a high level of energy and a low level of tension (i.e., calm energy), while *bad moods* tend towards a low level of energy combined with a high level of tension (i.e., tense tiredness). Further, calm energy is associated with pleasure and happiness, while tense tiredness is associated with despair (refer to Figure 2.7 for a biopsychological model of mood).

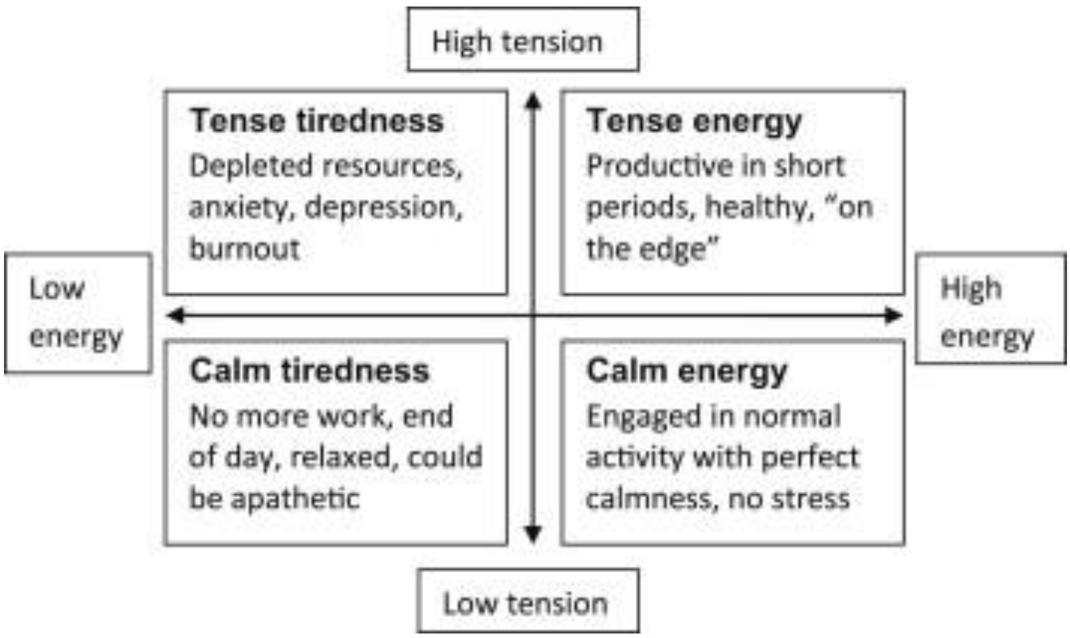


Figure 2.7. A model highlighting two basic biopsychological dimensions of mood (i.e., tension and energy; taken from Thayer, 2001).

From this biopsychological perspective, moods can be vital indicators of healthy physiological functioning. Changes in one homeostatic system (e.g., changes in blood sugar levels) may potentially influence changes in another (i.e., the phenomenological sensation of mood; Thayer, 1989, 2001). This relationship was reproduced by Gold et al. (1995) while investigating the effects of biological changes on mood states. When an acute hypoglycaemic state was induced in nondiabetic patients (a placebo control study was also implemented), participants experienced a significant increase in feelings of tense arousal and a decrease in hedonic tone, a mood state otherwise referred to as tense tired by Thayer (2001). While some studies have failed to detect hedonic changes corresponding with blood-glucose fluctuations (see Weinger, Jacobson, Draelos, Finkelstein, & Simonson, 1995), numerous studies have replicated many behaviour-endocrine relationships (see Gonder-Frederick, Cox, Bobbitt, & Pennebaker, 1989; Sommerfield, Deary, & Frier, 2004; Strachan, Deary, Ewing, & Frier, 2000). Mood mediated immune alterations affecting physiological responses to pathogens and antigens have also been identified (i.e., changes in B and T lymphocytes, macrophages, leukocytes, and antibodies; Maier et al., 1994).

As well as the endocrine system and hormones such as adrenaline and cortisol (insulin is one of many hormones that appear to mediate mood; see Houser, 2004; Nelson, 2005; Suchy, 2011; Wieck, 1996), the autonomic and central nervous systems have also been found to impact psychological functioning (Izard, 1984; Zajonc, 1984). More specifically, the nervous system consists of billions of neurons, each separated by a gap known as the synaptic cleft (Westen et al., 2006). Healthy physiological functioning relies on communication between neurons, so junctures between synapses are bridged by neurotransmitters that communicate electrical impulses (Westen et al., 2006). While hormones pass slowly through the circulatory system, the nervous systems produce rapid physiological responses (Thayer, 2001).

While the nervous system has the power to link “mind and body” (Hobson, 1999, p. 184), the two divisions of the autonomic nervous system have been described as the “key to energy, mood, and health” (Hobson, 1999, p. 184). For instance, where the sympathetic sub-system requires energy expenditure (i.e., ergotropic) the parasympathetic branch is concerned with energy conservation (i.e., trophotropic; Kandel, Schwartz, & Jessell, 1995, Thayer, 2001). Neurotransmitters such as norepinephrine and acetylcholine each affect the autonomic nervous system creating either an ergotropic (i.e., energy-generating) or trophotropic (i.e., calming) effect (Kandel et al., 1995; Thayer, 2001). This physiological interaction clearly articulates a connection between arousal and mood.

Although researchers continue to isolate the precise brain systems that underlie hedonic tone, the reticular activating system (located at the base of the brain) is perhaps the best known arousal instrument (Thayer, 2001). Consisting of a network of neurons, the reticular formation regulates wakefulness, alertness, and attention, as well as producing the neurotransmitters serotonin, norepinephrine, and dopamine (each of which have been found to influence mood states; Thayer, 2001). The dopaminergic theory of positive affect suggests that increased dopamine levels mediate many cognitive effects of positive mood states (Ashby, Isen, & Turken, 1999; Ashby, Valentin, & Turken, 2002). The influence of the reticular mechanisms on arousal extends to both higher areas of the brain (refer to Figure 2.8), as well as into the rest of the body thereby affecting muscular and motor activity (Thayer, 2001).

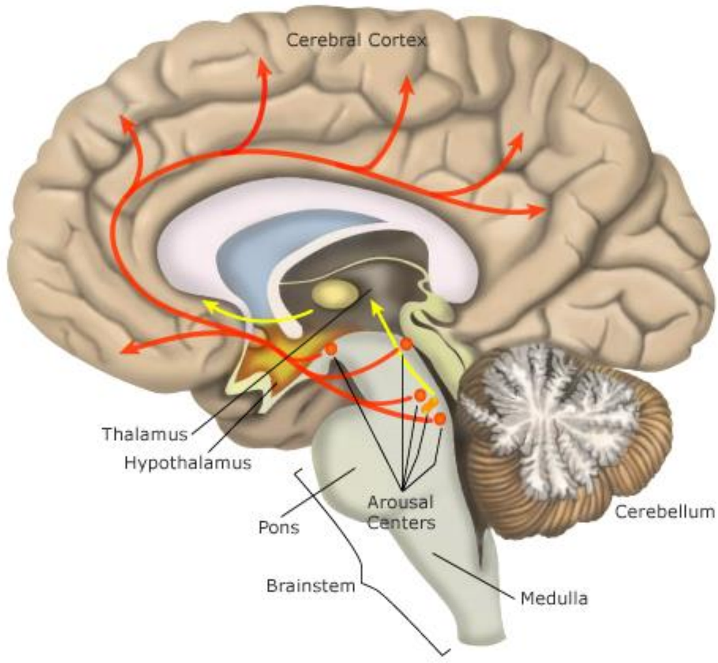


Figure 2.8. A cross-section of the human brain highlighting areas associated with arousal (taken from the Healthy Sleep website, 2007).

While Thayer (2001) recognised arousal as a key concept underlying mood, the limbic cortices have also been pinpointed as contributing mechanisms. This system of interconnected structures—the hypothalamus, hippocampus, and amygdala—influence the cerebral cortex, as well as many vital physiological functions (e.g., the autonomic and somatic areas; LeDoux, 1996; Popper, Eccles, John, & Carew, 1977; Thayer, 2001). The limbic system, sometimes referred to as *the emotional brain* (Izard, 1984), regulates motivated behaviour described as fleeing, feeding, fighting, and reproductive behaviour (Isaacson, 1974; McEllistrem, 2004). Although fear and anxiety are both mediated by the prefrontal cortex (Davidson, 2002; Sotres-Bayon, Cain, & LeDoux, 2006) as well as the endocrine connections of the hypothalamus, the limbic system also plays an integral part (refer to Figure 2.9; Thayer, 2001). Hence, fear responses have been regarded as closely related to the affective state tense arousal as defined by Thayer.

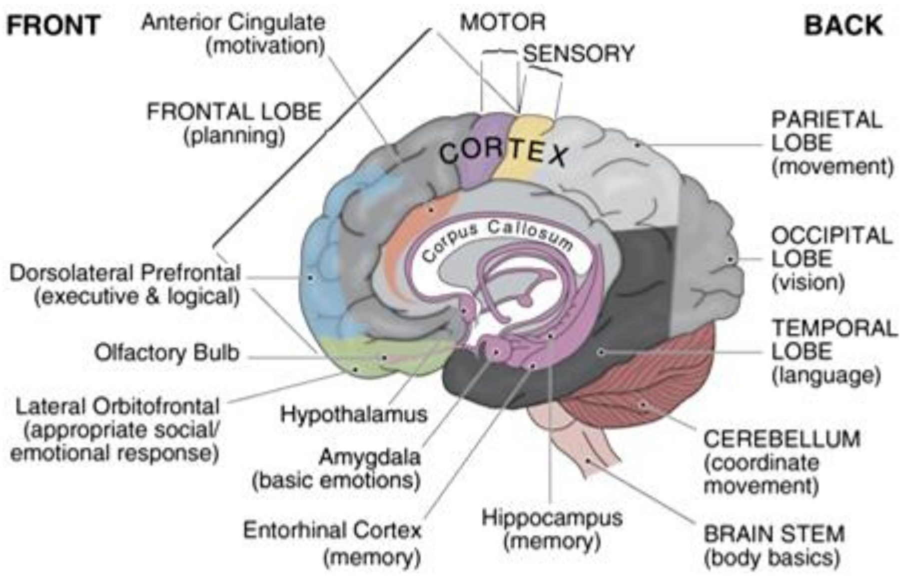


Figure 2.9. The limbic system of the human brain (taken from Gamon & Bragdon, 2003).

Overall however, daily emotions generally require higher-level and more elaborate processing (Suchy, 2011). For example, cognitive appraisal (in the prefrontal cortex) of visceral signals from the limbic cortices (Davidson, 2002; Farb, Anderson, & Segal, 2012; Scherer, Schorr, & Johnstone, 2001; Vytal & Hamann, 2010). Happiness, joy, interest, and anger demonstrate left frontal cortical activation while sadness shows reduced left lateralised patterning (Baas et al., 2008; Depue & Iacono, 1989; Murphy et al., 2003). In contrast, fear and disgust have been found to activate right frontal cortical areas (Schmidt & Trainor, 2001). However, alternative theories of lateralisation have also been proposed (see Buck, 1999; Gainotti, Caltagirone, & Zoccolotti, 1993; Silberman & Weingartner, 1986).

In any case, while the nonmontonic mood construct has so far eluded a delineating description, dimensional theories continue to prove popular. There is now strong evidence to suggest that mood encompasses a number of differentially related dimensions (i.e., tension, depression, anger, vigour, fatigue, and confusion). It is clear, however, that multiple interrelated systems (i.e., physiological and psychological) operating synergistically underlie what is experienced as *mood* (Panksepp & Watt, 2011; Suchy, 2011; Thayer, 1989, 2001; Valdimarsdottir & Bovbjerg, 1997).

2.3 Theoretical Distinctions between Mood and Emotion

The distinction between mood and emotion has been the subject of considerable discussion between affective scientists, and as Beedie, Lane, and Terry (2005) highlight, "the terms emotions and mood represent a conundrum for psychologists" (p. 847). It is important to emphasise the complexity of the mood-emotion distinction, as well as acknowledge that affective terms have traditionally been used interchangeably (Lane et al., 2009; Terry & Lane, 2011). Although a variety of distinctions have been theorised, conceptualisations and categorisations have typically been constructed within domains of preferred interest areas (Beedie, Terry et al., 2005), rather than approached from a generalisable perspective.

For example, as highlighted by Beedie, Terry et al. (2005), a psychophysiologist may differentiate mood from emotion by comparing neural or somatic processes. Alternatively, a psycholinguist might promote semantic differences in languages (Beedie, Terry et al., 2005), even though Ekman (1994) asserted that language does not always correspond with psychological reality. Criteria constructed from physiological, neurological, behavioural, and social standpoints have each been proposed (see Ekman, 1994; Ketai, 1975; Vallerand & Blanchard, 2000; Watson & Clark, 1997). Certainly, Beedie, Terry et al. suggest that the two concepts likely warrant separation according to more than one criterion (e.g., antecedents, duration, object-relatedness, and consequences).

Taken together, such practices have created confusion amongst affective scientists (e.g., Ekman & Davidson, 1994; Ketai, 1975; Lormand, 1985), and perhaps even predicated equivocal findings (Beedie, Terry et al., 2005). To further complicate already convoluted theoretical matters, the mood and emotion concepts share a number of similarities. For example, each are experienced as valanced subjective feeling states (i.e., negative or positive); each operate as a function of competing priorities (e.g., those involving the person/environment; Beedie, 2005); and each demonstrate a recursive nature. Additionally, many feeling states can be experienced as either mood and/or emotion, such as anxiety and anger (Beedie, 2005).

Notwithstanding these obvious challenges, many theorists believe that mood and emotion can—*and should*—be distinguished (Beedie, 2005). In the search for conceptual clarity Beedie, Terry et al. (2005) conducted a comprehensive assessment of mood-emotion distinctions via content analysis. Sixty-five published studies were examined with an aim to contribute to the development of a clear scientific distinction. From the definitions of mood and emotion provided by academics from multiple fields (i.e., sport and exercise psychology, general psychology, psychiatry, and philosophy), a number of differentiating themes emerged, such as duration (62%), intentionality (41%), cause (31%), consequences (31%) and function (18%). Additionally, physiology and awareness of cause were also mentioned.

Further to this, Beedie, Terry et al. (2005) also explored perceived differences between the mood and emotion constructs among a sample of 106 non-academic participants. In this case, inductive content analysis identified a total of 16 themes, with cause (65%), duration (40%), control (25%), experience (15%), and consequences (14%) being the most commonly cited exemplars. When eight themes cited by academic authors and non-academic participants were rank ordered, an agreement rate of 60% was identified (refer to Table 2.4 for a data-derived summary of mood-emotion distinctions). Interestingly, affect was not mentioned by any participant, which according to Beedie, Terry et al. supports the notion that the term is used almost exclusively by psychologists.

Table 2.4

Selected Distinctions Between Mood and Emotion (taken from Beedie, Terry et al., 2005)

Criterion	Emotion	Mood
Awareness of cause	Individual is aware of cause	Individual may be unaware of cause
Cause	Caused by a specific event or object	Cause is less well defined
Consequences	Largely behavioural and expressive	Largely cognitive
Control	Not controllable	More controllable
Display	Displayed	Less visible
Duration	Brief	Enduring
Intensity	Intense	Diffuse
Intentionality	About something	Not about anything in particular
Stability	Fleeting and volatile	More stable
Timing	Rises and dissipates quickly	Rises and dissipates slowly

Parkinson, Totterdell, Briner, and Reynolds (1996) stated that “emotions are caused by specific events localised in time, whereas moods build up as a consequence of either a concatenation of minor incidents, persistent conditions in the environment, and/or internal metabolic or cognitive processes” (p. 6). The view that emotions tend to involve an antecedent, whereas mood comprises a more global feeling state with no particular trigger (Frijda, 1986; Lucas, Diener, & Larsen, 2003), is perhaps the most commonly agreed distinction. Additionally, a difference in intensity and duration is also well recognised (Barsade & Gibson, 2007; Clark &

Isen, 1982; Frijda, 1986; Larsen, 2000; Gross & Thompson, 2007; Parkinson et al., 1996). As proposed by one participant "emotions come and go far quicker than moods. My emotions are quick flashes of light; they are feelings generated from experiences and events. Moods are far more prolonged ... a mood could last all day or longer" (Beedie, Terry et al., 2005, p. 864). This comment clearly highlights the duration distinction between the two experiential entities.

Although there is general agreement that the underlying phenomena are fundamentally dissimilar (albeit closely related; Lane et al., 2009; Beedie, Terry et al., 2005), some argue that mood and emotion interact and potentially overlap (Lang, 1979; Reed, 2005). A number of dynamic relationships have been hypothesised. For example, Ekman (1994) suggested that mood interacts with emotion, thereby altering the emotion threshold (i.e., the point at which an emotion is experienced). Alternatively, Stevens (2007) argued that mood influences emotional reactions in contextual situations, with consequential feeling states then contributing to mood. Similarly, Parkinson et al. (1996) posited that emotions contribute to more enduring moods, and are cognitively interpreted depending on the mood state. Indeed, DeLancey (2006) stated that certain moods *are* emotions, in that "some moods are the continual or frequent presence of an emotion" (p. 527).

Unfortunately, such conceptualisations appear unable to fully elucidate a mood/emotion distinction. The extant research suggests that there are a number of reciprocal relationships at play (Ekman, 1994; Stevens, 2007), and despite obvious similarities and conspicuous differences, the constructs continue to elude scientific conceptualisation and disentanglement. It is for this reason that scientists continue to try to distinguish mood from emotion, as well as quantify underlying physiological mechanisms and investigate affect-related phenomena (i.e., circadian rhythms, sleep, mood disorders, etc.; Augustine & Hemenover, 2009). In the words of Beedie, Terry et al. (2005), “emotion and mood may be different words for the same construct or different words for different constructs” (p. 848).

2.4 The Effects of Mood on Performance

The role of mood in predicting performance has been well documented, with the effects typically investigated within the context of sport (Beedie et al., 2000; Hanin, 1997; Terry, Janover, & Diment, 2004). While some studies have identified a measurable relationship (Hoffman, Bar-Eli, & Tenenbaum, 1999; Newby & Simpson, 1994; Terry & Slade, 1995), previous research suggests that mood-performance relationships appear to vary (Lane & Chappell, 2001; Craighead, Privette, Vallianos, & Byrkit, 1986; Terry et al., 2004). Within- and between-subject analyses indicate that idiomatic performance appears highly dependent on mood for some individuals, but remains considerably independent for others (Hanin, 1997; Lane & Chappell, 2001; Terry et al., 2004; Totterdell, 1999).

In a combination design study by Lane and Chappell (2001), idiographic and cross-sectional data were investigated with a specific goal to compare mood-performance relationships. The POMS-A (Terry et al., 1999) and the Performance Satisfaction Questionnaire were used to quantify mood and performance (respectively) in a sample of 10 basketball players. The results indicated that mood was significantly related to performance for the within-subject analyses (n = 5), with 40% of the variance accounted for. However, an association was unable to be identified in the remaining five players. Further, multiple regression on data from all participants suggested that mood accounted for only 9% of the variance overall. Disparate findings such as these affirm that the strength of the mood-performance relationship may be partly governed by idiosyncratic differences, including personality factors (Larsen, 2000; Shockley et al., 2012) and previous experience (Lane & Chappell, 2001).

Assuming there is large inter-individual variability, the individual zone of optimal functioning (IZOF) model suggests that emotional experiences are differentially related to successful and poor performances (refer to Figure 2.10; Jokela & Hanin, 1999). This framework contends that enhanced performance is contingent upon experiencing idiosyncratic *zones* of high, moderate, and low levels of arousal. Arousal levels experienced outside of any specific IZOF zone predict deterioration in performance (Russell & Cox, 2000). This framework originally focused on optimal levels of precompetition anxiety in elite sportspersons using the Stait Trait Anxiety Inventory (STAXI; discussed later) and intra- and inter-individual retrospective analyses (Hanin, 1993; Jokela & Hanin, 1999). However, a multidimensional approach has since been taken, thereby extending the model to include positive and negative affective experiences (Hanin & Syrjä, 1995a, 1995b) as well as mood states (Prapavessis & Grove, 1991).

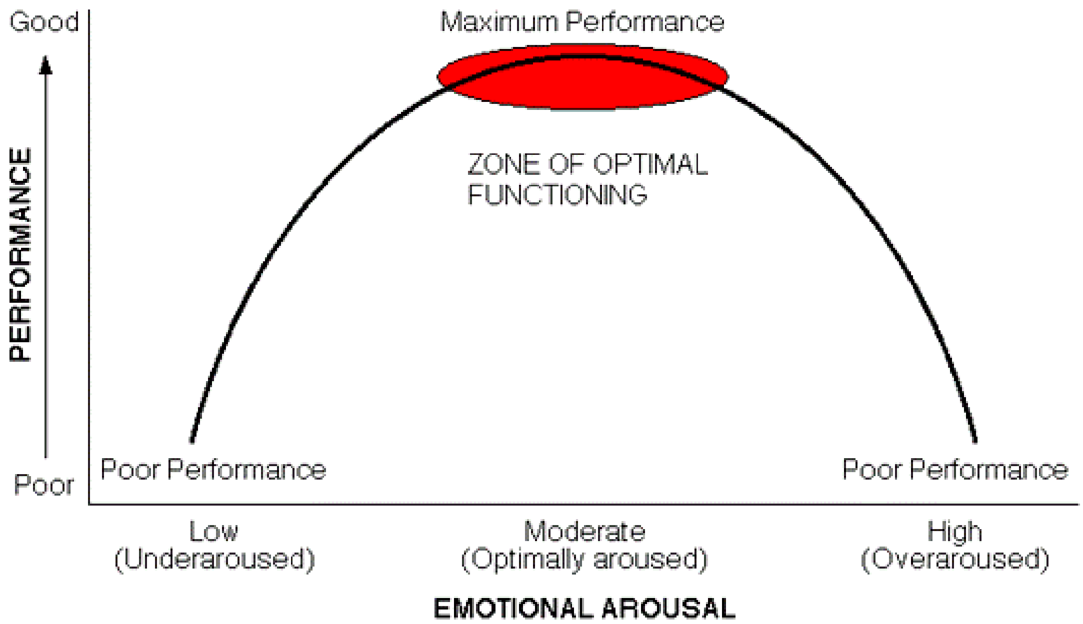


Figure 2.10. A diagram illustrating the zone of optimal performance.

Alternatively, Baumeister, Vohs, DeWall, and Zhang (2007) posit that individuals develop beliefs about emotions from a combination of previous feeling states and experiences, consequently learning which states are ideal for performance. According to this theory, previous emotional reactions and learned meta-emotional beliefs influence how discrete emotions are regulated, being in accordance with anticipated feelings/corresponding outcomes (refer to Figure 2.11a and 2.11b; Baumeister et al., 2007; Lane et al., 2011). For example, activities such as running enable an athlete to experience the same repetitive physical action repeatedly (Lane et al., 2011), which allows learned associations relating to optimal or dysfunctional performances to be reinforced (refer to Figure 2.11c; Baumeister et al., 2007).

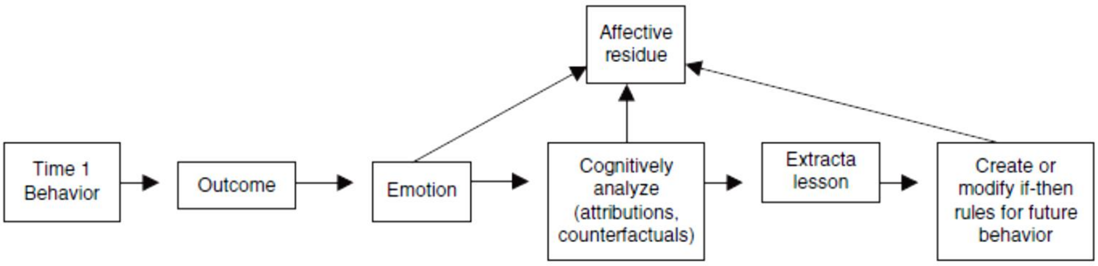


Figure 2.11a. A diagram of the process of emotion and learning for future behaviour (taken from Baumeister et al., 2007).

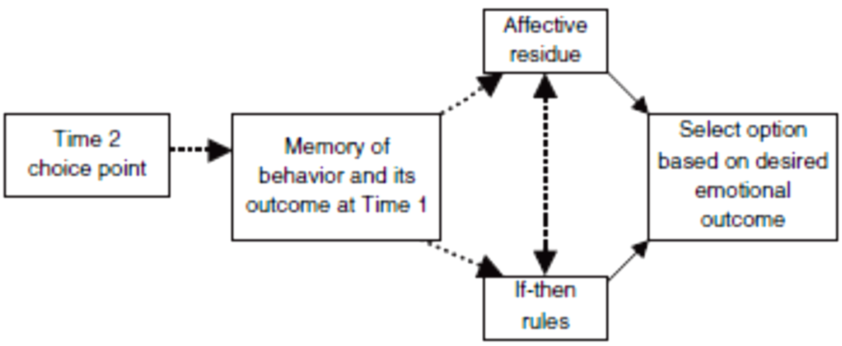


Figure 2.11b. A diagram of how past emotion influences subsequent behaviour. Solid lined arrows indicate causal relationships in that the process creates the actual effect, while dash lined arrows indicate associative relationships whereby the process activates a set of associations (taken from Baumeister et al., 2007).

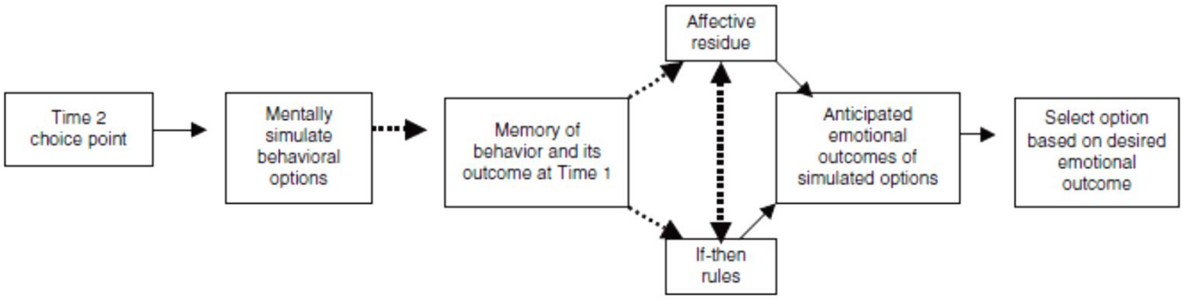


Figure 2.11c. A diagram of how anticipated emotional outcomes guide subsequent behaviour. Again, solid lined arrows indicate causal relationships in that the process creates the actual effect, while dash lined arrows indicate associative relationships whereby the process activates a set of associations (taken from Baumeister et al., 2007).

Conversely, it has been argued that mood-performance relationships should be investigated using discrete mood dimensions, rather than single construct conceptualisations (Brief & Weiss, 2002; Lane & Terry, 2000). As highlighted by Beedie et al. (2000), the use of the POMS to examine mood states was pioneered by Morgan and colleagues (e.g., Morgan, 1974; Morgan & Johnson, 1978; Morgan & Pollock, 1977; Nagle, Morgan, Hellickson, Serfass, & Alexander, 1975). Built on a foundation of evidenced-based research, Morgan's (1980, 1985) mental health model predicts an inverse relationship between psychopathology and sport performance. From this viewpoint, athletic success is associated with psychological health, whereas psychopathology is generally related to an increased incidence of failure (Rowley, Landers, Kyllo, & Etnier, 1995). Morgan found that many successful competitors experienced mood profiles that differed from population norms. The graphical representation of POMS raw scores outlined an *iceberg* shape, with test norms signifying a *water line* (see Figure 2.12). Parsimoniously termed the *iceberg profile,* this mood profile comprises of a combination of high vigour with low tension, depression, anger, fatigue, and confusion (Morgan, 1980; Terry, 1995).

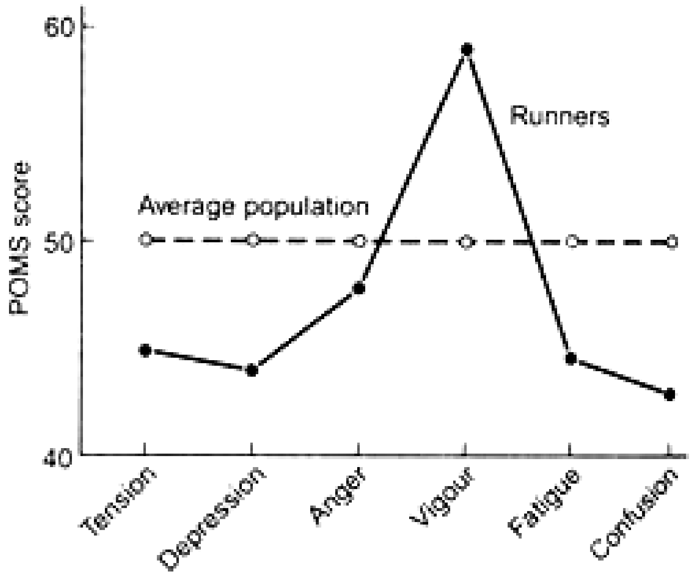


Figure 2.12. Morgan's (1980, 1985) mental health model. The iceberg profile consists of low scores on the negative mood dimensions, together with a high score on the positive mood dimension vigour (Rowley et al., 1995).

Attracting the attention of researchers, the iceberg profile has received strong support (e.g., Beedie et al., 2000; Gill, 1986; Rowley et al., 1995; Terry & Lane, 2000; Terry & Hall, 1996). Further, two additional profiles have been found. In line with Mogan's hypothesis that "successful athletes possess more of an iceberg profile than less successful athletes" (Rowley et al., 1995, p. 186), an *Everest profile* has been identified (Terry, 1995). Characterised by significantly high levels of vigour (i.e., > 60%) and low levels of tension, depression, anger, fatigue, and confusion (i.e., < 40%) this profile has been found to facilitate performance and is further associated with high levels of achievement. Conversely, the *inverse iceberg profile* (i.e., below average vigour, and above average tension, depression, anger, fatigue, and confusion; Terry, 2005) typically debilitates performance efforts.

However, inconsistencies have cast doubt on the ability of mood profiling to predict athletic achievement (Terry & Lane, 2011). For example, a review by Landers' (1991) identified that only 53% of the results were in line with the mental health model, a percentage not significantly different from that which would be expected by chance. However, the methodology of the study meant the magnitude of the effect was unable to be determined. Further, in the meta-analysis by Rowley et al. (1995), the iceberg profile accounted for less than 1% of the variance in performance outcome, suggesting that the "utility of the POMS in predicting athletic success is questionable" (p. 185).

Further, in a meta-analytic study by Beedie et al. (2000), relationships between mood and athletic achievement *(n* = 13) and between mood and performance outcome *(n* = 16) were investigated. Results showed that effect sizes for level of *achievement* were minimal, consistent with previous findings by Rowley et al. (1995). However, larger effects were identified for level of *performance*. The effects for vigour, confusion, and depression; for anger and tension; and for fatigue were moderate, small, and very small, respectively. Given that all results were in line with Morgan's (1985) mental health model, it was concluded that the POMS had utility in the prediction of performance outcome, but not in the prediction of level of achievement.

Reviews by Renger (1993) and Terry (1995) suggest that such associations are likely to be subtle and complex. Further, a transactional relationship could be present (Stevens, Lane, & Terry, 2006). This notion is not surprising, given that happiness has been identified as independent of other positive mood states, with differential effects on performance (Lane & Terry, 2000). Indeed, happiness has been found to negatively impact performance through superficial cognitive processing (Sinclair & Mark, 1992) and potential attentional overload (Hirt, Melton, McDonald, & Harackiewics, 1996). Conversely, high vigour has consistently been associated with increased effort towards performance goals (Lane & Terry, 2000) thereby facilitating improved performance. Additionally, negative mood states such as tension, depression, anger, fatigue, and confusion have also been found to differentially influence performance (Lane & Terry, 1998, 2000).

In an attempt to provide a conceptual basis for the mood-performance relationship, Lane and Terry (2000) developed a framework using the BRUMS (discussed in Section 2.7.3) involving six dimensions of mood; namely tension, depression, anger, vigour, fatigue, and confusion. Although high vigour often evokes greater effort expenditure, confusion, depression, and fatigue have been consistently associated with debilitated performance. Findings on the dimensions of anger and tension suggest that they can either debilitate or facilitate performance, depending on the co-existence or absence of depressed mood (refer to Figure 2.13).

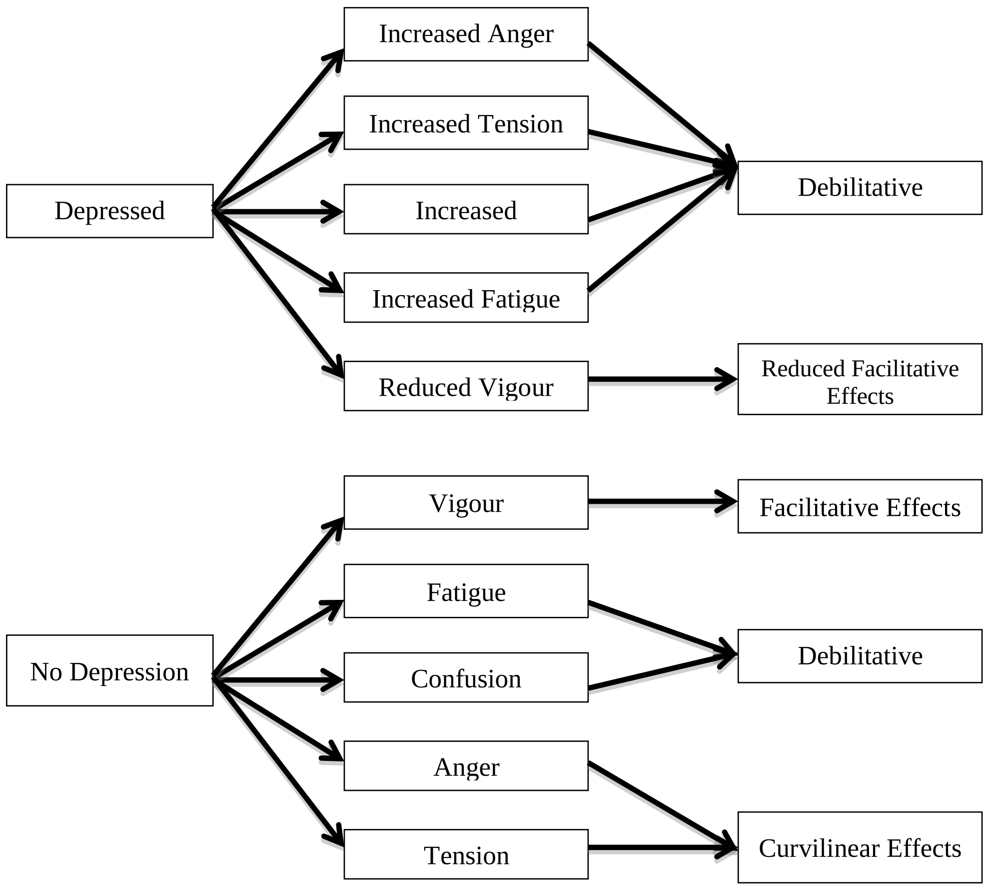


Figure 2.13. A conceptual model to predict performance from pre-performance mood (taken from Lane & Terry, 2000).

Given that the strength of inter-correlations appeared connected to the intensity of the depression score (Lane & Terry, 2000), central to this model is the role of depressed mood. Negative cognitive patterns have been found to re-direct concentration towards the recall of negative material. This impeded thinking style can contribute to reduced coping ability and capableness, or encourage behavioural inaction (Abramson, Metalsky, & Alloy, 1989; Rokke, 1993). Additionally, merely regulating depressed mood generally requires amplified effort and additional cognitive resources (Muraven, Tice, & Baumeister, 1998). Taken together, a perception of low competency combined with depletion in mental capacity would reduce overall ability to regulate performance—physical or otherwise (Muraven et al., 1998). Lane and Terry (2000) further proposed that with its global negative self-schema, depression may stimulate other negative mood dimensions such as anger, confusion, fatigue, and/or tension.

Unfortunately, the tendency to inhibit anger is often closely associated with depressed mood (Spielberger, 1991). According to Spielberger (1991), the underlying nature of the anger construct can be expressed in two ways: internally and externally. Suppression, otherwise known as an internal expression of anger, has been found to typically accompany depression, and has often been associated with self-blame and hopelessness. However, in the absence of depressed mood, anger is more likely to be externalised (i.e., external expression) and displaced onto outside sources. Whereas suppression is generally linked with negative outcomes (Spielberger, 1991), externalisation of anger can be channelled into determination, thereby translating into more positive performances (Lane & Terry, 2000).

Similarly, tension can be functional by indicating that some form of action is required, such as increased effort or concentration (Lane & Terry, 2000; Schwarz &

Bless, 1991). Yet for an individual experiencing depressed mood, such signals are more likely to be viewed and interpreted in the context of the current feeling state (i.e., as a potential threat). Additionally, high levels of tension can direct cognitive resources towards worry. Alternatively, and in the absence of depressed mood heightened anger and tension can prove functional through increased arousal levels and engagement in positive actions (Bless, 2001; Schwarz, 1990). In terms of other mood dimensions, confusion has also been consistently linked with attentional and concentration problems, while fatigue has also been associated with decreased confidence and effort. Confusion and fatigue have both been found to debilitate performance, regardless of the presence or absence of depressed mood (Lane & Terry, 2000).

Overall, mood-performance research has traditionally lacked a clear conceptualisation creating inconsistency in methodologies and research questions (Beedie et al., 2000). Although findings on the mood-performance relationship have been somewhat mixed (as have the nature of such relationships and specific mechanisms involved), the conceptual model provided by Lane and Terry (2000) has received general support. Overall, a depressed mood experienced prior to performance has been linked with low scores in vigour, together with high scores in anger, tension, fatigue, and confusion (Janover & Terry, 2002; Lane, 2001; Lane & Chappell, 2001; Lane et al., 2002; Lane & Terry, 2000, 2005; Lane, Terry, Beedie, Curry, & Clark, 2001; Lane, Terry, Beedie, & Stevens, 2004). Alternatively, and devoid of depressed mood, independent feelings of anger and tension are more likely to be interpreted in line with the most recently experienced dispositional state, which consequently are more likely to be associated with self-confidence, vigour, and increased effort (Lane & Terry, 2000).

2.5 Mood Regulation Strategies

The ability to self-regulate mood and emotion forms an inexorable part of effective and adaptive psychological functioning (Freud, 1961; Gross & Muñoz, 1995; Larsen, 2000). Born over a century ago from Freud's psychoanalytic theorising on rudimentary defences (Breuer & Freud, 1895/1957; Freud, 1946; Gross, 2002; Torre, 2011); scientists have investigated affect modulation using related terms. Some examples include emotional control, affect regulation, emotion regulation, emotion management, etc., (Cole, Martin, & Dennis, 2004; Gross, 1998a, 1998b; Kállay, Ţincaş, & Benga, 2009; Thompson, 1994). While this practice highlights an underlying degree of psychological complexity, unfortunately using a selection of arbitrary terms obscures already entwined issues, such as those relating to different forms of regulation, coping styles, defences, emotions, appraisals, etc., (Kállay et al., 2009). As an observation of the literature, many generalised coping techniques (e.g., cognitive, behavioural, religious/spiritual, etc.; see Moos, 1987; Thuné-Boyle, Stygall, Keshtgar, & Newman, 2006), do in fact mirror those that have the ability to regulate mood.

According to Lane et al. (2011), autonomous regulation involves a collection of automatic and controlled processes that are concerned with "the initiation, maintenance, and modification of the occurrence, intensity, and duration of affective states" (p. 400; Gross & Thompson, 2007; Webb, Miles, & Sheeran, 2012). Therefore, individuals apply both conscious and subconscious processes to regulate intense feeling states (Demaree, Pu, Robinson, Schmeichel, & Everhart, 2006; Egloff, Schmukle, Burns, & Schwerdtfeger, 2006; Lane et al., 2011; Solanki & Lane, 2010). A range of culturally sanctioned mood-regulating activities exists. Exercising, listening to music, seeking social support, engaging in positive self-talk, suppression, catharsis, sleep, and less socially-desirable tactics such as drinking alcohol and smoking (Clemes & Dement, 1967; Geen & Quanty, 1977; Larsen & Prizmic, 2004; Solanki & Lane, 2010) are examples of more than 300 strategies identified in the literature (Augustine & Hemenover, 2009; Fordyce, 1977, 1983; Larsen, 2000; Parkinson & Totterdell, 1999; Terry & Lane, 2011).

In a study involving a sample of athletes, Stevens and Lane (2000) found the most commonly used activities were listening to music, controlling thoughts, talking to or having someone else around, and exercising. Similarly, a study by Terry et al. (2006) investigating the effectiveness of mood regulation behaviours used before competition, found that athletes engaged in multiple strategies often as a function of regulating different mood dimensions (i.e., anger, confusion, depression, fatigue, tension, and vigour). However, the strategies most commonly chosen were not always considered the most effective. As Totterdell and Parkinson (1999) point out "some strategies might be used a lot because they are considered effective, whereas in practice they may not actually improve mood" (p. 219).

While various strategies may be favoured over others, it is not always obvious which techniques are actually effective in alleviating negative mood states. For example, Terry et al. (2006) found that the most popular strategies employed to regulate feelings of anger were (a) letting the feeling out, (b) spending time alone, (c) confiding in someone about the feelings, (d) dealing with the cause of the feelings, (e) using humour, and (f) trying to put the feelings into perspective. However, the most effective strategies reported were (a) dealing with the cause of the feelings, (b) using relaxation techniques, (c) spending time alone, (d) focusing on competition strategies, (e) trying to place feelings into perspective, and (f) avoiding the cause of the feelings (Terry et al., 2006). An overview of the most popular and effective strategies for regulating each of the six dimensions of mood according to the BRUMS are presented in Table 2.5.

Table 2.5

List of Most Popular and Effective Strategies used to Regulate Mood Dimensions

Mood Dimension	Most Popular	Most Effective
Tension	• Physical activity • Focus on competition strategies • Relaxation techniques • Give myself a pep talk • Talk with others to distract myself • Spend time alone	• Relaxation techniques • Sport-related imagery • Physical activity • Superstitious things • Positive thinking • Deal with the cause of the feelings
Depression	• Spend time alone • Talk to someone about my feelings • Talk with others to distract myself • Seek physical affection • Use humour • Think about something else	• Think positively • Deal with the cause of the feelings • Talk to someone about my feelings • Put feelings into perspective • Seek physical affection • Think about something else
Anger	• Let the feeling out • Spend time alone • Talk to someone about my feelings • Deal with the cause of the feeling • Use humour • Try to put my feelings into perspective	• Deal with the cause of the feelings • Use relaxation techniques • Spend time alone • Focus on competition strategies • Try to put my feelings into perspective • Avoid the cause of the feelings
Vigour	• Physical activity • Fast, upbeat music • Use humour • Sport-related imagery • Focus on competition strategies • Give myself a pep talk	• Physical activity • Think positively • Sport-related imagery • Fast, upbeat music • Focus on competition strategies • Put feelings into perspective

(Table 2.5 continues)

(Table 2.5 continued)

Mood Dimension	Most Popular	Most Effective
Fatigue	• Take a shower • Rest, take a nap or sleep • Splash face with cold water • Eat something • Physical activity • Focus on competition strategies	• Relaxation techniques • Take a shower • Rest, take a nap or sleep • Put feelings into perspective • Have a massage • Deal with the cause of the feelings
Confusion	• Talk to someone about my feelings • Give myself a pep talk • Use humour • Spend time alone • Talk with others to distract myself • Engage in physical activities	• Focus on competition strategies • Positive thinking • Deal with the cause of the feelings • Talk to someone about my feelings • Mentally switch off • Avoid the cause of the feelings

Thayer, Newman, and McClain (1994) used factor analysis to compose a taxonomy on affect regulation. With a focus on frequency and effectiveness, 32 strategies were classified into a six-factor solution: seeking pleasurable activities and distraction, passive mood management, social support/ventilation/gratification, direct tension reduction, and withdrawal/avoidance. The most commonly used strategies were those that positively influenced the biopsychological dimensions of energy (e.g., self-talk, music, showering, exercising, taking a nap, keeping busy, eating, or ingesting caffeine). Further, the most commonly used strategies to reduce tension, nervousness, or anxiety involved affiliative-communicative behaviours such as calling, talking, or spending time with another person. Other techniques identified included exercising, relaxation, resting, listening to music, and food consumption.

However, Totterdell and Parkinson (1999) argued that mood regulation could not be adequately represented by 32 items. Therefore, in conjunction with an examination of the existing literature, questionnaires, interviews, group discussions, and a card-sort task; Totterdell and Parkinson explicated 162 distinct mood regulation strategies according to 24 classifications. According to a hierarchical cluster analysis, two high-level groupings of cognitive and behavioural strategies were identified. The obtained typology also provided support for distinctions between diversion and engagement, active distraction and direct avoidance, as well as lower level groupings of venting, reappraisal, and seeking social support (refer to Table 2.6 for a table taken from Totterdell & Parkinson, 1999).

Table 2.6

Classification for Affect Regulation Strategies

		Cognitive	Behavioural
DIVERSION			
Disengagement		Avoid thinking about the problem	Avoid problematic situation
Distraction	SEEK PLEASURE OR RELAXATION	Think about something pleasant	Do something pleasant
		Think about relaxing thoughts	Do something relaxing
	REALLOCATE RESOURCES	Think about something that occupies attention	Perform a demanding activity
ENGAGEMENT		Reappraise (usually affect-directed)	Vent feelings (usually affect-directed)
			Seek help or comfort from others
		Think about how to solve problem (usually situation-directed)	Take action to solve problem (usually situation-directed)

Cognitive emotion regulation ranges from situation selection, to attention deployment, or cognitive reappraisal (Gross, 1998a; 1998b; Larsen & Prizmic, 2004). Recently, cognitive reappraisal has been the topic of many research agendas (see Goldin, McRae, Ramel, & Gross, 2008; Mauss, Cook, Cheng, & Gross, 2007; McRae, Ochsner, Mauss, Gabrieli, & Gross, 2008) and encompasses a broad class of related implicit processes involving reinterpretation (Ray & Zald, 2011). Neuroscientists highlight different regions of the brain activated during this strategy (refer to Figure 2.14) and describe deployment of top-down, *cold* cognitive control regions of the pre frontal cortex to down regulate bottom-up, *hot* reactive processes involving subcortical limbic regions (e.g., the amygdala; Ray & Zald, 2011).

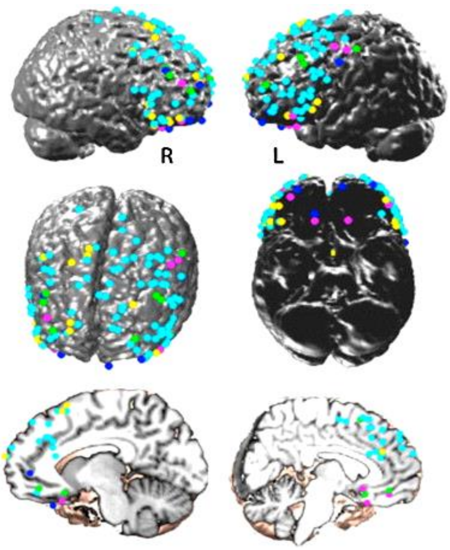


Figure 2.14. Areas activated during emotional regulation of negative emotions. The cyan markers are surface renderings of coordinates reported as more engaged in reappraisal to decrease negative emotion than a non-regulated condition. The blue markers are coordinates reported as more responsive to inhibition or suppression of negative emotion than a non-regulation condition. The yellow markers are coordinates reported as more active in reappraisal when decreasing positive emotion than in a non-regulated condition. The green markers designate those coordinates

reported as increased during distraction over an unregulated condition. The pink markers are coordinates reported as more active during the recall of positive or soothing memories or images to regulate anxiety or sadness (taken from Ray & Zald, 2011).

Investigating regions of the brain associated with the cognitive control of emotion, and those associated with emotional responses, are of great importance given that deficits in these processes have been implicated in psychopathologies relating to maladjustment (Kállay et al., 2009; Ray & Zald, 2011). A range of epidemiological data highlights a relationship between inability to remediate mood and psychological disturbance (Bradley, 1990; Greenspan & Porges, 1984; Larsen, 2000; van Praag, 1990). Additionally, empirical works have also demonstrated that emotional stimuli can synergistically influence a variety of cognitive processes, such as creative problem solving, episodic memory, and working memory (Ashby et al., 1999; Larsen, 2000; Ray & Zald, 2011).

While the purview of research has generally attempted to organise mood and emotion regulation according to biopsychological and/or cognitive-behavioural categories, Gross (1998a) proposed a process approach involving a time-course cycle. Built on the general model of emotion (Gross & Muñoz, 1995), essentially this theory suggests that emotions are valanced responses to stimuli (i.e., external or internal) that change according to response tendencies (i.e., experiential, behavioural, and physiological; refer to Figure 2.15a; Torre, 2011). This conception defines emotion as having an identifiable trigger, and further highlights a distinction between two broad classes of regulation techniques: antecedent-focused and response-focused strategies (Gross, 1998a). *Antecedent-focused* strategies encompass those that influence input, while *response-focused* techniques involve those that moderate the output of the emotion generation process (Gross, 1998a; Torre, 2011; refer to Figure 2.15b for more detail). It is important to note the focus on *identifiable triggers* in this model, thus differentiating emotions from moods (which lack a specific object; Ochsner & Gross 2005).

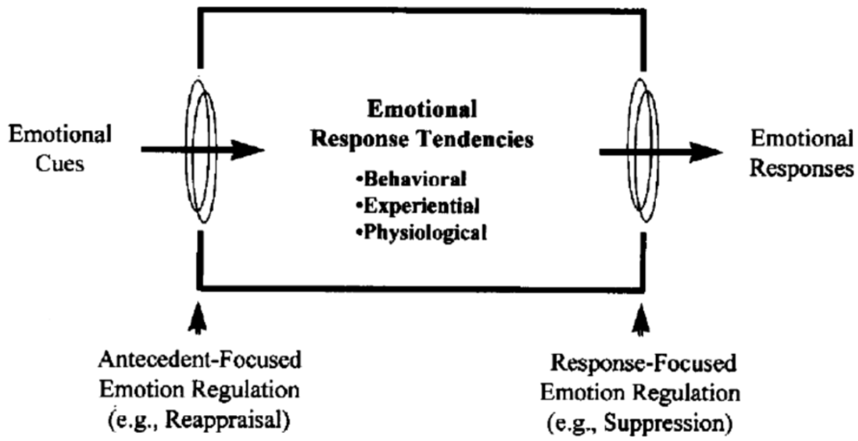


Figure 2.15a. A consensual process model of emotion that highlights two major classes of emotion regulation (taken from Gross, 1998a).

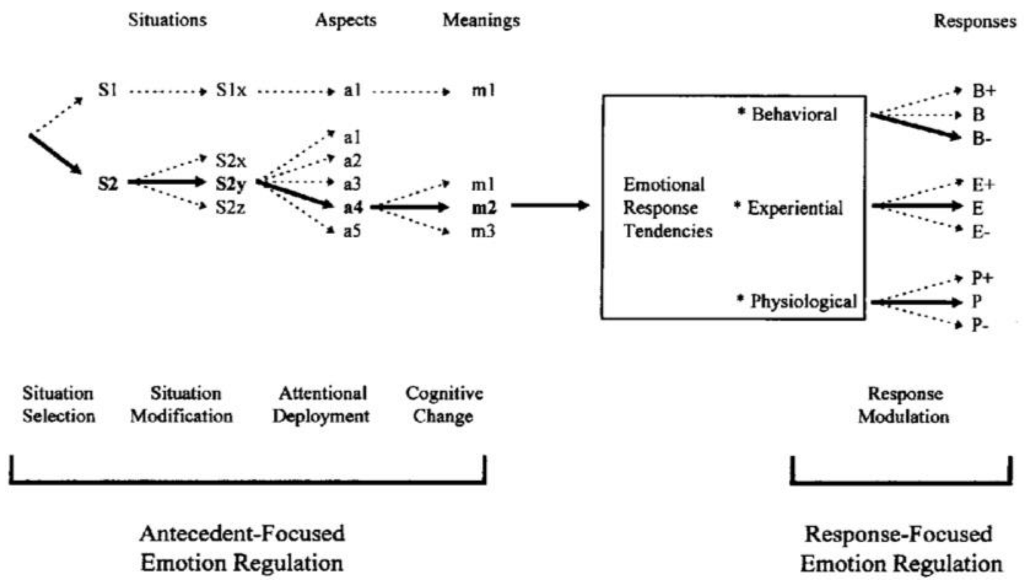


Figure 2.15b. The family of antecedent-focused regulation strategies comprises *situation selection, situation modification, attentional deployment, and cognitive change* (i.e., self- focused and situation-focused reappraisal), while *response modulation* (i.e., suppression) is labelled under the classification response-focused emotion regulation.

In summary, various research traditions have approached the study of affective modulation in different ways, using different terminologies. As demonstrated by Totterdell and Parkinson (1999), a large number of differential mood regulation strategies exist. More specifically, individuals have been found to use a variety of techniques to facilitate a hedonic shift, with pharmacologic, cognitive, behavioural, and/or environmental change methods being examples (Carmody, 1989). The following section will describe in detail three commonly used autonomous strategies that have been shown to be effective in the regulation of mood: exercise, music, and food consumption.

2.5.1 The effects of physical activity on mood. Described as a "universal panacea" in the doctrine of exercise psychology, regular physical activity can instantiate numerous health advantages (Yeung, 1996, p. 123). Research over the past 30 years has shown that aside from physical benefits relating to coronary heart disease, hypertension, diabetes, certain types of cancer, obesity, and osteoporosis (Bouchard, Shephard, & Stephens, 1994; Kesaniemi et al. as cited in Tsang, 2011; Shephard, 1995), physical activity has a therapeutic capacity to improve well-being (Anderson & Brice, 2011; Berger & Owen, 1983; North et al., 1990; Tsang, 2011). Indeed, the International Society for Sport Psychology (1992) has outlined a number of psychological benefits relating to positive mood changes, and a meta-analysis involving 158 studies has mirrored such findings (Reed & Ones, 2006).

More specifically, the empirical review by Reed and Ones (2006) concluded that increases in positive affect were experienced following a typical session of acute aerobic exercise, while decreases were found in control-condition comparisons. However, large standard deviations suggested that extenuating variables, possibly relating to individual differences, moderated the effects. In a similar vein, Guszkowska and Sionek (2009) investigated mood and personality traits during a 12-week aerobic exercise program. The pre-post design study aimed to establish a relationship, as well as identify personality factors that predict mood changes. Results showed that not only did mood improve (i.e., tense arousal decreased, and hedonic tone and energetic arousal increased), but personality traits also positively changed. Trait anxiety decreased, while levels of self-efficacy and optimism increased. However, quasi-experimental design studies do not meet experimental requirements, meaning that causative factors cannot be attributed to exercise alone. No relationships were found between mood and personality changes, with the authors concluding that feelings improved "irrespective of positive changes in personality traits" (Guszkowskal & Sionek, 2009, p. 163).

Further, Lane, Milton, and Terry (2005) found no interaction between exercise-induced mood enhancement and personality among female exercises. While this finding appears to lend support to a robust exercise-mood relationship (irrespective of personality factors), unfortunately it remains unknown if results were anomalous to the sample alone (N = 90). In any case, many studies have demonstrated exercise-mood findings. Meta-analyses and comprehensive summaries have highlighted exercise-induced reductions in depression (see North et al., 1990 for a review) and self-reported anxiety (Biddle, 2000; Petruzzello, Landers, Hatfield, Kubitz, & Salazar, 1991). Benefits of exercise on self-esteem have also been substantiated (McAuley, Blissmer, Katula, Duncan, & Mihalko, 2000). Indeed, physical activity is considered a primary mood regulation strategy (Tsang, 2011). It has been widely used as a treatment for anxiety (i.e., state, trait, and psychophysiological correlates of anxiety; Petruzzello et al., 1991) and clinical depression (Mather et al., 2002; Salmon, 2001). Interestingly, not only was exercise self-rated as “the most successful at changing a bad mood” (Thayer et al., 1994, p. 921), but was also considered the most efficacious approach for altering dysphoric mood when incorporated into an active mood management strategy.

In terms of mode, both aerobic and anaerobic exercise appear capable of decreasing depressive states, while simultaneously and positively influencing specific mood dimensions (Tsang, 2011). In a pre-post design study by Rokka, Mavridis, and Kouli (2010), the effects of a high-intensity and moderate-intensity aerobic dance session on mood were explored. A modified version of the POMS (McNair et al., 1971; Zervas, Ekkekakis, Emmanuel, Psychoudaki, & Kakkos, 1993) was used to assess participants (N = 136) both before and after partaking in each condition. The repeated measures ANOVA showed a statistically significant decrease in tension, depression, aggressiveness, and confusion; together with an increase in energy (no change in fatigue was identified). It was concluded that both exercise programs positively influenced mood. While a corpus of literature suggests that cardiovascular exercise engenders the greatest improvements (Ekkekakis, Hall, VanLanduyt, & Petruzzello, 2000; Hassmén, Koivula, & Uutela, 2000; Yeung, 1996), quantification inconsistencies have prevented empirically tested comparisons of intensity (Yeung, 1996).

Similarity, researchers are yet to systematically investigate parameters such as exercise duration (Yeung, 1996), although various allocations of time have been considered. For example, Ekkekakis et al. (2000) suggested that a 10- to 15-minute walk could improve mood, while Thayer and associates concluded that a brisk 10-minute walk was sufficient to increase energy and reduce tension (Thayer, 1987, 2001; Thayer, Peters, Takahaski, & Birkhead-Flight, 1993). Further, a meta-analysis by Petruzzello et al. (1991) found a *minimum* duration of 21 minutes was necessary to reduce state- and trait- anxiety.

Alternatively, Berger and Motl (2000) proposed that exercise sessions should be at least 20 to 30 minutes in duration, and incorporated on a weekly basis. Berger and Motl further developed a model highlighting considerations that facilitate optimal mood amelioration (see Figure 2.16). The central tenet of this theory is enjoyment. Berger and Motl suggested that engaging in an enjoyable activity (compared with a session perceived as less enjoyable) would tend to produce greater effects. Additionally, the authors proposed that competitive environments diminished overall enjoyment, which subsequently negated mood improvements. Previous findings by Motl, Berger, and Leuschen (2000) partially supported this notion in that participants' cognitive focus was altered from enjoyment to winning during competition.

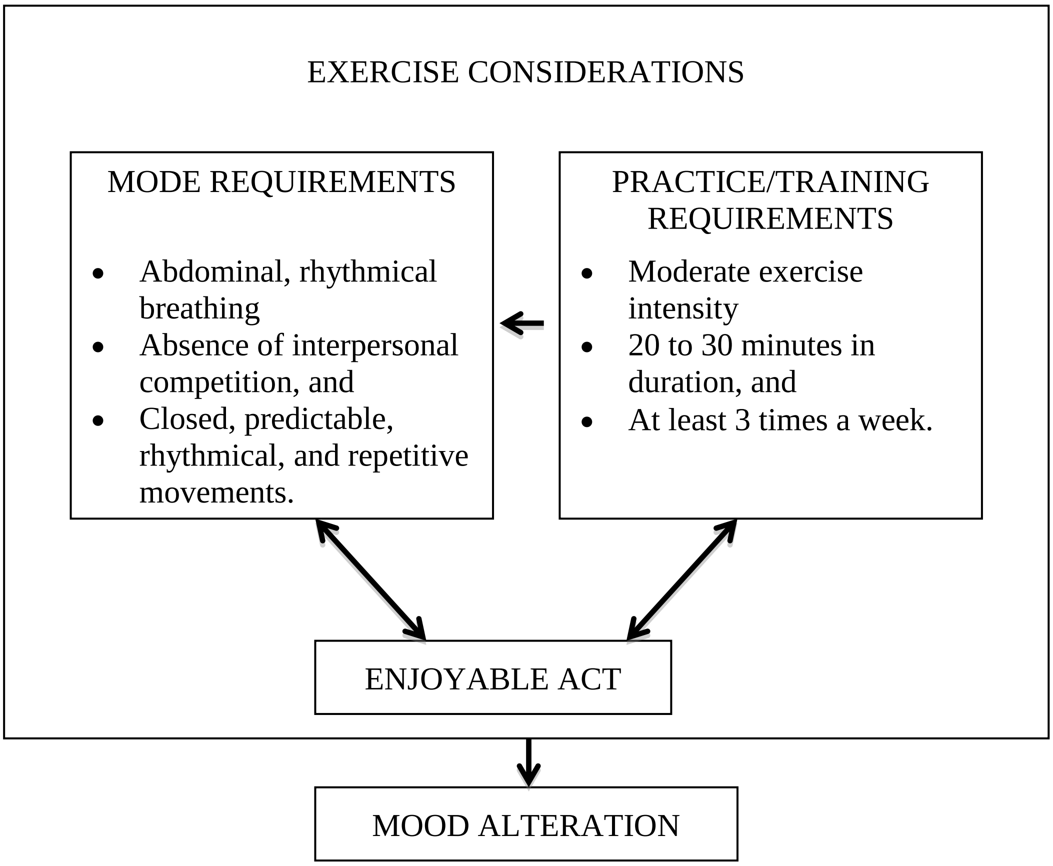


Figure 2.16. A preliminary taxonomy for enhancing the psychological benefits of

exercise (taken from Berger & Motl, 2000). According to this model, mode requirements refer to various types of physical activity, while practice/training requirements refers to the intensity, duration, and frequency of exercise. Enjoyment refers to level of enjoyment experienced during the chosen exercise activity. Mode requirements involve four aspects of exercise: abdominal and rhythmic breathing, non-competition, predictability, rhythmic and repetitive movements. Practice and training requirements involve three requirements: intensity, duration, and frequency.

Further support for the model lies in that predictable and repetitive activities have been found to assist positive mood changes (see Berger, 1994, 1996; Berger & Mackenzie, 1980; Berger & McInman, 1993). Yoga (Berger & Owen, 1992), tai chi, and meditation (Jin, 1992) each meet the mode requirements in terms of Berger and Motl’s (2000) framework, as well as provide opportunity for self-reflection and free-association which have also been linked to mood improvements. Overall, it appears that physical activity has the potential to evoke profound positive mood changes, some of which may persist for up to 24 hours (Maroulakis & Zervas, 1993). However, the pervasive processes by which this happens remain obfuscatory (Yeung, 1996).

A number of physiological and psychological mechanisms have been proposed in an attempt to elucidate the exercise-mood relationship (see deVries, 1981; Mohammadi-Nezhad, 2011; Thorén, Floras, Hoffman, & Seals, 1990). However, it is the endorphin hypothesis that has so far attracted the most attention (Lane et al., 2005; Yeung, 1996). According to this theory, physical activity releases endorphins that bind to receptor sites causing a state of euphoria (Steinberg & Sykes, 1985). Alternatively, the distraction hypothesis suggests that engaging in physical activity serves as a distraction from daily stressors. It is proposed that this diversion of attention from negative cognitive material subsequently supports improvements in self-concept, increased feelings of self-efficacy, and an increase in sense of control (Berger, 1996). Although there is some support for this hypothesis (see Bahrke & Morgan, 1978; Brown, Morgan, & Raglin, 1993), Fillingim, Roth, and Haley (1989) point out that distraction alone cannot fully account for the mood benefits of physical activity. Similarly, and despite its intuitive appeal, a review by Yeung (1996) deemed the endorphin hypothesis largely unsupported.

Other possible mood-exercise explanations involve the cognitive-behavioural hypothesis (Lane et al., 2005), the mastery hypothesis (Simon, McGowan, Epstein, Kupfer, & Robertson, 1985), and the thermogenic hypothesis (with limited support; Reeves, Levinson, Justesen, & Lubin, 1984; Yeung, 1996). However, the precise mechanisms mediating the anxiolytic effects of physical activity remain unknown (Mohammadi-Nezhad, 2011). What is clear is that a hedonic shift appears dependent upon a number of interacting factors, with preference, modality, familiarity, duration, and practice conditions each being implicated (Berger & Motl, 2000; Daley & Maynard, 2003; Lane et al., 2005; Solanki & Lane, 2010; Thayer et al., 1994).

2.5.2 The effects of music on mood. Ancient Greek writings have described music as “that which permeates the depths of the soul, allows the innate and introspective to come forth, and uplifts the emotions” (No author as cited in Shinoda, 2001, p. 457). Music has been a source of healing since the era of renowned Greek physician Hippocrates in 400BC (Shinoda, 2001). From these ancient roots, psychologists and music therapists have long proposed that music has the ability to influence emotional states (Boothby & Robbins, 2011; Vuoskoski & Eerola, 2011; Zentner, Grandjean, & Scherer, 2008). The pervasiveness of music is facilitated by technological developments such as radio, record players, cassette players, hi-fi equipment, TV, and more recently portable audio digitalised formats, and audio exchange files (Gaye, Holmquist, Behrendt, & Tanaka, 2006; Ter Bogt, Mulder, Raaijmakers, & Gabhainn, 2011). Miniaturisation of electronics and high-capacity digital storage systems mean that portable MP3 players can now hold a complete library of music (Gaye et al., 2006).

Affective scientists measure emotional responses to music perception using a number of approaches, with various paradigms affording differing methodologies (Hunter & Schellenberg, 2010). Advanced devices capable of measuring physiological responses such as diastolic blood pressure, cardiac inter-beat-interval, respiration depth, skin conductance, finger temperature, and zygomatic activity (Hunter & Schellenberg, 2010), as well as brain imaging techniques provide ideal objective means of investigation. Indeed, dichotic studies often involve positron emission tomographies (PET), electroencephalographs (ECG), and functional magnetic resonance imaging (fMRI; for examples see Barber, McKenzie, & Helme, 1997; Blood & Zatorre, 2001; Menon & Levitin, 2005). However, such methods remain somewhat insensitive to obscure feeling states, other than those related to level of arousal and the pleasant/unpleasant continuum (Hunter & Schellenberg, 2010). Given this, many researchers predominately use self-report questionnaires (Hunter & Schellenberg, 2010).

Music comprises of intricate blends of highly complex and varied sound patterns, with rhythm and pitch being the primary underlying dimensions (Bunt, 1994; Krumhansl, 2000). The five elements of sound include rhythm, melody, pitch, harmony, and interval (Bunt, 1994). According to Hunter, Schellenberg, and Griffith (2011), the interval and harmony of music (amongst other cues) can act as strong emotional prompts. For example, a fast tempo and major mode (i.e., a harmony based in the major scale) has been found to invoke happiness, while a slow tempo and minor mode (i.e., a harmony based in the minor scale) has been found to stimulate sadness (Crowder, 1984; DiGiacomo & Kirby, 2006; Hunter et al., 2011). A relatively strong feeling of happiness (i.e., fast-major) or sadness (i.e., slow-minor) can be felt when these cues align. However, when conflicting (i.e., fast-minor or slow-major), a mixture of both happiness and sadness may be experienced (DiGiacomo & Kirby, 2006; Hunter, Schellenberg, & Schimmack, 2010; Hunter et al., 2011). Interestingly, in such cases hedonic tone may have a moderating influence (e.g., happy listeners often focus on fast tempi or major modes, and sad listeners often focus on slow tempi or minor modes; Hunter et al., 2010, 2011).

Indeed, there is strong evidence to suggest a happy/sad connotation exists (see Gundlach, 1935; Juslin, 1997; Webster & Weir, 2005; Wedin, 1972), with Crowder (1984) describing it as “the most solid link we have between music structure and the language of human emotions” (p. 4). For example, in a study by Wales (1985 as cited in Karageorghis, 1992) individuals were exposed to music differing in tempi (i.e., fast versus slow) and feel (i.e., positive versus negative) during a submaximal 30-minute cycle ergometer test. An interaction effect was identified, whereby fast-positive music was found to decrease anger, depression, and fatigue throughout the duration of the test. Such findings suggest that music with a fast tempo may not only be associated with hedonic tone, but also facilitate positive mood states.

Similarly, Terry, Karageorghis et al. (2012) investigated the ergogenic, psychological, and psychophysical benefits of music in elite athletes (*n* = 11) during sub-maximal and exhaustive treadmill running. Ergogenic effects refers to the notion that music may increase performance or endurance, while psychophysical effects refers to altered perceptions of physiological processes (e.g., perceived exertion) facilitated by music (Terry & Karageorghis, 2011). The results from the repeated-measures laboratory design study found that participants' mood states (as measured by the Feeling Scale and BRUMS; Hardy & Rejeski, 1989; Terry et al., 1999) remained more positive throughout the duration of testing when exposed to motivational music (i.e., music with a fast tempo of > 120 beats per minute), compared with either neutral music or no music. Further, motivational music curtailed increases in depressed mood, anger, and confusion (Terry, Karageorghis et al., 2012). Terry et al. (1999) concluded, "the motivational qualities of music may be less important than the prominence of its beat and the degree to which participants are able to synchronise their movements to its tempo" (p. 52), highlighting the role of music tempo in its capacity to alter moods and enhance athletic performance.

However, if music is to facilitate positive psychophysical effects, characteristics of both the individual and music require consideration. Karageorghis, Terry, and Lane (1999) developed a conceptual model of the motivational quality of music involving four intertwining factors: rhythm response, musicality, cultural impact, and association (see Figure 2.17). According to Karageorghis, Priest, Terry, Chatzisarantis, and Lane (2006), rhythm response refers to the rhythmical components of music (e.g., tempo), whereas musicality refers to the response to the combination of notes (e.g., harmony, and melody). Cultural impact refers to the pervasiveness of the music within a cultural context, while association refers to the thoughts, feelings, and images stimulated by the music. These four contributors form a hierarchical structure, with rhythm response identified as the most important, and association as the least, in the prediction of psychophysical responses to music (Karageorghis, Terry et al., 1999; Karageorghis et al., 2006).

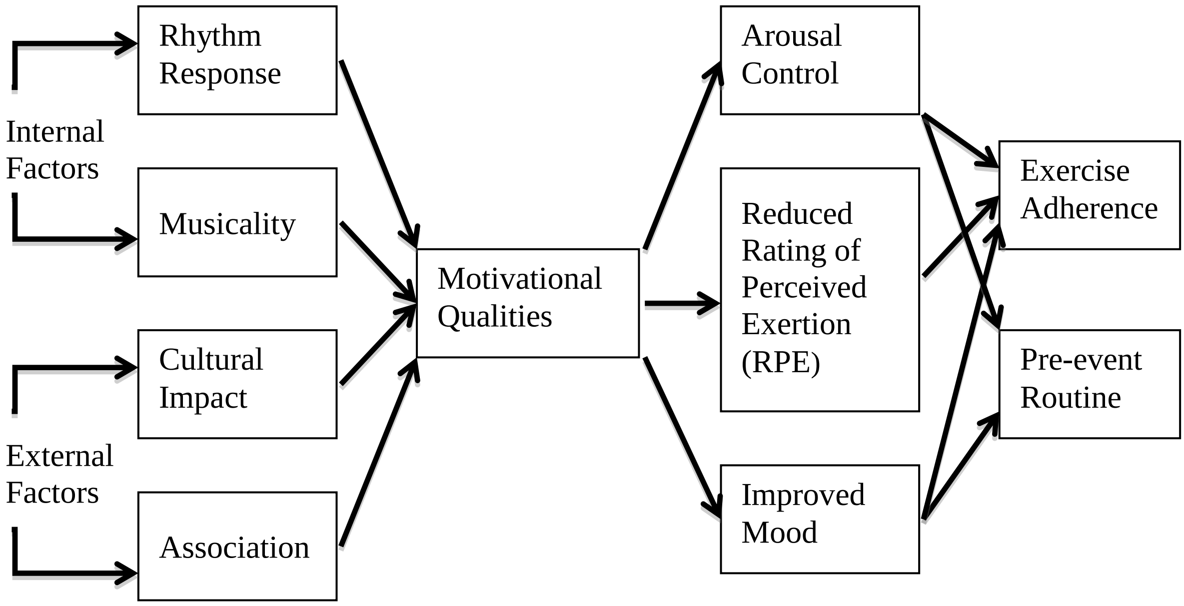


Figure 2.17. Conceptual framework for the prediction of responses to motivational music in sport and exercise (Karageorghis, Terry et al., 1999). Rhythm response and musicality are considered internal factors as they relate to the combination of elements of sound. Cultural impact and association are considered external factors as they involve individual perceptions. RPE = Reduced rating of perceived exertion.

Terry and Karageorghis (2006) updated the conceptual framework following the identification of an interacting relationship. Personal and situational factors were highlighted in that variables involving age and cultural background (i.e., personal factors) as well as activity type and context (i.e., situational factors) were each incorporated into the revised model (refer to Figure 2.18). Therefore, personal/situational factors as well as rhythm response, musicality, cultural impact, and association are each thought to contribute to the potential benefits of music (e.g., arousal control, reduced RPE, improved mood, greater work output, improved skill acquisition, flow state, enhanced performance).

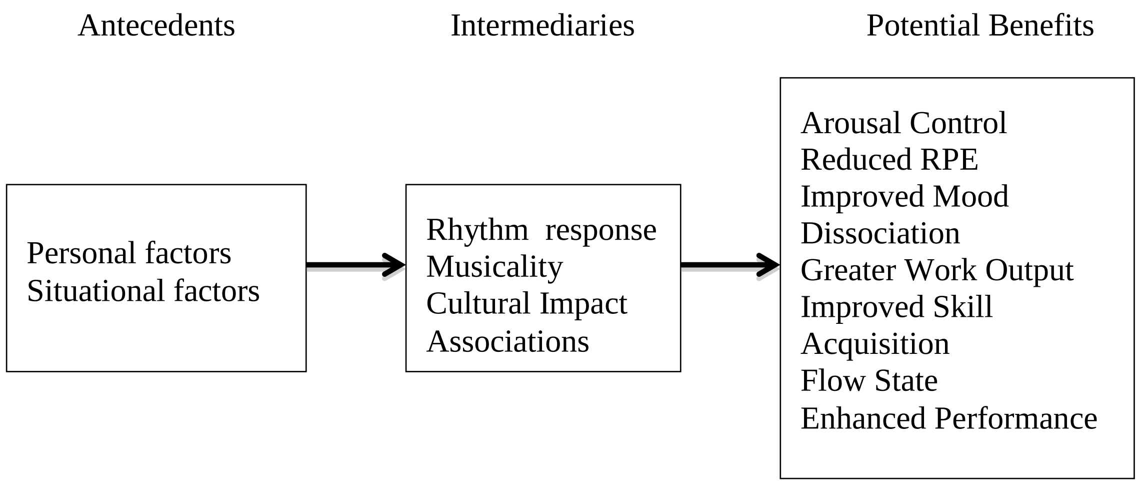


Figure 2.18. The updated four-factor model on the potential benefits of music in sport and exercise contexts (Terry & Karageorghis, 2006).

Cultivated from the four aforementioned key factors, Karageorghis, Terry et al. (1999) developed and validated a psychometric instrument to assist in the identification of music with motivational qualities. The Brunel Music Rating Inventory (BMRI) was developed for use in sport and exercise contexts; however, limitations within the measure meant that the scale was revised (Karageorghis et al., 2006; Karageorghis, Terry et al., 1999). The BMRI-2 is considered a valid and internally consistent tool that provides exercise leaders, sports coaches, participants, and researchers with a standardised measure through which to identify music intended to have motivational effects (e.g., improved mood, reduced exertion, and arousal control; Lane et al., 2011).

On a different note, while some music has the ability to positively influence feeling states and promote endurance and performance (Terry, Karageorghis et al., 2012; Tsang, 2011), other music may encourage negative outcomes. Music that sounds sad can negatively affect mood, arousal levels, and spatial abilities (Thompson, Schellenberg, & Husain, 2001), as well as educe brain activation patterns characteristic of avoidance motivation (Harmon-Jones & Sigelman, 2001;

Hunter et al., 2010; Schmidt & Trainor, 2001). From a neuroanatomical perspective, dynamic interactions between the mesolimbic reward system and the hypothalamus have been implicated (Blood & Zatorre, 2001; Menon & Levitin, 2005). Given this, it is not surprising that sad music tends to receive lower liking ratings compared with music that sounds happy (Hunter et al., 2010). However, when listeners were asked to rate positive and negative feelings in response to sad music, elevated levels on both self-report scales were reported (i.e., ambivalence), although only positive feelings were depicted after listening to happy music (Hunter et al., 2010, 2011; Hunter, Schellenberg, & Schimmack, 2008).

Considering the significant role of music cognition and its obvious physiological connectivity, its effectiveness as a mood regulation strategy has potential for individuals experiencing emotional distress. Pelletier (2004) used meta-analytic methodology to distinguish 22 quantitative, experimental studies investigating the effects of music on stress. Additionally, Jones (2006) identified 94 studies using music as an intervention (versus control). According to the results of these reviews, music had the ability to reduce negative feelings. In the same vein, a study by Arnett (1991) found that individuals who preferred listening to loud music such as heavy metal reported doing so in an effort to *vent* negative mood states such as anger, suggesting that different types of music can affect individuals differently (Tsang, 2011). Indeed, many studies have found that this genre of music can minimise or alleviate negative mood states such as sadness and/or loneliness (Avery, 1979; DeNora, 1999; Larson, 1995).

Ter Bogt et al. (2011) constructed a typology of music listeners based on the level of importance individuals attributed to music. Mood amelioration, coping with problems, defining personal identity, and marking social identity were each investigated according to three groups (i.e., high-involved, medium-involved, and low-involved). According to the results, high-involved listeners highly valued music according to a range of genres (i.e., pop, rock, highbrow, urban, and dance) and often used the medium for mood enhancement, coping with distress, identity construction, and social identity formation. Further, these individuals experienced the most intense positive feelings when listening. Alternatively, medium- and low-involved listeners formed two distinct groups, and viewed music as less important. Interestingly, both high- and medium-involved groups reported more negative emotions when listening (i.e., anger and sadness), compared to the low-involved group. However, even the low-involved group listened to music frequently, and used music to enhance mood.

It is generally agreed upon that music can influence a broad range of emotional states, and does so via cortical neural networks and parietal brain regions (Altenmüller, Schürmann, Lim, & Parlitz, 2002; Peretz, 1990; Platel et al., 1997). Despite this, there remains disagreement on the exact nature of the feelings. *Emotivists* maintain that music educes true emotions (e.g., Juslin & Västfjäll, 2008); whereas *cognitivists* assert that, such responses are aesthetic rather than emotional (Konečni, 2008). Still others argue that the feelings evoked are true emotions, however these feelings differ from utilitarian emotions because they involve two distinct levels: an emotional response to tone, and a cognitive appraisal involving liking/disliking (Hunter et al., 2008, 2010; Scherer, 2004). However, according to Juslin and Västfjäll (2008) cognitive appraisals are only one way that emotions can be stimulated. Other mechanisms involve brain stem reflexes, conditioning, contagion (i.e., perceptions spread to feelings), visual imagery, episodic memory, and expectancies (from Meyer, 1956; Hunter & Schellenberg, 2010).

Overall, genre preferences and the amount of time reserved for listening to music largely depend on idiosyncratic factors (Bunt, 1994; Ter Bogt et al., 2011). The extant evidence suggests that listening to music can function as an effective mood regulation strategy in a variety of contexts. Whatever the specific physical and/or psychophysical processes involved, or labels assigned to resultant feeling states, it is clear that individuals often use music to encourage coping as well as to ameliorate mood. Taken together, conjectures suggest that listening to music is more than a cognitive process involving audible stimuli (Altenmüller et al., 2002). It is a psychophysical phenomenon. Indeed, those who listen to music regularly, “benefit most from music’s capacity to enliven and enlighten life” (Ter Bogt et al., 2011, p. 147).

2.5.3 The effects of food consumption on mood. Numerous studies have suggested that, aside from physiological, environmental, and social cues, eating may be both influenced by and associated with feelings (Dingemans, Martijn, van Furth, & Jansen, 2009; Hendy, 2012; Macht & Dettmer, 2006). Hendy (2012) posited that the connection between mood and food could be explained using various mood regulation (Dingemans et al., 2009) and self-medication theories (Leibenluft, Fiero, Bartko, Moul, & Rosenthal, 1993). For example, individuals may consume food to provide comfort or distraction (Hepworth, Mogg, Brignell, & Bradley, 2010), thereby abandoning or violating other adaptive self-regulatory behaviours to prioritise unpleasant feelings (Dingemans et al., 2009).

According to Hendy (2012), individuals learn through association that the consumption of high-fat and high-carbohydrate food may improve negative moods, albeit for a short period. Retrospective questionnaires have supported such findings by identifying correlations between negative mood states and increased consumptions of food high in calories, carbohydrates, saturated fat, and sodium (i.e., *comfort foods*; Christensen, 2001; Christensen & Brooks, 2006; Hendy, 2012; Oliver & Wardle, 1999). This association has attracted a great deal of attention (Christensen & Brooks, 2006), and intense urges to eat are strongly related to the tense tiredness mood state as outlined by Thayer (2001). Unfortunately however, research on the cyclic nature of the food-mood relationship in emotionally-distressed individuals is sparse (Christensen, 2001).

While unidirectional associations have been consistently demonstrated, many propose that the association between food consumption and mood is bidirectional (Christensen & Brooks, 2006). Research investigating physiological mechanisms has demonstrated such findings. For example, studies on rats have found that stress can trigger the hypothalamic-pituitary-adrenal (HPA) stress pathway with the release of hormones (i.e., glucocorticoids), which in turn increases the consumption of comfort foods. This then reduces the activation of the HPA system (Dallman, Pecoraro, & la Fleur, 2005 as cited in Hendy, 2012). Ioakimidis et al. (2011) also highlighted a possible bidirectional relationship via neural pathways stimulated by eating. The physiology of the neural network for mastication includes the orbitofrontal cortex and brainstem, which partially overlaps the neural network for mood (refer to Figure 2.19). Given the shared neuroanatomy, Ioakimidis et al. (2011) proposed that mood changes are facilitated by cortical activity during chewing, and hypothesised that both positive and negative feelings could be caused by changes in actual eating behaviour.

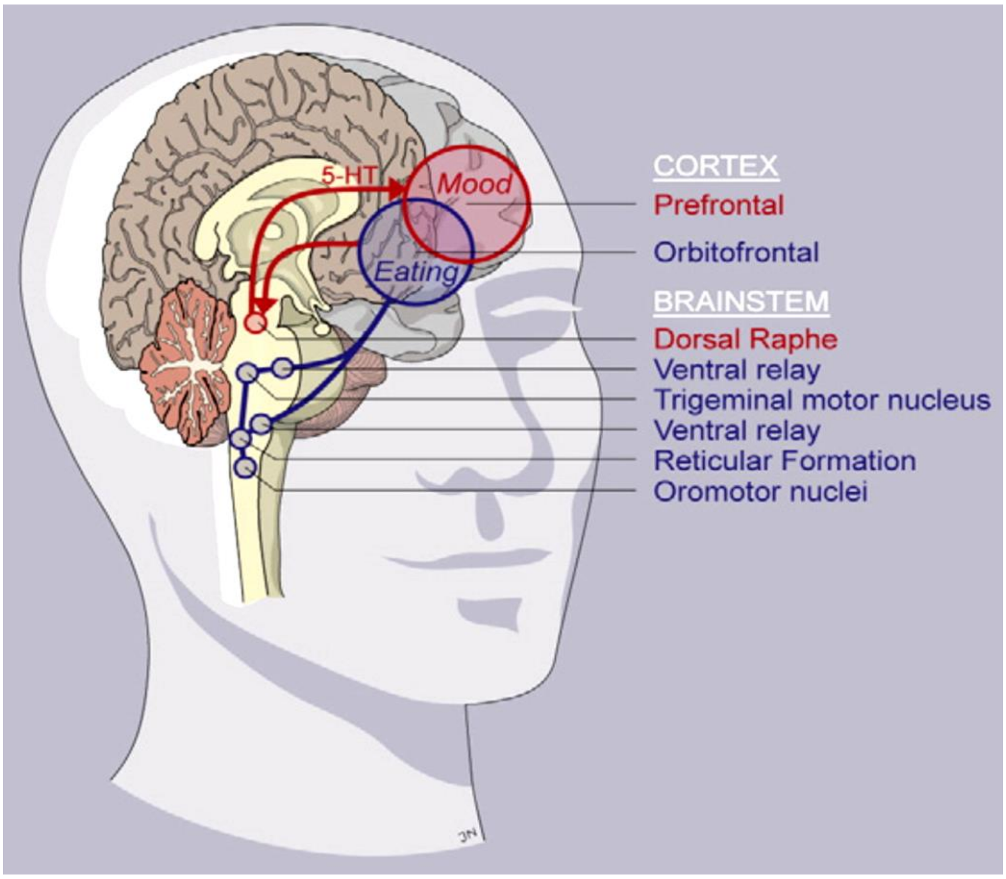


Figure 2.19. The orbitofrontal and prefrontal cortex and brainstem areas stimulated by eating (shown in blue) are hypothesised to mediate mood fluctuations via the serotonin (i.e., 5-HT) projections (shown in red). Bidirectional pathways are demonstrated by lines without arrows (taken from Ioakimidis et al., 2011).

A number of other hypotheses involving physiological mechanisms have also been proposed. For example, some scientists suggest that the consumption of carbohydrates increases the availability of intrasynaptic serotonin, which facilitates temporary hedonic shifts (Fernstrom & Wurtman, 1971; Wurtman & Wurtman, 1995). However, other scientists suggest that the time required for carbohydrate absorption makes this notion unlikely (Christensen & Brooks, 2006). Further, the synthesis of serotonin can be blocked if protein is consumed in addition to carbohydrates (Christensen & Brooks, 2006).

In a similar vein, physiology combined with expectancy learning theory may also provide some insight. Expectancy learning theory posits that individuals form expectations of the consequences of behaviour as a function of what has previously been learnt (Rotter, 1954; Tolman, 1932). This cognitive mechanism influences future behavioural choices, and the expectations formed about possible consequences (Dingemans et al., 2009). From this perspective, physiological mechanisms are influenced by the perceived pleasure and palatability of consuming comfort food, which subsequently stimulates a release of endogenous opioids, therefore creating a temporary mood improvement (Hendy, 2012).

Importantly, gender differences are often present within food-mood relationships. Females are more likely to increase consumption of comfort foods when experiencing negative mood states (Christensen & Brooks, 2006; Hendy, 2012). One explanation involves the finding that females partake in restrained eating as a strategy to maintain body weight. Restrained eating is a pattern of behaviour in which individuals eat less high-fat foods than preferred (Hendy, 2012; Polivy & Herman, 1985), meaning that when negative feelings are experienced a *disinhibition* occurs, exhibited as an increased consumption of comfort foods (Hendy, 2012; Polivy & Herman, 1985). Other gender differences include: females desire carbohydrates more often than males (Christensen & Pettijohn, 2001); males consume a higher number of calories than females (De Castro, 1987); and males more often prefer high-fat, high-carbohydrate, and high-calorie foods when experiencing positive or neutral moods, rather than when experiencing negative feeling states as shown in females (Christensen & Brooks, 2006; De Castro, 1987; Hendy, 2012).

From another viewpoint, negative reinforcement models predict that the incentive of food would be increased for individuals experiencing negative mood states, as would attentional biases for food cues (Hepworth et al., 2010). In a study conducted by Loxton, Dawe, and Cahill (2011), the urge to eat was examined. Female participants (N = 160) were divided into either a negative or neutral mood condition, and exposed to either a preferred food cue or a non-food cue. Contrary to the hypotheses, urge to eat was found to decrease following mood induction for the negative mood condition. Further, urge to eat was not influenced by eating style (i.e., restrained or disinhibited), but rather increased following exposure to the food cue (but not the non-food cue). Negative mood and eating style were both found to have a moderating effect, with disinhibited eating being positively associated with urge to eat (for those in the negative mood condition). Overall, negative moods were associated with the propensity to overeat, but only in the context of preferred food cues, and in individuals with a disinhibited eating style.

In summary, the current state of research on the association between mood and food suggests there is still a lot to be learned. The specific psychological and physiological mechanisms that moderate the effects of negative mood states on urge to eat (and therefore eating behaviour), remain unclear (Hepworth et al., 2010). Indeed, the notion that “just as foods determine our moods so do our moods determine what we eat” (Lyman, 1989, p. 44) may perhaps be the most accurate description of the mood-food relationship at this time.

2.6 Mood Assessment Issues

The following section will outline three important issues to consider in the measurement of the mood construct. These include construct validity in psychology, self-report measures and mood, and mood measurement and response timeframes.

2.6.1 Construct validity in psychology. The validity of psychometric tests measuring abstract concepts has undergone evolving changes over the past century. Construct validity has become the unifying approach to validity testing (Kane, 2001; Messick, 1989), and epitomises the central idea of validity today (Colliver, Conlee, & Verhulst, 2012). Developed by Cronbach and Meehl in the mid-1950s, construct validity in its simplest terms refers to “whether a test, or a measurement instrument, measures what it purports to measure” (Colliver et al., 2012, p. 367). It is important to note that the original underlying notion involving explicit theories and vital nomological networks (i.e., elaborate networks of concepts connected by theoretical law) was regarded as ingenious. Indeed, Landy (1986) described validation as hypothesis testing. However, in more recent times construct validity theory is not without its criticism (see Borsboom, Cramer, Kievit, Scholten, & Franic, 2009; Colliver et al., 2012).

It has been suggested that the domain of psychology lacks the nomological networks necessary to adequately and rigorously test abstract phenomenon. Indeed, Cronbach and Meehl (1955) conceded, “psychology works with crude, half-explicit formulations” (p. 293), and maintained that in order to declare that a specific test actually measures an unobservable construct, “a nomological net surrounding the concept must exist” (p. 291). It was acknowledged that *psychological laws* remained vague (Hempel, 1952; Kaplan, 1946; Pap, 1953), and it was expected that the natural laws would be investigated and learnt over time (Cronbach & Meehl, 1955).

Unfortunately, the domain of psychology appears no closer to the formation of the nomological networks needed to support construct validity theory, as the *laws* continue to remain largely unknown. As Borsboom et al, (2009) put it "psychology simply had no nomological networks of the sort positivism required in 1955, neither vague nor clear ones, just as it has none today. For this reason, the idea of construct validity was born dead … [it] never saw any research action" (p. 138). So, in an effort to salvage the construct validity approach, the current technique seeks to establish a validity argument based on evidence for interpretation of a latent phenomenon, but no longer within the constraints of a rigorous nomological network (Colliver et al., 2012). As Gray and Watson (2007) suggest, numerous self-report measures indeed have good construct validity, citing correlations with personality trait inventories and various psychometric measures of affective experience as evidence of this (Jacobs et al., 2012).

2.6.2 Self-report measures and mood. Self-report methodologies assessing affect dimensions, discrete emotions, and/or mood are popular within the domain of the social sciences (Jacobs et al., 2012; Schwarz, 1999). The PANAS (discussed in Section 2.7.1), POMS (including various derivatives), and BRUMS are commonly utilised inventories, although alternate indirect and objective measurements are also utilised (Jacobs et al., 2012). Given the subjectivity of the mood construct, elicited responses can provide information of increased accuracy (Feldman-Barrett, 2006; Paulhus & Vazire, 2007). Indeed, as suggested by Paulhus and Vazire (2007), "no one else has access to more information than oneself" (p. 227).

In general, self-report inventories are designed to quantify experiential components by gaining insight into memories, anticipations, or general emotional dispositions (Jacobs et al., 2012). Innumerable psychometric scales have been devised, and typically consist of descriptors or response categories ranked according to Likert or analogue scales. Further, some instruments involve adjective checklists, thereby indicating the presence or absence of an emotional state (Larsen & Fredrickson, 1999). A major advantage of these basic models centres on their ability to measure otherwise unobservable phenomenon (e.g., past or anticipated emotions; Jacobs et al., 2012; Robinson & Clore, 2002). Additionally, such scales eliminate perceptual variance attributable to observer effects (Gottschalk, 1974). Other key benefits involve a simplistic design, convenience, ease, limited financial cost, as well as the ability to generate a large *N* relatively quickly (Kline, 1993; Westen & Rosenthal, 2005).

However, given that non-random error can lead to inflated reliability estimates (Green & Citrin, 1994), several caveats require deliberation. As convincingly articulated by Judd and McClelland (1998), self-report inventories are based on the presupposition that potential respondents “have access to the psychological property that the researcher wishes to measure… and are willing to report that property” (p. 202). In addition, self-report measures are vulnerable to *response artefacts* such as extreme and acquiescent responding, response bias (Moskowitz, 1986), social desirability, ambient mood effects, moral beliefs about happiness, and happiness image management (Diener, Sandvik, Pavot, & Gallagher, 1991; Mauss & Robinson, 2009; Paulhus & Vazire, 2007; Randall & Fernandes, 1991; Welte & Russell, 1993).

Furthermore, individuals may malinger or fake good (Gottschalk, 1974). Cognitive fatigue can also inadvertently mediate feeling states under consideration (Poels & Dewitte, 2006). Other potential problems lie in that some individuals may not be sufficiently attuned to feelings (Gottschalk, 1974), or may be unable to successfully verbalise affective experiences (Larsen & Fredrickson, 1999; Mauss & Robinson, 2009). In addition, recall or anticipation of experiences may be biased (Robinson & Clore, 2002). To add to this, self-report measures are not equipped to capture unconscious epiphenomena. Further to this, Paulhus and Vazire (2007) highlight the issue of diversity of response styles according to cultural differences. Despite a question of accuracy due to potential sources of error, self-report scales remain renowned tools of choice. In the words of Feldman-Barrett (2006), “verbal report, even with all of its failings, may be the only means of assessing the experience of emotion. If we want to know whether a person is experiencing an emotion, we have to ask them” (p. 24).

2.6.3 Mood measurement and response timeframes. According to Terry, Stevens, and Lane (2005), the response modes associated with self-report measures require due consideration when assessing mood. The term *response timeframe* refers to the chosen temporal reference period relating to a question (Terry, Stevens et al., 2005). Different psychometric scales engender various formats, although ‘How have you felt over the past week including today?’, ‘How do you feel today?’ and ‘How do you feel right now?’ are all options illustrated in the PANAS, POMS, and BRUMS. Additionally, ‘How do you feel generally?’ is another example. However, given that previously experienced intensities of mood rely on both adequate perception and accurate memory retrieval (amongst other considerations), response modes involving reflection potentially threaten test accuracy (Rasmussen, Jeffrey, Willingham, & Glover, 1994; Winkielman, Knäuper, & Schwarz, 1998).

The impact of response timeframes on psychometric assessments have been clearly enunciated (see Nisbett & DeCamp Wilson, 1977; Nisbett & Ross, 1980). This is despite somewhat limited literature (Terry, Stevens et al., 2005). A study by

Watson (1988b) investigating the effects of response mode and six different PA and NA scales found that while the factor structure remained relatively unchanged, the discriminant correlations differed as a function of timeframe, as did the test-retest coefficients. Indeed, the weakest NA-PA correlations and highest test-retest coefficients involved the ‘Past year’ period, suggesting the capturing of a trait-like construct (Terry, Stevens et al., 2005; Watson et al., 1988). In contrast, the ‘Right now’ timeframe yielded high correlations amongst differential mood dimensions, as well as low test-retest coefficients. ‘Right now’ appeared to reflect the assessment of a person-environment interaction (Terry, Stevens et al., 2005).

Further, Winkielman et al. (1998) systematically examined the conversational differences of using shorter versus longer temporal periods (i.e., ‘Have you felt angry today?’ versus ‘Have you felt angry this week?’). Anger, memory bias, and question interpretation were each investigated. Participants reported less intense experiences in the longer timeframe condition, apparently assuming that the researchers were interested in stronger feelings of anger, more serious events, and less frequent events, respectively. Anger frequency was not found to differ significantly. According to the conversational analysis methodology, the length of reference period influenced both interpretation and frame of reference.

Similarly, Rasmussen et al. (1994) reported statistically significant differences when ‘Over time’ reference periods were compared with multiple ‘Right now’ timeframes. This finding was mirrored by Stevens, Lane, and Terry (2001) in that higher scores were reported in the ‘Past week’ condition compared with multiple ‘Right now’ mood assessments. In particular, high scores were associated with the mood experienced at the time of recall for vigour, depression, and confusion. Terry, Stevens et al. (2005) also reported that mood scores were higher when utilising ‘Past week' timeframes compared with the mean of 'Right now' responses, giving credence to the notion that temporal proximity has the capacity to unduly inflate the intensity of reported mood responses.

Various researchers have highlighted potential inaccuracies associated with mood-congruent effects and 'Over time' reference periods (Ptacek, Smith, Epse, & Raffety, 1994; Smith, Leffingwell, & Ptacek, 1999). While a number of explanations have been proposed (e.g., memory decay, recall misrepresentation, and faulty/incomplete encoding; Smith et al., 1999), mood-congruent recall appears particularly important (see Blaney, 1986 for a review). Previous research indicates that memories are more accessible according to the similarity of mood at time of encoding and retrieval (Blaney, 1986; Bower, 1981). Seminally, ambient mood alone may also influence recall (Terry, Stevens et al., 2005). For example, Bower (1981) asserted "a person in a depressed mood will tend to recall only unpleasant events and to project a bleak interpretation onto the common events of life, and these depressing memories and interpretations feed back to intensify and prolong the depressed mood" (p. 145). Conversely, Parrot and Sabini (1990) argued that some individuals experiencing negative affect do recall positive memories, and do so to increase hedonic tone or prevent a further anti-hedonic shift.

In terms of the 'Right now' response timeframe, Terry, Stevens et al. (2005) identified one possible limitation. While both mood and emotion *can* be defined using differentiating theoretical and definitional conventions, the concepts have so far proven difficult to distinguish using psychometric measures (Lane et al., 2011). Given this, respondents may inadvertently report fleeting or transient emotions rather than underlying mood (Terry, Stevens et al., 2005). Overall however, Terry, Stevens et al. (2005) proposed that multiple 'Right now' responses should be generated when investigating mood profiles over time to minimise potential sources of bias.

2.7 Mood Assessment Measures

The following section will outline three popular assessments used in the measurement of the mood construct. These self-report scales are known as the PANAS (Watson et al., 1988), the POMS (McNair et al., 1971, 1992), and the BRUMS (Terry et al., 1999).

2.7.1 The Positive and Negative Affect Schedule (PANAS). The PANAS developed by Watson et al. (1988) measures two dominant and supposedly independent affective states: positive affect (PA) and negative affect (NA). PA refers to the extent to which an individual feels enthusiastic, active, and alert; while NA is characterised by a degree of anger, contempt, disgust, guilt, fear, and/or nervousness. Among “anomalous and inconsistent findings” (Watson et al., 1988, p. 1,063; see Brenner, 1975; Diener & Emmons, 1984; Kammann, Christie, Irwin, & Dixon, 1979), these two distinguishing constructs can be represented as orthogonal dimensions in factor analytic studies (Watson et al., 1988). According to Tellegen (1985 as cited in Watson et al., 1988), the PA and NA subscales correspond with positive and negative emotional reactivity (i.e., factors of extraversion and anxiety/neuroticism).

The 20-item self-report PANAS contains 10 mood descriptors in each of two underlying PANAS PA and PANAS NA subscales. These include: attentive, interested, alert, excited, enthusiastic, inspired, proud, determined, strong, active, and distressed, upset, hostile, irritable, scared, afraid, ashamed, guilty, nervous, jittery (Watson et al., 1988). High PA scores indicate a high level of energy, full concentration, and pleasurable engagement, while low PA scores reflect a degree of sadness and lethargy. Alternatively, NA generally involves distress and negative engagement. This dimension subsumes a number of subjective states (i.e., anger, contempt, disgust, guilt, fear, and nervousness), with low NA scores suggesting a level of calmness and serenity. Further, low PA combined with high NA is characteristic of depression and anxiety. Participants respond according to a timeframe of 'At the moment', 'Today', 'In the past few days', 'In the past week', 'In the past few weeks', 'In the past year', or 'In general'; on a 5-point Likert scale of 1 (*very slightly or not at all*), 2 (*a little*), 3 (*moderately*), 4 (*quite a bit*), and 5 (*extremely*; Watson et al., 1988).

In terms of development and validation of the scale, 60 affective terms from the Zevon & Tellegen (1982) study were originally included in the factor analyses and principle-component analysis to provide a "broad and representative sample of mood descriptors" (Watson et al., 1988, p. 1,064). Following this, and to ensure the relative purity of the terms, a cut-off of .25 was eventually employed to encourage a near-zero secondary loading. The dataset used to validate the PANAS comprised of Southern Methodist University students and staff members. Participants were asked to complete the questionnaire on how they felt using the temporal instructions 'In the past few weeks' (n = 164), and 'In the past few days' (n = 50). Additionally, a small sample of adults not affiliated with the university completed the scale describing how they felt 'At the moment' (n = 53). No systematic differences were identified between the samples. The PANAS demonstrated high internal consistency. Cronbach's coefficients alpha for the six different response timeframes ranged from .86 to .90 for the PANAS PA scale, and .84 to .87 for the PANAS NA scale. The test-retest reliability coefficients ranged from .47 to .68 for the PANAS PA scale, and from .39 to .71 for the PANAS NA scale, following an 8-week retest interval (Watson et al., 1988).

The PANAS has since been validated using a large non-clinical adult population (N = 1,003), although random sampling was not employed making salient the issue of bias (Crawford & Henry, 2004). However, the external validity of the PANAS has been supported via correlations with other valid measures on distress and psychopathology, such as the Beck Depression Inventory (BDI; a 21-item self-report measure on depressive symptomatology; Beck, Ward, Mendelson, Mock, & Erbaugh, 1961), the Hopkins Symptom Checklist (HSCL; a 58-item self-report scale on distress and dysfunction; Derogatis, Lipman, Rickels, Uhlenhuth, & Covi, 1974), and the State-Trait Anxiety Inventory State Anxiety Scale (A-State; a 20-item self-report measure on current affect; Spielberger, Gorsuch, & Lushene, 1970). Watson et al. (1988) reported high positive correlations for the HSCL (r = .74, r = .65), the BDI (r = .56, r = .58), and the A-State (r = .51) with the PANAS NA scale using different response timeframes, and modest negative correlations for the HSCL (r = –.19, r = –.29), the BDI (r = –.35, r = –.36), and the A-State (r = –.35) with the PANAS PA scale. The timeframes analysed were ‘In the past few weeks’, ‘Today’, ‘In the past few days’, ‘In the past few weeks’, and ‘In the past few weeks’, respectively, for each scale. Additionally, Watson and Clark (1992a) verified strong relationships between PA and the Big-Five Extraversion scale, as well as NA and the Big-Five Neuroticism scale.

Conversely, the psychometric properties of an expanded version of the PANAS (Watson & Clark, 1994) is considered questionable (Bagozzi, 1993). The 60-item PANAS-X was derived in line with the criteria proposed by Campbell and Fiske (1959) for multitrait-multimethod matrices. The development of the scale was based on the premise that two broad higher order affective dimensions comprised of several correlated, although ultimately distinguishable, feeling states (Watson &

Clark, 1992b). However, any findings in support of the hierarchically structured PANAS-X framework should be regarded as “inconclusive” according to Bagozzi (1993, p. 836), given that the initial guidelines were “common-sense desideratum” (p. 83) rather than rigid standards.

In any case, although a number of PA-NA scales have been developed (see Bradburn, 1969; Diener & Iran-Nejad, 1986; Diener & Larsen, 1984; Diener, Larsen, Levine, & Emmons, 1985; Hedges, Jandorf, & Stone, 1985; McAdams & Constantian, 1983; Stone, 1987; Stone, Hedges, Neale, & Satin, 1985; Warr, Barter, & Brownbridge, 1983) the original PANAS has proven utility when assessing intraindividual fluctuations in the milieus of mood (Watson et al., 1988). The PANAS has been described as a reliable, valid, and efficient (e.g., takes 2 to 3 minutes to complete) self-report inventory. It is capable of qualitatively and independently measuring PA and NA according to an extent- and frequency-type response format (Watson et al., 1988). Indeed, 3,554 applications of the scale have been involved in validation studies (Terry, Lane et al, 2003). However, the question of bias in the generation of the normative data remains.

2.7.2 The Profile of Mood States (POMS). The original POMS is a 65-item self-report questionnaire that assesses six underlying dimensions of the mood construct (Terry, Lane et al., 2003). Developed by McNair et al. (1971, 1992), the 5-point Likert scale of 0 (*not at all*) to 4 (*extremely*) asks individuals to rate how they feel in response to descriptive adjectives according to a timeframe of ‘Right now’, ‘Today’, ‘In the last week’, or ‘In the last 3 minutes’ (LeUnes & Burger, 2000). Scores for each of the underlying dimensions of tension-anxiety, depression-dejection, anger-hostility, vigour-activity, fatigue-inertia, and confusion-bewilderment are provided (Curran, Andrykowski, & Studts, 1995; LeUnes &

Burger, 2000). Example items from each of the subscales include nervous and anxious (i.e., tension-anxiety subscale), miserable and downhearted (i.e., depression-dejection subscale), annoyed and angry (i.e., anger-hostility subscale), alert and energetic (i.e., vigour-activity subscale), tired and exhausted (i.e., fatigue-inertia subscale), and mixed up and uncertain (i.e., confusion-bewilderment subscale; Buckworth & Dishman, 2002; Lane, Hewston, Redding, & Whyte, 2003). A 'Total Mood Disturbance' score can be calculated by using the following formula: tension-anxiety + depression-dejection + anger-hostility + fatigue-inertia + confusion-bewilderment + (24 – vigour-activity).

Tests of the reliability and validity of the POMS have yielded mixed results (Bourgeois, LeUnes, & Meyers, 2010). Original psychometric data reported internal consistency results ranging from .84 to .95, with 8 of the 12 alpha coefficients reported at .90 or above (LeUnes & Burger, 2000). Additionally, LeUnes and Burger (2000) noted that six factor analytic replications have supported the factorial validity of the scale. Other studies have provided at least partial support for construct validity (see Boyle, 1987, 1988; Morris & Salmon, 1994; Norcross, Guadagnoli, & Prochaska, 1984; Reddon, Marceau, & Holden, 1985). However, Fernandez, Fernandez, and Pesqueira (2000) as well as Lindgren, Masten, Tiburzi, Ford, and Bleeker (1999) found little support for all six subscales. Overall however, data on predictive and construct validity involving controlled outpatient drug trials, emotion-inducing studies, and studies on concurrent validity coefficients together strengthen the reliability and validity of the measure (LeUnes & Burger, 2000).

Initially developed in 1971 to access psychological distress in psychiatric populations, the administration of the POMS took up to 20 minutes to complete (the completion time of the original POMS for psychologically healthy individuals is 3 to

7 minutes; Bourgeois et al., 2010; LeUnes & Burger, 2000). This placed "undue burden" on the patients (Curran et al., 1995, p. 80), leading to the development of several abbreviated versions. Examples of these variations include the 11-item Brief POMS (Cella et al., 1987), the 6-item Incredibly Short POMS (ISP; Dean, Whelan & Mayers, 1990), the 30-item Educational and Industrial Testing Service (EDITS) POMS (EPOMS; Curran et al., 1995; Bourgeois et al., 2010), the 27-item POMS-C (Terry, Keohane, & Lane, 1996), and the 24-item BRUMS (formally known as the POMS-Adolescents [POMS-A]; Terry, Lane et al., 2003; Terry et al., 1999). Additionally, a 40-item version provided by Grove and Prapavessis (1992) included a 5-item esteem-related affect scale, while Shacham (1983) proposed a shortened version (i.e., POMS-SF) consisting of 37 items. Predominantly, the abbreviated versions exclude confusing or less psychometrically sound descriptions (e.g., the 7-item measure on 'friendliness'; Bourgeois et al., 2010) in a bifurcated attempt to both preserve the psychometric properties of the original measure (i.e., avoid psychometric drift), as well as reduce the response burden for completion (Curran et al., 1995).

The most recent versions of the POMS have established clinical and research utility using large normative samples, with the full-length versions including a measure of 'friendliness' (Heuchert & McNair, 2012). Level of friendliness is scored separately, and does not contribute to the Total Mood Disturbance score. The POMS 2–A for adults (i.e., 18+ years) includes 65 items, while the POMS 2–Y for adolescents (i.e., 13 to 17 years) contains 60 items. The 35-item POMS–2 Short Versions comprise of descriptors taken from each of the full-length scales. One final noteworthy issue, the POMS and BRUMS both measure six dimensions of mood compared with the PANAS, which assesses two orthogonal dimensions of affect.

2.7.3 The Brunel Mood Scale (BRUMS). As mentioned previously, the BRUMS is a shortened version of the original POMS designed to assess mood states among both adolescent and adult populations (Terry et al., 1999; Terry, Lane et al., 2003). With a completion time of approximately 1 to 2 minutes, the BRUMS is a 24-item self-report scale made up of basic mood descriptors using a standard response timeframe of ‘How you feel right now?’ Alternative timeframes can also be utilised (i.e., ‘How you have felt during the past week including today?’, ‘How have you felt over the past month?’, and/or ‘How do you normally feel?’). Participants rate responses on a 5-point Likert scale of 0 (*not at all*), 1 (*a little*), 2 (*moderately*), 3 (*quite a bit*), and 4 (*extremely*; Terry & Lane, 2010). The measure consists of six subscales (i.e., anger, confusion, depression, fatigue, tension, and vigour) with each containing four items. Total subscale scores range from 0 to 16 (Terry & Lane, 2010).

Developed by Terry et al. (1999), the BRUMS is one of the few variations of the original POMS that has undergone rigorous validity testing (Terry, Lane et al., 2003). Each of the six subscales has been validated via multi-sample confirmatory factor analysis, across four different samples: adult students (n = 656), adult athletes (n = 1,984), young athletes (n = 676), and schoolchildren (n = 596; Terry & Lane, 2010; Terry, Lane et al., 2003). Moreover, the BRUMS has demonstrated high internal consistency, with Cronbach coefficient alphas ranging from .74 to .90 for each of the subscales (Terry et al., 1999). The test-retest reliability reported coefficients ranging .26 to .53 over a one-week period, which is appropriate for a measure of transient feeling states.

Further, concurrent validity of the measure has also been supported (Terry, Lane et al., 2003). A strong positive correlation was found between the BRUMS vigour subscale and the PANAS PA scale (Watson et al., 1988), with only a minimum correlation identified with the other BRUMS subscales. Additionally, correlations between the BRUMS subscales of anger, confusion, depression, fatigue, and tension were also found with the PANAS NA scale (Watson et al., 1988). No relationships were identified between the five BRUMS subscales and vigour (Terry et al., 1999; Terry, Lane et al., 2003). Further, a strong correlation was identified between the State-Trait Anger Expression Inventory (STAXI; Spielberger, 1991) and the BRUMS anger subscale (Terry et al., 1999; Terry, Lane et al., 2003), and a moderate correlation was identified between the BRUMS depression subscale and the depression scale of the Hospital Anxiety and Depression Scale (HADS; Terry, Lane et al., 2003; Zigmond & Snaith, 1983).

Overall, there is strong evidence to support the psychometric integrity of the BRUMS (Terry et al., 1999; Terry, Lane et al., 2003), and its brevity ensures the measure is user-friendly. Various timeframes can be utilised, which speaks to assessment flexibility. The measure is now available in several languages other than English, including Afrikaans (Terry, Potgieter, & Fogarty, 2003), Farsi (Terry, Malekshahi, & Delva, 2012), French (Rouveix, Duclos, Gouarne, Beauvieux, & Filaire, 2006), Hungarian (Lane, Soos, Leibinger, Karsai, & Hamar, 2007), Italian (Lane et al., 2007), Malay (Hashim, Zulkifli, & Yusof, 2010) and Portuguese (Rohlfs et al., 2008). Further, the BRUMS is available upon permission free of charge.

2.8 Internet-Delivered Interventions (e-Interventions)

The advent of the World Wide Web has provided a powerful means by which to communicate, and has consequently revolutionised the previously known landscape of knowledge acquisition (Goggin, 2004). Originally, web interaction was limited to stationary central processing units. However, microtechnological advances and emerging mobile commerce means that handheld devices are fast becoming both popular and commonly available (Dhir, 2004; Lorence & Park, 2006). Aside from a desktop or laptop computer, computer-mediated communication is now possible via wireless telecommunication networks on portable devices such as Internet-enabled cell phones, tablets, and gaming consoles (Dhir, 2004). Such rapid and continuous digital and technological advances mean that there are now in excess of 2 billion users globally (Miniwatts Marketing Group, 2012). Further, 88.8% of the Australian population use the Internet frequently (Miniwatts Marketing Group, 2012).

With the popularity of the Internet growing exponentially, many users are *going online* on a daily basis (Buchanan, 2002; Ewing & Thomas, 2012; Fallows, 2004). Indeed, health-related information is a popular search topic (Leung, 2008; Oh, Jorm, & Wright, 2009; Taylor, 2002), and was ranked amongst the top 10 online activities in Australia by the Victorian Department of Health (2011). Otherwise known as *cyberchondriacs*, this term describes any individual who searches for health-related information via the Internet (Smith, Fox, Davies, & Hamidi-Manesh, 2006; Taylor, 1999). Globally, there is evidence to suggest that the number of cyberchondriacs is quite substantial (see Erdem, 2008; Höglund, Macevičiūtė, & Wilson, 2004; Leykin, Muñoz, & Contreras, 2012; Smith et al., 2006; Taylor, 2002).

For example, an American study found that 85% of a sample of physicians (*N* = 1,050) had experienced the act of a patient bringing information from the Internet into a consultation (Murray et al., 2003). Similarly, a report by the Picker Institute (2006) in the United Kingdom identified that approximately 80% of patients had utilised the Internet to gain information, a finding mirrored in the American Harris Poll (2010, August 4). More specifically, this nationwide survey, which specifically investigates health-seeking behaviour on the Internet, has noted a steady increase in incidents. The number of cyberchondriacs was approximately 50 million in 1998, but increased to 117 million in 2005. More recently, 175 million cyberchondriacs were identified in 2010, being the highest number since the Harris Polls' inception (Harris Poll, 2010, August 4).

In this digital age, the propensity to seek health-related information via the Internet is not only likely to continue, but expected to substantially increase (Kolata, 2000; Lorence & Park, 2006; Oliver & Whiston, 2000; Ritterband et al., 2003). Technology initiatives, public-access Internet as well as decreased financial costs (e.g., for hardware, software, Internet portals, and hand-held devices) suggest that access is likely to continue to grow (Dhir, 2004; Lorence & Park, 2006).

2.8.1 Internet-delivered mental health services. Although Internet-delivered mental health services are not new (Clarke, 2004), the evolution of technological communication modalities have provided innovative approaches (Baños, Botella, Quero, & García-Palacios, 2012; Rey & Alcañiz, 2012). Deriving from a range of heterogeneous theoretical orientations (Day & Schneider, 2000; Grohol, 2001; Laszlo, Esterman, & Zabko, 1999; Maheu & Gordon, 2000; Rabasca, 2000), and distinct from typical approaches to psychotherapy (Grohol, 1999), there now exists a proliferation of psychological services for a broad range of interpersonal issues (Baños et al., 2012; Ybarra & Eaton, 2005).

Internet-delivered therapist-led sessions and self-directed services, otherwise known as *e-mental health services* have existed for more than a decade, and continue to evolve rapidly (Barak, Hen, Boniel-Nissim, & Shapira, 2008; Heinlen, Welfel, Richmond, & O'Donnell, 2003). With an underlying motive of citizen empowerment (Wyatt, 2000), the term e-mental health services encompasses the provision of interactional psychological assistance involving electronic media. For example, provision of information via e-mail, chat technology, virtual reality technology, video/audio conferencing, and direct therapeutic intervention (see Childress, 2000; Heinlen et al., 2003; Lambousis, Politis, Markidis, & Christodoulou, 2002; Lewis, Coursol, & Herting, 2004; Manhal-Baugus, 2001; Rey & Alcañiz, 2012). However, with such rapid developments in an emerging field, both synchronous (i.e., real time) and asynchronous (i.e., delayed) Internet-supported interventions lack working definitions (Andersson, 2009; Barak et al., 2008; Barak, Klein, & Proudfoot, 2009).

Various terminologies have been used to describe the broad spectrum of online therapeutic activities (Barak et al., 2009). E-therapy, e-psychiatry, evidence-based computer therapy, online therapy, cybertherapy, web counselling, web-based therapy, cybercounselling, behavioural telehealth, telemedicine, and telepsychiatry are some typical examples (see Baños et al., 2012; Bloom, 1998; Bloom & Walz, 2000; Escoffery, McCormick, & Bateman, 2004; Lambousis et al., 2002; Manhal-Baugus, 2001; Nickelson, 1996; Norman, 2006; Rochlen, Zack, & Speyer, 2004). More recently, Klein (2010) used the term e-Interventions, which encompasses interventions focused on promoting, preventing, treating, and managing mental and behavioural issues online (accompanied or otherwise).

Unfortunately, interchangeable terms used by professionals and laypersons alike have contributed to a diffuse and unstructured field (Barak et al., 2009). Further, limited intercommunication between disciplines together with a shortage of professional leadership and governing ethical/legal standards have also impacted fundamental clarity and consistency (Barak et al., 2009; Childress & Asamen, 1998; Shapiro & Schulman, 1996). In response to this issue, Barak et al. (2009) argued the need to define, describe, and categorise different online interventions in order to "advance the field in a purposeful, coherent, and understandable way" (p. 5). Similarly, Abbott, Klein, and Ciechomski (2008) highlighted the value of delineating conceptualisations to appreciate the diversity of web-based psychological services, and further outlined a taxonomy involving (a) e-therapy, (b) e-counselling, (c) mental health information websites, (d) self-guided treatment program websites, (e) online support groups, and (f) online mental health screening and assessments.

Indeed, there exists numerous legitimate health-related websites offering a wide range of services from psychological testing (Barak & English, 2002; Buchanan, 2002) and career assessment (Clark, Horan, Tompkins-Bjorkman, Kovalski, & Hackett, 2000; Gati & Saka, 2001; Oliver & Whiston, 2000), to marriage counselling (Jedlicka & Jennings, 2001). Other computer-mediated services involve mood/emotional disorders and psychopathology (i.e., major depression, bipolar disorder, posttraumatic stress disorder, anxiety disorders, substance abuse, anorexia nervosa, suicidality, etc.; see Andersson, 2009; Christensen & Griffiths, 2002; Heinlen et al., 2003; Kenardy, McCafferty, & Rosa, 2003, 2006; Lange, van de Ven, & Schrieken, 2003). Online health interventions effecting behavioural change such as smoking, alcohol consumption, headache minimisation, phobias, eating disorders, and obesity, etc., have also been shown to be beneficial (for additional detail see Feil, Noell, Lichtenstein, Boles, & McKay, 2003; Rey & Alcañiz, 2012; Rothert et al., 2006; Strom, Pettersson, & Andersson, 2000; White et al., 2010; Zabinsky, Celio, Wilfley, & Taylor, 2003).

2.8.2 Advantages and risks of Internet-delivered interventions. Internet-delivered interventions can generate a strong therapeutic alliance (Andersson, 2009; Cohen & Kerr, 1999; Cook & Doyle, 2002; Knaevelsrud & Maercker, 2007) and have been proposed to have additional benefits compared with traditional psychological interventions (Ritterband et al., 2003). Many practical and emotional barriers to in-house psychotherapy can be overcome (Alvidrez & Azocar, 1999; Mohr et al., 2006; Regier, Narrow, Rae, & Manderscheid, 1993). For example, researchers have argued cost-effectiveness (Bell, 2007; Crone et al., 2004; Pier et al., 2006; Ritterband et al., 2003), and convenience (Baños et al., 2012; Manhal-Baugus, 2001; Schmidt, 1997). Additionally, anonymity has been found to negate perceived stigmas associated with conventional in-house therapies via disinhibition, as well as positively influence self-disclosure and self-reflection (Baños et al., 2012; Feigelson & Dwight, 2000; Joinson, 2001; Kummervold et al., 2002; Metanoia, 2001; Rochlen et al., 2004; Suler, 2002).

A computer-mediated delivery method has further implications for the provision of high quality mental health care in remote geographical locations (Jameson & Blank, 2007; Pullman, VanHooser, Hoffman, & Heflinger, 2010). The extent of Internet penetration enables web-based interventions and services to connect with previously isolated populations (Fotheringham et al., 2000; Griffiths et al., 2006; Jerome et al., 2000; Pier et al., 2006), meaning that shortages of qualified personnel can also be addressed (Jameson & Blank, 2007). Additionally, physical impairment and mobility restrictions can be circumvented (Baños et al., 2012; Barak, 1999; Pier et al., 2006; Suler, 2000). Taken together, web-based technological developments have enabled psychological services to be delivered to a greater, more diverse audience (Buchanan & Smith, 1999; Musch & Reips, 2000; Riva, Teruzzi, & Anolli, 2003; Schmidt, 1997).

Although it may be increasingly common to disseminate treatments online, unfortunately this medium is not without disadvantages and potential risks (see

Carlbring & Andersson, 2006). For example, Heinlen et al. (2003) highlighted possible equipment (i.e., hardware and software) failures that may impede treatments. Other researchers accentuate the importance of encryption software and passwords to maintain security and confidentiality (Manhal-Baugus, 2001; Stricker, 1996). Poor computer knowledge, skill, and experience levels also warrant mention. Although Abbott et al. (2008) suggested that such problems have become less prevalent; *technoanxious* and *computerphobic* clients (i.e., those individuals fearful and avoidant of computers) have been identified (Ford, 1994; Kupersmith, 1992; Yu et al., 2009).

Additionally, Tantam (2006) contended that communication of false information, deliberately or otherwise, also proved problematic. Similarly, Alleman (2002) and Barak (1999) alluded to the difficulty of obtaining accurate representational data (e.g., age, gender, etc.) and vital diagnostic information in an absence of interpersonal cues (i.e., auditory, verbal, and physical) from the client. There are also ethical concerns during emergency crises (Maheu & Gordon, 2000; Stricker, 1996). Additionally, the task of would-be clients to independently verify professional credentials can also be difficult via the Internet (Manhal-Baugus, 2001).

In a similar vein, the predominately unregulatory nature of the Internet may potentially exploit consumers (Shapiro & Schulman, 1996) through ineffective legal mechanisms and unreliable computer-based information and treatments (Bell, 2007; Eysenbach, Powell, Kuss, & Sa, 2002; Griffiths & Christensen, 2002). Indeed, a lack of peer-reviewed online-information has been recognised (Tantam, 2006). Self-diagnoses and/or misdiagnoses in the context of unsubstantiated treatments may inadvertently lead to inappropriate as well as ineffective remedies (Kiley, 2002; Ritterband et al., 2003). Additionally, such practices can have potentially adverse health effects (Kiley, 2002). Alarmingly, Bupa Australia (2011, February 9) revealed that approximately 47% of the 80% of individuals who acknowledged health-seeking behaviour via the Internet admitted to undertaking a self-diagnosis.

2.8.3 Efficacy of Internet-delivered interventions. As Internet popularity increases, supporting evidence converges on the effectiveness of many web-based interventions (Australian Psychological Society, 2008; Barak et al., 2008). Indeed, a number of computer-mediated treatments have demonstrated efficacy for a variety of mental health problems (see Klein & Richards, 2001; Klein, Richards, & Austin, 2006; Richards & Alvarenga, 2002; Wims, Titov, & Andrews, 2008). For example, the value of an Internet-delivered cognitive behavioural therapy (CBT) program for panic disorder was investigated by Klein et al. (2006). Participants (N = 55) were randomly assigned to an Internet-delivered CBT program (including therapist interaction via e-mail), a self-administered manualised CBT workbook condition, or an information only control group. The results revealed that both CBT groups were associated with improvements in ratings of physical health, as well as decreases in symptoms, cognitions, and negative affect. In addition, these effects were maintained 3 months later. Similar findings were reported by Wims et al. (2008), in that seven of 10 participants no longer met the DSM-IV criteria for panic disorder post-treatment following web-therapy.

The value of online interventions and self-help programs have also been demonstrated in the areas of anxiety and depression (see Andersson et al., 2005; Christensen, Griffiths, & Jorm, 2004; Houston, Cooper, & Ford, 2002; Proudfoot et al., 2003, 2004). Christensen et al. (2004) and Andersson et al. (2005) each found that self-help Internet-delivered services could reduce symptoms of depression, with Andersson and colleagues concluding that such programs should be explored as an alternative or adjunctive treatment. Additionally, the positive effects of computer-mediated therapy were maintained at 6-month follow-up. Similarly, Proudfoot et al. (2003) investigated the efficacy of a web-based treatment program for anxiety and depression. Participants reported significant and greater improvements post-treatment, and these improvements were maintained 6 months later. Proudfoot et al. (2004) replicated similar improvements. Taken together, Internet-delivered CBT appears broadly applicable as a treatment for anxiety and depression.

Research comparing Internet-delivered therapeutic interventions with traditional face-to-face psychotherapy has generally demonstrated comparable outcomes (Jacobs et al., 2001). Although empirically tested web-based psychological services appear a viable option with remarkable potential, Ritterband et al. (2003) cautions against altogether replacing conventional methodologies. According to Ritterband et al., Internet-delivered interventions are best considered an alternative or complementary service wherein barriers to traditional treatments exist. In any case, it is important to exercise scepticism and thoroughly contemplate the potential risks (see Alleman, 2002; Barak, 1999; Barak & English, 2002; Jerome et al., 2000; Suler, 2000), as well as inherent advantages of evolving online therapies.

2.8.4 Internet-delivered Interventions and the future. There now exists a proliferation of new electronic modalities for therapist-led and self-directed services (Ybarra & Eaton, 2005). Given the propensity of increasing public interest (see Ewing & Thomas, 2012), such interventions are likely to continue to contribute to the changing perspective of healthcare (Klein, 2010). Many self-guided and therapist-supported programs exist, including the Black Dog Institute (http://www.blackdoginstitute.org.au; Figure 2.20), Mental Health Online (http://www.anxietyonline.org.au), e-couch (http://www.ecouch.anu.edu.au), MoodGym (http://www.moodgym.anu.edu.au), Beyond Blue (http:// www.beyondblue.org.au), Fear Drop (http://www.feardrop.com), and Brave Program (http://www.brave.psy.uq.edu.au). While some risks have been identified (Bell, 2007; Eysenbach et al., 2002; Griffiths & Christensen, 2002; Kiley, 2002; Shapiro & Schulman, 1996; Tantam, 2006), the feasibility and initial efficacy of many online interventions have been demonstrated (Tate, Finkelstein, Khavjou, & Gustafson, 2009). However, rigorous scientific testing continues (Ritterband et al., 2003).

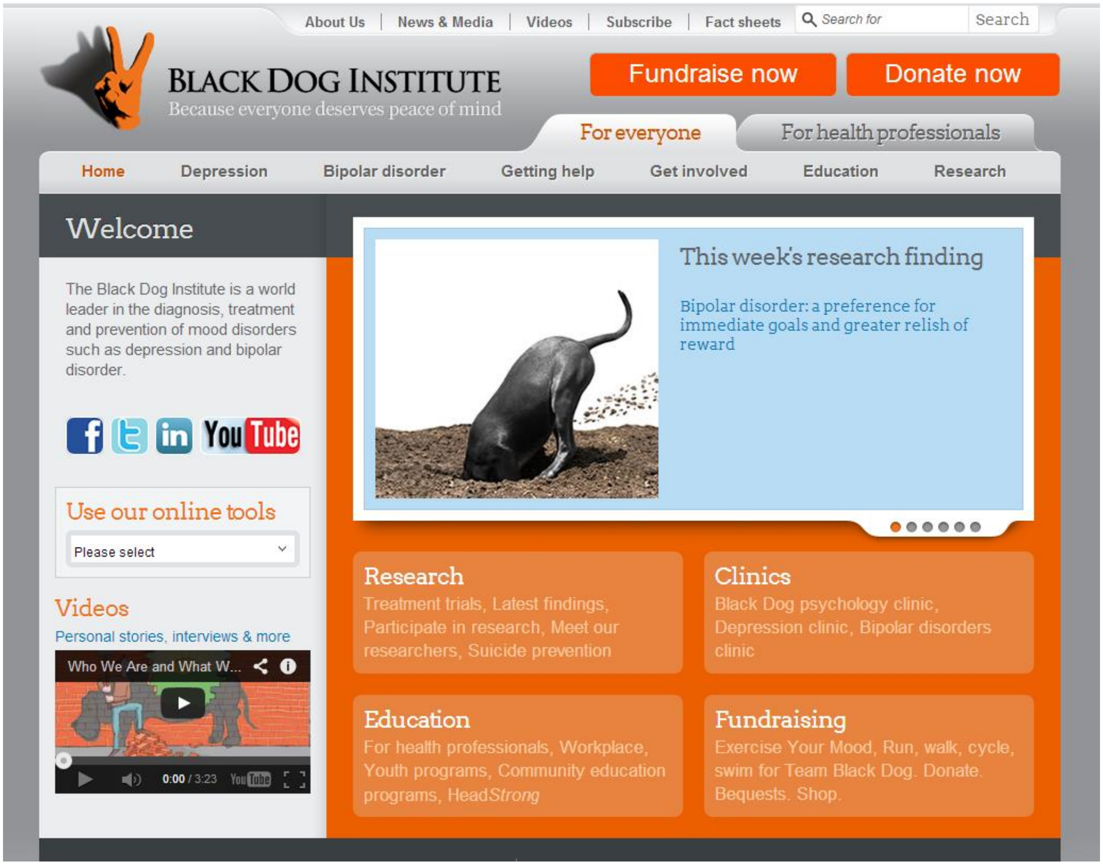


Figure 2.20. Homepage of the Black Dog Institute.

Internet-delivered services are crucial, if not vital in Australia if the increasing demand for public health resources is to be adequately addressed (Australian Psychological Society, 2011, April 6). Indeed, psychologists are obligated to develop and disseminate safe, accessible services that promote self-care (Klein, 2010). Many governing bodies (i.e., policymakers and stakeholders) are attempting to resolve the absence of rigid ethical codes and guidelines (American Counseling Association, 2005; American Psychological Association, 2002; Australian Psychological Society, 2011), meaning that web-based disadvantages and potential risks may be further minimised over time.

Overall, the purview of research signals that online self-guided and supported programs can bestow a significant contribution to a therapists' armamentarium. This sentiment is shared by numerous health care professionals across several scientific domains. Recognising the full potential and capabilities of the Internet was the catalyst for the *In The Mood* website. Harnessing this power enables *In The Mood* to connect with a diverse audience. Web-based mood profiling is now used around the world for purposes as diverse as monitoring the psychological well-being of cardiac rehabilitation patients, assessing adolescent responses to life skills training, and quantifying the psychological benefits of music. This is in addition to its traditional uses in sport (see Terry, 2005). The recently developed *In The Mood* website (Lim & Terry, 2011) is one such example of a web-based mood profiling measure.

2.9 Structure and Overview of the *In The Mood* Website

In line with "advancing and championing the field of Internet-delivered interventions" (Lim, 2011, p. 65), construction of the *In The Mood* (http://www.moodprofiling.com) website was established in three stages. Firstly, the theoretical framework underpinning the content was converted into an Internet-based protocol using computer-scripted language. Next, the design and appearance of the website was developed according to enhanced appeal, usability, and interactivity. Finally, a pilot-testing phase was undertaken to ensure correct functionality.

Lim and Terry (2011) selected a collection of performance-related images for the interface to reflect not only the underlying purpose of *In The Mood*, but to "enhance the website's visual appeal element and foster lasting first impressions" (p. 98). A number of other conventional standards were also taken into consideration. The total width of the homepage collage was kept to within pixel size recommendations as outlined by Barron (1998), and the font type/size (i.e., 12-point Trebuchet MS font) were chosen in line with Microsoft Corporation (1998) suggestions, and ease of legibility (see Hill & Scharff, 1997; Lazar, 2001).

A grey, white, and orange colour scheme was adopted to create contrast between written text and background information (see Barron, 1998; Hall & Hanna, 2004; Hill & Scharff, 1997), and paragraphs were kept short and succinct to minimise cognitive strain (Nielsen, 2000). To add to this, the authors' credentials were clearly outlined to enable independent verification (Manhal-Baugus, 2001). For the sake of simplicity, and to better facilitate understanding, a traffic light analogy was employed to complement the interpretation of mood scores. Finally, to harness the popularity of social networking sites, a number of features designed to facilitate website exposure were embedded within the website.

The pilot-testing phase was conducted to identify and rectify functionality problems before *In The Mood* was officially released into the public domain on March 15, 2011. During the data collection period, Google Analytics website utilisation findings revealed that the website was generally well received. A total of 2,010 visits were recorded from numerous different countries, with 29% returning to the site at least once (Lim, 2011). Furthermore, the User Experience Survey (N = 175) revealed that *In The Mood* was perceived as generally user-friendly, given that a large portion of participants rated the content, delivery, and usability favourably overall. A complete overview of the published version of the Lim and Terry (2011) website follows.

2.9.1 Screenshots of website pages from *In The Mood*. Upon navigation to the original Lim and Terry (2011) *In The Mood* website, users were presented with the *In The Mood* interface (see Figure 2.21), from which three primary pages could be accessed: 'About', 'Take the test', and 'Leave feedback'.

Figure 2.21. The *In The Mood* homepage.

This 'About' page provided basic information and was grouped according to four related sections (see Figure 2.22). As the name suggests, the 'About this website' page provided basic information on the underlying rationale and purpose of the website, and included an introduction into the role of mood in performance, as well as an outline of what users could expect.

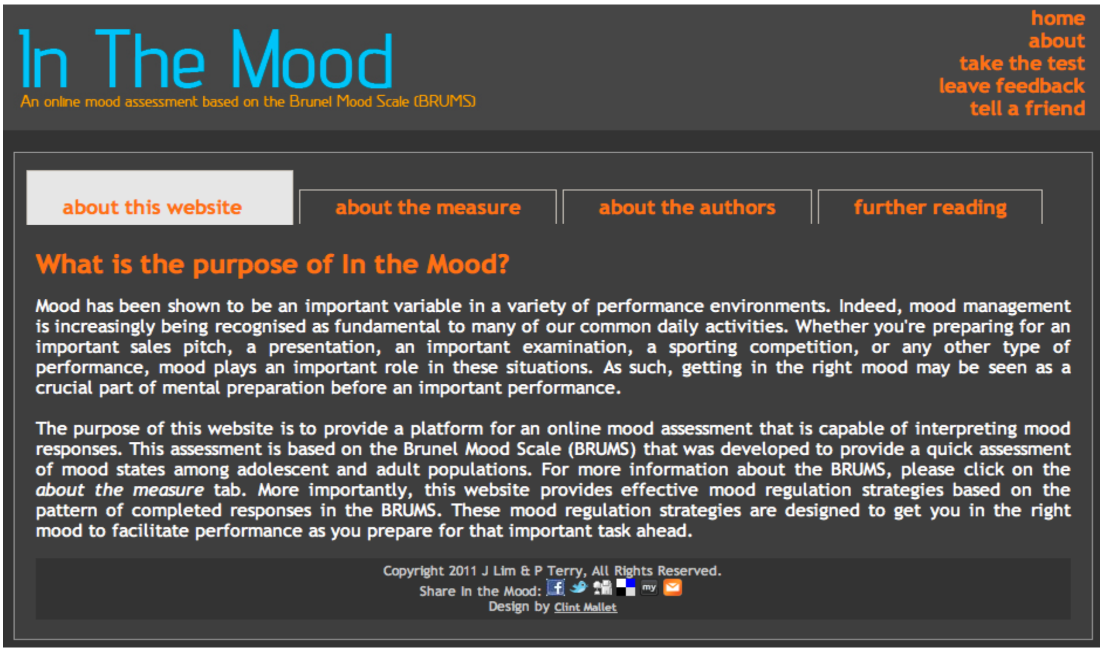


Figure 2.22. The *In The Mood* 'About this website' page.

The 'About the measure' page provided a quick overview of the BRUMS (i.e., utility, validity, and reliability; refer to Figure 2.23), while the 'About the authors' page supplied a brief background on Professor Peter Terry and Dr Julian Lim (refer to Figure 2.24). The 'Further reading' page listed additional information for the POMS, BRUMS, and the mood regulation strategies (refer to Figure 2.25).

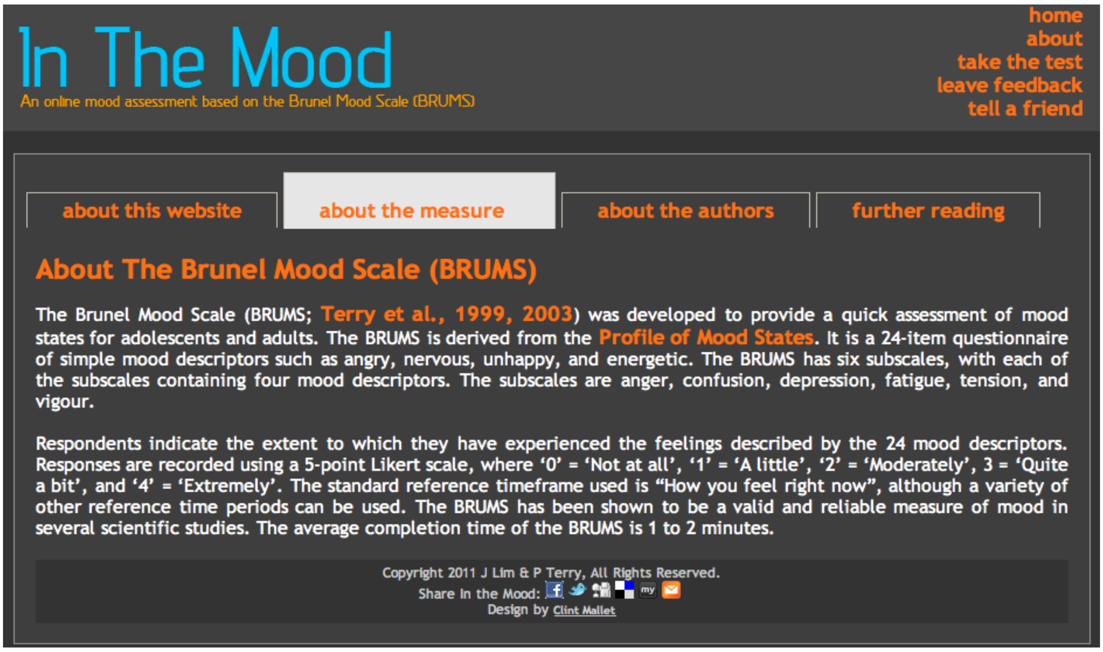


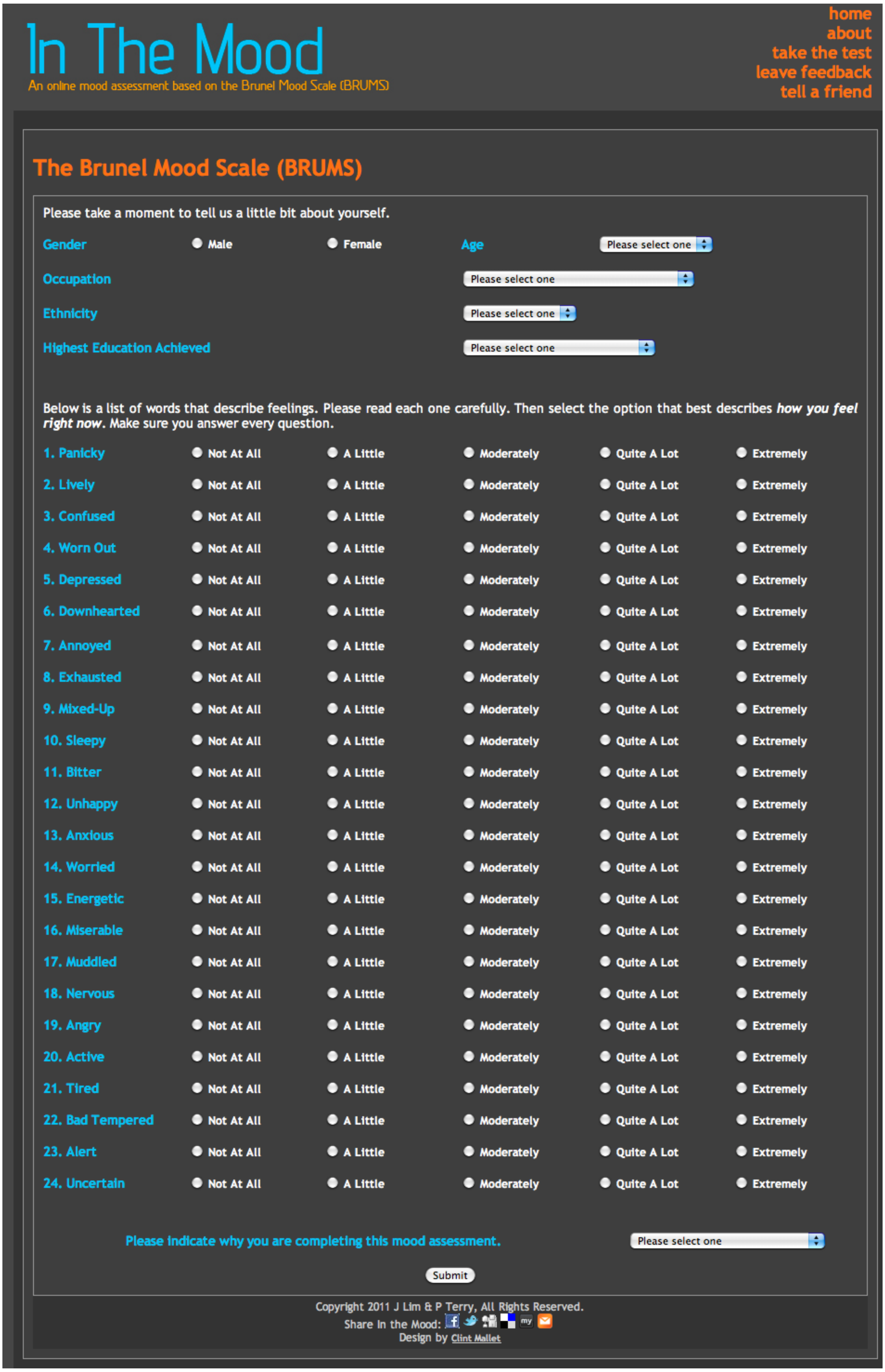
Figure 2.23. The *In The Mood* 'About the measure' page.

Figure 2.24. The *In The Mood* ‘About the authors’ page.

Figure 2.25. The *In The Mood* ‘Further reading’ page.

The 'Take the test' page was designed to ease discomfort, as well as obtain informed consent (see Figure 2.26). Consent was obtained by clicking a checkbox that read 'I agree' that subsequently initiated a link to the BRUMS (see Figure 2.27) and 'Results' page (see Figure 2.28 and Figure 2.29). Alternatively, users could navigate away from the website or withdraw from the study by clicking 'I do not wish to participate, take me away'. Closing the browser window also exited the *In The Mood* website without data collection.

Figure 2.26. The *In The Mood* 'Take the test' page.



In The Mood

An online mood assessment based on the Brunel Mood Scale (BRUMS)

home
about
take the test
leave feedback
tell a friend

The Brunel Mood Scale (BRUMS)

Please take a moment to tell us a little bit about yourself.

Gender ○ Male ○ Female Age [Please select one]

Occupation [Please select one]

Ethnicity [Please select one]

Highest Education Achieved [Please select one]

Below is a list of words that describe feelings. Please read each one carefully. Then select the option that best describes ***how you feel right now***. Make sure you answer every question.

1. Panicky	Not At All	A Little	Moderately	Quite A Lot	Extremely
2. Lively	Not At All	A Little	Moderately	Quite A Lot	Extremely
3. Confused	Not At All	A Little	Moderately	Quite A Lot	Extremely
4. Worn Out	Not At All	A Little	Moderately	Quite A Lot	Extremely
5. Depressed	Not At All	A Little	Moderately	Quite A Lot	Extremely
6. Downhearted	Not At All	A Little	Moderately	Quite A Lot	Extremely
7. Annoyed	Not At All	A Little	Moderately	Quite A Lot	Extremely
8. Exhausted	Not At All	A Little	Moderately	Quite A Lot	Extremely
9. Mixed-Up	Not At All	A Little	Moderately	Quite A Lot	Extremely
10. Sleepy	Not At All	A Little	Moderately	Quite A Lot	Extremely
11. Bitter	Not At All	A Little	Moderately	Quite A Lot	Extremely
12. Unhappy	Not At All	A Little	Moderately	Quite A Lot	Extremely
13. Anxious	Not At All	A Little	Moderately	Quite A Lot	Extremely
14. Worried	Not At All	A Little	Moderately	Quite A Lot	Extremely
15. Energetic	Not At All	A Little	Moderately	Quite A Lot	Extremely
16. Miserable	Not At All	A Little	Moderately	Quite A Lot	Extremely
17. Muddled	Not At All	A Little	Moderately	Quite A Lot	Extremely
18. Nervous	Not At All	A Little	Moderately	Quite A Lot	Extremely
19. Angry	Not At All	A Little	Moderately	Quite A Lot	Extremely
20. Active	Not At All	A Little	Moderately	Quite A Lot	Extremely
21. Tired	Not At All	A Little	Moderately	Quite A Lot	Extremely
22. Bad Tempered	Not At All	A Little	Moderately	Quite A Lot	Extremely
23. Alert	Not At All	A Little	Moderately	Quite A Lot	Extremely
24. Uncertain	Not At All	A Little	Moderately	Quite A Lot	Extremely

Please indicate why you are completing this mood assessment. [Please select one]

Submit

Copyright 2011 J Lim & P Terry, All Rights Reserved.
Share In the Mood:
Design by Clint Mallet

Figure 2.27. The BRUMS questionnaire.

Figure 2.28. An example of the iceberg profile 'Results' page.

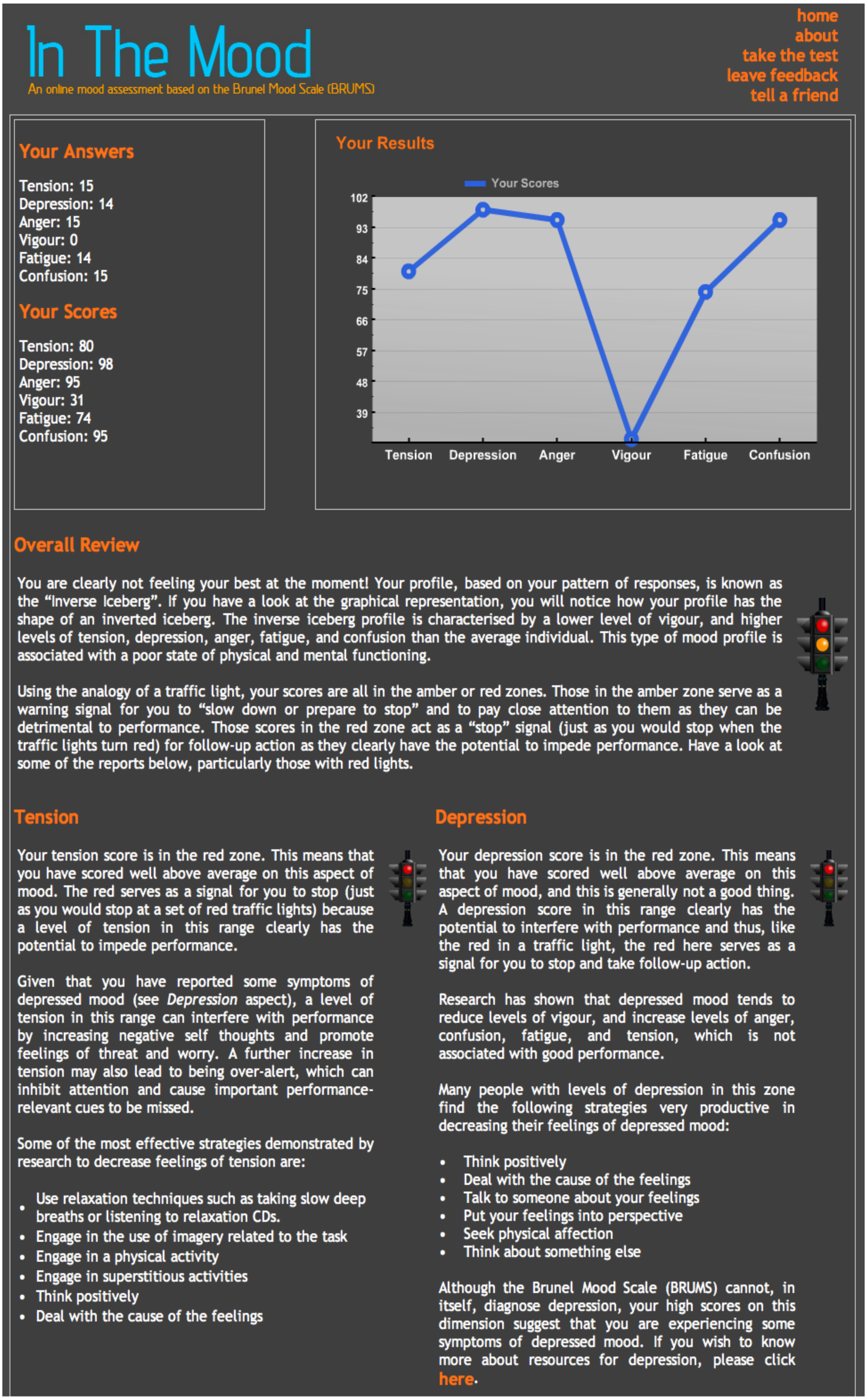


Figure 2.29. An example of the inverse iceberg profile 'Results' page.

The link for the 'Leave feedback' page was embedded within the 'Results' page. Here participants could complete the User Experience Survey comprising of a series of brief questions concerning attractiveness, overall appeal, content, load time, and usability of the site (refer to Figure 2.30). Four optional open-ended questions were also available. User feedback was acknowledged following submission of responses (see Figure 2.31).

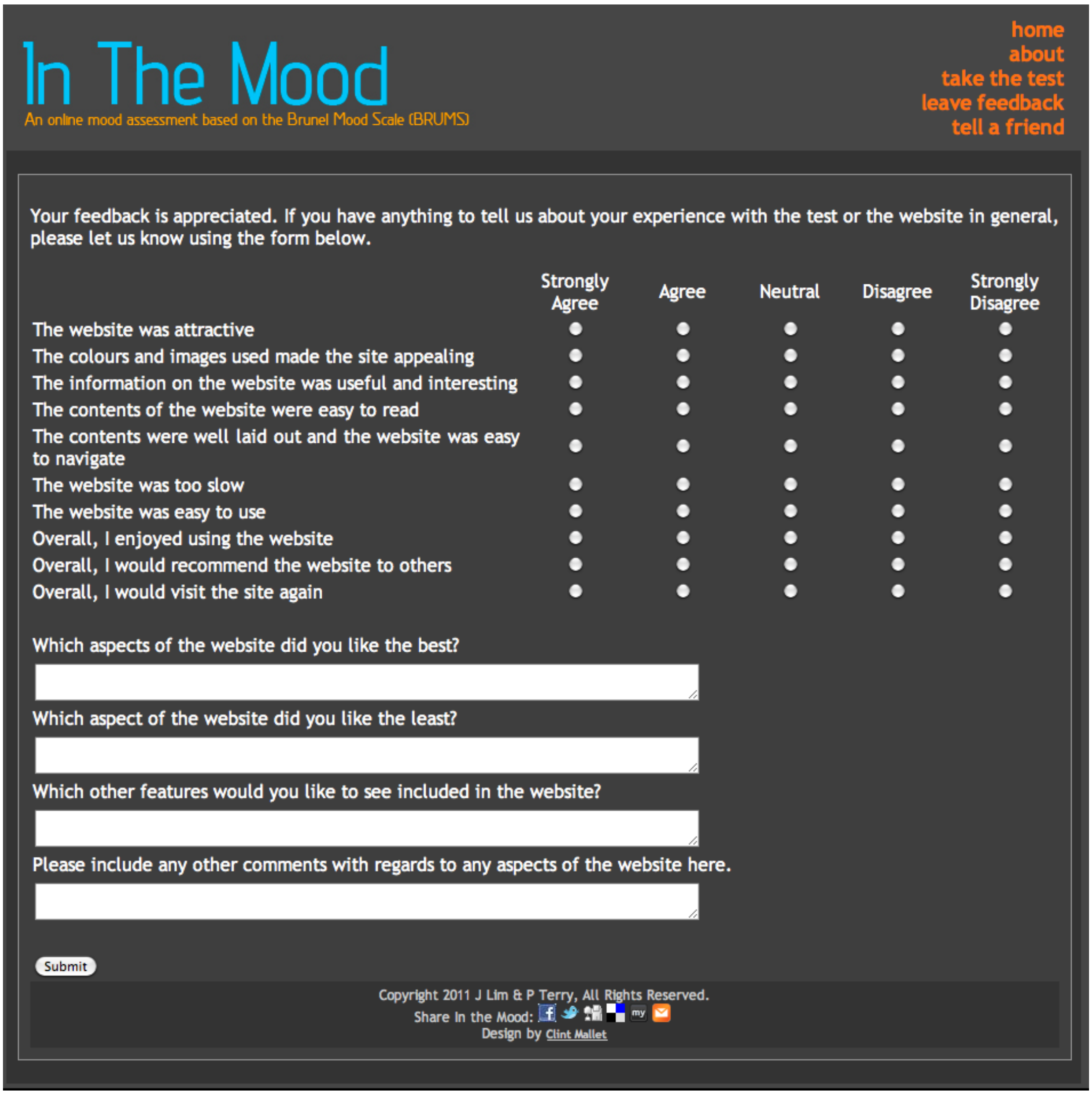


Figure 2.30. The *In The Mood* 'Leave feedback' page.

Figure 2.31. Page acknowledging receipt of user feedback.

In The Mood had a number of features designed primarily to facilitate website exposure. For example, the 'Tell-a-Friend' link (see Figure 2.32) enabled users to e-mail invitations to visit the website (refer to Figure 2.33).

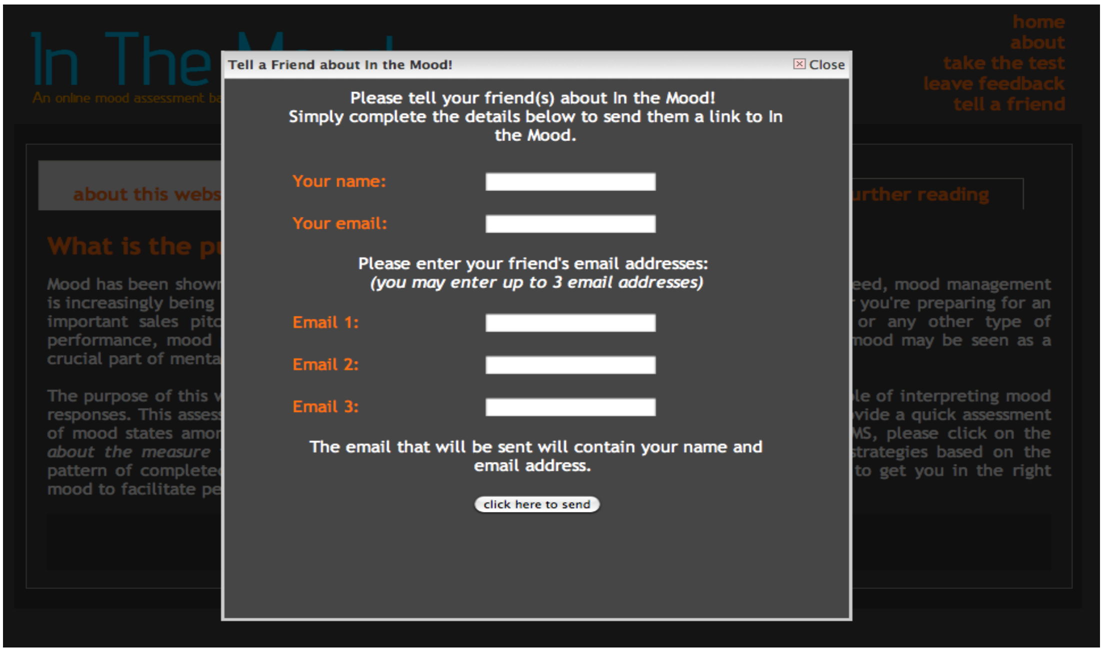


Figure 2.32. The *In The Mood* 'Tell-a-Friend' feature.

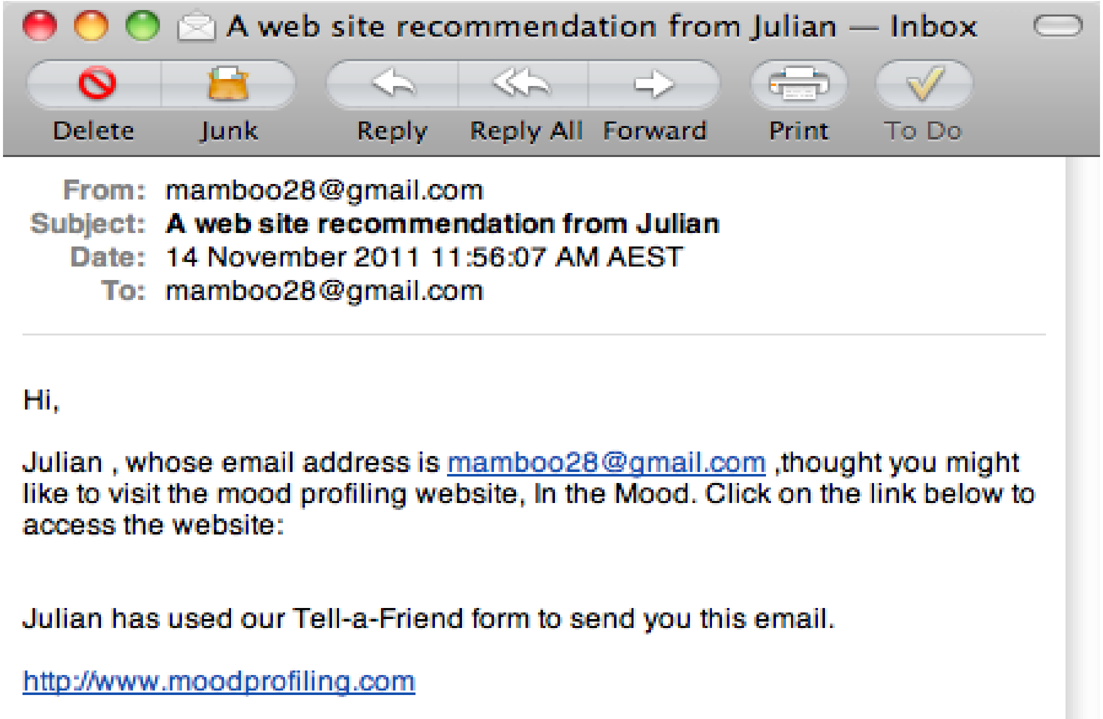


Figure 2.33. Sample e-mail invitation.

Additionally, to harness the popularity of social networking sites users could share the website via Facebook and Twitter (see Figure 2.34), or MySpace and Digg through hyperlinks displayed as icons.

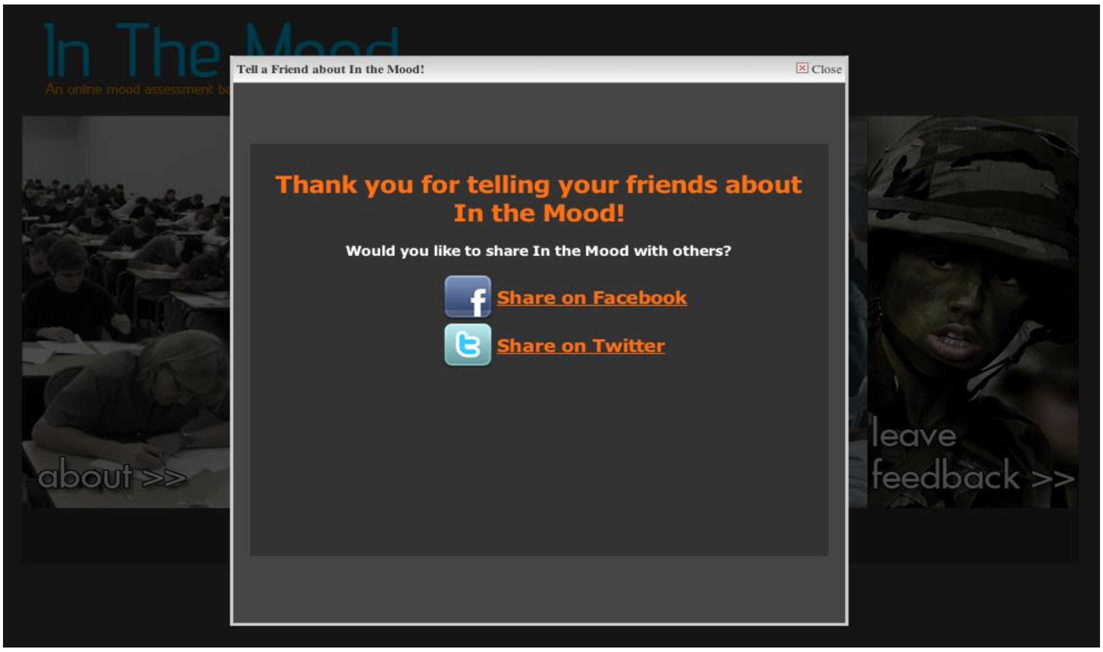


Figure 2.34. Acknowledgment of successful submission of the ‘Tell-a-Friend’ form.

2.9.2 Verbatim profile summary reports from *In The Mood*.

2.9.2.1 Everest profile. Based on your pattern of responses, you have what is known as the Everest profile. If you take a look at the graphical representation of your profile, you will notice that it has a peak like that of Mount Everest. You have obtained this profile because you are currently exhibiting significantly higher levels of vigour than the average individual and lower levels of tension, depression, anger, fatigue, and confusion than the average individual. The Everest profile is often associated with champion athletes, which means that you are currently exhibiting the same mood as champions! Using the analogy of a traffic light, your scores are all in the green zone (green symbolising Go!) and are associated with good performance!

2.9.2.2 Iceberg profile. Based on your pattern of responses, you have what is known as the Iceberg profile. If you take a look at the graphical representation, you will notice that your profile has the shape of an iceberg, hence its name. This profile is characterised by higher levels of vigour and lower levels of tension, depression, anger, fatigue, and confusion than the average individual. The Iceberg profile is often associated with elite athletes, which means that you are currently exhibiting the same mood as an elite athlete. Using the analogy of a traffic light, your scores are all in the green zone (green symbolising Go!) and are associated with good performance!

2.9.2.3 Inverse iceberg profile. You are clearly not feeling your best at the moment! Your profile, based on your pattern of responses, is known as the Inverse Iceberg. If you have a look at the graphical representation, you will notice how your profile has the shape of an inverted iceberg. The inverse iceberg profile is characterised by a lower level of vigour, and higher levels of tension, depression, anger, fatigue, and confusion than the average individual. This type of mood profile is associated with a poor state of physical and mental functioning. Using the analogy of a traffic light, your scores are all in the amber or red zones. Those in the amber zone serve as a warning signal for you to slow down or prepare to stop and to pay close attention to them, as they can be detrimental to performance. Those scores in the red zone act as a signal (just as you would stop when the traffic lights turn red) for follow-up action as they clearly have the potential to impede performance. Have a look at some of the reports below, particularly those with red lights.

2.9.2.4 'Other' profile. Your profile, based on your pattern of responses, contains both strengths and weaknesses. Using the analogy of a traffic light, your scores vary across the green, amber, and red zones. Scores in the green zone are associated with good performance (green symbolising Go!), while those in amber serve as a warning signal for you to show caution, as they can be detrimental to performance. Those scores in the red zone can be seen as a stop signal (just as you would stop when the traffic lights turn red) for follow-up action as they clearly have the potential to impede performance. Have a close look at your individual reports below, especially those with amber or red lights.

2.9.3 Verbatim profile summary reports according to mood dimension.

2.9.3.1 Tension dimension of mood.

Green category: Your tension score is in the green zone, which means that you have a low score on this aspect of mood. In general, this is a good thing and the green is a signal that you are ready to Go! as your level of tension is associated with good performance.

Amber category: Your tension score is in the amber range. This means that you have scored average-to-above average on this aspect of mood, which is generally a good thing as it is associated with good performance. A level of tension in this range can increase alertness and narrow attention to focus on task-relevant cues, leading to a readiness to perform that facilitates performance. However, be cautious because a further increase in tension may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Engage in the use of imagery related to the task
- Engage in a physical activity
- Engage in superstitious activities
- Think positively
- Deal with the cause of the feelings

Red category: Your tension score is in the red zone and means that you have scored well above average on this aspect of mood. The red light serves as a signal for you to stop (just as you would stop at a set of red traffic lights) as they clearly have the potential to impede performance. Be aware that a level of tension in this range signals the likelihood that performance will be affected unless some form of action is taken, such as increasing effort or concentration. Be aware too that a further increase in tension can lead to being over-alert, which may inhibit attention and cause performance-relevant cues to be missed, potentially interfering with performance. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Engage in the use of imagery related to the task

- Engage in a physical activity
- Engage in superstitious activities
- Think positively
- Deal with the cause of the feelings

2.9.3.2 Depression dimension of mood.

Green category: Your depression score is in the green zone. This means that you have a low score on this aspect of mood, which in general, is a good thing. Your depression score is associated with good performance, and the green signals that you are all set to Go!

Amber category: Your depression score is in the amber zone, which means that you have scored average-to-above average on this aspect of mood. Be cautious because a depression score in this range clearly has the potential to impede performance. Research has shown that depressed mood tends to reduce levels of vigour and increase levels of anger, confusion, fatigue, and tension, which is not associated with good performance. Many people with levels of depression in this zone find the following strategies very productive in decreasing their depressed mood:

- Think positively
- Deal with the cause of the feelings
- Talk to someone about your feelings
- Put your feelings into perspective
- Seek physical affection
- Think about something else

Although the Brunel Mood Scale (BRUMS) cannot, in itself, diagnose depression, your above average scores on this dimension suggest that you are experiencing some symptoms of depressed mood. If you wish to know more about resources for depression, please see below.

Sometimes, when people fill out mood questionnaires, they become more aware of their own negative feelings. If this happens to you, and if you are concerned about your mood or are feeling depressed, it is recommended that you consider seeking help either from your General Practitioner or seek useful resources from one of the local institutes listed below:

- Lifeline Australia 13 11 14
- Beyond Blue 1300 22 4636
- Black Dog Institute

Red category: Your depression score is in the red zone. This means that you have scored well above average on this aspect of mood, and this is generally not a good thing. A depression score in this range clearly has the potential to interfere with performance and thus, like the red in a traffic light, the red here serves as a signal for you to stop and take follow-up action. Research has shown that depressed mood tends to reduce levels of vigour, and increase levels of anger, confusion, fatigue, and tension, which is not associated with good performance. Many people with levels of depression in this zone find the following strategies very productive in decreasing their feelings of depressed mood:

- Think positively
- Deal with the cause of the feelings
- Talk to someone about your feelings
- Put your feelings into perspective
- Seek physical affection
- Think about something else

Although the Brunel Mood Scale (BRUMS) cannot, in itself, diagnose depression, your above average scores on this dimension suggest that you are experiencing some symptoms of depressed mood. If you wish to know more about resources for depression, please see below.

Sometimes, when people fill out mood questionnaires, they become more aware of their own negative feelings. If this happens to you, and if you are concerned about your mood or are feeling depressed, it is recommended that you consider seeking help either from your General Practitioner or seek useful resources from one of the local institutes listed below:

- Lifeline Australia 13 11 14
- Beyond Blue 1300 22 4636
- Black Dog Institute

2.9.3.3 Anger dimension of mood.

Green category: Your anger score is in the green zone, and that is generally, a good thing. This means that you have a low score on this aspect of mood. Like the green in a set of traffic lights, the green is the signal that you are indeed good to Go! as your anger score is associated with good performance.

Amber category: Your anger score is in the amber zone, which means that you have scored average-to-above average on this aspect of mood. That is generally a good thing as anger levels in this range is generally associated with good performance. A level of anger in this range can be channeled productively into determination to succeed. The result is an increase in effort, which facilitates performance. However, do be cautious because a further increase in anger may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Deal with the cause of the feelings
- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Spend some time alone
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective
- Avoid the cause of the feelings

Red category: Your anger score is in the red zone. This means that you have scored well above average on this aspect of mood. Like the red light you would encounter at a set of traffic lights, this serves as an indication for you to stop because scores in this zone clearly have the potential to interfere with performance. While anger can be channeled productively into determination to succeed, be aware that a level of anger in this range can result in being over-alert. This can inhibit attention and cause performance-relevant cues to be missed, which may lead to a decline in performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Deal with the cause of the feelings
- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Spend some time alone
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective
- Avoid the cause of the feelings

2.9.3.4 Vigour dimension of mood.

Green category: Your vigour score is in the green zone, which means that you have scored well above average on this aspect of mood. This is generally a good thing as it is associated with good performance (the green symbolises that you are set to go, just as the green in a set of traffic light is a signal to Go!). Vigour scores in this zone are closely associated with superior performances as they serve to enhance confidence and effort, which facilitates performance.

Amber category: Your vigour score is in the amber zone, which means that you have scored in the average-to-above average range on this aspect of mood. Generally speaking, this is not associated with good performance. Do proceed with caution because a level of vigour in this range can cause a decrease in confidence and effort, which can potentially interfere with performance. Some of the most effective strategies demonstrated by research to increase feelings of vigour are:

- Engage in a physical activity
- Think positive
- Engage in the use of imagery related to the task
- Listen to fast, upbeat music
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective

Red category: Your vigour score is in the red zone, which means that you have a low score on this aspect of mood. Generally speaking, this is not associated with good performance. A level of vigour in this range can lead to a reduction in effort and confidence, and thus, like a set of traffic lights, the red is a signal for you to stop as your level of vigour clearly has the potential to impede performance. Some of the most effective strategies demonstrated by research to increase feelings of vigour are:

- Engage in a physical activity

- Think positive
- Engage in the use of imagery related to the task
- Listen to fast, upbeat music
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective

2.9.3.5 Fatigue dimension of mood.

Green category: Your fatigue score is in the green zone. This means that you have a low score on this aspect of mood. Generally, this is a good thing as fatigue scores in this zone are associated with good performance (green being the signal that you are indeed Good to Go!).

Amber category: Your fatigue score is in the amber zone. This means that you have scored average-to-above average on this aspect of mood, and is in general, not associated with good performance. Do be cautious because a level of fatigue in this range can lead to a reduction in confidence and effort, which may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of fatigue are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Take a shower
- Have a rest, take a nap or go to sleep
- Put your feelings into perspective
- Have a massage
- Deal with the cause of the feelings

Red category: Your fatigue score is in the red zone, which means that you have scored well above average on this aspect of mood. Scores in the red zone serve as a stop signal as they clearly have the potential to impede performance. A level of fatigue in this range can lead to a reduction in effort and confidence, which can interfere with performance. Some of the most effective strategies demonstrated by research to decrease feelings of fatigue are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Take a shower
- Have a rest, take a nap or go to sleep
- Put your feelings into perspective
- Have a massage
- Deal with the cause of the feelings

2.9.3.6 Confusion dimension of mood.

Green category: Your confusion score is in the green zone, which means that you have a low score on this aspect of mood. This is generally a good thing as confusion scores in this zone are associated with good performance (green symbolising Go for it!).

Amber category: Your confusion score is in the amber zone. This means that you have scored average-to-above average on this aspect of mood, which is generally not associated with good performance. Proceed with caution because a confusion score in this range may lead to difficulties with attention and concentration, which can impede performance. Some of the most effective strategies demonstrated by research to decrease feelings of confusion are:

- Focus on strategies related to successfully completing the task
- Think positively
- Deal with the cause of the feelings

- Talk to someone about how you are feeling
- Mentally switch off
- Avoid the cause of the feelings

Red category: Your confusion score is in the red zone, which means that you have scored well above average on this aspect of mood. Scores in this zone serve as a stop signal for follow-up action as they clearly have the potential to impede performance. A level of confusion in this range can lead to difficulties with attention and concentration, which can interfere with performance. Some of the most effective strategies demonstrated by research to decrease feelings of confusion are:

- Focus on strategies related to successfully completing the task
- Think positively
- Deal with the cause of the feelings
- Talk to someone about how you are feeling
- Mentally switch off
- Avoid the cause of the feelings

2.9.4 Verbatim profile summary reports for the moderating effects of depression on tension and anger. To account for the moderating effects of depression on the dimensions of anger and tension, four additional reports were written for anger and tension when depressed mood was present as reflected by scores on the BRUMS. These reports, as used in the website, are presented below.

2.9.4.1 Tension dimension of mood.

Amber category: Your tension score is in the amber zone, which means that you have scored in the average-to-above average range on this aspect of mood. In general, this is not associated with good performance. A level of tension in this range can intensify the negative symptoms of depressed mood that you have reported (see Depression aspect), and raise feelings of threat and worry which can impede performance. Increasing levels of tension may also lead to being over-alert, which can impair attention and result in important performance-relevant cues being missed. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Engage in the use of imagery related to the task
- Engage in a physical activity
- Engage in superstitious activities
- Think positively
- Deal with the cause of the feelings

Red category: Your tension score is in the red zone. This means that you have scored well above average on this aspect of mood. The red serves as a signal for you to stop (just as you would stop at a set of red traffic lights) because a level of tension in this range clearly has the potential to impede performance. Given that you have reported some symptoms of depressed mood (see Depression aspect), a level of tension in this range can interfere with performance by increasing negative self-thoughts and promote feelings of threat and worry. A further increase in tension may also lead to being over-alert, which can inhibit attention and cause important performance-relevant cues to be missed. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Engage in the use of imagery related to the task

- Engage in a physical activity
- Engage in superstitious activities
- Think positively
- Deal with the cause of the feelings

2.9.4.2 Anger dimension of mood.

Amber category: Your anger score is in the amber range, which means that you have scored average-to-above average on this aspect of mood. Scores in this range are usually not associated with good performance. As you have reported some symptoms of depressed mood (see Depression aspect), there is likelihood that you will turn this anger on yourself. This can intensify feelings of frustration, hopelessness, and/or self-blame, which can impede performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Deal with the cause of the feelings
- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Spend some time alone
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective
- Avoid the cause of the feelings

Red category: Your anger score is in the red zone. This means that you have scored well above average on this aspect of mood. Very much like how you would stop at the red lights along a traffic junction, the red here serves as a signal for you to stop because a level of anger in this range clearly has the potential to interfere with performance. Given that you have reported some symptoms of depressed mood (see Depression aspect), this can lead to a reduction in self-confidence. There is also a possibility that you may turn this anger on yourself, which may subsequently intensify feelings of frustration, hopelessness, and/or self-blame. This can lead to a reduction in motivation that is detrimental to performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Deal with the cause of the feelings
- Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs
- Spend some time alone
- Focus on strategies related to successfully completing the task
- Put your feelings into perspective
- Avoid the cause of the feelings

2.10 Research Aims

In summary, mood profiling has been in effect for nearly 40 years. Traditionally, the extent of the mood-performance literature has involved athletic samples. As previously mentioned, Morgan (1980) discovered that many successful competitors experienced mood profiles that differed from the general population, whose test norms according to the POMS (McNair et al., 1971, 1992) closely resembled a *water line*. It is from this standpoint that three dissimilar mood profiles have previously been found: iceberg profile (Morgan, 1980), Everest profile, and inverse iceberg profile (Terry, 2004).

Somewhat perplexingly, however, despite in excess of 300 published studies, it remains unknown if distinct mood profile clusters can be found within the general population. More specifically, previous studies have demonstrated a clear preference for investigating how mood profiles within athletic samples differ from the general population, and how these differences relate to sporting performance (see Beedie et al., 2000; Prapavessis, 2000; Terry, 1995 for meta-analyses and reviews). Research examining potential differences in mood (i.e., tension, depression, anger, vigour, fatigue, and confusion) as measured by the BRUMS (Terry et al., 1999) within the general population has not been conducted to date.

Therefore, the proposed research takes a new logical step. The fundamental aim of the present research was to investigate whether distinct mood profile clusters exist within the general population. Three datasets from the *In The Mood* website will be analysed using cluster analytic methodology. The website will also be revised and improved according to respondent feedback and recommendations from the Lim (2011) study. Despite a strong interest, use of web-based mood profiling linking mood responses with specific mood regulation strategies has not previously been widely available.

The recent version of the BRUMS designed specifically for online testing (Lim & Terry, 2011) has opened up the potential for its application in performance environments that have not been previously researched. With an aim to further generalise the scale, the proposed project will investigate the mood responses in high-risk vocational groups not previously considered: individuals employed in the construction and mining industries. The variables that potentially moderate the mood-performance relationship for each population will also be examined (e.g., age, gender, state, vocation, role, and roster). Given the relationship between mood and performance outcomes in athletes (Pieter & Pieter, 2008; Terry & Lane, 2011; Zehsaz, Azarbaijani, Farhangimaleki, & Tiidus, 2011), and given that safety behaviour has been associated with a reduction in accidents and injuries (Clarke, 2012; Neal & Griffin, 2006), the proposed research will also investigate the possibility of a link between mood and performance in the context of safety.

CHAPTER 3:
Mood Profiles Investigation: Sample A

As mentioned previously, the hierarchically structured *In The Mood* website was guided by the theoretical framework of the BRUMS (see Figure 3.1; Terry et al., 1999; Terry, Lane et al., 2003) and the conceptual framework of Lane and Terry (2000). The psychometric robustness of the BRUMS makes it a particularly appropriate measure in several performance environments, and its brevity readily lends itself to web-based mood profiling.

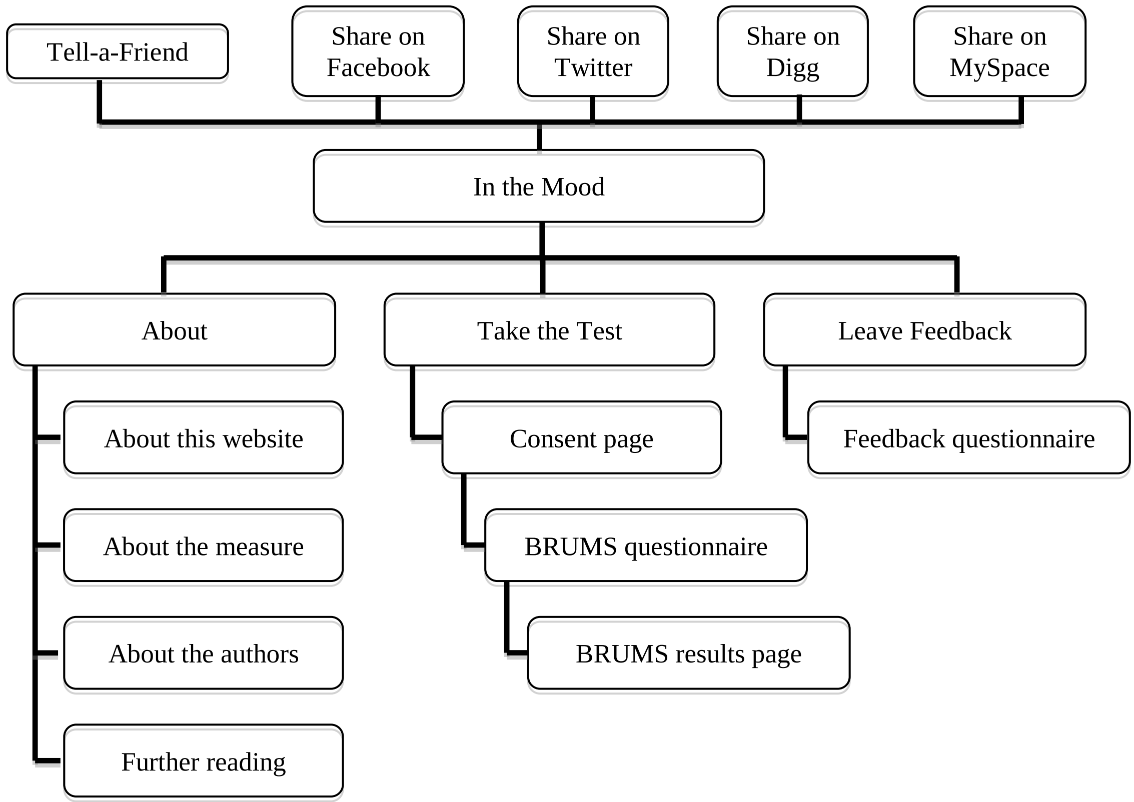


Figure 3.1. Website map outlining the structure of *In The Mood* (taken from Lim, 2011).

In a nutshell, the synchronous *In The Mood* website (Lim & Terry, 2011) allows respondents to complete an online version of the BRUMS, receive an automated profile summary report (interpreting mood scores for six mood dimensions, with reference to normative scores) as well as receive a brief summary of the potential influence of obtained mood scores on performance. Additionally, a series of evidence-based mood regulation strategies corresponding with each mood dimension are provided. Raw and standard scores, as well as a graphical representation of the individual mood profile are also generated. Figure 3.2 shows the output process of *In The Mood.*

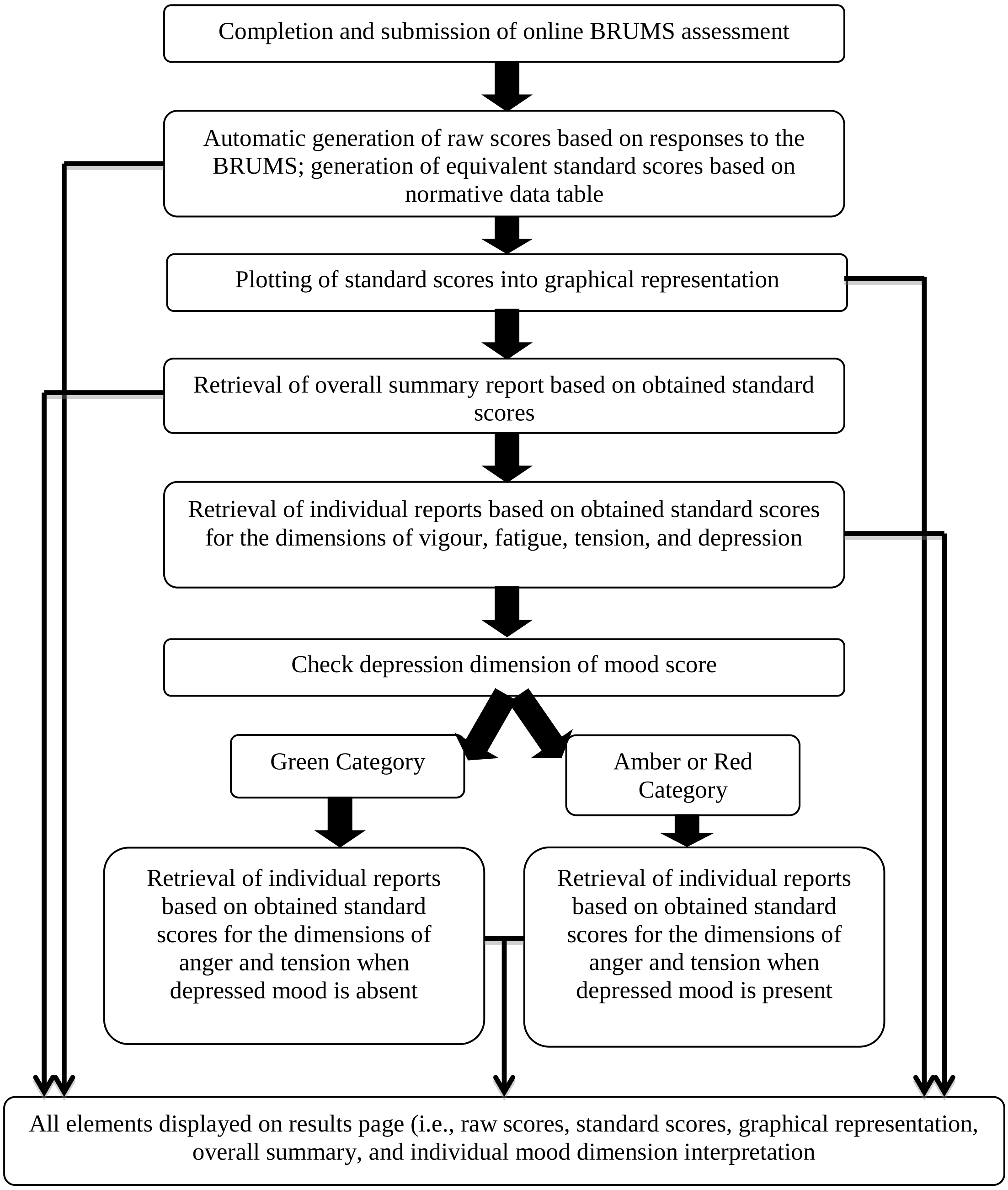


Figure 3.2. A schematic representation of the general output process of the online BRUMS assessment (taken from Lim, 2011).

Previous research has identified three mood profiles using self-report measures: iceberg profile (Morgan, 1980), Everest profile, and inverse iceberg profile (Terry, 2004). The aim of the present research was to investigate whether discrete mood profiles could be identified within the general population. Given this, the existing Lim (2011) data from the *In The Mood* website (i.e., Sample A) was explored using cluster analytic methodology. A multiple DFA and MANOVA were used to provide support for the accuracy of the final cluster solution, and a series of chi-squared tests for goodness-of-fit were used to describe demographic characteristics of mood profiles (i.e., gender, age, and level of education).

3.1 Introduction to Cluster Analysis

Over the past five decades, cluster analysis has been well utilised in the social sciences as well as across a range of multi- and inter-disciplinary fields (Blashfield & Aldenderfer, 1978). Cluster analysis is a general exploratory technique that describes various statistical procedures used to delineate natural groups undefined *a priori* (Anderberg, 1973; Cormack, 1971). Researchers from the human, earth, mathematical, computer, and physical sciences readily utilise cluster analysis for data categorisation according to nominated variables (see Eisen, Spellman, Brown, & Botstein, 1998; Fovell & Fovell, 1993; Massart & Kaufman, 1983; Mohammadi & Prasanna, 2003; Rousseeuw, 1987; Sturn, Quackenbush, & Trajanoski, 2002). This complex methodology has also been popular within the doctrine of psychology, involving areas such as depression (Paykel, 1971), personality (Wood, Winston-Salem, & Nye, 2010), suicide (Paykel & Rassaby, 1978), dementia (Whitwell et al., 2009), and substance abuse (Herrera, Norwalk, Okonek, Parent, & Roy, 1988).

With more than 200 algorithms and 50 proximity measures to choose from (Blashfield, 1980), the effectiveness of procedures to group datasets into meaningful profiles rely upon a series of judicious decisions (refer to Figure 3.3; Mooi & Sarstedt, 2011). Indeed, given the underlying principle of classification, hierarchical and partitioning computations will group even random unrelated data (Clatworthy, Hankins, Buick, Weinman, & Horne, 2007; Mooi & Sarstedt, 2011; Scheibler & Schneider, 1985). Decisions concerning variables (e.g., interval-scaled, ratio, metric, ordinal, nominal, binary, etc.), standardisation methods (e.g., *z* scores, 0–1 or –1 to 1 ranges, etc.), proximity measures (e.g., euclidean distance, squared euclidean distance, city-block distance, chebychev distance, etc.), similarity measures (e.g., Pearsons correlation, etc.), as well as appropriate algorithms (i.e., single linkage, complete linkage, average linkage, Ward's method, centroid, etc.), and methods (i.e., agglomerative versus divisive) can each significantly alter the stability and validity of results (Mooi & Sarstedt, 2011).

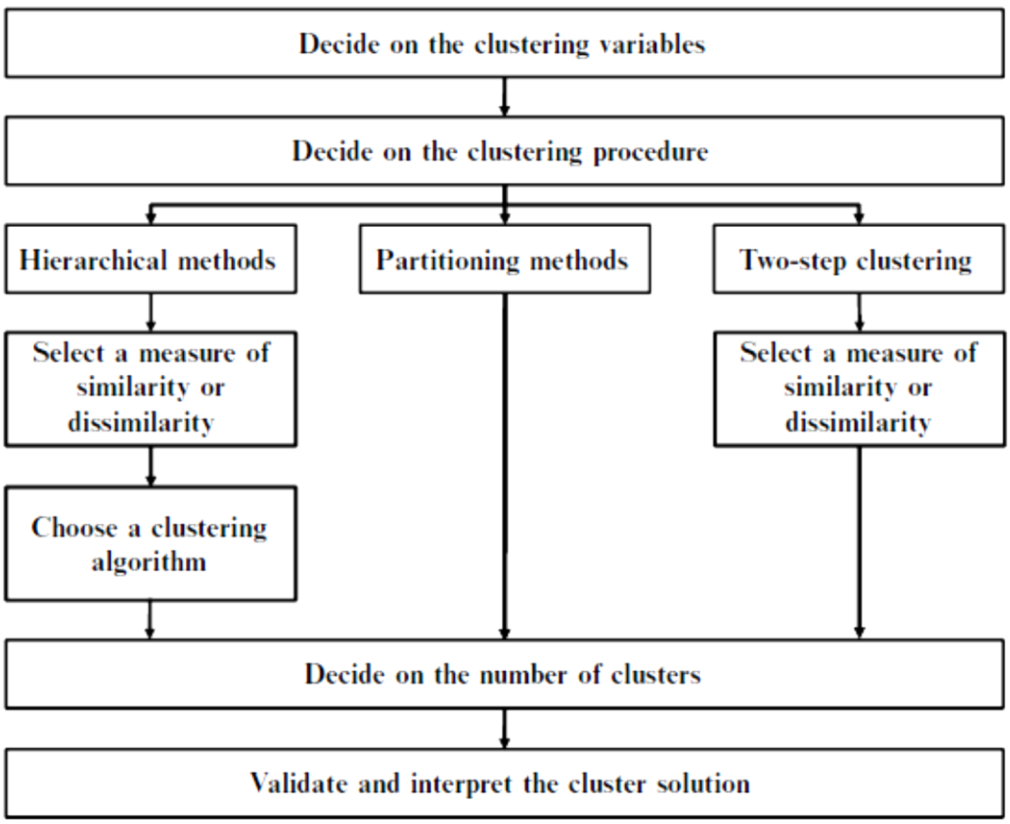


Figure 3.3. Decision-making processes involved with cluster analysis techniques (taken from Mooi & Sarstedt, 2011).

This makes salient the importance of theoretical and orientation considerations, as well as continual evaluations at successive steps before findings can be generalised to true-to-life settings (Bijnen, 1973; Blashfield, 1976; Blashfield & Aldenderfer, 1978; Kos & Psenicka, 2000). A number of caveats have been identified relating to the overriding problem of naive empiricism, so in an effort to circumvent potential methodological issues, Blashfield (1980) outlined a series of propositions. According to Blashfield, a clear description of the analytic method, similarity measure, and software should be clearly outlined. Additionally, the procedure for cluster identification should be detailed, as should the evidence of validity of the final parameter solution. Given the obvious degree of subjectivity associated with the final steps, such information enables other researchers to comprehensively evaluate whether data were *forced* into a solution, or if the multivariate cluster structures are in fact adequately represented.

Although summarising large quantities of data is not without limitation, these powerful clustering techniques continue to increase in popularity (Blashfield, 1980). Generally speaking, average linkage, complete linkage, and the Ward's method are the preferred hierarchical approaches, with k-means being the favoured partitioning procedure (Clatworthy et al., 2007). Ward (1963) suggested that by considering all possible $n(n - 1)/2$ pairings, the case with the least error sum of squares can be selected, meaning that the variance within each subset can be minimised. Similarly, Formann (1984 as cited in Mooi & Sarstedt, 2011) recommended a ratio of $2m$ whereby m equals the number of variables. Importantly, however, as Mooi and Sarstedt (2011) point out, every additional variable potentially increases the degree of collinearity, meaning that in these cases variables are more likely to be similar than different.

Overall, while methods such as average linkage and k-means provide an adequate recovery of the cluster metrics, the Ward's method (to determine cluster numbers and cluster centroids), followed by a k-means method (to further fine-tune cluster boundaries) is the recommended approach according to Milligan (1981) and Clatworthy et al. (2007). Hierarchical approaches better aid the identification of the number of clusters to be retained, while k-means cluster analysis is superior in determining cluster memberships. As an iterative procedure, cluster memberships are re-evaluated, and proximity metrics are recalculated, to minimise within-group variance and maximise between-group variance (Everett, 1993). Additionally, agglomerative techniques are considered superior to divisive hierarchical procedures, and the squared euclidean distance is the suggested proximity measure for a Ward's analysis using the Statistical Package for the Social Sciences (SPSS). Although the Ward's method is considered ideal for large datasets ($n > 100$), Meehl (1995) highlighted that a minimum sample size of 300 is required to infer valid groupings.

3.2 Method

3.2.1 Participants. Adult participants (i.e., aged 18 or above) were recruited from the general population by Lim (2011) through the *In The Mood* website (Lim & Terry, 2011). There were no other exclusion criteria. The snowballing technique via social networking sites (i.e., Facebook, Twitter, Digg, MySpace, etc.) and e-mail were used during the data collection period from March 15, 2011 to October 31, 2011. The final sample comprised of 51.6% males and 48.4% females. A large majority (59.9%) were aged 18–24, and reported a high school level of education (51.6%). A further 30% had completed an undergraduate degree, while 16.6% indicated they were postgraduates. A small portion of the sample (1.7%) selected 'Less than high school certificate'. Additionally, approximately half (55.3%) of the sample selected an occupation listed as ‘Other’, and 40% identified as being Caucasian ethnicity with a further 43% of the sample responding as ‘Other’ ethnicity. Among reasons for completing the BRUMS, a large proportion (46.2%) wanted to help with research, with 19.8% indicating some other reason, and 18.5% selecting ‘General interest’.

3.2.2 Measures. The BRUMS is a 24-item scale made up of basic mood descriptors with a standard response timeframe of ‘How do you feel right now?’. Alternative timeframes can also be utilised (i.e., ‘How you have felt during the past week including today?’, ‘How have you felt over the past month?’, and/or ‘How do you normally feel?’). Participants rate their responses on a 5-point Likert scale of 0 = *not at all*, 1 = *a little*, 2 = *moderately,* 3 = *quite a bit*, and 4 = *extremely* (Terry & Lane, 2010). The measure consists of six subscales (i.e., anger, confusion, depression, fatigue, tension, and vigour), with each containing four items.

Tension is typified by nervousness, apprehension, worry, and anxiety, while, depression is associated with a negative self-schema (i.e., hopelessness, personal deficiency, worthlessness, and self-blame; Beck & Clark, 1988; Terry et al., 1999; Terry, Lane et al., 2003). Anger refers to feelings that vary in intensity (i.e., from mild annoyance or aggravation to fury and rage), and is linked with arousal of the autonomic nervous system (Terry et al., 1999; Terry, Lane et al., 2003; Spielberger, 1991). Vigour describes feelings of excitement, alertness, and physical energy, while fatigue involves the experience of mental and physical tiredness. Confusion describes a feeling state characterised by bewilderment and uncertainty, and a general failure to control attention and emotions (Terry et al., 1999; Terry, Lane et al., 2003). Total subscale scores may range from 0–16 (Terry & Lane, 2010). Each subscale is made up of the following items:

- Tension: panicky, anxious, worried, nervous (items 1, 13, 14, 18).
- Depression: depressed, downhearted, unhappy, miserable (items 5, 6, 12, 16).
- Anger: annoyed, bitter, angry, bad tempered (items 7, 11, 19, 22).
- Vigour: lively, energetic, active, alert (items 2, 15, 20, 23).
- Fatigue: worn out, exhausted, sleepy, tired (items 4, 8, 10, 21).
- Confusion: confused, mixed up, muddled, uncertain (i.e., items 3, 9, 17, 24).

3.2.3 Procedure. The research was granted ethical approval by the University of Southern Queensland's Office of Research and Higher Degrees, Human Research Ethics Committee (approval number: H13REA169; see Appendix A). All analyses were performed using IBM SPSS Software Version 22.0 (2013).

3.3 Results

A total of 2,525 cases from the *In The Mood* website (Lim & Terry, 2011) were screened for missing values, abnormal and unusual responses by Lim (2011). No missing values were detected. However, a total of 161 cases of nil values were identified. These cases were explained by Lim by ways of the respondents' navigation of the website interacting with the implicit design of the website. For example, if an individual reached the results page and decided to explore other pages, and then attempted to retrieve their mood assessment (using the back or forward buttons), the browser consequently transmitted data in the form of nil values to the secure database. Therefore, the 161 cases of nil values were deleted by Lim, given that they could not be classified as valid BRUMS responses.

Although significant univariate non-normality was evident for some subscales (e.g., depression), it is typical that the distribution of negative mood scores show large numbers at the lower end of the scale and small numbers at the upper end (see Terry et al., 1999). Following visual inspection of the frequency distributions for skewness and kurtosis, Lim (2011) concluded that deviations from normal distribution were unlikely to make a substantive difference to the analyses, and no trimming of the dataset occurred. Lim identified 87 multivariate outliers based on a Mahalanobis distance at $p < .001$, but scrutiny of responses suggested that they were viable. Given this, all multivariate outliers were retained, and the final sample of online BRUMS respondents from the general population was 2,364 (i.e., Sample A). Scores ranged from 0–16 on each of the BRUMS subscales (i.e., tension, depression, anger, vigour, fatigue, and confusion). A complete summary of the demographic composition is presented in Table 3.1.

Table 3.1

Demographic Characteristics of the BRUMS Respondents (N = 2,364)

Dependent Variable	*n*	%
Gender		
Male	1,219	51.6
Female	1,145	48.4
Age Group		
18–24	1,416	59.9
25–35	356	15.1
36–45	353	14.9
46–55	138	5.8
56–65	87	3.7
65+	14	0.6
Education		
< High School Certificate	41	1.7
High School Certificate	1,221	51.6
Undergraduate	709	30.0
Postgraduate	393	16.6

(Table 3.1 continues)

(Table 3.1 continued)

Dependent Variable	*n*	%
Occupation		
Agricultural, Animal & Primary Industries	28	1.2
Architecture, Building & Planning	18	0.8
Art, Design, Music & Entertainment	11	0.5
Business, Administration & Sales	122	5.2
Chemicals, Plastics, Rubber, etc.	21	0.9
Computer & Information Services	80	3.4
Education	440	18.6
Engineering & Technical	16	0.7
Food Processing	8	0.3
Furniture & Wood Products	51	2.2
General Retail	21	0.9
Health & Community Services	185	7.8
Hospitality & Tourism	19	0.8
Law, Security & Defence	12	0.5
Literature & Social Services	5	0.2
Metal, Electrical & Automotive	4	0.2
Natural Sciences & Mathematics	6	0.3
Printing & Paper	0	0.0
Textiles, Clothing & Footwear	1	< .1
Transport & Storage	9	0.4
Other	1,307	55.3
Ethnicity		
African	123	5.2
Asian	136	5.8
Caucasian	962	40.7
Indigenous	39	1.6
Middle Eastern	81	3.4
Other	1,023	43.3

(Table 3.1 continues)

(Table 3.1 continued)

Dependent Variable	*n*	%
Reason for Completing BRUMS		
General Interest	438	18.5
Not Feeling my Normal Self	84	3.6
Preparing for a Presentation	41	1.7
Preparing for a Sales Pitch	24	1.0
Preparing for a Sport Competition	173	7.3
Preparing for an Examination	43	1.8
Wanting to Help with Research	1,092	46.2
Other	469	19.8

Lim (2011) found that mood responses from the *In The Mood* website showed no significant differences from the traditional pen and paper version of the BRUMS, meaning that a single set of normative values developed from both the online and offline BRUMS assessments (see Appendix B) was justifiable, and used hereafter for all t-scores. The means, standard deviations, and 95% confidence intervals (CI) for each mood dimension are provided in Table 3.2.

Table 3.2

Descriptive Statistics of the BRUMS Subscales (N = 2,364)

Mood Dimension	*M*	*SD*	95% CI
Tension	46.65	7.81	[46.33, 46.96]
Depression	49.95	10.26	[49.54, 50.36]
Anger	49.80	8.29	[49.46, 50.13]
Vigour	48.59	9.12	[48.22, 48.95]
Fatigue	52.26	9.55	[51.88, 52.65]
Confusion	49.81	9.53	[49.43, 50.20]

3.3.1 Hierarchical and k-means cluster analysis. To identify relatively homogeneous groups, data were analysed using agglomerative, hierarchical cluster analysis. Ward's method was the chosen clustering algorithm, given that the theoretical orientation of the research suggested an investigation of both the shape and magnitude of mood profiles was required. Squared euclidean distance was used as the proximity measure to maximise differences between heterogeneous groups. In line with Blashfield's (1980) propositions, to increase the validity of findings three separate checks were conducted to determine and verify the clusters at successive steps. Firstly, a visual examination of the trend line intersection on the scree plot (see Figure 3.4) showed a clear change in the trajectory at a six-cluster solution.

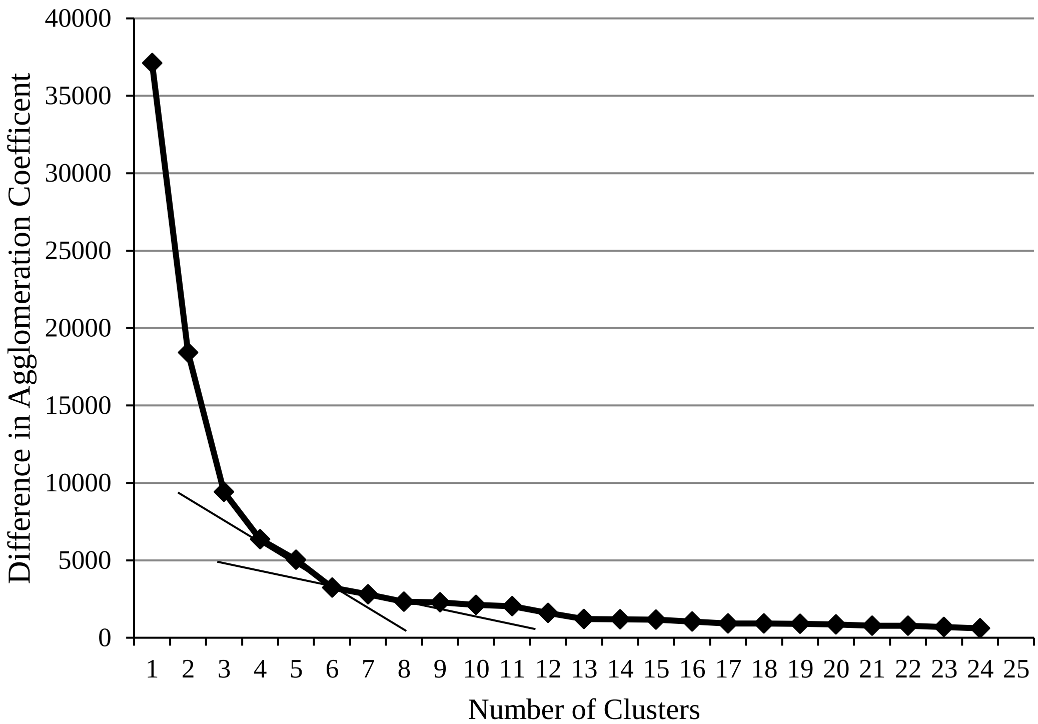


Figure 3.4. Scree plot diagram of the hierarchical cluster solutions (*N* = 2,364).

Secondly, the last 25 cases of the agglomeration schedule (see Table 3.3) were reviewed. A change in the distance coefficients was identified at case 2,358, and given that the sample size was 2,364, the agglomeration schedule indicated that there were six distinct clusters.

Table 3.3

Final 25 Cluster Allocation Cases of Agglomeration Schedule (N = 2,364)

	Cluster Combined			Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next Stage
2,339	28	117	33,432.684	2,323	2,302	2,349
2,340	4	13	34,038.534	2,335	2,279	2,346
2,341	24	30	34,733.128	2,338	2,325	2,352
2,342	228	477	35,499.171	2,320	2,314	2,356
2,343	2	40	36,274.165	2,309	2,326	2,358
2,344	18	50	37,127.361	2,307	2,328	2,349
2,345	171	200	38,021.508	2,337	2,255	2,359
2,346	4	8	38,938.303	2,340	2,322	2,354
2,347	15	97	39,858.557	2,317	2,299	2,348
2,348	1	15	40,901.553	2,329	2,347	2,355
2,349	18	28	42,059.209	2,344	2,339	2,355
2,350	422	573	43,246.617	2,334	2,321	2,353
2,351	49	75	44,461.200	2,332	2,336	2,352
2,352	24	49	46,057.392	2,341	2,351	2,359
2,353	306	422	48,098.185	2,333	2,350	2,360
2,354	3	4	50,207.514	2,331	2,346	2,362
2,355	1	18	52,488.541	2,348	2,349	2,358
2,356	72	228	54,812.484	2,330	2,342	2,357
2,357	23	72	57,603.919	2,327	2,356	2,361
2,358	1	2	60,835.508	2,355	2,343	2,361
2,359	24	171	65,866.908	2,352	2,345	2,360
2,360	24	306	72,219.709	2,359	2,353	2,363
2,361	1	23	81,627.517	2,358	2,357	2,362
2,362	1	3	100,043.220	2,361	2,354	2,363
2,363	1	24	137,156.994	2,362	2,360	0

The third and final check of the cluster structures involved tracing the fate of members. Each cluster solution was reviewed, including the member contributions for each possible solution (Table 3.4 displays 4 to 8 solutions; Appendix C displays 2 to 15 solutions). Five distinct clusters were traced back from step six: H2 (*n* = 109), H3 (*n* = 474), H4 (*n* = 455), H5 (*n* = 302), and H6 (*n* = 630). H1 (*n* = 394) was not as stable in comparison to the other five clusters, evident in that H1 (*n* = 284) and H2 (*n* = 110) combined immediately before the sixth step. However, given the scree plot showed a distinct elbow and the increase in distance coefficients from 2,358, it was decided that a six-cluster solution was an appropriate fit to data. The three separate checks all signalled a similar outcome.

Table 3.4

Fate of Members to Determine Number of Clusters (N = 2,364)

Solution	H1	H2	H3	H4	H5	H6	H7	H8
4	394	109	474	1,387				
5	394	109	474	757	630			
6	**394**	**109**	**474**	**455**	**302**	**630**		
7	284	110	109	474	455	302	630	
8	284	110	109	106	455	368	302	630

Note. H1, H2, ... H8 denotes a hierarchical cluster found within Sample A.

Table 3.5 presents the inter-correlations between the six clusters according to the hierarchical analysis. It is important to note that given the large sample size, even small correlations were likely to reach statistical significance. The purpose of examining cluster inter-correlations was to evaluate the extent to which the clusters were mutually exclusive. In this context, the proportion of shared variance seemed an appropriate measure. An arbitrary criterion of < .70 signified that positive inter-correlations shared less than 50% variance, being indicative of substantial interdependence. Additionally, large negative correlations did not denote similarity, but rather reverse cluster patterning.

Table 3.5

Inter-correlation Matrix of the Hierarchical Clusters (N = 2,364)

Profile	H2	H3	H4	H5	H6
H1	–0.04	0.90	0.48	0.56	0.37
H2		–0.10	–0.88	–0.82	–0.94
H3			0.42	0.64	0.42
H4				0.92	0.96
H5					0.96

Note. H1, H2, ... H6 denotes a hierarchical cluster found within Sample A. H1(n = 394), H2 (n = 109), H3 (n = 474), H4 (n = 455), H5 (n = 302), H6 (n = 630).

A strong positive relationship was found between cluster H1 and H3, with 81.0% shared variance. Additionally, H4, H5, and H6 were also found to be closely related, sharing from 84.6% to 92.2% common variance. Although these findings suggested that the clusters shared a disproportionate amount of variance, it was found that the clusters shared a similar shape. Well-defined differences in the magnitude of differential mood dimensions would satisfy the criteria of a heterogeneous group according to a Ward's analysis, and given the underlying linear nature of Pearson correlation tests (Field, 2009), this type of distinctiveness would not be adequately reflected in the *r*-value.

Following the initial identification of the six clusters, a partitioning method was used to validate the findings, and further refine the final parameter solution. K-means clustering was conducted using random aggregation centres with a prescribed six-cluster solution. The inter-correlation matrix of the relationship between the six-cluster solution found using the hierarchical and k-means methodologies can be found in Table 3.6.

Table 3.6

Inter-correlation Matrix of the Hierarchical and K-means Clusters (N = 2,364)

Profile	**H1**	**H2**	**H3**	**H4**	**H5**	**H6**
K1	0.97	0.18	0.89	0.27	0.38	0.15
K2	–0.03	1.00	–0.06	–0.89	–0.80	–0.93
K3	0.57	–0.83	0.50	0.99	0.93	0.94
K4	0.37	–0.94	0.41	0.97	0.96	1.00
K5	0.90	0.02	0.99	0.33	0.55	0.31
K6	0.67	–0.76	0.70	0.93	0.99	0.93

Note. H1, H2, ... H8 denotes a hierarchical cluster found within Sample A.
K1, K2, ... K6 denotes a k-means cluster found within Sample A.
H1(n = 394), H2 (n = 109), H3 (n = 474), H4 (n = 455), H5 (n = 302), H6 (n = 630).
K1(n = 244), K2 (n = 64), K3 (n = 349), K4 (n = 695), K5 (n = 409), K6 (n = 603).

As can be seen, the hierarchical and k-means techniques both produced clusters that pooled a very large proportion of shared variance. Clusters H2 and K2, as well as H6 and K4 both shared 100% of common variance. Further, clusters H3 and K5, H4 and K3, and H5 and K6 all shared 98.0% of common variance, while H1 was related to K1 with 94.1% of the variance accounted for.

Additionally, the inter-correlations between the prescribed K-means solution yielded a similar result to the inter-correlations from the hierarchical cluster analysis. A positive relationship was found between K1 and K5, with those clusters again sharing a high percentage of common variance (i.e., 82.8%), while clusters K3, K4, and K6 were also found to be related to one another, sharing from 88.4% to 90.3% of common variance. Table 3.7 shows the inter-correlation matrix of the K-means clusters.

Table 3.7

Inter-correlation Matrix of the K-means Clusters (N = 2,364)

Profile	K2	K3	K4	K5	K6
K1	0.19	0.36	0.16	0.91	0.49
K2		–0.84	–0.93	0.06	–0.74
K3			0.95	0.40	0.95
K4				0.31	0.94
K5					0.61

Note. K1, K2, ... K6 denotes a k-means cluster found within Sample A.
K1(n = 244), K2 (n = 64), K3 (n = 349), K4 (n = 695), K5 (n = 409), K6 (n = 603).

Taken together, these findings provided strong evidence that the cluster structures were both independent and stable. The mean *t* scores according to each mood dimension that formed the final cluster centroids are presented in Table 3.8. A graphical representation superimposing the six mood profiles can be found in Figure 3.5.

Table 3.8

Cluster Centroids of the Six-cluster Solution (N = 2,364)

Mood Dimension	C1[a] (n = 244)	C2[a] (n = 64)	C3[a] (n = 349)	C4[a] (n = 695)	C5[a] (n = 409)	C6[a] (n = 603)
Tension	56.65	67.70	51.90	42.84	44.42	43.23
Depression	63.86	87.17	50.68	44.98	48.97	46.34
Anger	59.82	79.05	52.26	46.26	48.00	46.50
Vigour	45.73	42.50	53.51	57.33	41.12	42.52
Fatigue	60.80	68.80	51.46	45.72	64.16	46.99
Confusion	63.20	80.39	54.20	44.80	47.47	45.99

Note. [a] denotes clusters found within Sample A.

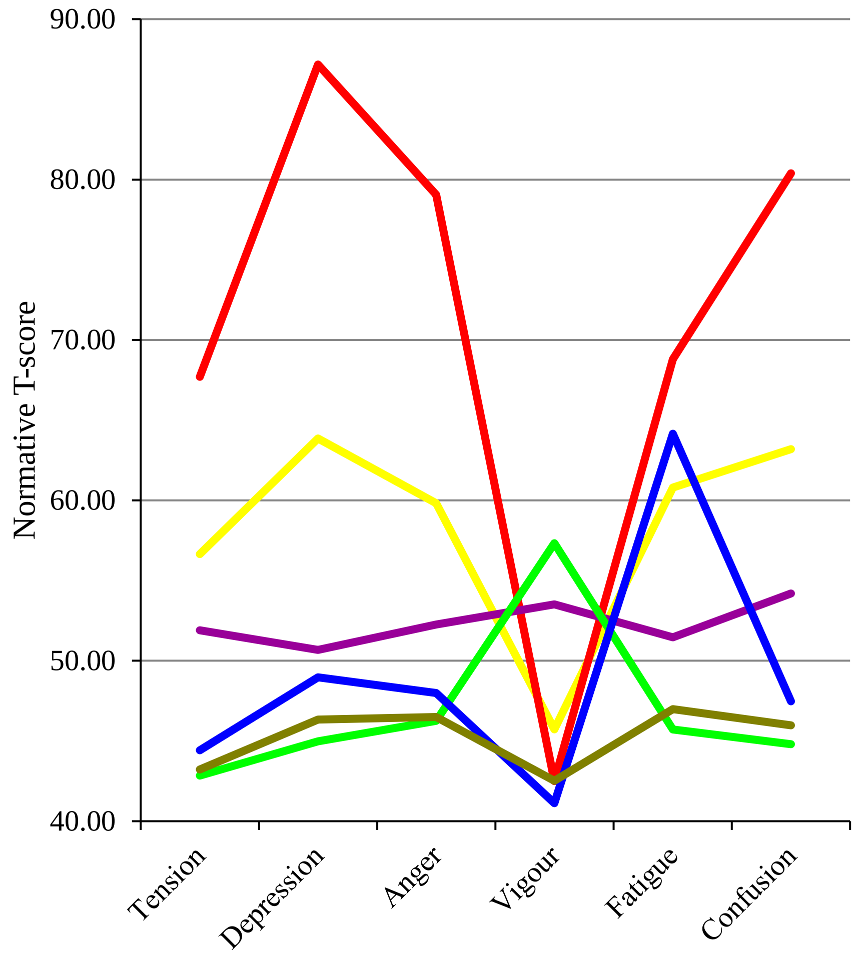


Figure 3.5. Graphical representation of the six-cluster solution (*N* = 2,364): **C1**[a] (*n* = 244), C2[a] (*n* = 64), C3[a] (*n* = 349), **C4**[a] (*n* = 695), C5[a] (*n* = 409), and C6[a] (*n* = 603).

3.3.2 Independence of clusters C1[a] to C6[a]. A between-groups MANOVA was performed to investigate whether the groups identified via the k-means cluster analysis differed to one another according to a combination of variables. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .034, $F(30, 2{,}364) = 418.11$, $p < .001$, partial $\eta^2 = .492$, observed power = 1.00. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for each dimension of mood: tension, $F(5, 2{,}358) = 610.77$, $p < .001$, partial $\eta^2 = .564$, observed power = 1.00; depression, $F(5, 2{,}358) = 884.44$, $p < .001$, partial $\eta^2 = .652$, observed power = 1.00; anger, $F(5, 2{,}358) = 704.34$, $p <$

.001, partial η^2 =.599, observed power = 1.00; vigour, $F(5, 2{,}358) = 608.67$, $p < .001$, partial η^2 =.563, observed power = 1.00; fatigue, $F(5, 2{,}358) = 881.35$, $p < .001$, partial η^2 = .651, observed power = 1.00; and confusion, $F(5, 2{,}358) = 856.34$, $p < .001$, partial η^2 = .645, observed power = 1.00.

An examination of the mean scores for each dependent variable (see Table 3.9) revealed that the magnitude of tension varied significantly between each cluster excluding C4[a] (*M* = 42.84, *SD* = 3.59, 95% CI [42.58, 43.11]) and C6[a] (*M* = 43.23, *SD* = 4.18, 95% CI [42.89, 43.56]), which were found to be at a similar level. The magnitude of depression was also found to vary significantly between each cluster, as did the magnitude of anger, excluding C4[a] (*M* = 46.26, *SD* = 2.69, 95% CI [46.06, 46.47]) and C6[a] (*M* = 46.50, *SD* = 3.14, 95% CI [46.25, 46.75]), which were again found to be at a similar level. The magnitude of vigour was found to vary significantly between each cluster excluding C2[a] (*M* = 42.50, *SD* = 10.64, 95% CI [39.84, 45.16]) and C5[a] (*M* = 41.12, *SD* = 6.58, 95% CI [40.48, 41.76]); as well as C2[a] (*M* = 42.50, *SD* = 10.64, 95% CI [39.84, 45.16]) and C6[a] (*M* = 42.52, *SD* = 4.67, 95% CI [42.15, 42.89]), which were found to be at a similar level, while the magnitude of fatigue and confusion were both found to vary significantly between each cluster.

Table 3.9

Descriptive Statistics of the Six-cluster Solution (N = 2,364)

Mood Dimension	C1[a] (*n* = 244)			C2[a] (*n* = 64)			C3[a] (*n* = 349)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	56.65	7.64	[55.69, 57.61]	67.70	8.64	[65.54, 69.86]	51.90	6.10	[51.26, 52.54]
Depression	63.86	9.95	[62.61, 65.11]	87.17	11.95	[84.19, 90.16]	50.68	7.14	[49.93, 51.43]
Anger	59.82	9.20	[58.66, 60.98]	79.05	10.81	[76.35, 81.75]	52.26	7.02	[51.52, 53.00]
Vigour	45.73	7.54	[44.77, 46.68]	42.50	10.64	[39.84, 45.16]	53.51	6.34	[52.85, 54.18]
Fatigue	60.80	8.38	[59.74, 61.85]	68.80	7.23	[67.02, 70.58]	51.46	5.85	[50.84, 52.07]
Confusion	63.20	8.23	[62.16, 64.24]	80.39	11.22	[77.59, 83.19]	54.20	7.16	[53.44, 54.95]

Mood Dimension	C4[a] (*n* = 695)			C5[a] (*n* = 409)			C6[a] (*n* = 603)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	42.84	3.59	[42.58, 43.11]	44.42	5.23	[43.91, 44.92]	43.23	4.18	[42.89, 43.56]
Depression	44.98	2.58	[44.79, 45.17]	48.97	6.67	[48.32, 49.62]	46.34	4.75	[45.96, 46.72]
Anger	46.26	2.69	[46.06, 46.47]	48.00	4.58	[47.55, 48.45]	46.50	3.14	[46.25, 46.75]
Vigour	57.33	5.32	[56.93, 57.73]	41.12	6.58	[40.48, 41.76]	42.52	4.67	[42.15, 42.89]
Fatigue	45.72	4.69	[45.37, 46.07]	64.16	6.22	[63.55, 64.76]	46.99	4.51	[46.63, 47.35]
Confusion	44.80	3.38	[44.55, 45.05]	47.47	5.59	[46.93, 48.02]	45.99	4.65	[45.61, 46.36]

A *post hoc* simultaneous multiple DFA was used to calculate how well the clusters were classified, and how accurately the model could predict results. DFA is typically used to predict membership in naturally occurring groups, and is not affected by unequal sample sizes (Tabachnick & Fidell, 2013). According to Borgen and Seling (1978), DFA has the ability to better depict the underlying dimensionality of the data, as well as the contribution of individual variables. From this perspective, a follow-up DFA supports interpretation and understanding of the dataset (Borgen & Seling, 1978). DFA is a two-step statistical procedure which involves significance testing of discriminant functions (i.e., independent or orthogonal), followed by a computational process of classification.

The sample was randomly drawn from the population, so the groups were considered a valid estimate of the population proportions in each group. Therefore, the best estimates of actual group sizes and the prior probabilities were not equal values, but the sample proportions. The groups were defined according to the six-cluster solution identified via the k-means cluster analysis (i.e., C1[a] [n = 244], C2[a] [n = 64], C3[a] [n = 349], C4[a] [n = 695], C5[a] [n = 409], and C6[a] [n = 603]). The ratio of cases to independent variables was 394 to 1, which satisfied the preferred requirement of ≥ 20 to 1. The number of cases in the smallest group was 64, being larger than the number of independent variables (i.e., 6), and thus exceeded the preferred number of cases (i.e., ≥ 20) per group. The maximum number of possible discriminant functions was five, being number of groups minus one.

The canonical correlation analysis determines the successive functions and canonical roots, thereby grouping cases according to the comparison of canonical functions and individual classification scores. The eigenvalues indicate the percent of variance accounted for with each function. The five canonical discriminant functions extracted accounted for 100% of the variance, and each function was able to predict an outcome at a significant level. As can be seen in Table 3.10, discriminant function 1 (DF[a]) accounted for R^2 = 85.01% of the between-group variance, Wilks' Λ = .034, $\chi^2(30, N = 2{,}364) = 7{,}984.54$, $p < .001$. Discriminant function 2 (DF[2a]) accounted for R^2 = 62.88% of the between-group variance, Wilks' Λ = .226, $\chi^2(20, N = 2{,}364) = 3{,}509.05$, $p < .001$. Discriminant function 3 (DF[3a]) accounted for R^2 = 33.18% of the between-group variance, Wilks' Λ = .608, $\chi^2(12, N = 2{,}364) = 1{,}173.75$, $p < .001$. Discriminant function 4 (DF[4a]) accounted for R^2 = 8.58% of the between-group variance, Wilks' Λ = .910, $\chi^2(6, N = 2{,}364) = 221.59$, $p < .001$. Discriminant function 5 (DF[5a]) accounted for R^2 = 0.45% of the between-group variance, Wilks' Λ = .996, $\chi^2(2, N = 2{,}364) = 10.54$, $p < .01$. The significance of the Wilks' lambda in the maximum number of discriminant functions supported the interpretation of a solution using five discriminant functions. Table 3.11 shows the group centroids (vector of means) on the five new canonical variables formed by applying the discriminant function weights.

Table 3.10

Eigenvalues for the Discriminant Function (N = 2,364)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
DF[1a]	5.678	71.3	71.3	.922
DF[2a]	1.693	21.3	92.5	.793
DF[3a]	0.498	6.2	98.8	.576
DF[4a]	0.094	1.2	99.9	.293
DF[5a]	0.004	0.1	100.0	.067

Note. [a] denotes canonical discriminant functions created using Sample A.

Table 3.11

Functions at Group Centroids (N = 2,364)

Cluster	Function				
	DF[1a]	DF[2a]	DF[3a]	DF[4a]	DF[5a]
C1[a]	3.971	0.369	–0.067	–0.066	–0.161
C2[a]	9.525	1.461	–0.627	0.876	0.208
C3[a]	0.709	1.145	0.171	–0.615	0.060
C4[a]	–1.907	1.120	0.446	0.236	–0.009
C5[a]	0.574	–2.327	0.837	0.011	0.022
C6[a]	–1.219	–0.680	–1.087	0.010	0.004

Note. C1[a] (*n* = 244), C2[a] (*n* = 64), C3[a] (*n* = 349), C4[a] (*n* = 695), C5[a] (*n* = 409), C6[a] (*n* = 603).

In line with the cut-off, only predictor variables with loadings of ±0.30 were interpreted (only loadings of ±0.30 were interpreted hereafter). Based on the structure matrix, the mood dimensions strongly associated with DF[1a] included high levels confusion, fatigue, tension, depression, and anger. The predictor variables strongly associated with DF[2a] included high levels of vigour, and low levels of fatigue. The predictor variables strongly associated with DF[3a] included high levels of vigour and fatigue. The predictor variables strongly associated with DF[4a] included low levels of tension and high levels of depression, while the predictor variables strongly associated with DF[5a] included low levels of confusion and depression, and a high level of anger. The number and composition of the dimensions of discrimination between groups can be found in Table 3.12, and the unstandardised canonical coefficients are shown in Table 3.13.

Table 3.12

Structure Matrix (N = 2,364)

Mood Dimension	Function				
	DF[1a]	DF[2a]	DF[3a]	DF[4a]	DF[5a]
Confusion	.546*	.250	–.155	–.255	–.404
Vigour	–.176	.728*	.663	.012	.015
Fatigue	.444	–.545	.706*	–.082	.015
Tension	.445	.268	–.063	–.691*	–.126
Depression	.560	.149	–.169	.673*	–.303
Anger	.494	.234	–.114	.259	.781*

Note. * Largest absolute correlation between each variable and any discriminant function.

Table 3.13

Unstandardised Canonical Coefficients (N = 2,364)

Mood Dimension	Function				
	DF[1a]	DF[2a]	DF[3a]	DF[4a]	DF[5a]
Tension	.178	.108	–.059	–.341	.007
Depression	.255	.089	–.026	.451	–.304
Anger	.254	.118	–.078	.044	.571
Vigour	–.064	.301	.278	.049	–.026
Fatigue	.182	–.239	.311	–.013	.005
Confusion	.234	.122	–.075	–.112	–.228

The DFA found that cluster membership was correctly classified with a high degree of accuracy. The percentage of correct classifications were: inverse iceberg profile = 92.2%, inverse Everest profile = 98.4%, surface profile = 82.8%, iceberg profile = 100%, shark fin profile = 94.4%, and submerged profile = 98.3%. Prior probabilities from C1[a] to C6[a] inclusive were 10.3%, 2.7%, 14.8%, 29.4%, 17.3%, and 25.5% (respectively). The proportional by chance accuracy rate was computed by squaring and summing the proportion of cases in each group from the table of prior probabilities for groups (i.e., $0.103^2 + 0.027^2 + 0.148^2 + 0.294^2 + 0.173^2 + 0.255^2 = 0.215$; the proportional by chance accuracy rate was computed via this method hereafter). Additionally, when the discriminant functions were used to predict group membership, the hit ratio was very high. Cases were classified according to the similarity between each vector of scores and group centroids. A total of 95.2% of the cases were correctly reclassified back into the original categories. This percentage was notably higher than the minimum classification accuracy rate of 46.5% (i.e., the proportional by chance accuracy rate + 25%), suggesting that the overlap of the distributions was small, and the function was a good discriminator between groups. Table 3.14 and Table 3.15 list the classification function coefficients and DFA classification results, respectively.

Table 3.14

Classification Function Coefficients (N = 2,364)

Mood Dimension	Cluster					
	C1[a]	**C2[a]**	**C3[a]**	**C4[a]**	**C5[a]**	**C6[a]**
Tension	1.201	2.023	0.878	0.102	0.227	0.198
Depression	1.734	3.575	0.651	0.378	0.584	0.328
Anger	1.351	3.186	0.698	0.006	0.206	0.085
Vigour	1.094	0.945	1.571	1.852	0.753	0.829
Fatigue	1.551	2.116	0.854	0.458	1.859	0.540
Confusion	1.550	2.838	0.875	0.158	0.306	0.237

Note. C1[a] (n = 244), C2[a] (n = 64), C3[a] (n = 349), C4[a] (n = 695), C5[a] (n = 409), C6[a] (n = 603).

Table 3.15

Classification of Results (N = 2,364)

	Predicted Group Membership						
Cluster	1	2	3	4	5	6	*n*
C1[a]	225	0	12	0	7	0	244
C2[a]	1	63	0	0	0	0	64
C3[a]	10	0	289	35	5	10	349
C4[a]	0	0	0	695	0	0	695
C5[a]	1	0	1	4	386	17	409
C6[a]	2	0	8	0	0	593	603

3.3.3 Characteristics of clusters C1[a] to C6[a]. Figure 3.6 to Figure 3.11 inclusive present the graphical representations (using mean *t* scores) of the six clusters (i.e., C1[a], C2[a], C3[a], C4[a], C5[a], C6[a]) derived from the K-means analysis.

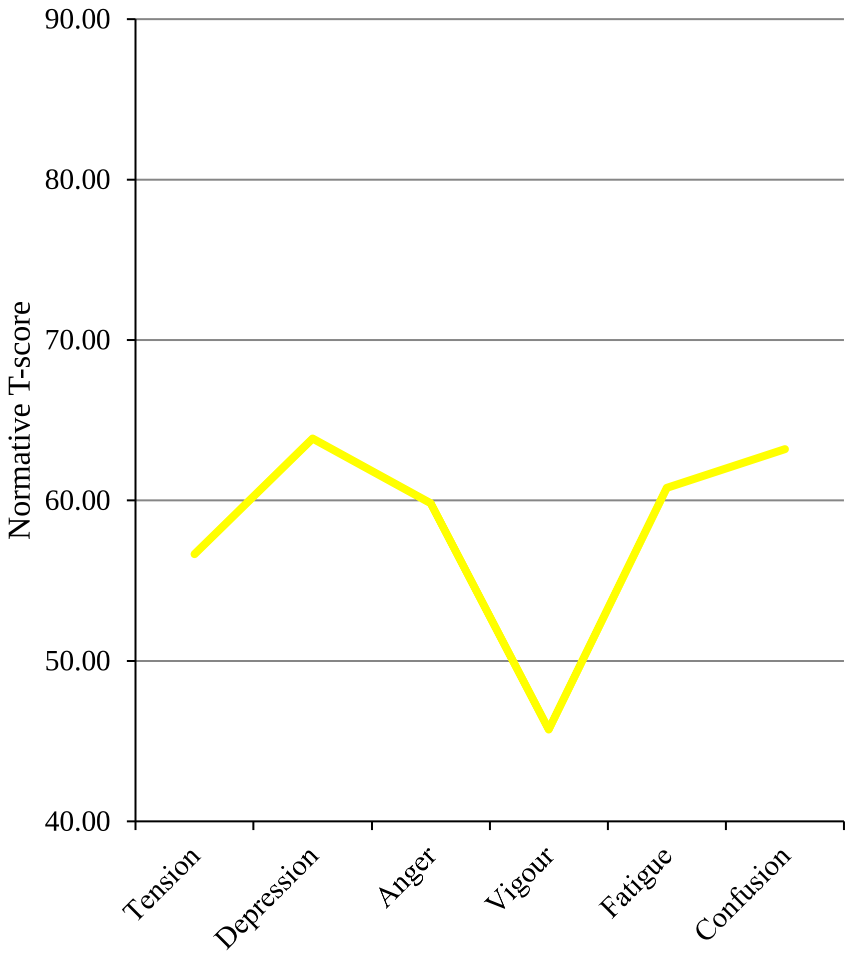


Figure 3.6. Graphical representation of **C1[a]** (*n* = 244).

C1[a] had previously been identified in the literature as the inverse iceberg profile (see Terry, 2005), or a negative version of the mental health model (see Morgan, 1985). Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 56.65, *SD* = 7.64, 95% CI [56.01, 57.30]; depression, *M* = 63.86, *SD* = 9.95, 95% CI [63.10, 64.62]; anger, *M* = 59.82, *SD* = 9.20, 95% CI [59.17, 60.48]; vigour, *M* = 45.73, *SD* = 7.54, 95% CI [44.97, 46.48]; fatigue, *M* = 60.80, *SD* = 8.38, 95% CI [60.09, 61.51]; and confusion, *M* = 63.20, *SD* = 8.23, 95% CI [62.48, 63.91].

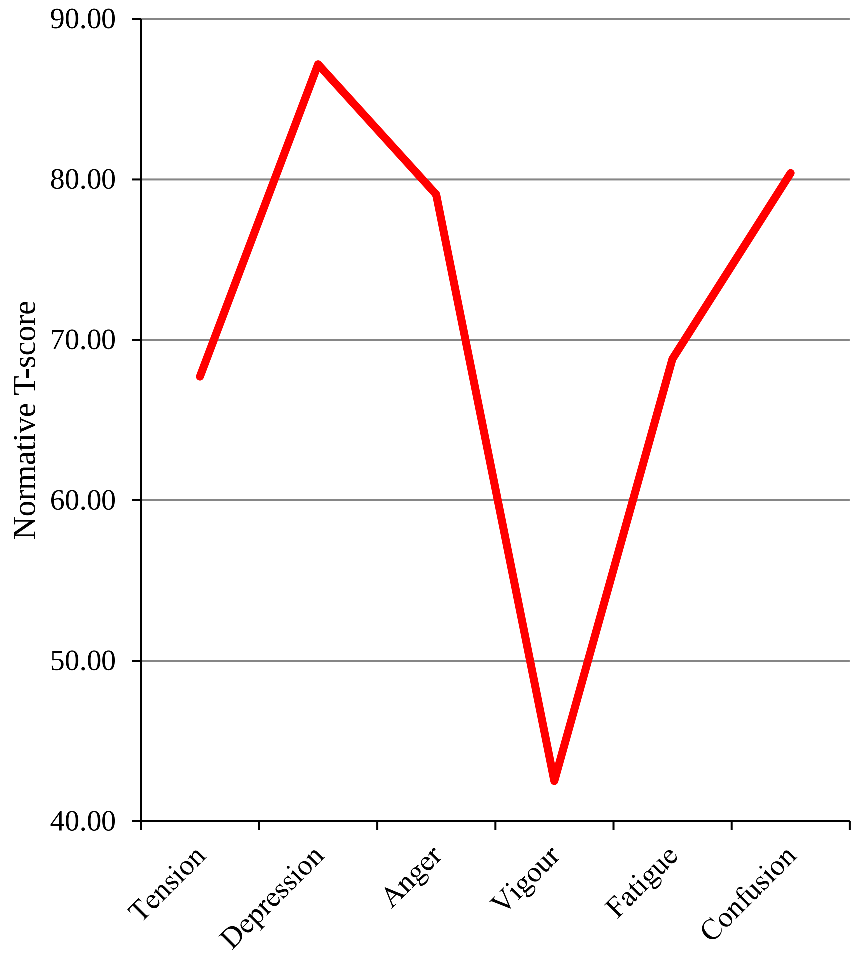


Figure 3.7. Graphical representation of C2[a] (n = 64).

C2[a] had not previously been identified in the literature. This mood profile was termed the inverse Everest profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 67.70, SD = 8.64, 95% CI [66.44, 68.97]; depression, M = 87.17, SD = 11.95, 95% CI [85.68, 88.66]; anger, M = 79.05, SD = 10.81, 95% CI [77.76, 80.33]; vigour, M = 42.50, SD = 10.64, 95% CI [41.03, 43.98]; fatigue, M = 68.80, SD = 7.13, 95% CI [67.41, 70.18]; and confusion, M = 80.39, SD = 11.22, 95% CI [79.00, 81.78].

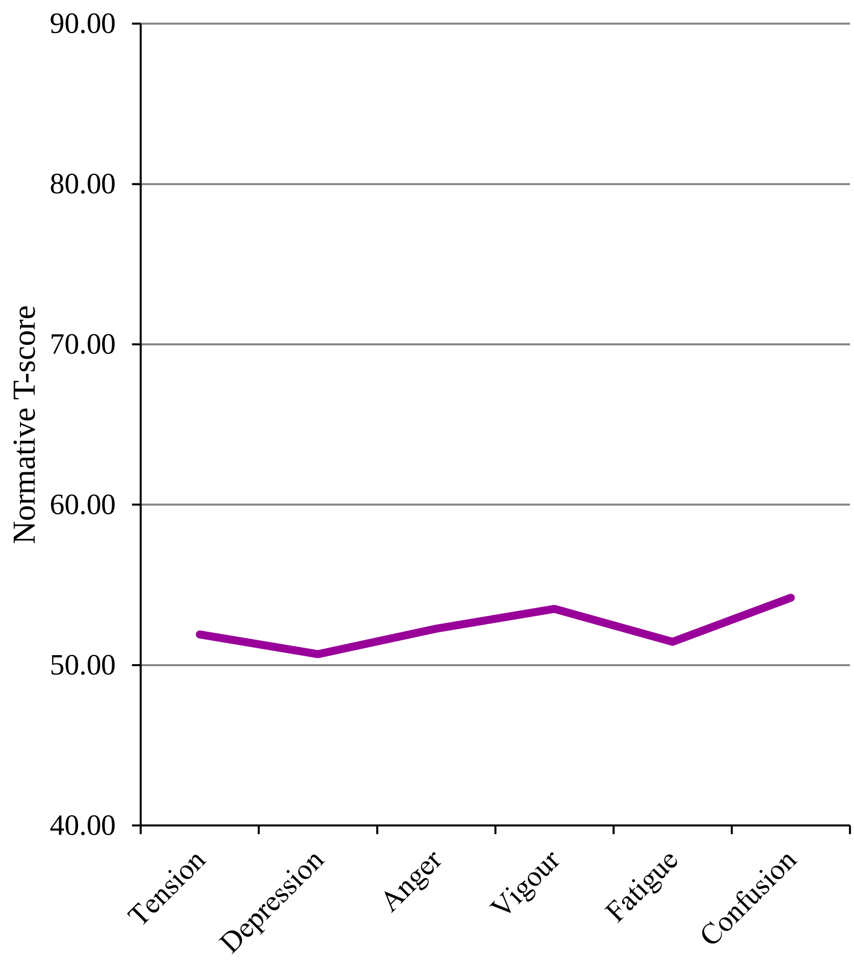


Figure 3.8. Graphical representation of C3[a] (n = 349).

C3[a] had not previously been identified in the literature. This mood profile was termed the surface profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 51.90, SD = 6.10, 95% CI [51.36, 52.44]; depression, M = 50.68, SD = 7.14, 95% CI [50.04, 51.32]; anger, M = 52.26, SD = 7.02, 95% CI [51.71, 52.81]; vigour, M = 53.51, SD = 6.34, 95% CI [52.88, 54.14]; fatigue, M = 51.46, SD = 5.85, 95% CI [50.86, 52.05]; and confusion, M = 54.20, SD = 7.16, 95% CI [53.60, 54.79].

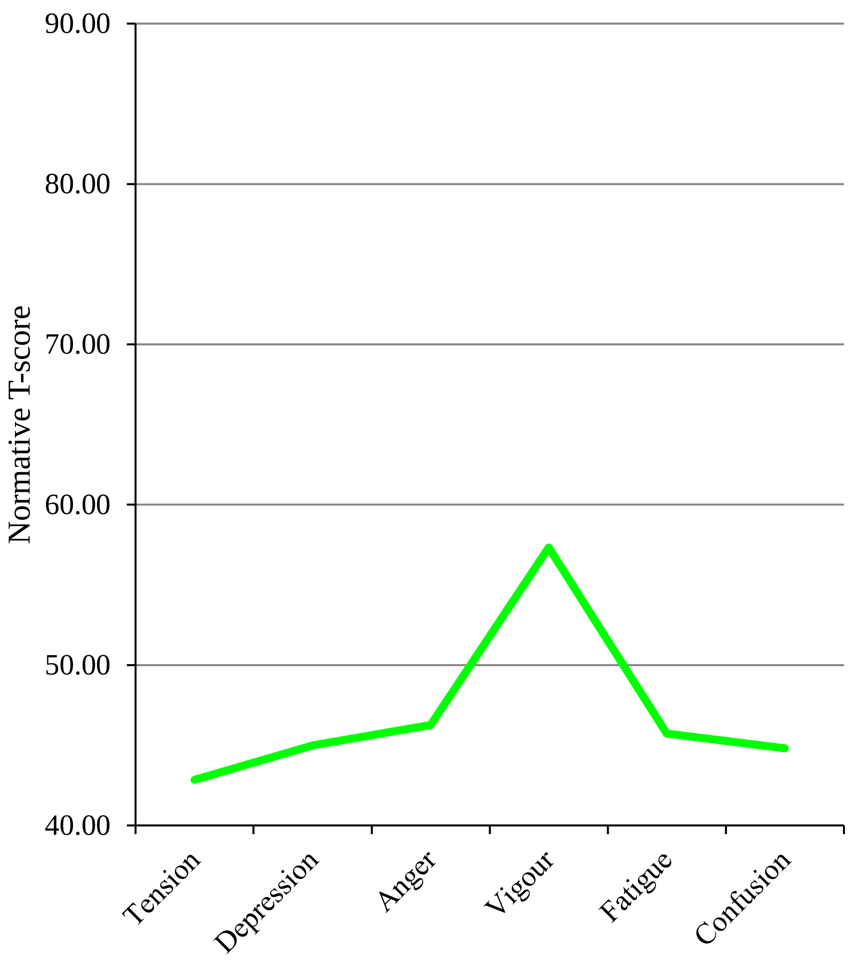


Figure 3.9. Graphical representation of **C4[a]** (n = 695).

C4[a] had previously been identified in the literature as the iceberg profile (see Morgan, 1980, 1985; Terry, 1995). Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 42.84, SD = 3.59, 95% CI [42.46, 43.23]; depression, M = 44.98, SD = 2.58, 95% CI [44.53, 45.44]; anger, M = 46.26, SD = 2.69, 95% CI [45.88, 46.65]; vigour, M = 57.33, SD = 5.32, 95% CI [56.88, 57.78]; fatigue, M = 45.72, SD = 4.69, 95% CI [45.30, 46.14]; and confusion, M = 44.80, SD = 3.38, 95% CI [44.38, 45.22].

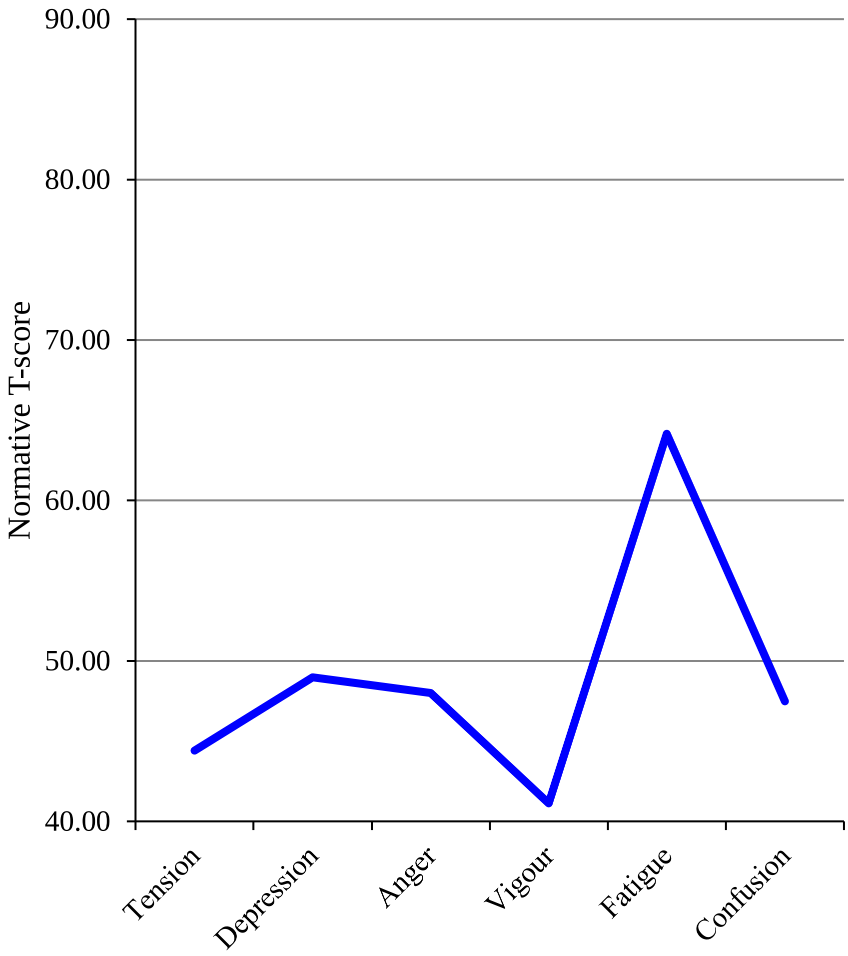


Figure 3.10. Graphical representation of C5[a] (*n* = 409).

C5[a] had not previously been identified in the literature. This mood profile was termed the shark fin profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 44.42, *SD* = 5.23, 95% CI [43.92, 44.92]; depression, *M* = 48.97, *SD* = 6.67, 95% CI [48.38, 49.56]; anger, *M* = 48.00, *SD* = 4.58, 95% CI [47.49, 48.51]; vigour, *M* = 41.12, *SD* = 6.58, 95% CI [40.54, 41.71]; fatigue, *M* = 64.16, *SD* = 6.22, 95% CI [63.61, 64.71]; and confusion, *M* = 47.47, *SD* = 5.59, 95% CI [46.92, 48.03].

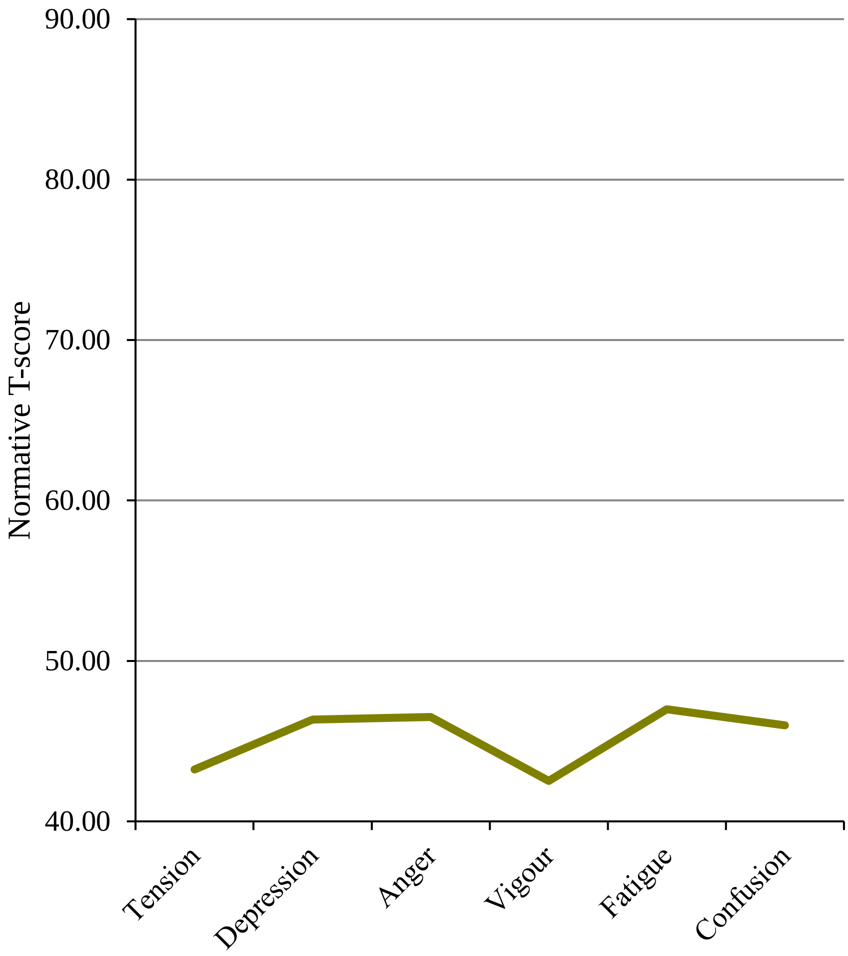


Figure 3.11. Graphical representation of **C6[a]** (*n* = 603).

C6[a] had not previously been identified in the literature. This mood profile was termed the submerged profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 43.23, *SD* = 4.18, 95% CI [42.82, 43.64]; depression, *M* = 46.34, *SD* = 4.75, 95% CI [45.86, 46.83]; anger, *M* = 46.50, *SD* = 3.14, 95% CI [46.08, 46.92]; vigour, *M* = 42.52, *SD* = 4.67, 95% CI [42.04, 43.00]; fatigue, *M* = 46.99, *SD* = 4.51, 95% CI [46.54, 47.44]; and confusion, *M* = 45.99, *SD* = 4.65, 95% CI [45.53, 46.44].

3.3.4 Demographics of clusters C1^a to C6^a. A series of chi-square tests of goodness-of-fit were performed to determine whether the inverse iceberg (C1^a), inverse Everest (C2^a), surface (C3^a), iceberg (C4^a), shark fin (C5^a), and submerged (C6^a) mood profiles varied according to distributions of gender, age, and level of education. According to the assumptions underlying chi-square tests, the expected counts should be no less than 5. However, the integrity of the test is sound providing "no more than 20% of the expected counts are less than 5 and all individual expected counts are 1 or greater", according to Yates, Moore, and McCabe (1999, p. 734). The sample met the two assumptions of randomness and independence (i.e., one observation per subject) underlying non-parametric techniques (Pallant, 2009).

Firstly, a chi-square test of goodness-of-fit was used to investigate potential differences between mood profiles according to gender. The overall sample consisted of an unequal distribution of males and females, being 51.6% and 48.4%, respectively. As can be seen in the bar chart and frequencies cross tabulations (Figure 3.12 and Table 3.16), the distributions were significantly different from expected values, $\chi^2(5, N = 2{,}364) = 25.48$, $p < .001$, suggesting an association between gender and cluster.

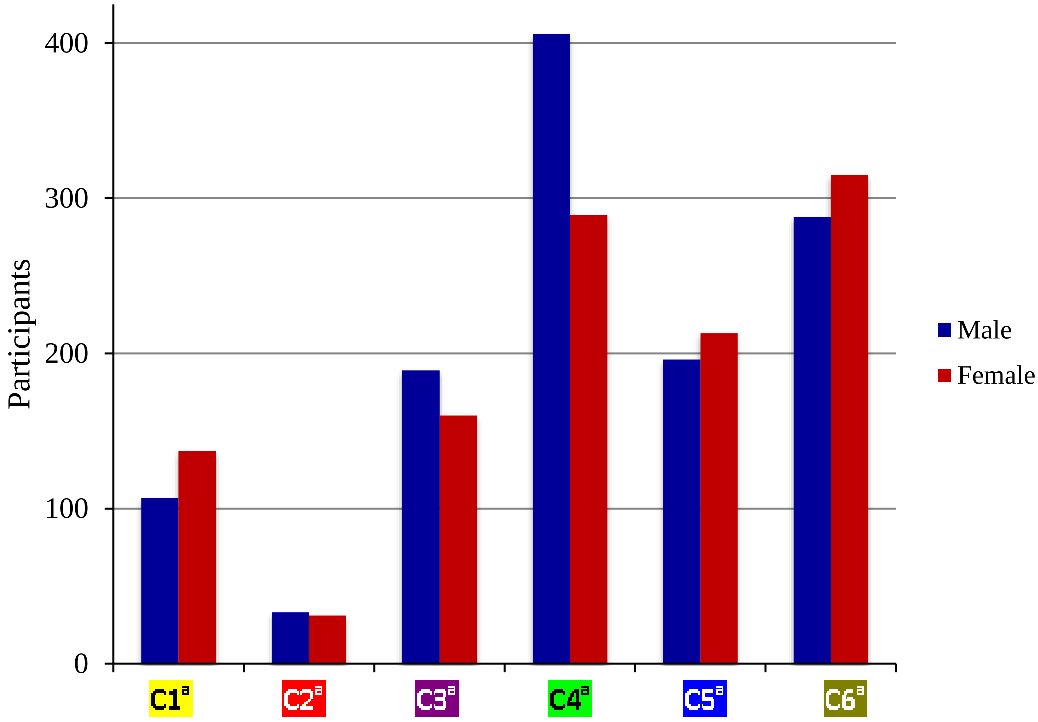


Figure 3.12. Distribution of gender across clusters (*N* = 2,364). Overall number of participants according to gender: male (*n* = 1,219), female (*n* = 1,145). C1[a] (*n* = 244) = inverse iceberg profile, C2[a] (*n* = 64) = inverse Everest profile, C3[a] (*n* = 349) = surface profile, C4[a] (*n* = 695) = iceberg profile, C5[a] (*n* = 409) = shark fin profile, and C6[a] (*n* = 603) = submerged profile.

Table 3.16

Crosstabulations of Clusters C1[a] to C6[a] by Gender (N = 2,364)

Gender	C1[a] (*n* = 244)	C2[a] (*n* = 64)	C3[a] (*n* = 349)	C4[a] (*n* = 695)	C5[a] (*n* = 409)	C6[a] (*n* = 603)
Male						
Actual	107	33	189	406	196	288
Expected	126	33	180	358	211	311
Female						
Actual	137	31	160	289	213	315
Expected	118	31	169	336	198	292

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
Male (*n* = 1,219), Female (*n* = 1,145). Expected frequencies are rounded to whole numbers.

To determine the magnitude of differences between the actual and expected counts within each cell, the over- and under-representations for each cluster were calculated in terms of percentages. The percentage of increase between the actual and expected frequencies were computed using the standard formula represented in Equation 1.

$$x - y = z / y * 100 \quad (1)$$

Where x represents the actual frequency, y represents the expected frequency, and z represents the difference. The percentage of decrease between the actual and expected frequencies were computed using the standard formula represented in Equation 2.

$$x - y = z / x * 100 \quad (2)$$

Where x represents the expected frequency, y represents the actual frequency, and z represents the difference (all over- and under-representations for actual/expected counts were calculated using Equation 1 and Equation 2 hereafter).

The distribution of gender within the inverse iceberg profile ($C1^a$) included: male = 43.9% and female = 56.1%. $C1^a$ had an over-representation of females by 16.1% and an under-representation of males by 15.1%. The distribution of gender within the inverse Everest profile ($C2^a$) included: male = 51.6% and female = 48.4%. $C2^a$ had a gender split that matched the chi-square expected count. The distribution of gender within the surface profile ($C3^a$) included: male = 54.2% and female = 45.8%. $C3^a$ had an over-representation of males by 5.0% and an under-representation of females by 5.3%. The distribution of gender within the iceberg profile ($C4^a$) included: male = 58.4% and female = 41.6%. $C4^a$ had an over-representation of males by 13.4% and an under-representation of females by 14.0%. The distribution of gender within the shark fin profile ($C5^a$) included: male = 47.9%

and female = 52.1%. C5[a] had an over-representation of females by 7.6% and an under-representation of males by 7.1%. The distribution of gender within the submerged profile (C6[a]) included: male = 48.4% and female = 51.6%. C6[a] had an over-representation of females by 7.9% and an underrepresentation of males by 7.4%. Table 3.17 lists the within gender percentages according to each cluster.

Table 3.17

Cluster Membership According to Within Gender Percentage (N = 2,364)

Gender	**C1[a]** (*n* = 244)	**C2[a]** (*n* = 64)	**C3[a]** (*n* = 349)	**C4[a]** (*n* = 695)	**C5[a]** (*n* = 409)	**C6[a]** (*n* = 603)
Male	8.8%	2.7%	15.5%	33.3%	16.1%	23.6%
Female	12.0%	2.7%	14.0%	25.2%	18.6%	27.5%

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
Male (*n* = 1,219), Female (*n* = 1,145).

A *post hoc* review of the adjusted residuals identified which groups made the largest contributions to the significant chi-square result (refer to Table 3.18). In line with Field (2009), the adjusted residuals were assessed against the critical values of ±1.96, ±2.58, and ±3.29 all adjusted residuals are compared with these critical values hereafter indicating a significant difference from zero at $p < .05$, $p < .01$, and $p < .001$, respectively. The gender split within the iceberg profile (C4[a]) was found to have made the highest contribution, with adjusted residuals of 4.3 = $p < .001$ (males) and –4.3 = $p < .001$ (females). The inverse iceberg (C1[a]) and submerged (C6[a]) profiles both shared a similar contribution, being –2.5 = $p < .05$ (males) and 2.5 = $p < .05$ (females), and –2.2 = $p < .05$ (males) and 2.2 = $p < .05$ (females), respectively. No relationship was found between gender and cluster for the inverse Everest (C2[a]), surface (C3[a]), and shark fin profiles (C5[a]).

Table 3.18

Standardised and Adjusted Residuals for Gender (N = 2,364)

Gender	**C1[a]** (n = 244)	**C2[a]** (n = 64)	**C3[a]** (n = 349)	**C4[a]** (n = 695)	**C5[a]** (n = 409)	**C6[a]** (n = 603)
Male						
Std	–1.7	0.0	0.7	2.5	–1.0	–1.3
Adj	–2.5*	0.0	1.0	4.3***	–1.6	–2.2*
Female						
Std	1.7	0.0	–0.7	–2.6	1.1	1.3
Adj	2.5*	0.0	–1.0	–4.3***	1.6	2.2*

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
Male (n = 1,219), Female (n = 1,145).
* $p < .05$, ** $p < .01$, *** $p < .001$.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the inverse iceberg (C1[a]), inverse Everest (C2[a]), surface (C3[a]), iceberg (C4[a]), shark fin (C5[a]), and submerged (C6[a]) mood profiles according to differential age groupings. Figure 3.13 and Table 3.19 illustrate that the frequencies were significantly different from expected values, $\chi^2(25, N = 2,364) = 78.30$, $p < .001$, suggesting an association between age and cluster.

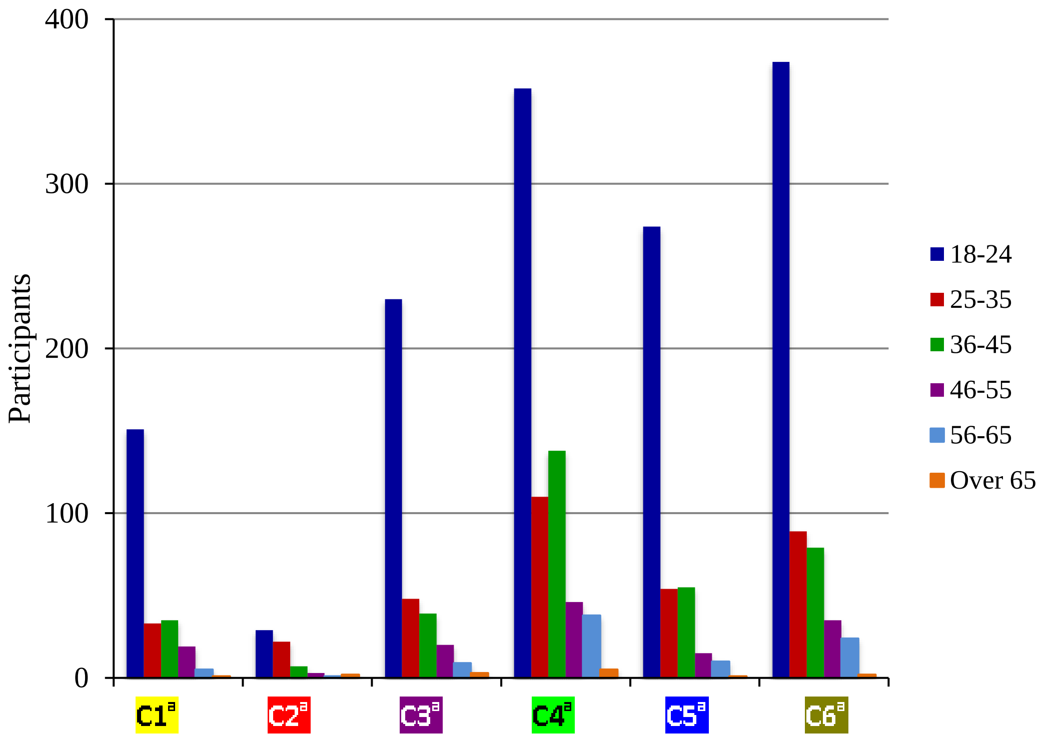


Figure 3.13. Distribution of age across clusters (N = 2,364). Overall number of participants according to age grouping: 18–24 (n = 1,416), 25–35 (n = 356), 36–45 (n = 353), 46–55 (n = 138), 56–65 (n = 87), 65+ (n = 14). C1[a] (n = 244) = inverse iceberg profile, C2[a] (n = 64) = inverse Everest profile, C3[a] (n = 349) = surface profile, C4[a] (n = 695) = iceberg profile, C5[a] (n = 409) = shark fin profile, and C6[a] (n = 603) = submerged profile.

Table 3.19

Crosstabulations of Clusters C1ᵃ to C6ᵃ by Age Grouping (N = 2,364)

Age	**C1**[a] (*n* = 244)	**C2**[a] (*n* = 64)	**C3**[a] (*n* = 349)	**C4**[a] (*n* = 695)	**C5**[a] (*n* = 409)	**C6**[a] (*n* = 603)
18–24						
Actual	151	29	230	358	274	374
Expected	146	38	209	416	245	361
25–35						
Actual	33	22	48	110	54	89
Expected	37	10	53	105	62	91
36–45						
Actual	35	7	39	138	55	79
Expected	36	10	52	104	61	90
46–55						
Actual	19	3	20	46	15	35
Expected	14	4	20	41	24	35
56–65						
Actual	5	1	9	38	10	24
Expected	9	2	13	26	15	22
65+						
Actual	1	2	3	5	1	2
Expected	1	0	2	4	2	4

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
18–24 (*n* = 1,416), 25–35 (*n* = 356), 36–45 (*n* = 353), 46–55 (*n* = 138), 56–65 (*n* = 87), 65+ (*n* = 14).
Expected frequencies are rounded to whole numbers.

The distribution of age within the inverse iceberg profile (C1[a]) included: 18–24 = 61.9%, 25–35 = 13.5%, 36–45 = 14.3%, 46–55 = 4.7%, 56–65 = 2.0%, and 65+ = 0.4%. C1[a] had an over-representation of the 18–24 and 46–55 age groups by 3.4% and 35.7%, respectively, and an under-representation of the 25–35, 36–45, and 56–65 age groups by 10.8%, 2.8%, and 44.5%, respectively, while the 65+ age group matched the chi-square expected count. The distribution of age within the inverse Everest profile (C2[a]) included: 18–24 = 45.3%, 25–35 = 34.2%, 36–45 = 10.9%, 46–

55 = 4.7%, 56–65 = 1.6%, and 65+ = 0.1%. C2[a] had an over-representation of the 25–35 and 65+ age groups by 120.0% and 200.0%, respectively, and an under-representation of the 18–24, 36–45, 46–55, and 56–65 age groups by 23.7%, 30.0%, 25.0%, and 50.0%, respectively. The distribution of age within the surface profile (C3[a]) included: 18–24 = 45.3%, 25–35 = 34.2%, 36–45 = 10.9%, 46–55 = 4.7%, 56–65 = 1.6%, and 65+ = 0.1%. C3[a] had an over-representation of the 18–24 and 65+ age groups by 10.0% and 50.0%, respectively, and an under-representation of the 25–35, 36–45, and 56–65 age groups by 9.4%, 25.0%, and 30.8%, respectively, while the 46–55 age group matched the chi-square expected count.

Further, the distribution of age within the iceberg profile (C4[a]) included: 18–24 = 51.5%, 25–35 = 15.8%, 36–45 = 19.9%, 46–55 = 6.6%, 56–65 = 5.5%, and 65+ = 0.7%. C4[a] had an over-representation of the 25–35, 36–45, 46–55, 56–65, and 65+ age groups by 4.8%, 32.7%, 12.2%, 46.2%, and 25.0%, respectively, and an under-representation of the 18–24 age group by 13.9%. The distribution of age within the shark fin profile (C5[a]) included: 18–24 = 67.0%, 25–35 = 13.2%, 36–45 = 13.4%, 46–55 = 3.7%, 56–65 = 2.4%, and 65+ = 0.2%. C5[a] had an over-representation of the 18–24 age group by 11.8%, and an under-representation of the 25–35, 36–45, 46–55, 56–65, and 65+ age groups by 12.9%, 9.8%, 37.5%, 33.4%, and 50.0%, respectively. The distribution of age within the submerged profile (C6[a]) included: 18–24 = 62.0%, 25–35 = 14.8%, 36–45 = 13.1%, 46–55 = 5.8%, 56–65 = 4.0%, 65+ = 0.3%. C6[a] had an over-representation of the 18–24 and 56–65 age groups by 3.6% and 9.1%, respectively, and an under-representation of the 25–35, 36–45, and 65+ age groups by 2.2%, 12.3%, and 50.0%, respectively, while the 46–55 age group matched the chi-square expected count.

Although the overall significant chi-square result indicated a relationship between age and mood profile, the underlying assumption concerning cell counts was violated. Eight of the 36 expected cell counts (i.e., 22.3%) were < 5. These expected frequencies appeared to be an artefact of sample sizes for the inverse Everest profile (C2[a], n = 64) and the 65+ age group (n = 14), meaning that the over- and under-representations should be considered with caution given that the small sample sizes may not adequately represent the underlying population. Consequently, only significant adjusted residuals corresponding with expected cell counts of ≥ 5 were considered separately hereafter. Table 3.20 lists the within age grouping percentages according to each cluster.

Table 3.20

Cluster Membership According to Within Age Group Percentage (N = 2,364)

Age	**C1[a]** (n = 244)	**C2[a]** (n = 64)	**C3[a]** (n = 349)	**C4[a]** (n = 695)	**C5[a]** (n = 409)	**C6[a]** (n = 603)
18–24	10.7%	2.0%	16.2%	25.3%	19.4%	26.4%
25–35	9.3%	6.2%	13.5%	30.9%	15.2%	25.0%
36–45	9.9%	2.0%	11.0%	39.1%	15.6%	22.4%
46–55	13.8%	2.2%	14.5%	33.3%	10.9%	25.4%
56–65	5.7%	1.1%	10.3%	43.7%	11.5%	27.6%
65+	7.1%	14.3%	21.4%	35.7%	7.1%	14.3%

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
18–24 (n = 1,416), 25–35 (n = 356), 36–45 (n = 353), 46–55 (n = 138), 56–65 (n = 87), 65+ (n = 14).

Following a *post hoc* review of the adjusted residuals, the inverse Everest (C2[a]), surface (C3[a]), iceberg (C4[a]), and shark fin (C5[a]) profiles were found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for C2[a] were –2.4 = p < .05 (18–24 group), and 4.4 = p < .001 (25–35 group). The significant adjusted residuals for C3[a] were 2.5 = p < .05 (18–24 group) and –2.1 = p < .05 (36–45 group). The significant adjusted residuals for C4[a] were –5.4 = p < .001 (18–24 group), 4.3 = p < .001 (36–45 group), and 3.0 = p < .01 (56–65 group). Finally, the significant adjusted residuals for C5[a] were 3.2 = $p < .01$ (18–24 group), and –2.1 = $p < .05$ (46–55 group). No relationship was found between age and cluster for the inverse iceberg (C1[a]) and submerged (C6[a]) profiles. Table 3.21 lists the standardised and adjusted residuals for each cluster solution.

Table 3.21

Standardised and Adjusted Residuals for Age Grouping (N = 2,364)

Age	C1[a] (*n* = 244)	C2[a] (*n* = 64)	C3[a] (*n* = 349)	C4[a] (*n* = 695)	C5[a] (*n* = 409)	C6[a] (*n* = 603)
18–24						
Std	0.4	–1.5	1.4	–2.9	1.9	0.7
Adj	0.7	–2.4*	2.5*	–5.4***	3.2**	1.2
25–35						
Std	–0.6	4.0	–0.6	0.5	–1.0	–0.2
Adj	–0.7	4.4***	–0.7	0.7	–1.2	–0.2
36–45						
Std	–0.2	–0.8	–1.8	3.4	–0.8	–1.2
Adj	–0.3	–0.9	–2.1*	4.3***	–0.9	–1.5
46–55						
Std	1.3	-	–0.1	0.9	–1.8	0.0
Adj	1.4	-	–0.1	1.0	–2.1*	0.0
56–65						
Std	–1.3	-	–1.1	2.5	–1.3	0.4
Adj	–1.4	-	–1.2	3.0**	–1.5	0.5
65+						
Std	-	-	-	-	-	-
Adj	-	-	-	-	-	-

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
18–24 (*n* = 1,416), 25–35 (*n* = 356), 36–45 (*n* = 353), 46–55 (*n* = 138), 56–65 (*n* = 87), 65+ (*n* = 14).
* $p < .05$, ** $p < .01$, *** $p < .001$.
- denotes uninterpretable data.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the inverse iceberg (C1[a]), inverse Everest (C2[a]), surface (C3[a]), iceberg (C4[a]), shark fin (C5[a]), and submerged (C6[a]) mood profiles according to level of education. Figure 3.14 and Table 3.22 both illustrate that the frequencies were significantly different from expected values, $\chi^2(15, N = 2{,}364) = 41.86$, $p < .001$, suggesting an association between level of education and cluster.

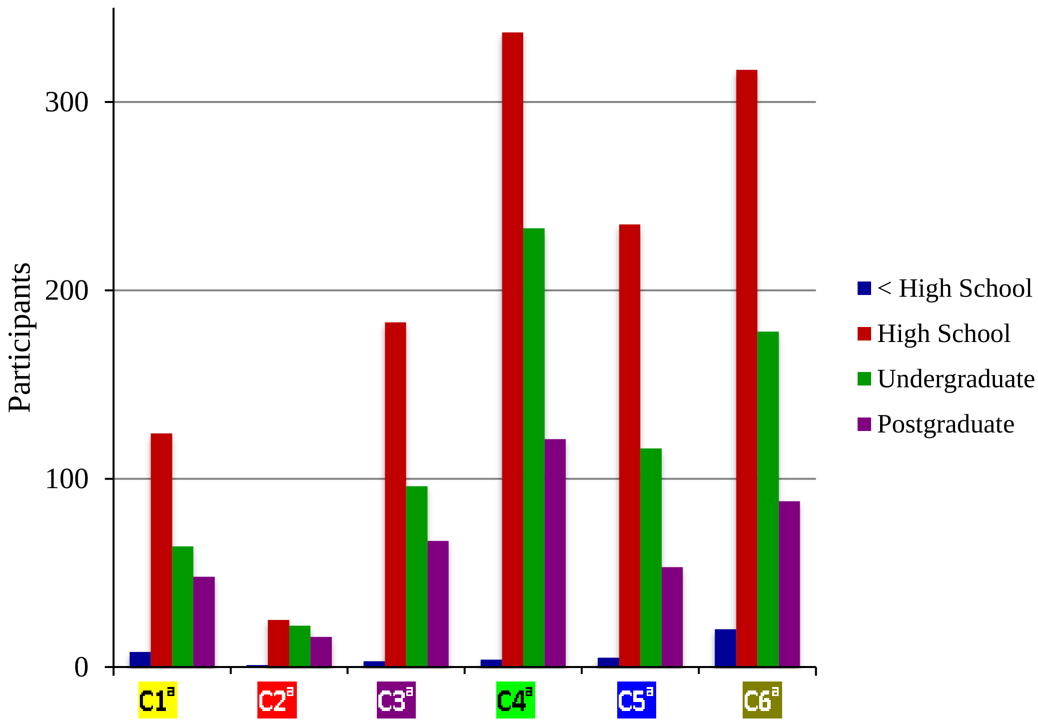


Figure 3.14. Distribution of education across clusters (N = 2,364). Overall number of participants according to level of education: < high school (n = 41), high school (n = 1,221), undergraduate (n = 709), postgraduate (n = 393). C1[a] (n = 244) = inverse iceberg profile, C2[a] (n = 64) = inverse Everest profile, C3[a] (n = 349) = surface profile, C4[a] (n = 695) = iceberg profile, C5[a] (n = 409) = shark fin profile, and C6[a] (n = 603) = submerged profile.

Table 3.22

Crosstabulations of Clusters C1^a to C6^a by Level of Education (N = 2,364)

Education	C1[a] (*n* = 244)	C2[a] (*n* = 64)	C3[a] (*n* = 349)	C4[a] (*n* = 695)	C5[a] (*n* = 409)	C6[a] (*n* = 603)
< High School						
Actual	8	1	3	4	5	20
Expected	4	1	6	12	7	11
High School						
Actual	124	25	183	337	235	317
Expected	126	33	180	359	211	311
Undergraduate						
Actual	64	22	96	233	116	178
Expected	73	19	105	208	123	181
Postgraduate						
Actual	48	16	67	121	53	88
Expected	41	11	58	116	68	100

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
< High School (*n* = 41), High School (*n* = 1,221), Undergraduate (*n* = 709), Postgraduate (*n* = 393).
Expected frequencies are rounded to whole numbers.

The distribution of education within the inverse iceberg profile (C1[a]) included: < high school = 3.3%, high school = 50.8%, undergraduate = 26.2%, and postgraduate = 19.7%. C1[a] had an over-representation of those with a < high school and postgraduate level of education by 50.0% and 17.1%, respectively, and an under-representation of those with a high school and undergraduate level of education by 1.6% and 12.3%, respectively. The distribution of education within the inverse Everest profile (C2[a]) included: < high school = 1.6%, high school = 39.1%, undergraduate = 34.4%, and postgraduate = 25.0%. C2[a] had an over-representation of those with an undergraduate and postgraduate level of education by 15.8% and 45.5%, respectively, and an under-representation of those with a high school level of education by 24.2%, while those with a < high school level of education matched the chi-square expected count. The distribution of education within the surface profile ($C3^a$) included: < high school = 0.9%, high school = 52.4%, undergraduate = 27.5%, and postgraduate = 19.2%. $C3^a$ had an over-representation of those with a high school and postgraduate level of education by 1.7% and 15.5%, respectively, and an under-representation of those with a < high school and undergraduate level of education by 50.0% and 8.6%, respectively.

Further, the distribution of education within the iceberg profile ($C4^a$) included: < high school = 0.6%, high school = 48.5%, undergraduate = 33.5%, and postgraduate = 17.4%. $C4^a$ had an over-representation of those with an undergraduate and postgraduate level of education by 12.0% and 4.3%, respectively, and an under-representation of those with a < high school and high school level of education by 66.7% and 6.1%, respectively. The distribution of education within the shark fin profile ($C5^a$) included: < high school = 1.2%, high school= 57.5%, undergraduate = 28.4%, and postgraduate = 13.0%. $C5^a$ had an over-representation of those with a high school level of education by 11.4%, and an under-representation of those with a < high school, undergraduate, and postgraduate level of education by 28.6%, 5.7%, and 22.1%, respectively. The distribution of education within the submerged profile ($C6^a$) included: < high school = 3.3%, high school = 52.6%, undergraduate = 29.5%, and postgraduate = 14.6%. $C6^a$ had an over-representation of those with a < high school and high school level of education by 81.1% and 1.9%, respectively, and an under-representation of those with an undergraduate and postgraduate level of education by 1.7% and 12.0%, respectively.

The overall significant chi-square result indicated a relationship between level of education and mood profile. In this case, 2 of the 24 expected cell counts were < 5 (i.e., 8.4%) and none of the expected counts were < 1, suggesting the integrity of the test remained sound. Unfortunately once again the small expected frequencies appeared to be an artefact of sample size for the inverse iceberg (C1[a], n = 244) and inverse Everest (C2[a], n = 64) profiles, as well as the < high school (n = 41) level of education group. Consequently the affected over- and under-representations for these groupings should be considered with caution. Table 3.23 lists the within level of education grouping percentages according to each cluster.

Table 3.23

Cluster Membership According to Within Education Group Percentage (N = 2,364)

Education	**C1[a]** (n = 244)	**C2[a]** (n = 64)	**C3[a]** (n = 349)	**C4[a]** (n = 695)	**C5[a]** (n = 409)	**C6[a]** (n = 603)
< High School	19.5%	2.4%	7.3%	9.8%	12.2%	48.8%
High School	10.2%	2.0%	15.0%	27.6%	19.2%	26.0%
Undergraduate	9.0%	3.1%	13.5%	32.9%	16.4%	25.1%
Postgraduate	12.2%	4.1%	17.0%	30.8%	13.5%	22.4%

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
< High School (n = 41), High School (n = 1,221), Undergraduate (n = 709), Postgraduate (n = 393).

A *post hoc* review of the adjusted residuals was conducted to identify which groups made the largest contributions to the significant chi-square result. The inverse Everest (C2[a]), iceberg (C4[a]), shark fin (C5[a]), and submerged (C6[a]) profiles were each found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for C2[a] were –2.0 = p < .05 (high school). The significant adjusted residuals for C4[a] were –2.8 = p < .05 (< high school), –2.0 = p < .05 (high school), and 2.4 = p < .05 (undergraduate). The significant adjusted residuals for C5[a] were 2.6 = p < .05 (high school) and –2.2 = p < .05 (postgraduate). Finally, the significant adjusted residuals for C6[a] were 3.4 = p < .001 (< high school). No relationship was found between level of education and cluster for the inverse iceberg (C1[a]) and surface (C3[a]) profiles. Table 3.24 lists the standardised and adjusted residuals for each cluster solution.

Table 3.24

Standardised and Adjusted Residuals for Level of Education (N = 2,364)

Education	C1[a] (*n* = 244)	C2[a] (*n* = 64)	C3[a] (*n* = 349)	C4[a] (*n* = 695)	C5[a] (*n* = 409)	C6[a] (*n* = 603)
< High School						
Std	-	-	–1.2	–2.3	–0.8	3.0
Adj	-	-	–1.4	–2.8**	–0.9	3.4***
High School						
Std	–0.2	–1.4	0.2	–1.2	1.6	0.3
Adj	–0.3	–2.0*	0.3	–2.0*	2.6**	0.5
Undergraduate						
Std	–1.1	0.6	–0.8	1.7	–0.6	–0.2
Adj	–1.4	0.8	–1.1	2.4*	–0.8	–0.3
Postgraduate						
Std	1.2	1.6	1.2	0.5	–1.8	–1.2
Adj	1.4	1.8	1.4	0.7	–2.2*	–1.6

Note. C1[a] = inverse iceberg profile, C2[a] = inverse Everest profile, C3[a] = surface profile, C4[a] = iceberg profile, C5[a] = shark fin profile, C6[a] = submerged profile.
< High School (*n* = 41), High School (*n* = 1,221), Undergraduate (*n* = 709), Postgraduate (*n* = 393).
* $p < .05$, ** $p < .01$, *** $p < .001$.
- denotes uninterpretable data.

3.4 Summary

The mood responses of 2,364 participants were analysed using a two-step clustering procedure. An agglomerative, hierarchical cluster analysis together with a Ward’s clustering algorithm was used to explore the Lim (2011) dataset for distinct mood profiles not previously identified. The inverse scree plot, agglomeration schedule, and fragmentation of cluster groupings each converged upon a six-cluster solution. Following this, a k-means iterative technique using random seeds was used to further refine the final group parameters. The hierarchical and k-means analyses both produced clusters that were corresponding highly correlated, being evidence that the clusters were satisfactorily dissimilar from one another and robust across differential methodologies. The mood profiles identified were termed the inverse iceberg (C1[a]), inverse Everest (C2[a]), surface (C3[a]), iceberg (C4[a]), shark fin (C5[a]), and submerged (C6[a]) profiles. A MANOVA showed significant differences between clusters on each dimension of mood, and a DFA indicated that cluster membership could be correctly classified with a high degree of accuracy (ranging from 82.8% to 100%).

The inverse iceberg profile was characterised by a low level of vigour (0.43 *SD* below *M* = 50.00), together with high levels of tension, depression, anger, fatigue, and confusion (0.67, 1.39, 0.98, 1.08, and 1.32 *SD* above *M* = 50.00, respectively). The inverse Everest profile was characterised by a low level of vigour (0.75 *SD* below *M* = 50.00), together with high levels of tension and fatigue (1.77 and 1.88 *SD* above *M* = 50.00), as well as very high levels of depression, anger, and confusion (3.72, 2.91, and 3.04 *SD* above *M* = 50.00, respectively). The surface profile was characterised by slightly above average levels of each mood dimension, being tension, depression, anger, vigour, fatigue, and confusion (0.19, 0.07, 0.23, 0.35, 0.15, and 0.42 *SD* above *M* = 50.00, respectively). The iceberg profile was characterised by a high level of vigour (0.73 *SD* above *M* = 50.00), together with low levels of tension, depression, anger, fatigue, and confusion (0.72, 0.50, 0.37, 0.43, and 0.52 *SD* below *M* = 50.00, respectively). The shark fin profile was characterised by below average levels of tension, depression, anger, vigour, and confusion (0.56, 0.10, 0.20, 0.89, 0.25 *SD* below *M* = 50.00, respectively) together with a high level of fatigue (1.42 *SD* above *M* = 50.00). Finally, the submerged profile was characterised by slightly below average levels of each mood dimension, being tension, depression, anger, vigour, fatigue, and confusion (0.68, 0.37, 0.35, 0.75, 0.30, and 0.40 *SD* below *M* = 50.00, respectively).

A series of chi-square tests of goodness-of-fit indicated that gender, age, and level of education were unequally distributed across clusters (relative to the sample size and demographic groupings). More specifically, an estimated equal number of males and females experienced the inverse Everest, surface, and shark fin profiles. Males were more likely to experience the iceberg profile, while females were more likely to experience the inverse iceberg and submerged profiles compared with males.

Additionally, an estimated equal number of individuals across all age groups experienced the inverse iceberg and submerged profiles. Those aged 18–24 were more likely to experience the shark fin and surface profiles, and less likely to experience the iceberg, and inverse Everest profiles. Those aged 25–35 were more likely to experience the inverse Everest profile, while those aged 36–45 were more likely to experience the iceberg profile, and less likely to experience the surface profile. Those aged 46–55 were less likely to experience the shark fin profile, while those aged 56–65 were more likely to experience the iceberg profile. Although those aged over 65 were more likely to experience the inverse Everest profile compared with each of the other five mood profiles, these general trends should be considered with caution given the violation of the underlying assumption regarding minimum cell counts.

Further, an estimated equal number of individuals across all levels of education experienced the surface profile. Those with a less than high school level of education were more likely to experience the inverse iceberg and submerged profiles, and less likely to experience the iceberg profile. However, the findings relating to the inverse iceberg profile were ultimately deemed uninterpretable due to small sample sizes. Those with a high school level of education were more likely to experience the shark fin profile, and less likely to experience both the inverse Everest and iceberg profiles. Those with an undergraduate level of education were more likely to experience the iceberg profile, while those with a postgraduate level of education were less likely to experience the shark fin mood profile.

Overall, the hierarchical and k-means cluster analysis techniques both produced clusters that pooled a very large proportion of shared variance. Additionally, the multivariate cluster structures were found to be functionally independent and theoretically meaningful.

CHAPTER 4:
Replication of Mood Profiles: Sample B

A second sample from the *In The Mood* website (i.e., Sample B) was used to replicate the findings of Sample A. Again, cluster analytic methodology was used to potentially identify clusters of mood responses in the general population. A multiple DFA and MANOVA were used to provide support for the accuracy of the final cluster solution, and a series of chi-squared tests for goodness-of-fit were used to describe the demographic characteristics of the mood profiles (i.e., gender, age, and level of education).

4.1 Method

4.1.1 Participants. Adult participants (i.e., aged 18 or above) were again recruited from the general population through the *In The Mood* website. There were no other exclusion criteria. Although the website was not actively promoted, the previously used snowballing technique in the Lim (2011) study yielded a large number of responses during the data collection period from October 31, 2011 to October 31, 2013. The initial sample comprised 79.5% males and 18.1% females. A large majority (68.3%) were aged 18–24, and approximately half of the population reported an ‘Undergraduate’ level of education (52.2%). Additionally, more than half (68.5%) of the sample selected an occupation listed as ‘Education’, and 61.9% identified as being Asian ethnicity. Among reasons for completing the BRUMS, a large proportion (59.2%) reported ‘Preparing for a sport competition’.

4.1.2 Measures. The online version of the BRUMS on the *In The Mood* website was again used to measure mood with the standard response timeframe of ‘How do you feel right now?’

4.1.3 Procedure. The research was conducted under the previous Human Research Ethics Committee Approval No., H13REA169. Again, all analyses were performed using IBM SPSS Software Version 22.0 (2013).

4.2 Results

A total of 6,763 cases were screened for missing values, abnormal and unusual responses. No missing values were detected. However, 163 cases of nil values were identified, and subsequently deleted. A visual inspection of the dataset was undertaken, and abnormalities were detected. It became apparent that the website was being used by other researchers to collect large amounts of data. These individuals appeared to have specific and unknowable agendas. This is not surprising given that *In The Mood* provides both raw scores and normative data, meaning that the added work of physically transforming scores for data analysis is eliminated. A subsample of 3,731 were identified as sharing an unusually high number of commonalities. These respondents all reported being ‘Male’, ‘Asian’, listed ‘Education’ as their vocation, and gave ‘Preparing for a Sporting Competition’ as their reason for completing the BRUMS. Additionally, these responses were logged in large blocks with consecutive case identification (ID) numbers (e.g., 4,689 to 5,067, and 5,128 to 5,740).

A group of 6 scored 12 on each dimension of mood (i.e., case ID number 8,830 to 8,835), and a group of 40 scored 4 on each dimension (i.e., case ID number 8,635 to 8,674), while 10 participants scored 1 on fatigue only (i.e., case ID 8,607 to 8,616). While these patterns of responses would not usually draw attention, the consecutive numeric order of these groups, and an unusually high number of similarities between participants suggested that these individuals were involved in other research projects. For example, for the group of 6, each of the participants listed being ‘Male’, aged ‘18–24’, a ‘Postgraduate’, involved in ‘Business, Administration, and Sales’, ‘Caucasian’, and ‘Wanting to Help with Research’, while the group of 40 were all ‘Male’, ‘25–35’, completed a ‘High School Certificate’, involved with ‘Architecture, Building and Planning’, ‘African’, and ‘Preparing for an examination’. Finally, 10 participants were all listed as ‘Male’, aged ‘25–35’, with a ‘High school’ level of education, involved in ‘Business, Administration and Sales, ‘African’, and completed the BRUMS for ‘Other’ reasons. Each of these groups of respondents were deleted, although any similar data with non-consecutive case ID numbers were retained given the potential likelihood of a genuinely valid response.

A subsample of 13 scored 16 on each dimension of mood, and 36 cases scored 0 for each dimension (suggesting these individuals did not feel anything at all). Further, 5 cases were also identified as abnormal responses. The case ID numbers from 2,561 to 2,565 suggested someone was exploring the site and purposefully eliciting different mood profiles by scoring 16 in one dimension alone, and 0 in each of the other 5 dimensions. Each of the above mentioned cases were deleted as they were judged to constitute invalid data. Additionally, 456 participants listing Asian as their ethnicity were also deleted given that Lim (2011) previously found a difference in subscale means compared to the normative data. Consequently, these data were investigated in a separate study which identified significant differences in the Asian male athletic population (see Mitchelson, 2014).

A check for multivariate outliers was conducted according to the statistical recommendations of Tabachnick and Fidell (2013). Using Mahalanobis distance, 48 outliers were found to exceed the critical value of 22.46. The presence of extreme values was not unexpected in a sample of this size, and should not be considered problematic according to Meyers, Gamst, and Guarino (2006), so all cases were retained. The final sample of online BRUMS respondents was 2,303 (i.e., Sample B). Scores ranged from 0–16 on each of the BRUMS subscales (i.e., tension, depression, anger, vigour, fatigue, and confusion). A complete summary of the demographic composition is presented in Table 4.1.

Table 4.1

Demographic Characteristics of the BRUMS Respondents (N = 2,303)

Dependent Variable	*n*	%
Gender		
Male	1,288	55.9
Female	1,015	44.1
Age Group		
18–24	1,491	64.7
25–35	420	18.2
36–45	201	8.7
46–55	120	5.2
56–65	54	2.3
65+	17	0.7
Education		
< High School Certificate	204	8.9
High School Certificate	745	32.3
Undergraduate	896	38.9
Postgraduate	458	19.8
Occupation		
Agricultural, Animal & Primary Industries	10	0.4
Architecture, Building & Planning	20	0.9
Art, Design, Music & Entertainment	49	2.1
Business, Administration & Sales	111	4.8
Chemicals, Plastics, Rubber, etc.	7	0.3
Computer & Information Services	26	1.1
Education	709	30.8
Engineering & Technical	25	1.1

(Table 4.1 continues)

(Table 4.1 continued)

Dependent Variable	*n*	%
Occupation		
Food Processing	9	0.4
Furniture & Wood Products	2	0.1
General Retail	37	1.6
Health & Community Services	239	10.4
Hospitality & Tourism	11	0.5
Law, Security & Defence	21	0.9
Literature & Social Services	9	0.4
Metal, Electrical & Automotive	5	0.2
Natural Sciences & Mathematics	66	2.9
Printing & Paper	4	0.2
Textiles, Clothing & Footwear	15	0.7
Transport & Storage	10	0.4
Other	917	39.8
Ethnicity		
African	137	5.9
Asian	0	0.0
Caucasian	1,628	70.7
Indigenous	19	0.8
Middle Eastern	68	3.0
Other	451	19.6
Reason for Completing BRUMS		
General Interest	706	30.7
Not Feeling my Normal Self	65	2.8
Preparing for a Presentation	132	5.7
Preparing for a Sales Pitch	18	0.8
Preparing for a Sport Competition	221	9.6
Preparing for an Examination	79	3.4
Wanting to Help with Research	514	22.3
Other	568	24.7

4.2.1 Parametric data screening. A visual inspection of the P-P plots and histograms of the raw scores for the BRUMS subscales indicated that the frequency distribution for vigour was approximately symmetrical, with a leptokurtic shape. The scores for tension, depression, anger, fatigue, and confusion deviated from the diagonal on the P-P plots, suggesting a positive skew for each mood dimension. The shape of these frequency distributions were approximately unimodal, skewed to the left, with some outliers identified for tension, depression, anger, and confusion. As expected, deviations from normal were present: tension (skewness = 1.385, kurtosis = 1.657), depression (skewness = 2.020, kurtosis = 4.171), anger (skewness = 1.865, kurtosis = 3.534), vigour (skewness = –0.029, kurtosis = –0.586), fatigue (skewness = 0.647, kurtosis = –.165), and confusion (skewness = 1.495, kurtosis = 2.220).

Due to the large sample size, skewness and kurtosis values were not transformed into *z* scores and compared with critical values, and given the sensitivity of the Kolmogorov-Smirnov and Shapiro-Wilk tests to large *N* samples (Field, 2009), the significance of the skewness and kurtosis values were not quantified. Additionally, square-root transformations were not considered due to Glass, Peckham, and Sanders' (1972) conclusion that "the payoff of normalising transformations in terms of more valid probability statements is low, and they are seldom considered to be worth the effort" (p. 241). Despite obvious deviations from normal distributions for at least five of the six BRUMS subscales, no further parametric data screening was undertaken given that skewness and kurtosis are not considered problematic according to Tabachnick and Fidell (2013). Additionally, departures from normal are unlikely to make a substantive difference to the analyses in a sample of this size (Tabachnick & Fidell, 2013). The means, standard deviations, and 95% CI's for each mood dimension are provided in Table 4.2.

Table 4.2

Descriptive Statistics of the BRUMS Subscales (N = 2,303)

Mood Dimension	*M*	*SD*	95% CI
Tension	47.24	8.52	[46.89, 47.59]
Depression	51.85	11.83	[51.37, 52.33]
Anger	52.15	10.28	[51.73, 52.57]
Vigour	49.44	9.26	[49.06, 49.82]
Fatigue	52.64	9.42	[52.26, 53.03]
Confusion	51.72	10.66	[51.29, 52.16]

4.2.2 K-means cluster analysis. K-means clustering using random aggregation centres with a prescribed six-cluster solution was used to replicate the previous findings in Sample A. The mean *t* scores of the final cluster centroids according to each mood dimension are presented in Table 4.3. A graphical representation superimposing the six mood profiles can be found in Figure 4.1.

Table 4.3

Cluster Centroids of the Six-cluster Solution (N = 2,303)

Mood Dimension	C1[b] (*n* = 83)	C2[b] (*n* = 586)	C3[b] (*n* = 686)	C4[b] (*n* = 346)	C5[b] (*n* = 318)	C6[b] (*n* = 284)
Tension	66.76	42.91	42.33	51.72	45.22	59.16
Depression	89.53	47.26	45.22	52.10	50.09	67.97
Anger	81.71	47.26	47.24	54.49	50.15	64.87
Vigour	42.71	42.51	57.13	55.66	42.59	47.25
Fatigue	67.59	49.21	45.11	51.11	65.11	61.45
Confusion	80.67	46.55	45.27	55.77	50.39	66.09

Note. [b] denotes clusters found within Sample B.

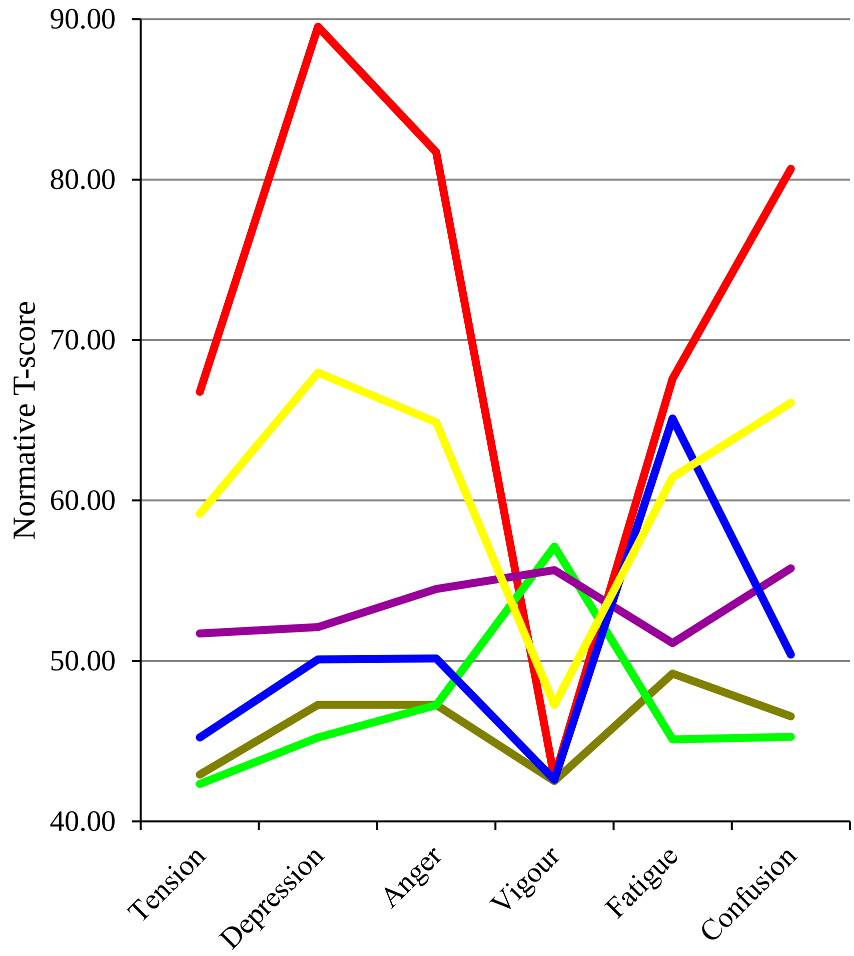


Figure 4.1. Graphical representation of the six-cluster solution (N = 2,303): **C1^b** (n = 83) = inverse Everest profile, **C2^b** (n = 586) = submerged profile, **C3^b** (n = 686) = iceberg profile, **C4^b** (n = 346) = surface profile, **C5^b** (n = 318) = shark fin profile, and **C6^b** (n = 284) = inverse iceberg profile.

4.2.3 Independence of clusters C1^b to C6^b. A between-groups MANOVA was performed to investigate whether the groups identified via the k-means cluster analysis differed to one another according to a combination of variables. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .033, F(30, 2,303) = 409.28, p < .001, partial η^2 = .493, observed power = 1.00. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for each dimension of mood: tension, F(5, 2,297) = 830.52, p

$< .001$, partial $\eta^2 = .644$, observed power = 1.00; depression, $F(5, 2{,}297) = 1{,}264.19$, $p < .001$, partial $\eta^2 = .733$, observed power = 1.00; anger, $F(5, 2{,}297) = 760.55$, $p < .001$, partial $\eta^2 = .623$, observed power = 1.00; vigour, $F(5, 2{,}297) = 491.87$, $p < .001$, partial $\eta^2 = .517$, observed power = 1.00; fatigue, $F(5, 2{,}297) = 941.02$, $p < .001$, partial $\eta^2 = .672$, observed power = 1.00; and confusion, $F(5, 2{,}297) = 986.79$, $p < .001$, partial $\eta^2 = .682$, observed power = 1.00.

An examination of the mean scores for each dependent variable (see Table 4.4) revealed that the magnitude of tension varied significantly between each cluster excluding $C2^b$ (*M* = 42.91, *SD* = 3.71, 95% CI [42.61, 43.21]) and $C3^b$ (*M* = 42.33, *SD* = 3.28, 95% CI [42.08, 42.57]), which were found to be at a similar level. The magnitude of depression was also found to vary significantly between each cluster, as did the magnitude of anger, excluding $C2^b$ (*M* = 47.26, *SD* = 4.02, 95% CI [46.93, 47.58]) and $C3^b$ (*M* = 47.24, *SD* = 4.68, 95% CI [46.89, 47.59]), which were again found to be at a similar level. The magnitude of vigour was found to vary significantly between each cluster excluding $C1^b$ (*M* = 42.71, *SD* = 10.52, 95% CI [40.41, 45.01]) and $C2^b$ (*M* = 42.51, *SD* = 5.17, 95% CI [42.09, 42.93]); as well as $C1^b$ (*M* = 42.71, *SD* = 10.52, 95% CI [40.41, 45.01]) and $C5^b$ (*M* = 42.59, *SD* = 7.44, 95% CI [41.77, 43.41]), which were found to be at a similar level, while the magnitude of fatigue and confusion were both found to vary significantly between each cluster.

Table 4.4

Descriptive Statistics of the Six-cluster Solution (N = 2,303)

Mood Dimension	C1[b] (*n* = 83)			C2[b] (*n* = 586)			C3[b] (*n* = 686)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	66.76	9.75	[64.63, 68.89]	42.91	3.71	[42.61, 43.21]	42.33	3.28	[42.08, 42.57]
Depression	89.53	10.30	[87.28, 91.78]	47.26	5.41	[46.82, 47.70]	45.22	2.85	[45.01, 45.44]
Anger	81.71	11.18	[79.27, 84.15]	47.26	4.02	[46.93, 47.58]	47.24	4.68	[46.89, 47.59]
Vigour	42.71	10.52	[40.41, 45.01]	42.51	5.17	[42.09, 42.93]	57.13	5.41	[56.72, 57.53]
Fatigue	67.59	7.54	[65.94, 69.24]	49.21	4.79	[48.82, 49.60]	45.11	4.66	[44.76, 45.46]
Confusion	80.76	10.00	[78.49, 82.86]	46.55	4.89	[46.16, 46.95]	45.27	3.61	[45.00, 45.54]
Mood Dimension	C4[b] (*n* = 346)			C5[b] (*n* = 318)			C6[b] (*n* = 284)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	51.72	6.44	[51.04, 52.40]	45.22	5.06	[44.67, 45.78]	59.16	7.01	[58.34, 59.98]
Depression	52.10	6.84	[51.37, 52.82]	50.09	6.57	[49.37, 50.82]	67.97	9.57	[66.85, 69.09]
Anger	54.49	7.59	[53.68, 55.29]	50.15	6.77	[49.40, 50.90]	64.87	8.83	[63.84, 65.90]
Vigour	55.66	6.59	[54.97, 56.36]	42.59	7.44	[41.77, 43.41]	47.25	8.01	[46.31, 48.18]
Fatigue	51.11	5.12	[50.57, 51.65]	65.11	5.88	[64.46, 65.76]	61.45	7.15	[60.62, 62.29]
Confusion	55.77	7.37	[54.99, 56.55]	50.39	6.92	[49.62, 51.15]	66.09	7.97	[65.16, 67.02]

Note. C1[b] = inverse Everest profile, C2[b] = submerged profile, C3[b] = iceberg profile, C4[b] = surface profile, C5[b] = shark fin profile, C6[b] = inverse iceberg profile.

A *post hoc* simultaneous DFA was once again calculated. The sample was drawn randomly from the population, so the groups were considered a valid estimate of the population proportions in each group. Therefore, the best estimates of actual group sizes and the prior probabilities were not equal values, but the sample proportions. The groups were defined according to the six-cluster solution identified via the k-means cluster analysis (i.e., $C1^b$ [n = 83] = inverse Everest profile, $C2^b$ [n = 586] = submerged profile, $C3^b$ [n = 686] = iceberg profile, $C4^b$ [n = 346] = surface profile, $C5^b$ [n = 318] = shark fin profile, and $C6^b$ [n = 284] = inverse iceberg profile). The ratio of cases to independent variables was 384 to 1, which satisfied the preferred requirement of ≥ 20 to 1. The number of cases in the smallest group was 83, being larger than the number of independent variables (i.e., 6), and thus exceeded the preferred number of cases (i.e., ≥ 20) per group. The maximum number of possible discriminant functions was five, being number of groups minus one.

The five canonical discriminant functions extracted accounted for 100% of the variance, and each function was able to predict an outcome at a significant level. As can be seen in Table 4.5, discriminant function 1 (DF^{1b}) accounted for R^2 = 86.86% of the between-group variance, Wilks' Λ = .033, $\chi^2(30, N = 2{,}303)$ = 7,803.74, $p < .001$. Discriminant function 2 (DF^{2b}) accounted for R^2 = 60.84% of the between-group variance, Wilks' Λ = .254, $\chi^2(20, N = 2{,}303)$ = 3,145.05, $p < .001$. Discriminant function 3 (DF^{3b}) accounted for R^2 = 28.20% of the between-group variance, Wilks' Λ = .650, $\chi^2(12, N = 2{,}303)$ = 988.83, $p < .001$. Discriminant function 4 (DF^{4b}) accounted for R^2 = 9.00% of the between-group variance, Wilks' Λ = .906, $\chi^2(6, N = 2{,}303)$ = 227.01, $p < .001$. Discriminant function 5 (DF^{5b}) accounted for R^2 = 0.42% of the between-group variance, Wilks' Λ = .996, $\chi^2(2, N = 2{,}303)$ = 9.79, $p < .01$. The significance of the Wilks' lambda in the maximum number of discriminant functions supported the interpretation of a solution using five discriminant functions. Table 4.6 shows the group centroids (vector of means) on the five new canonical variables formed by applying the discriminant function weights.

Table 4.5

Eigenvalues for the Discriminant Function (N = 2,303)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
DF^{1b}	6.607	76.3	76.3	.932
DF^{2b}	1.558	18.0	94.3	.780
DF^{3b}	0.393	4.5	98.8	.531
DF^{4b}	0.099	1.1	100.0	.300
DF^{5b}	0.004	0.0	100.0	.065

Note. ^{b} denotes canonical discriminant functions created using Sample B.

Table 4.6

Functions at Group Centroids (N = 2,303)

	Function				
Cluster	DF^{1b}	DF^{2b}	DF^{3b}	DF^{4b}	DF^{5b}
$C1^{b}$	8.420	0.834	–0.921	0.799	–0.172
$C2^{b}$	–1.312	–0.927	–0.874	–0.128	–0.004
$C3^{b}$	–2.148	1.014	0.197	0.287	0.016
$C4^{b}$	0.489	1.211	0.421	–0.535	–0.075
$C5^{b}$	0.608	–2.355	0.967	0.114	–0.021
$C6^{b}$	4.161	0.381	0.003	–0.140	0.134

Note. $C1^{b}$ (*n* = 83) = inverse Everest profile, $C2^{b}$ (*n* = 586) = submerged profile, $C3^{b}$ (*n* = 686) = iceberg profile, $C4^{b}$ (*n* = 346) = surface profile, $C5^{b}$ (*n* = 318) = shark fin profile, $C6^{b}$ (*n* = 284) = inverse iceberg profile.

Based on the structure matrix, the mood dimensions strongly associated with DF^{1b} included high levels of depression, confusion, tension, anger, and fatigue. The predictor variables strongly associated with DF^{2b} included a high level of fatigue and low fatigue. The predictor variables strongly associated with DF^{3b} included a high level of vigour and fatigue, together with a low level of depression. The predictor variables strongly associated with DF^{4b} included low depression and high tension, while the predictor variables strongly associated with DF^{5b} included low levels of anger and confusion, and a high level of tension. The number and composition of the dimensions of discrimination between groups can be found in Table 4.7, and the unstandardised canonical coefficients are shown in Table 4.8.

Table 4.7

Structure Matrix (N = 2,303)

Mood Dimension	Function				
	DF^{1b}	DF^{2b}	DF^{3b}	DF^{4b}	DF^{5b}
Depression	.630*	.169	–.354	.593	.298
Confusion	.560*	.211	–.039	–.255	–.412
Vigour	–.139	.700*	.671	.187	–.052
Fatigue	.449	–.590	.659*	.110	.052
Tension	–.500	.270	.032	–.647*	.485
Anger	.487	.225	–.112	.220	–.521*

Note. * Largest absolute correlation between each variable and any discriminant function.

Table 4.8

Unstandardised Canonical Coefficients (N = 2,303)

Mood Dimension	Function				
	DF^{1b}	DF^{2b}	DF^{3b}	DF^{4b}	DF^{5b}
Tension	.194	.128	.012	–.353	.285
Depression	.252	.121	–.164	.467	.352
Anger	.178	.044	–.069	–.011	–.341
Vigour	–.047	.274	.258	.107	.030
Fatigue	.180	–.273	.306	.060	.023
Confusion	.210	.089	.003	–.145	–.329

The DFA found that cluster membership was correctly classified with a high degree of accuracy. The percentage of correct classifications were: inverse Everest profile = 91.6%, submerged profile = 96.4%, iceberg profile = 99.7%, surface profile = 85.0%, shark fin profile = 90.9%, and inverse iceberg profile = 96.1%. Prior probabilities from $C1^b$ to $C6^b$ inclusive were 3.6%, 25.4%, 29.8%, 15.0%, 13.8%, and 12.3% (respectively). The proportional by chance accuracy rate was computed (i.e., $0.036^2 + 0.254^2 + 0.298^2 + 0.150^2 + 0.138^2 + 0.123^2 = 0.211$). Additionally, when the discriminant functions were used to predict group membership, the hit ratio was very high. A total of 94.7% of the cases were correctly reclassified back into the original categories. This percentage was notably higher than the minimum classification accuracy rate of 46.1%. These findings suggest that the overlap of the overall distribution was small, and the function was a good discriminator between groups. Table 4.9 and Table 4.10 list the classification function coefficients and DFA classification results, respectively.

Table 4.9

Classification Function Coefficients (N = 2,303)

Mood Dimension	Cluster					
	$C1^b$	**$C2^b$**	**$C3^b$**	**$C4^b$**	**$C5^b$**	**$C6^b$**
Tension	1.938	0.203	0.161	0.964	0.324	1.484
Depression	3.442	0.393	0.441	0.677	0.509	1.830
Anger	1.793	–0.064	–0.212	0.290	0.091	0.859
Vigour	0.854	0.750	1.642	1.539	0.769	1.079
Fatigue	2.083	0.773	0.447	0.885	2.086	1.673
Confusion	2.358	0.235	0.169	0.890	0.488	1.461

Note. $C1^b$ (n = 83) = inverse Everest profile, $C2^b$ (n = 586) = submerged profile, $C3^b$ (n = 686) = iceberg profile, $C4^b$ (n = 346) = surface profile, $C5^b$ (n = 318) = shark fin profile, $C6^b$ (n = 284) = inverse iceberg profile.

Table 4.10

Classification of Results (N = 2,303)

	Predicted Group Membership						
Cluster	1	2	3	4	5	6	*n*
C1^b	80	0	0	0	0	3	83
C2^b	0	568	3	15	0	0	586
C3^b	0	3	676	4	3	0	686
C4^b	0	2	5	331	3	5	346
C5^b	0	1	0	2	314	1	318
C6^b	10	0	0	9	1	264	284

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.

4.2.4 Characteristics of clusters C1^b to C6^b. Figures 4.2 to Figure 4.7 inclusive present the graphical representations (using mean *t* scores) of the six clusters (i.e., C1^b, C2^b, C3^b, C4^b, C5^b, C6^b) derived from the K-means analysis.

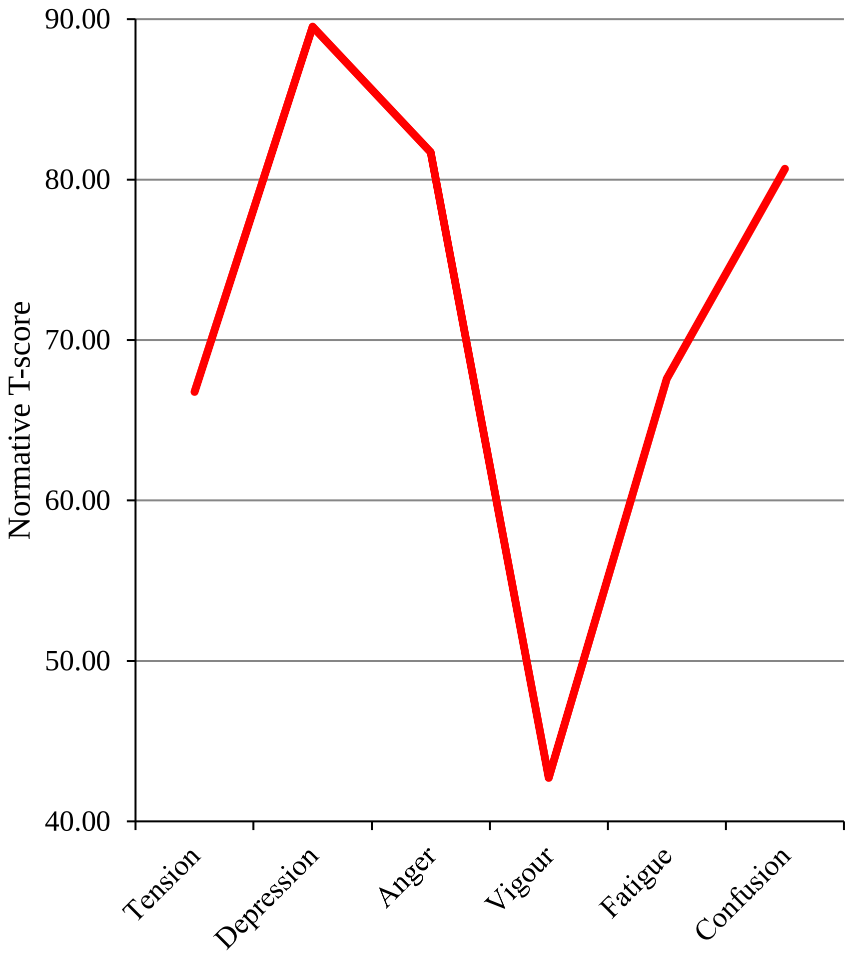


Figure 4.2. Graphical representation of C1^{b} (n = 83).

C1^{b} was identified as the inverse Everest profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 66.76, *SD* = 9.75, 95% CI [65.66, 67.85]; depression, *M* = 89.53, *SD* = 10.30, 95% CI [88.21, 90.86]; anger, *M* = 81.71, *SD* = 11.18, 95% CI [80.36, 83.07]; vigour, *M* = 42.71, *SD* = 10.52, 95% CI [41.32, 44.10]; fatigue, *M* = 67.59, *SD* = 7.54, 95% CI [66.42, 68.76]; and confusion, *M* = 80.67, *SD* = 10.00, 95% CI [79.38, 81.97].

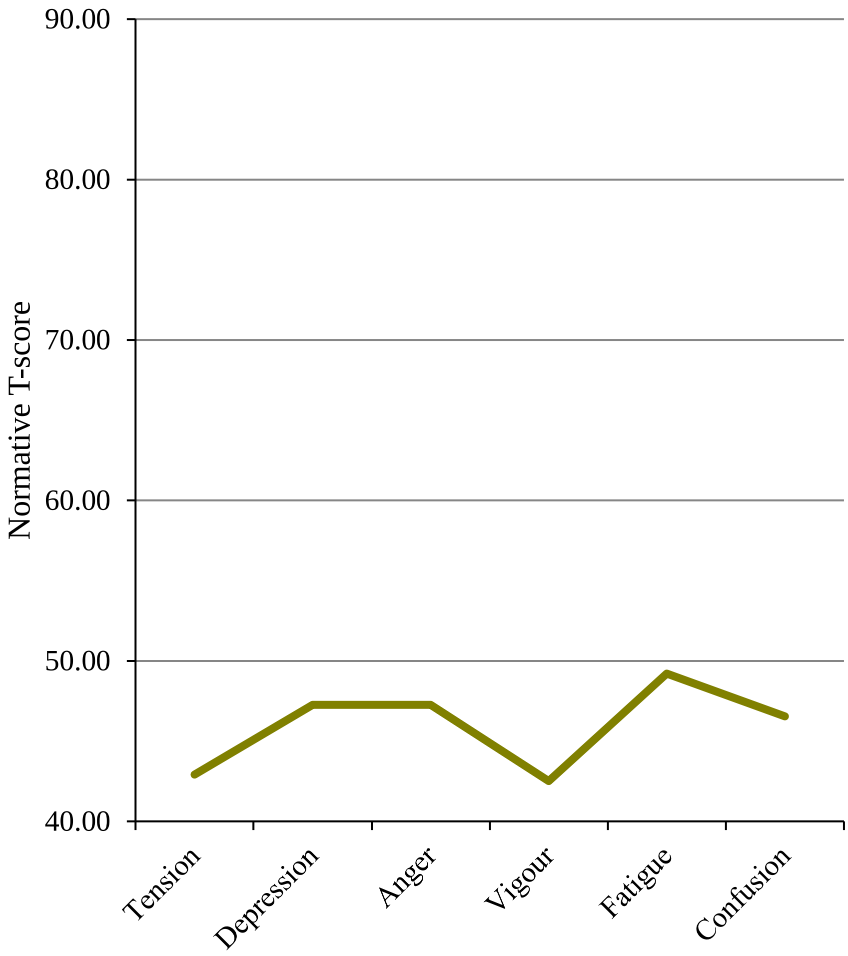


Figure 4.3. Graphical representation of C2^{b} (n = 586).

C2^{b} was identified as the submerged profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 42.91, SD = 3.71, 95% CI [42.50, 43.32]; depression, M = 47.26, SD = 5.41, 95% CI [46.76, 47.76]; anger, M = 47.26, SD = 4.02, 95% CI [46.75, 47.77]; vigour, M = 42.51, SD = 5.17, 95% CI [41.99, 43.03]; fatigue, M = 49.21, SD = 4.79, 95% CI [48.77, 49.65]; and confusion, M = 46.55, SD = 4.89, 95% CI [46.07, 47.04].

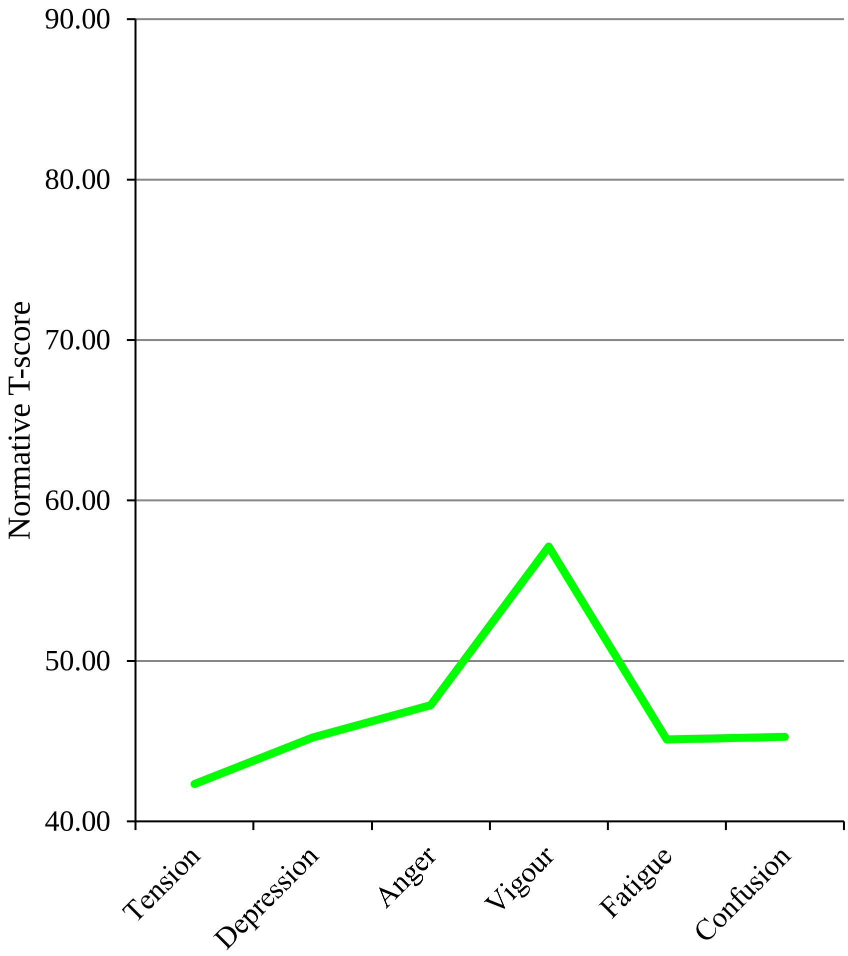


Figure 4.4. Graphical representation of **C3^b** (*n* = 686).

C3^b was identified as the iceberg profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 42.33, *SD* = 3.28, 95% CI [41.94, 42.71]; depression, *M* = 45.22, *SD* = 2.85, 95% CI [44.76, 45.68]; anger, *M* = 47.24, *SD* = 4.68, 95% CI [46.77, 47.71]; vigour, *M* = 57.13, *SD* = 5.41, 95% CI [56.65, 57.61; fatigue, *M* = 45.11, *SD* = 4.66, 95% CI [44.71, 45.52]; and confusion, *M* = 45.27, *SD* = 3.61, 95% CI [44.82, 45.72].

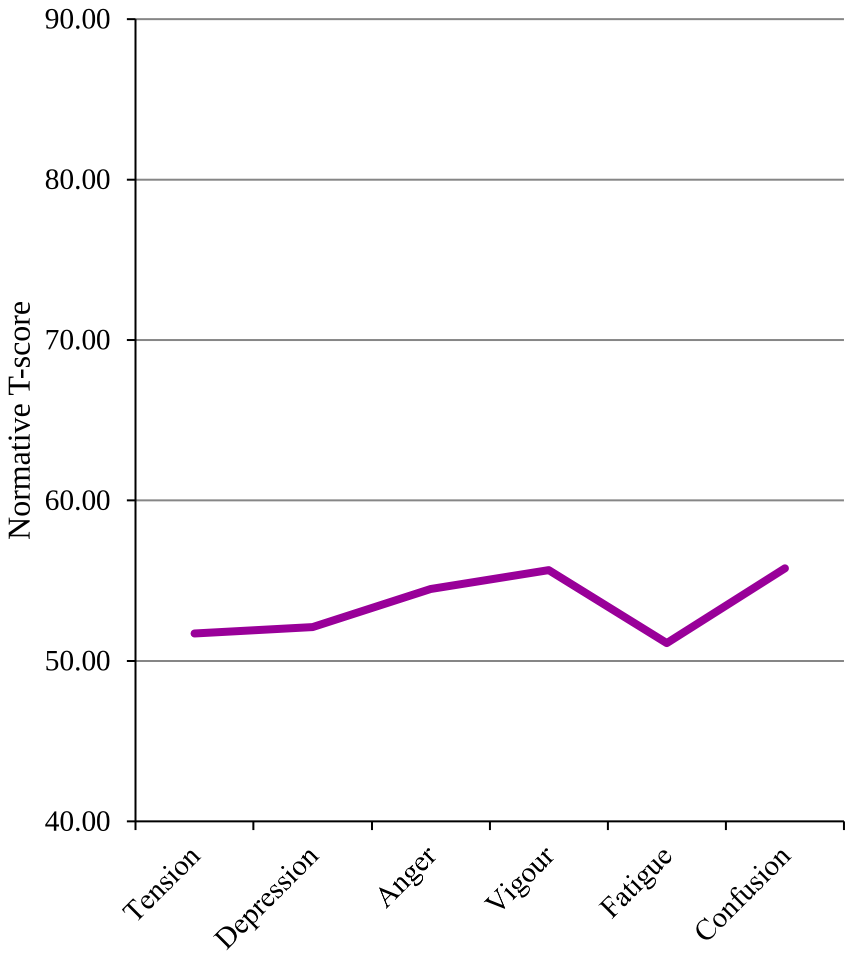


Figure 4.5. Graphical representation of C4^b (n = 346).

C4^b was identified as the surface profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 51.72, SD = 6.44, 95% CI [51.18, 52.25]; depression, M = 52.10, SD = 6.84, 95% CI [51.45, 52.74]; anger, M = 54.49, SD = 7.59, 95% CI [53.82, 55.15]; vigour, M = 55.66, SD = 6.59, 95% CI [54.98, 56.34]; fatigue, M = 51.11, SD = 5.12, 95% CI [50.54, 51.68]; and confusion, M = 55.77, SD = 7.37, 95% CI [55.14, 56.41].

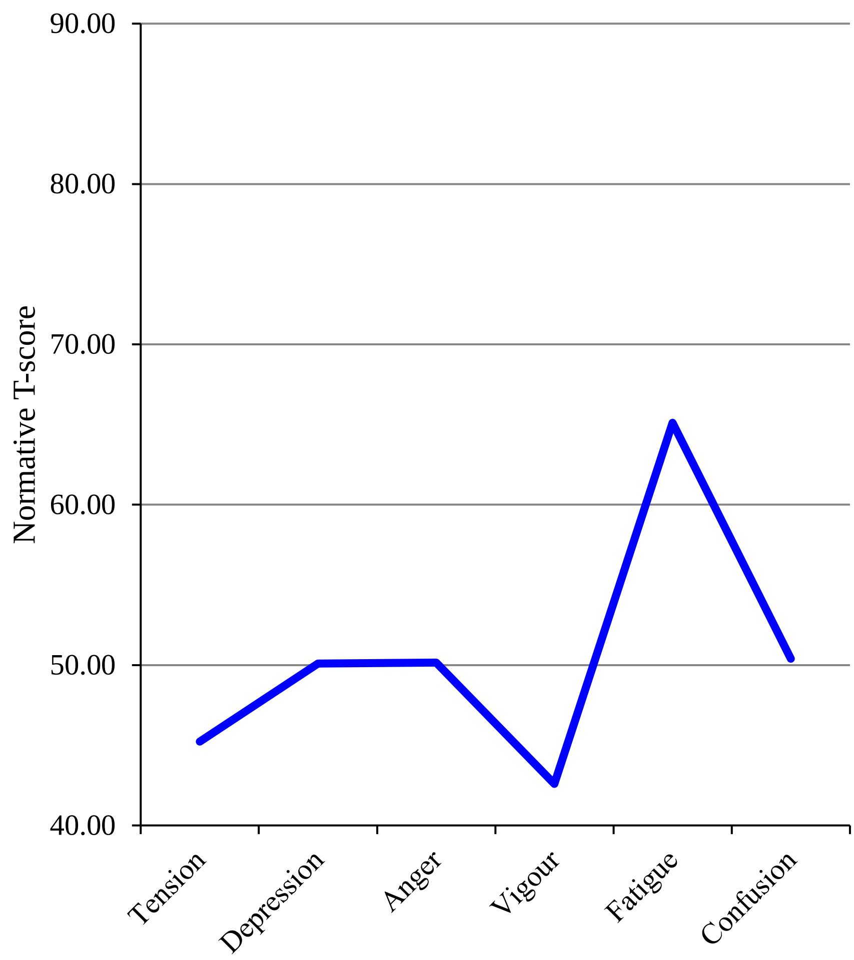


Figure 4.6. Graphical representation of C5^{b} (n = 318).

C5^{b} was identified as the shark fin profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 45.22, SD = 5.06, 95% CI [44.66, 45.78]; depression, M = 50.09, SD = 6.57, 95% CI [49.41, 50.77]; anger, M = 50.15, SD = 6.77, 95% CI [49.46, 50.84]; vigour, M = 42.59, SD = 7.44, 95% CI [41.88, 43.30]; fatigue, M = 65.11, SD = 5.88, 95% CI [64.51, 65.71]; and confusion, M = 50.39, SD = 6.92, 95% CI [49.73, 51.05].

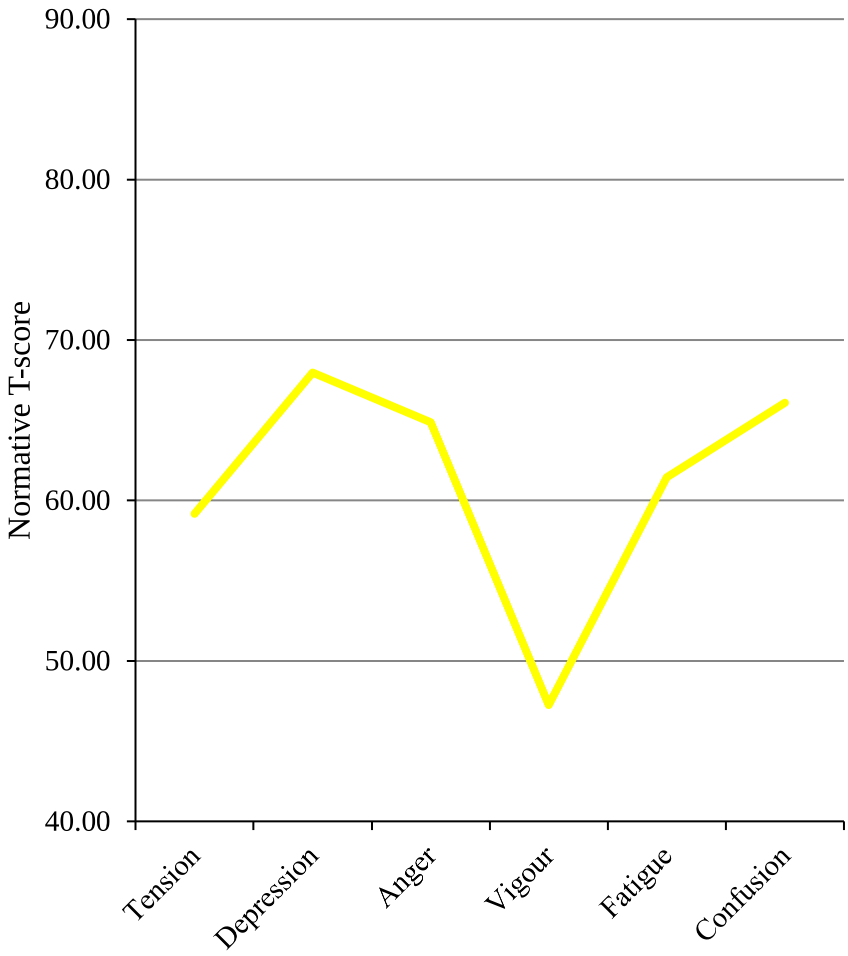


Figure 4.7. Graphical representation of **C6[b]** (*n* = 284).

C6[b] was identified as the inverse iceberg profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 59.16, *SD* = 7.01, 95% CI [58.57, 59.75]; depression, *M* = 67.97, *SD* = 9.57, 95% CI [67.25, 68.69]; anger, *M* = 64.87, *SD* = 8.83, 95% CI [64.14, 65.60]; vigour, *M* = 47.25, *SD* = 8.01, 95% CI [46.50, 48.00]; fatigue, *M* = 61.45, *SD* = 7.15, 95% CI [60.82, 62.09]; and confusion, *M* = 66.09, *SD* = 7.97, 95% CI [65.39, 66.79].

4.2.5 Demographics of clusters C1^b to C6^b. A chi-square test of goodness-of-fit was performed to determine whether the number of participants varied across the inverse Everest (C1^b), submerged (C2^b), iceberg (C3^b), surface (C4^b), shark fin (C5^b), and inverse iceberg (C6^b) mood profiles according to gender. The overall sample consisted of an unequal distribution of males and females, being 55.9% and 44.1%, respectively. As can be seen in the bar chart (refer to Figure 4.8) and frequencies cross tabulated in Table 4.11, the distributions were significantly different from expected values, $\chi^2(5, N = 2{,}303) = 30.80$, $p < .001$, suggesting an association between gender and cluster.

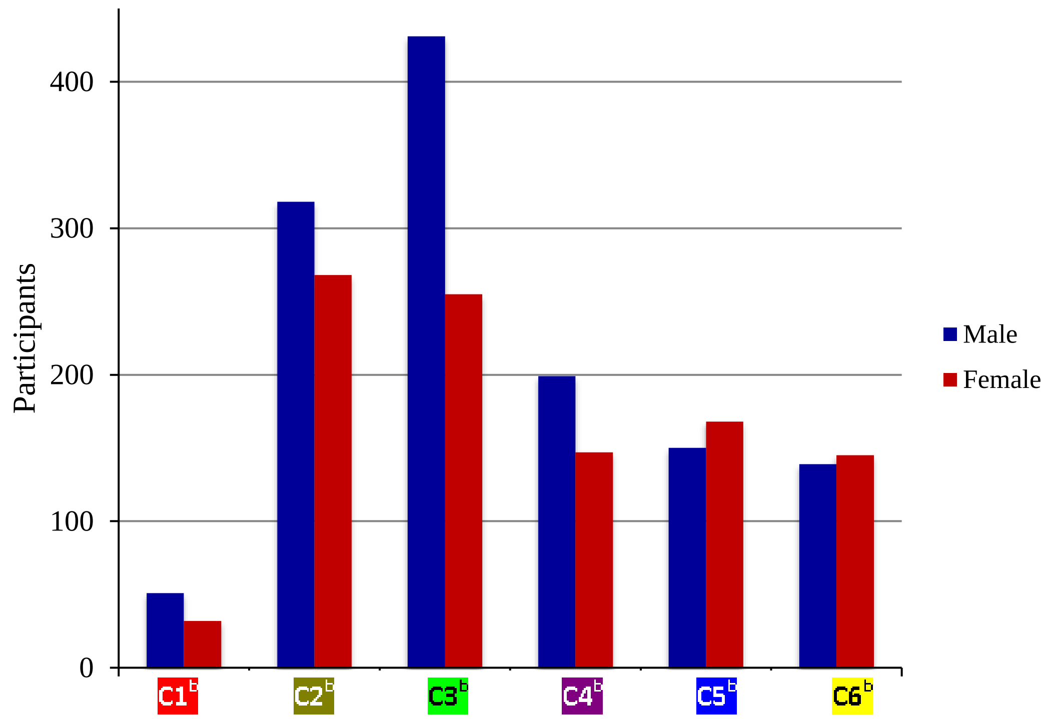


Figure 4.8. Distribution of gender across clusters (N = 2,303). Overall number of participants according to gender: male (n = 1,288), female (n = 1,015). C1^b (n = 83) = inverse Everest profile, C2^b (n = 586) = submerged profile, C3^b (n = 686) = iceberg profile, C4^b (n = 346) = surface profile, C5^b (n = 318) = shark fin profile, and C6^b (n = 284) = inverse iceberg profile.

Table 4.11

Crosstabulations of Clusters C1^b to C6^b by Gender (N = 2,303)

Gender	C1^b (*n* = 83)	C2^b (*n* = 586)	C3^b (*n* = 686)	C4^b (*n* = 346)	C5^b (*n* = 318)	C6^b (*n* = 284)
Male						
Actual	51	318	431	199	150	139
Expected	46	328	384	194	178	159
Female						
Actual	32	268	255	147	168	145
Expected	37	258	302	153	140	125

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
Male (*n* = 1,288), Female (*n* = 1,015).
Expected frequencies are rounded to whole numbers.

The distribution of gender within the inverse Everest profile (C1^b) included: male = 61.4% and female = 38.6%. C1^b had an over-representation of males by 10.9% and an under-representation of females by 13.5%. The distribution of gender within the submerged profile (C2^b) included: male = 54.3% and female = 45.7%. C2^b had an over-representation of females by 3.9% and an under-representation of males by 3.0%. The distribution of gender within the iceberg profile (C3^b) included: male = 62.8% and female = 37.2%. C3^b had an over-representation of males by 12.2% and an under-representation of females by 15.6%. The distribution of gender within the surface profile (C4^b) included: male = 57.5% and female = 42.5%. C4^b had an over-representation of males by 2.6% and an under-representation of females by 3.9%. The distribution of gender within the shark fin profile (C5^b) included: male = 47.2% and female = 52.8%. C5^b had an over-representation of females by 20.0% and an under-representation of males by 15.7%. The distribution of gender within the inverse iceberg profile (C6^b) included: male = 48.9% and female = 51.1%. C6^b had an over-representation of females by 16.0% and an under-representation of males by 12.6%. Table 4.12 lists the within gender percentages.

Table 4.12

Cluster Membership According to Within Gender Percentage (N = 2,303)

Gender	C1^b (*n* = 83)	C2^b (*n* = 586)	C3^b (*n* = 686)	C4^b (*n* = 346)	C5^b (*n* = 318)	C6^b (*n* = 284)
Male	4.0%	24.7%	33.5%	15.5%	11.6%	10.8%
Female	3.2%	26.4%	25.1%	14.5%	16.6%	14.3%

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
Male (*n* = 1,288), Female (*n* = 1,015).

Again, a *post hoc* review of the adjusted residuals identified which groups made the largest contributions to the significant chi-square result (refer to Table 4.13). The gender split within the iceberg profile (C3^b) was again found to have made the highest contribution, with adjusted residuals of 4.3 = $p < .001$ (males) and –4.3 = $p < .001$ (females). The shark fin (C5^b) and inverse iceberg (C6^b) profiles also contributed to the significant chi-square result with adjusted residuals of –3.4 = $p < .001$ (males) and 3.4 = $p < .001$ (females), and –2.5 = $p < .05$ (males) and 2.5 = $p < .05$ (females), respectively. Again, no relationship was found between gender and cluster for the inverse Everest (C1^b) and surface (C4^b) profiles. Additionally, no relationship was found for the submerged profile (C2^b).

Table 4.13

Standardised and Adjusted Residuals for Gender (N = 2,303)

Gender	C1b (n = 83)	C2b (n = 586)	C3b (n = 686)	C4b (n = 346)	C5b (n = 318)	C6b (n = 284)
Male						
Std	0.7	–0.5	2.4	0.4	–2.1	–1.6
Adj	1.0	–0.9	4.3***	0.6	–3.4***	–2.5*
Female						
Std	–0.8	0.6	–2.7	–0.4	2.4	1.8
Adj	–1.0	0.9	–4.3***	–0.6	3.4***	2.5*

Note. C1b = inverse Everest profile, C2b = submerged profile, C3b = iceberg profile, C4b = surface profile, C5b = shark fin profile, C6b = inverse iceberg profile.
Male (n = 1,288), Female (n = 1,015).
* $p < .05$, ** $p < .01$, *** $p < .001$.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the inverse Everest (C1b), submerged (C2b), iceberg (C3b), surface (C4b), shark fin (C5b), and inverse iceberg (C6b) mood profiles according to differential age groupings. Figure 4.9 and Table 4.14 both illustrate that the frequencies were significantly different from expected values, $\chi^2(25, N = 2{,}303) = 73.14$, $p < .001$, suggesting an association between age and cluster.

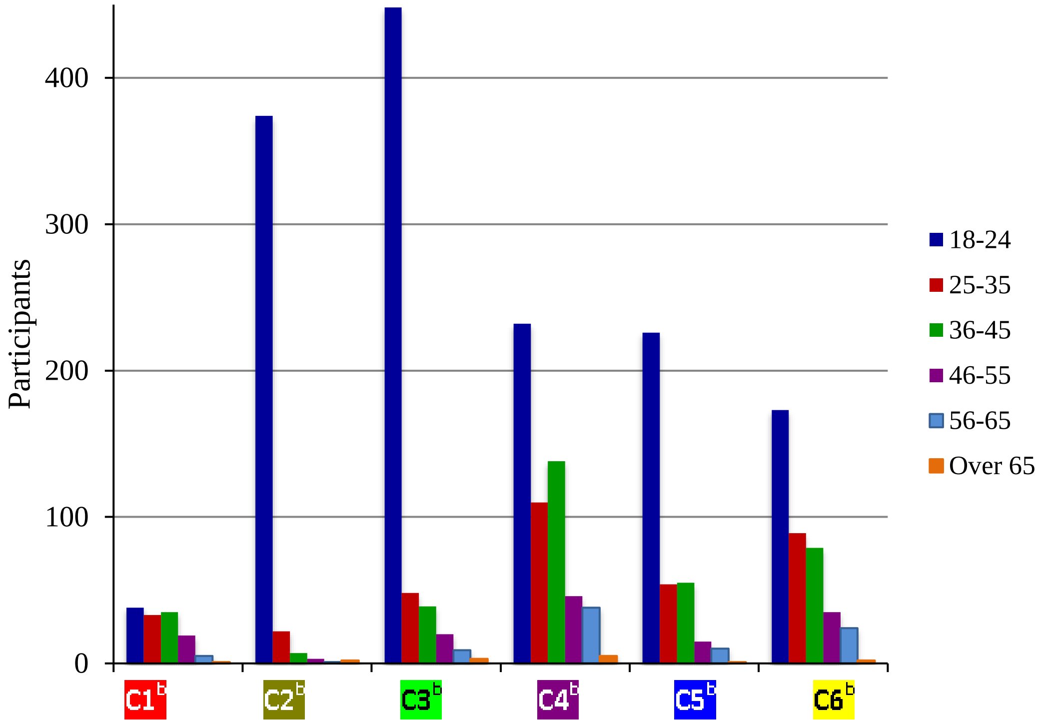


Figure 4.9. Distribution of age across clusters (*N* = 2,303). Overall number of participants according to age grouping: 18–24 (*n* = 1,491), 25–35 (*n* = 420), 36–45 (*n* = 201), 46–55 (*n* = 120), 56–65 (*n* = 54), over 65 (*n* = 17). $C1^b$ (*n* = 83) = inverse Everest profile, $C2^b$ (*n* = 586) = submerged profile, $C3^b$ (*n* = 686) = iceberg profile, $C4^b$ (*n* = 346) = surface profile, $C5^b$ (*n* = 318) = shark fin profile, and $C6^b$ (*n* = 284) = inverse iceberg profile.

Table 4.14

Crosstabulations of Clusters C1^b to C6^b by Age Grouping (N = 2,303)

Age	C1^b (*n* = 83)	C2^b (*n* = 586)	C3^b (*n* = 686)	C4^b (*n* = 346)	C5^b (*n* = 318)	C6^b (*n* = 284)
18–24						
Actual	38	374	448	232	226	173
Expected	54	379	444	224	206	183
25–35						
Actual	24	112	94	63	59	68
Expected	15	107	125	63	58	52
36–45						
Actual	10	61	67	26	22	15
Expected	7	51	60	30	28	25
46–55						
Actual	6	27	45	15	10	17
Expected	4	31	36	18	17	15
56–65						
Actual	2	8	23	10	1	10
Expected	2	14	16	8	8	7
65+						
Actual	3	4	9	0	0	1
Expected	1	4	5	3	2	2

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
18–24 (*n* = 1,491), 25–35 (*n* = 420), 36–45 (*n* = 201), 46–55 (*n* = 120), 56–65 (*n* = 54), 65+ (*n* = 17).
Expected frequencies are rounded to whole numbers.

The distribution of age within the inverse Everest profile (C1^b) included: 18–24 = 45.8%, 25–35 = 28.9%, 36–45 = 12.0%, 46–55 = 7.2%, 56–65 = 2.4%, and 65+ = 3.6%. C1^b had an over-representation of the 25–35, 36–45, 46–55, and 65+ age groups by 60.0%, 42.9%, 50.0%, and 200.0%, respectively, and an under-representation of the 18–24 age group by 29.6%, while the 56–65 age group matched the chi-square expected count. The distribution of age within the submerged profile (C2^b) included: 18–24 = 63.8%, 25–35 = 19.1%, 36–45 = 10.4%, 46–55 = 4.6%, 56–

65 = 1.4%, and 65+ = 0.7%. C2^{b} had an over-representation of the 25–35 and 36–45 age groups by 4.7% and 19.6%, respectively, and an under-representation of the 18–24, 46–55, and 56–65 age groups by 1.3%, 12.9%, 42.9%, respectively, while the 65+ age group matched the chi-square expected count. The distribution of age within the iceberg profile (C3^{b}) included: 18–24 = 65.3%, 25–35 = 13.7%, 36–45 = 9.8%, 46–55 = 6.6%, 56–65 = 3.4%, and 65+ = 1.3%. C3^{b} had an over-representation of the 18–24, 36–45, 46–55, 56–65, and 65+ age groups by 0.9%, 11.7%, 25.0%, 43.8%, and 80.0%, respectively, and an under-representation of the 25–35 age group by 24.8%.

Further, the distribution of age within the surface profile (C4^{b}) included: 18–24 = 67.1%, 25–35 = 18.2%, 36–45 = 7.5%, 46–55 = 4.3%, 56–65 = 2.9%, and 65+ = 0.0%. C4^{b} had an over-representation of the 18–24 and 56–65 age groups by 3.6% and 25.0%, respectively, and an under-representation of the 36–45, 46–55, and 65+ age groups by 13.4%, 16.7%, and 100.0%, respectively, while the 25–35 age group matched the chi-square expected count. The distribution of age within the shark fin profile (C5^{b}) included: 18–24 = 71.1%, 25–35 = 18.6%, 36–45 = 6.9%, 46–55 = 3.1%, 56–65 = 0.3%, and 65+ = 0.0%. C5^{b} had an over-representation of the 18–24 and 25–35 age group by 9.7% and 1.7%, respectively, and an under-representation of the 36–45, 46–55, 56–65, and 65+ age groups by 21.4%, 41.2%, 87.5%, and 100.0%, respectively. The distribution of age within the inverse iceberg profile (C6^{b}) included: 18–24 = 60.9%, 25–35 = 23.9%, 36–45 = 5.3%, 46–55 = 6.0%, 56–65 = 3.5%, and 65+ = 0.4%. C6^{b} had an over-representation of the 25–35, 46–55, and 56–65 age groups by 30.8%, 13.4%, and 42.9%, respectively, and an under-representation of the 18–24, 36–45, and 65+ age groups by 5.5%, 40.0%, and 50.0%, respectively.

The overall significant chi-square result indicated a relationship between age and mood profile. In this case 7 of the 36 expected cell counts were < 5 (i.e., 19.5%) and none of the expected counts were < 1, suggesting the integrity of the overall chi-square test remained sound. Once again these expected frequencies appeared to be an artefact of sample sizes for the inverse Everest profile ($C1^b$, $n = 83$) and the 65+ age group ($n = 17$), meaning that the subsequently affected over- and under-representations should be considered with caution. Table 4.15 lists the within age grouping percentages according to each cluster.

Table 4.15

Cluster Membership According to Within Age Group Percentage (N = 2,303)

Age	$C1^b$ ($n = 83$)	$C2^b$ ($n = 586$)	$C3^b$ ($n = 686$)	$C4^b$ ($n = 346$)	$C5^b$ ($n = 318$)	$C6^b$ ($n = 284$)
18–24	2.5%	25.1%	30.0%	15.6%	15.2%	11.6%
25–35	5.7%	26.7%	22.4%	15.0%	14.0%	16.2%
36–45	5.0%	30.3%	33.3%	12.9%	10.9%	7.5%
46–55	5.0%	22.5%	37.5%	12.5%	8.3%	14.2%
56–65	3.7%	14.8%	42.6%	18.5%	1.9%	18.5%
65+	17.6%	23.5%	52.9%	0.0%	0.0%	5.9%

Note. $C1^b$ = inverse Everest profile, $C2^b$ = submerged profile, $C3^b$ = iceberg profile, $C4^b$ = surface profile, $C5^b$ = shark fin profile, $C6^b$ = inverse iceberg profile.
18–24 (n = 1,491), 25–35 (n = 420), 36–45 (n = 201), 46–55 (n = 120), 56–65 (n = 54), 65+ (n = 17).

Following a *post hoc* review of the adjusted residuals, the inverse Everest ($C1^b$), iceberg ($C3^b$), shark fin ($C5^b$), and inverse iceberg ($C6^b$) profiles were each found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for $C1^b$ were –3.7 = $p < .001$ (18–24 group) and 2.6 = $p < .01$ (25–35 group). The significant adjusted residuals for $C3^b$ were –3.7 = $p < .001$ (25–35 group) and 2.1 = $p < .05$ (65+ group). The significant adjusted residuals for $C5^b$ were 2.5 = $p < .05$ (18–24 group) and –2.6 = $p < .01$ (56–65 group). Finally, the significant adjusted residuals for $C6^b$ were 2.7 = $p < .01$ (25–35 group) and –2.2 = p

< .05 (36–45 group). Again, no relationship was found between age and cluster for the submerged (C2^b) profile. Additionally, no relationship was found for the surface profile (C4^b). Table 4.16 lists the standardised and adjusted residuals for each cluster solution.

Table 4.16

Standardised and Adjusted Residuals for Age Grouping (N = 2,303)

Age	C1^b (*n* = 83)	C2^b (*n* = 586)	C3^b (*n* = 686)	C4^b (*n* = 346)	C5^b (*n* = 318)	C6^b (*n* = 284)
18–24						
Std	–2.1	–0.3	0.2	0.5	1.4	–0.8
Adj	–3.7***	–0.5	0.4	1.0	2.5*	–1.4
25–35						
Std	2.3	0.5	–2.8	0.0	0.1	2.3
Adj	2.6**	0.6	–3.7***	0.0	0.2	2.7**
36–45						
Std	1.0	1.4	0.9	–0.8	–1.1	–2.0
Adj	1.1	1.7	1.2	–0.9	–1.2	–2.2*
46–55						
Std	-	–0.6	1.5	–0.7	–1.6	0.6
Adj	-	–0.8	1.9	–0.8	–1.8	0.6
56–65						
Std	-	–1.5	1.7	0.7	–2.4	1.3
Adj	-	–1.8	2.1*	0.7	–2.6**	1.4
65+						
Std	-	-	1.7	-	-	-
Adj	-	-	2.1*	-	-	-

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
18–24 (*n* = 1,491), 25–35 (*n* = 420), 36–45 (*n* = 201), 46–55 (*n* = 120), 56–65 (*n* = 54), 65+ (*n* = 17).
* *p* < .05, ** *p* < .01, *** *p* < .001.
- denotes uninterpretable data.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the inverse Everest (C1^b), submerged (C2^b), iceberg (C3[b]), surface (C4[b]), shark fin (C5[b]), and inverse iceberg (C6[b]) mood profiles according to level of education. Figure 4.10 and Table 4.17 both illustrate that the frequencies were significantly different from expected values, $\chi^2(15, N = 2{,}303) = 35.84$, $p = .002$, suggesting an association between level of education and cluster.

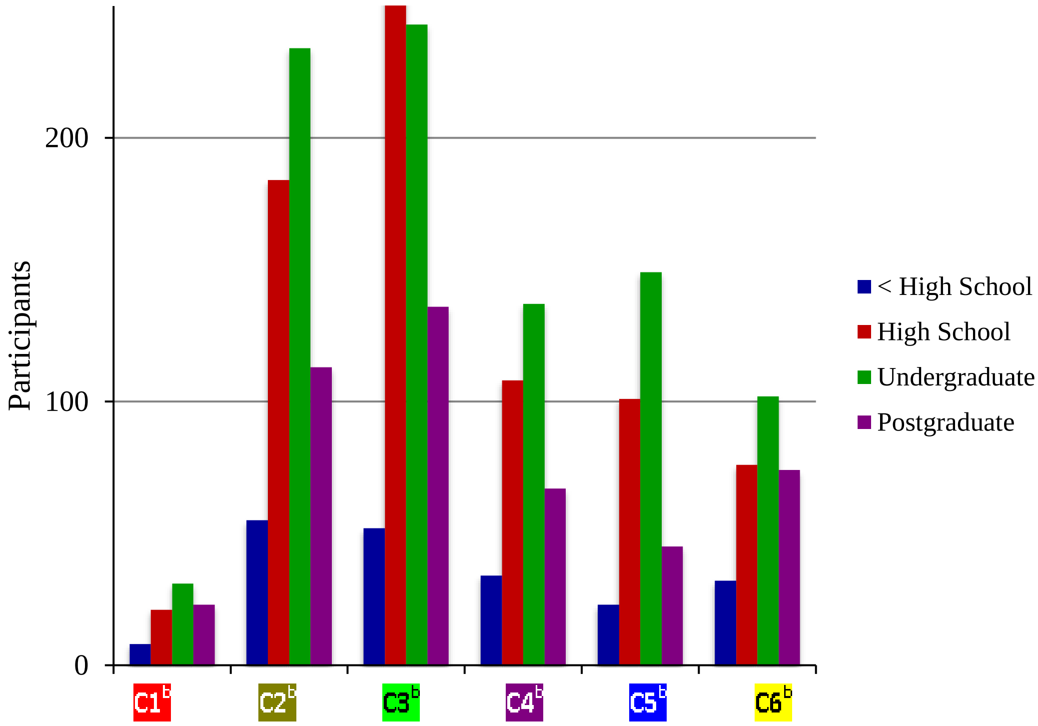


Figure 4.10. Distribution of education across clusters (N = 2,303). Overall number of participants according to level of education: less than high school (n = 204), high school (n = 745), undergraduate (n = 896), postgraduate (n = 458). C1[b] (n = 83) = inverse Everest profile, C2[b] (n = 586) = submerged profile, C3[b] (n = 686) = iceberg profile, C4[b] (n = 346) = surface profile, C5[b] (n = 318) = shark fin profile, and C6[b] (n = 284) = inverse iceberg profile.

Table 4.17

Crosstabulations of Clusters C1^b to C6^b by Level of Education (N = 2,303)

Education	C1^b (*n* = 83)	C2^b (*n* = 586)	C3^b (*n* = 686)	C4^b (*n* = 346)	C5^b (*n* = 318)	C6^b (*n* = 284)
< High School						
Actual	8	55	52	34	23	32
Expected	7	52	61	31	28	25
High School						
Actual	21	184	255	108	101	76
Expected	27	190	222	112	103	92
Undergraduate						
Actual	31	234	243	137	149	102
Expected	32	228	267	135	124	111
Postgraduate						
Actual	23	113	136	67	45	74
Expected	17	117	136	69	63	57

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
< High School (*n* = 204), High School (*n* = 745), Undergraduate (*n* = 896), Postgraduate (*n* = 458).
Expected frequencies are rounded to whole numbers.

The distribution of education within the inverse Everest profile (C1^b) included: < high school = 9.6%, high school = 25.3%, undergraduate = 37.3%, and postgraduate = 27.7%. C1^b had an over-representation of those with a < high school and postgraduate level of education by 14.3% and 35.3%, respectively, and an under-representation of those with a high school and undergraduate level of education by 22.3% and 3.1%, respectively. The distribution of education within the submerged profile (C2^b) included: < high school = 9.4%, high school = 31.4%, undergraduate = 39.9%, and postgraduate = 19.3%. C2^b had an over-representation of those with a < high school and undergraduate level of education by 5.8% and 2.6%, respectively, and an under-representation of those with a high school and postgraduate level of education by 3.2% and 3.4%, respectively. The distribution of education within the iceberg profile ($C3^{b}$) included: < high school = 7.6%, high school = 37.2%, undergraduate = 35.4%, and postgraduate = 19.8%. $C3^{b}$ had an over-representation of those with a high school level of education by 14.9%, and an under-representation of those with a < high school and undergraduate level of education by 14.8% and 9.0%, respectively, while those with a postgraduate level of education matched the chi-square expected count.

Further, the distribution of education within the surface profile ($C4^{b}$) included: < high school = 9.8%, high school = 31.2%, undergraduate = 39.6%, and postgraduate = 19.4%. $C4^{b}$ had an over-representation of those with a < high school and undergraduate level of education by 9.7% and 1.5%, respectively, and an under-representation of those with a high school and postgraduate level of education by 3.6% and 2.9%, respectively. The distribution of education within the shark fin profile ($C5^{b}$) included: < high school = 7.2%, high school = 31.8%, undergraduate = 46.9%, and postgraduate = 14.2%. $C5^{b}$ had an over-representation of those with an undergraduate level of education by 20.2%, and an under-representation of those with a < high school, high school, and postgraduate level of education by 17.9%, 1.9%, and 28.6%, respectively. The distribution of education within the inverse iceberg profile ($C6^{b}$) included: < high school = 11.3%, high school = 26.8%, undergraduate = 35.9%, and postgraduate = 26.1%. $C6^{b}$ had an over-representation of those with a < high school and postgraduate level of education by 28.0% and 29.8%, and an under-representation of those with a high school and undergraduate level of education by 17.4% and 8.1%, respectively. Table 4.18 lists the within level of education grouping percentages according to each cluster.

Table 4.18

Cluster Membership According to Within Education Group Percentage (N = 2,303)

Education	$C1^b$ (*n* = 83)	$C2^b$ (*n* = 586)	$C3^b$ (*n* = 686)	$C4^b$ (*n* = 346)	$C5^b$ (*n* = 318)	$C6^b$ (*n* = 284)
< High School	3.9%	27.0%	25.5%	16.7%	11.3%	15.7%
High School	2.8%	24.7%	34.2%	14.5%	13.6%	10.2%
Undergraduate	3.5%	26.1%	27.1%	15.3%	16.6%	11.4%
Postgraduate	5.0%	24.7%	29.7%	14.6%	9.8%	16.2%

Note. $C1^b$ = inverse Everest profile, $C2^b$ = submerged profile, $C3^b$ = iceberg profile, $C4^b$ = surface profile, $C5^b$ = shark fin profile, $C6^b$ = inverse iceberg profile.
< High School (*n* = 204), High School (*n* = 745), Undergraduate (*n* = 896), Postgraduate (*n* = 458).

A *post hoc* review of the adjusted residuals was conducted to identify which groups made the largest contributions to the significant chi-square result. The iceberg ($C3^b$), shark fin ($C5^b$), and inverse iceberg ($C6^b$) profiles were each found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for $C3^b$ were 3.2 = $p < .01$ (high school) and –2.2 = $p < .05$ (undergraduate). The significant adjusted residuals for $C5^b$ were 3.1 = $p < .01$ (undergraduate) and –2.8 = $p < .01$ (postgraduate). Finally, the significant adjusted residuals for $C6^b$ were –2.2 = $p < .05$ (high school) and 2.8 = $p < .01$ (postgraduate). Again, no relationship was found between level of education and cluster for the surface profile ($C4^b$). Additionally, no relationship was found for the inverse Everest ($C1^b$) and submerged ($C2^b$) profiles. Table 4.19 lists the standardised and adjusted residuals for each cluster solution.

Table 4.19

Standardised and Adjusted Residuals for Level of Education (N = 2,303)

Education	C1^b (n = 83)	C2^b (n = 586)	C3^b (n = 686)	C4^b (n = 346)	C5^b (n = 318)	C6^b (n = 284)
< High School						
Std	0.2	0.4	–1.1	0.6	–1.0	1.4
Adj	0.3	0.5	–1.4	0.7	–1.1	1.5
High School						
Std	–1.1	–0.4	2.2	–0.4	–0.2	–1.7
Adj	–1.4	–0.6	3.2**	–0.5	–0.2	–2.2*
Undergraduate						
Std	–0.2	0.4	–1.5	0.2	2.3	–0.8
Adj	–0.3	0.6	–2.2*	0.3	3.1**	–1.1
Postgraduate						
Std	1.6	–0.3	0.0	–0.2	–2.3	2.3
Adj	1.8	–0.4	0.0	–0.3	–2.8**	2.8**

Note. C1^b = inverse Everest profile, C2^b = submerged profile, C3^b = iceberg profile, C4^b = surface profile, C5^b = shark fin profile, C6^b = inverse iceberg profile.
< High School (n = 204), High School (n = 745), Undergraduate (n = 896), Postgraduate (n = 458).
* p < .05, ** p < .01, *** p < .001.

4.3 Summary

The mood responses of 2,303 participants were analysed using a k-means iterative procedure with random seeds, and a prescribed six-cluster solution. The findings from the Lim (2011) dataset were replicated. The mood profiles identified were the inverse Everest (C1^b), submerged (C2^b), iceberg (C3^b), surface (C4^b), shark fin (C5^b), and inverse iceberg (C6^b) profiles. Once again, a MANOVA showed significant differences between clusters on each dimension of mood, and a DFA indicated that cluster membership could be correctly classified with a high degree of accuracy (ranging from 85.0% to 99.7%).

As previously found, the inverse Everest profile was characterised by a low level of vigour (0.73 *SD* below *M* = 50.00), together with high levels of tension and fatigue (1.68 and 1.76 *SD* above *M* = 50.00), as well as very high levels of depression, anger, and confusion (3.95, 3.17, and 3.07 *SD* above *M* = 50.00, respectively). The submerged profile was characterised by slightly below average levels of each dimension of mood, being tension, depression, anger, vigour, fatigue, and confusion (0.71, 0.27, 0.35, 0.75, 0.08, and 0.35 *SD* below *M* = 50.00, respectively). The iceberg profile was characterised by a high level of vigour (0.71 *SD* above *M* = 50.00), together with low levels of tension, depression, anger, fatigue, and confusion (0.77, 0.48, 0.28, 0.49, and 0.47 *SD* below *M* = 50.00, respectively). The surface profile was characterised by slightly above average levels of each mood dimension, being tension, depression, anger, vigour, fatigue, and confusion (0.17, 0.21, 0.45, 0.57, 0.11, and 0.58 *SD* above *M* = 50.00, respectively). The shark fin profile was characterised by slightly below average levels of tension and vigour (0.48, and 0.74 *SD* below *M* = 50.00), and average levels of depression, anger, and confusion (0.01, 0.02, and 0.04 *SD* above *M* = 50.00), together with a high level of fatigue (1.51 *SD* above *M* = 50.00). Finally, the inverse iceberg profile was characterised by a low level of vigour (0.28 *SD* below *M* = 50.00), together with high levels of tension, depression, anger, fatigue, and confusion (0.92, 1.80, 1.49, 1.15, and 1.61 *SD* above *M* = 50.00, respectively).

Additionally, a series of chi-square tests of goodness-of-fit once again indicated that gender, age, and level of education were unequally distributed across clusters (relative to the sample size and demographic groupings). In the current sample, an estimated equal number of males and females experienced the inverse Everest, submerged, and surface profiles. Males were more likely to experience the iceberg profile, while females were more likely to experience the shark fin and inverse iceberg profiles compared with males.

An estimated equal number of individuals across all age groups experienced the submerged, and surface profiles. Those aged 18–24 were more likely to experience the shark fin profile, and less likely to experience the inverse Everest profile. Those aged 25–35 were more likely to experience the inverse iceberg and inverse Everest profiles, and less likely to experience the iceberg profile, while those aged 36–45 were less likely to experience the inverse iceberg profile. Those aged 46–55 had a relatively equal distribution across clusters, while those aged 56–65 were more likely to experience the iceberg profile, and less likely to experience the shark fin profile. Those aged over 65 were more likely to experience the inverse Everest and iceberg profiles, however these general trends should be considered with caution given the violation of the underlying assumption regarding minimum cell counts.

Further, an estimated equal number of individuals across all levels of education experienced the inverse Everest, submerged, and surface profiles. Those with a less than high school level of education had a relatively equal distribution across clusters, while those with a high school level of education were more likely to experience the iceberg profile, and less likely to experience the inverse iceberg profile. Those with an undergraduate level of education were more likely to experience the shark fin profile, and less likely to experience the iceberg profile. Those with a postgraduate level of education were more likely to experience the inverse iceberg profile, and less likely to experience the shark fin mood profile.

Overall, the k-means cluster analysis produced multivariate cluster structures which were found to be very similar to those identified in the previous sample. Further to this, the mood profiles found within the two samples also shared a number of demographic similarities.

CHAPTER 5:
Redevelopment of the *In The Mood* Website

As previously mentioned, the focus of the *In The Mood* website was to facilitate a prompt calculation and interpretation of individual responses to a brief mood scale, and further link specific mood profiles with mood regulation strategies to facilitate improved performance (Lim, 2011; Lim & Terry, 2011). Moreover, the website was designed according to a user-centred approach, and incorporated best practices in website design (Lim, 2011). Following the initial testing phase of a prototype, Lim (2011) conducted formal testing and evaluations with an underlying goal to “inform and enhance future revisions” (p. 71).

5.1 Overview of the Lim (2011) Findings

Google Analytics was used by Lim (2011) to gain an in-depth insight into usage patterns and engagement. The utilisation statistics indicated that a relatively stable stream of traffic visited the website during the initial data collection period (i.e., March 2010 to October 2010). A total of 1,438 individuals were classed as new or unique users, with the remaining 572 classified as return visitors. The geographical location of participants varied across 48 countries, with 64% of the sample positioned outside of Australia. Of the 10,449 page views, the ‘Results’ page was the most popular (i.e., 2,978) followed by the ‘Consent’ page (i.e., 2,750), and lastly the actual BRUMS assessment (2,416). Additionally, each user spent an average of 7 minutes navigating the site and viewed approximately 5.20 pages. While these findings may be considered encouraging, the bounce rate (i.e., single page visit) was 30%, meaning that a moderate percentage of users left *In The Mood* upon visiting the homepage.

General user perceptions of the website were gauged using the User Experience Survey. The User Experience Survey was designed to elicit feedback from respondents, and comprised of two parts (a sample was presented in Chapter 2: Section 2.9.1, Figure 2.30). The first part was a 10-item scale which measured content (i.e., 3 items), delivery (i.e., 3 items), and usability (i.e., 4 items) according to a 5-point Likert scale (i.e., 1 = *strongly disagree*, 2 = *disagree*, 3 = *neutral*, 4 = *agree*, and 5 = *strongly agree*). The results indicated that *In The Mood* was perceived as user-friendly overall, given that respondents (N = 175) rated all aspects of the content, delivery, and usability positively overall (see Table 5.1).

Table 5.1

User Ratings of the In The Mood Website (N = 175)

Questions	*M*	*SD*
Contents		
The information on the website was useful and interesting	4.17	0.75
The contents of the website were easy to read	4.47	0.58
The contents were well laid out and the website was easy to navigate	4.46	0.65
Delivery		
The website was attractive	4.22	0.70
The colours and images used made the site appealing	4.09	0.81
The website was too slow	1.78	0.80
Usability		
The website was easy to use	4.56	0.56
Overall, I enjoyed using the website	4.26	0.71
Overall, I would recommend the website to others	4.17	0.85
Overall, I would visit the site again	4.06	0.93

The second part of the User Experience Survey included four open-ended questions: ‘Which aspects of the website did you like the best?’, ‘Which aspects of the website did you like the least?’, ‘Which other features would you like to see included in the website?', and 'Please include any other comments with regards to any aspects of the website here'. A textual analysis on 123 responses was conducted using Leximancer software to quantify predominant themes and related thematic concepts. A concept map was produced, displaying each main theme according to a different colour (see Figure 5.1). Circle size represented relative importance, while each dot signified a related concept. Any associations between dots (or related thematic concepts) were displayed in terms of proximity (e.g., close proximity = more closely related).

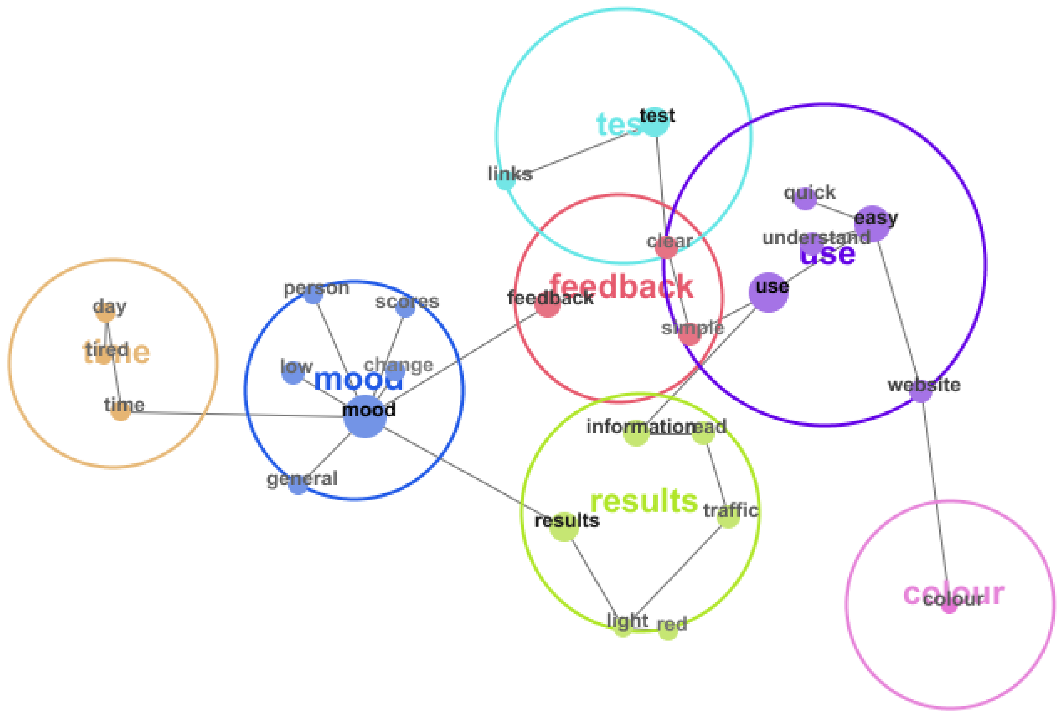


Figure 5.1. A Leximancer concept map (n = 123) of the open-ended responses received in the Lim (2011) study.

With a response rate of 70.3%, seven main themes were identified together with a number of thematic concepts. A mixture of predominantly positive comments were categorised according to Theme 1 (n = 44) = Use, Theme 2 (n = 47) = Mood, Theme 3 (n = 16) = Feedback, Theme 4 (n = 32) = Test, Theme 5 (n = 27) = Results, Theme 6 (n = 8) = Colour, and Theme 7 (n = 7) = Time. An example comment from each theme grouping include, “Easy to use and only took a minute” (Theme 1 = Use); “It’s a good way of teaching self-regulation of mood” (Theme 2 = Mood); “I really liked the way you gave feedback on the results even if I didn’t think they were completely compatible. However, I found that the suggestions that you included to help people change their moods and to offer help and suggestions was a superb touch” (Theme 3 = Feedback); “The survey was clear, precise, and accurate” (Theme 4 = Test); “The results were succinctly communicated and very accurate” (Theme 5 = Results); “The grey background was a little boring, something a little more interesting in terms of colour might be more appealing” (Theme 6 = Colour); and “The time of day the assessment was taken was not addressed” (Theme 7 = Time).

Interestingly, the most cohesive opinions related to Theme 6. However, the background colour was deemed “controversial” by Lim (2011, p. 172). Although an estimated 79% of participants endorsed strong agreement or agreement towards the item “The colours and images used made the site appealing” on the 10-item scale, the Leximancer concept map identified a different pattern within the open-ended responses. A number of negative comments were identified. For example: “Frontpage a little bland somehow, perhaps the background colour”; “A bit too much grey although I guess it was meant to be a neutral colour”; “The interface of this website should be a little more colourful to attract viewers”; “The colour is depressing”; “Don’t like the grey background, if going to use grey use a much lighter shade”; “Too much grey, bit depressing” (Lim, 2011, p. 163).

Following a review of the comments, and with a view to create a customer-centred design, Lim (2011) generated a list of recommended changes closely aligned with the scope and purpose of *In The Mood* (Lim & Terry, 2011). These recommendations were grouped according to two broad categories involving website colour and website content. However, the ultimate decision as to which suggestions were actually implemented in the revision depended on the underlying knowledge, skill, and experience required to formulate the changes. In light of the fact that the principle researcher possessed only basic computer technology skills, the original creator of *In The Mood* (i.e., Dr Julian Lim) was outsourced to make the necessary modifications. The conventional standards underlying website design (i.e., appeal, usability, and interactivity) were given due consideration throughout the re-development process.

5.2 Website Colour

Lim (2011) duly recognised that colours are displayed differently according to computer system capabilities, however, the Leximancer findings and the overwhelming response to the colour grey implied a thorough revision was required. One suggestion from Lim was to include a background colour selector tool listing predetermined options, although this idea required a high level of website design knowledge and for this reason was deemed inappropriate. This recommendation was in opposition to changing the background colour in its entirety, which "some users will likely find attractive but not others" (Lim, 2011, p. 172).

Additionally, the "alarming" bounce rate from Google Analytics suggested that a large portion of users left the website after visiting the homepage (Lim, 2011, p. 168). Internet users begin to form judgments about website content within 50 milliseconds (Lindgaard, Fernandes, Dudek, & Brown, 2006). As highlighted by Lim (2011), such *first impressions* have the potential to impact overall perceptions of website credibility as well as user-friendliness (Lindgaard et al., 2006). While any specific underlying reasons remain unknowable, it could be conjectured that potential users perceived an incongruencey between self-image and the images displayed on the homepage, whereby judging *In The Mood* (Lim & Terry, 2011) as having no utilitarian value (Cho & Kim, 2012). Perhaps the homepage simply "failed to make any lasting first impression" (Lim, 2011, p. 168). In any case, and in line with Nielsen's (2000) recommendation, the colour scheme and overall visual appeal of the website's interface was given meticulous consideration.

Colour perception involves visual and cognitive systems designed to process stimulus (Elliot & Maier, 2007; Kaya & Epps, 2004). More specifically, the band of energy within the electromagnetic spectrum forms a continuum, and is radiated as waves (Goldstein, 2010). A colour's hue (or gradation) is perceived by the peaks of its wavelength, with visible light ranging from approximately 400 to 700 nanometers (nm; where 1nm = 10^9 meters). Short wavelengths are often termed *cool* colours (e.g., violet, blue, etc.), while *warm* colours (e.g., red, orange, etc.) generally describe colours with longer wavelengths (refer to Figure 5.2; Valdez & Mehrabian, 1994; Yildirim, Hidayetoglu, & Capanoglu, 2011).

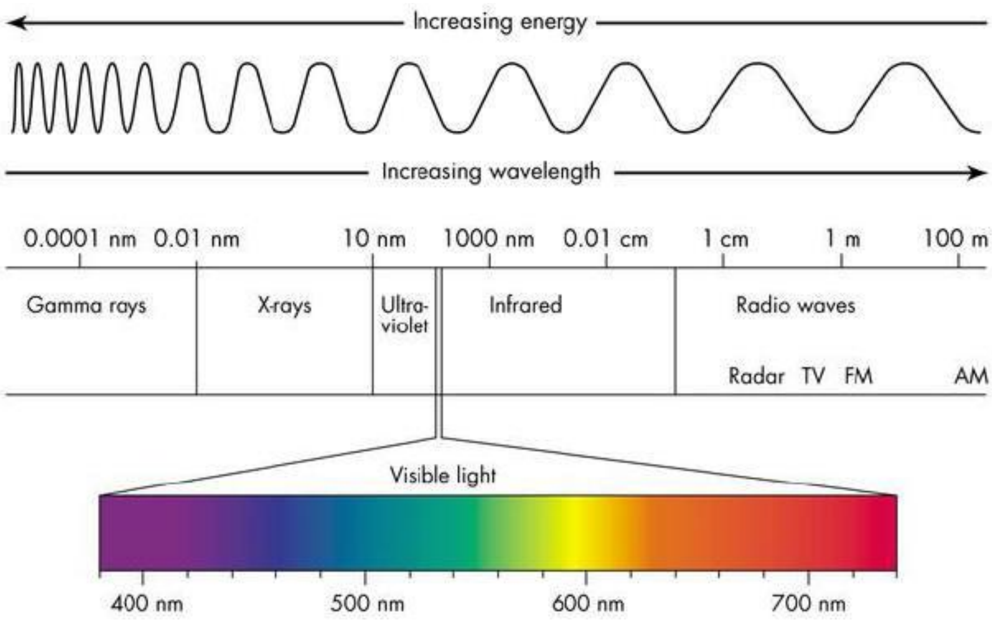


Figure 5.2. A diagram of the electromagnetic spectrum and visible light in nanometers (taken from http://9-4fordham.wikispaces.com).

Many areas of the brain are involved in vision and colour perception. From a bottom up perspective, signals travel from the retina via the optic nerve to the lateral geniculate nucleus (LGN) in the thalamus (a smaller proportion of these signals travel to the superior colliculus, an area involving eye movement, etc.; see Figure 5.3; Goldstein, 2010). From here, the LGN receives and regulates information from the cortex, brain stem, and other neurons. Although categorisation of information begins in the retina, the LGN organises the signals according to the eye (i.e., left versus right eye) and receptors in which they were generated. Importantly, the LGN receives more internally-generated input from the cortex than the actual retina. Following this, the information is transferred to the primary visual receiving area of the cortex via higher-order thalamic nuclei for further cognitive processing (Goldstein, 2010; Wurtz, McAlonan, Cavanaugh, & Berman, 2011).

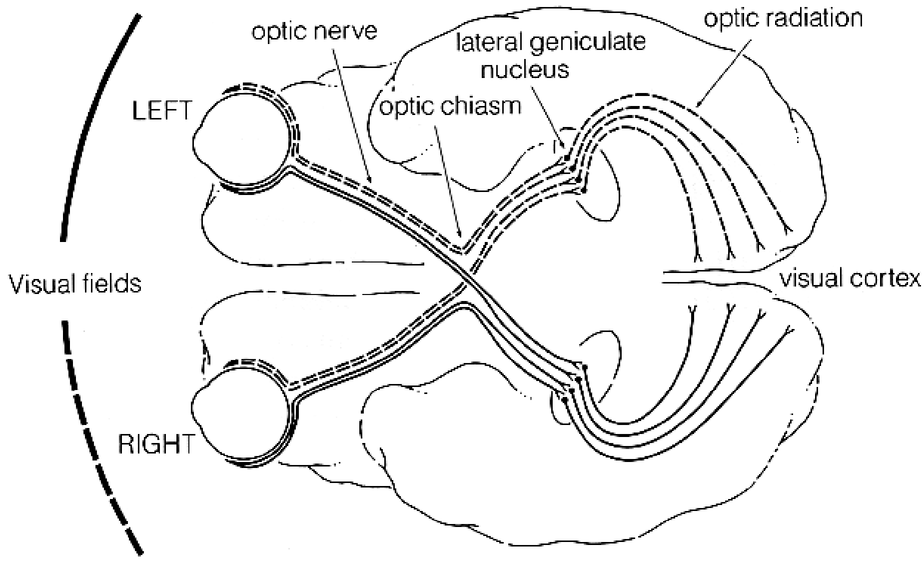


Figure 5.3. A diagram of the visual pathways (taken from http://www.thalamus.wustl.edu).

During this overall process, associated feelings otherwise known as *colour emotions* are often experienced (Billmeyer & Saltzman, 1981). This notion is not surprising, given that experimental data has found that the sensory pathways from the thalamic nuclei are essential for elements of emotional processing (LeDoux, 1986). Although colour and emotion are systematically related (Levy, 1984), the psychological effects of colour remains an under-developed area (Cyr, Head, & Larios, 2010). This is despite a large and complex field of research (Mahnke, 1996). From an evolutionary perspective, it has been argued that the phenomena has a biological basis (Elliot & Maier, 2007; Goldstein, 1939; Guilford, 1940, Wexner, 1954), while still other researchers suggest that the physiological mechanisms and environmental factors are yet to be analysed (Cyr et al., 2010). In any case, the literature is replete with colour-emotion association studies highlighting a relationship between colour (as well as colour combinations) and affective tones (Kobayashi, 1981).

For example, experimental research has identified that cool colours (i.e., blue and green) generally facilitate feelings of relaxation, while warmer hues (i.e., red and orange) are often perceived as more stimulating (Crowley, 1993; Nelson, Pelech, & Foster, 1984; Whitfield & Wiltshire, 1990). Similarly, in a study by Levy (1984), warm colours were found to evoke *active feelings* (e.g., anger from red, sadness from yellow), while cool colours were found to induce *calm feelings* (e.g., relaxation from blue, calmness from purple). Indeed, Adams and Osgood (1973) identified red as the most *active* colour, and black and grey as the most *passive* colours. To add to this, Valdez and Mehrabian (1994) have repeatedly demonstrated that colours with short wavelengths are often preferred over those with longer wavelengths. However, the psychological/physiological impact of colour in website design is perhaps best described as scant (Cyr et al., 2010).

In an effort to reduce potential colour-emotion influences in any specific direction, it was decided that the homepage would display a variety of warm and cool colours. Indeed, the BRUMS is a measure of mood (which as previously mentioned is interrelated with emotion), and colour emotions elicited during formation of first impressions (Lindgaard et al., 2006) may pose a risk of systematic error. For this reason, a collection of performance-related images were selected according to the inherently different colours each displayed. Additionally, due to the subjective nature of colour preferences, the likelihood of aesthetic appeal is improved by displaying a variety of colours.

Three of the original images were retained (i.e., defence, business, and health), while two were replaced (i.e., education and sport). Two additional pictures depicting construction and mining environments were added to the interface to facilitate self-congruency judgments (Cho & Kim, 2012), and therefore data collection for Study 3. Each of the graphics were less than 40 kilobytes to minimise download time (Barron, 1998). Further, the contrast and brightness for each image were increased to improve overall colour saturation, as well as provide "a more exuberant colour scheme", as suggested by Lim (2011, p. 168).

The website title was changed from Trebuchet MS to Bradley Hand ITC font to better encapsulate the underlying purpose of *In The Mood*. Although the font type/size remained unchanged throughout; a black, light grey, and blue colour scheme was adopted to maximise contrast, and therefore readability (Baron, 1998). The collage was slightly larger than the original version although it remained within Barron's (1998) pixel size recommendations (i.e., 472), thus eliminating the need to unnecessarily scroll. Each graphic was embedded with corresponding links to demographic information. This was implemented in an effort to aid navigation, however slight re-structuring of the 'About this website', 'Leave feedback', etc., hyperlinks were required. Additionally, the icons to share *In The Mood* (embedded within the footer) were reduced in an effort to make the most popular social networking sites more obvious (i.e., Facebook, LinkedIn, and Twitter). The email option was retained. A comparison of the original and re-developed versions of the *In The Mood* interface can be found in Figure 5.4 and Figure 5.5 (respectively).

Figure 5.4. The original version of the *In The Mood* homepage.

Figure 5.5. The re-developed version of the *In The Mood* homepage.

5.3 Website Content

5.3.1 Demographic information. In terms of website content, Lim and Terry (2011) recognised that the four options within the highest education achieved field were too "simplistic" (Lim, 2011, p. 170) and did not accurately represent diverse levels of education. More specifically, the proposed changes suggested options such as primary, college, diploma, and trade certificate. Indeed, as aptly summarised by one user, "More education options. I have completed Diplomas and a trade certificate but not year 12 or a degree and my only choice was below high school certificate which in fact is not accurate. This was offensive to a point as no other education was able to be chosen". For this reason, the highest education achieved options were expanded to include 'Less than high school certificate', 'High school certificate', 'Trade apprenticeship', 'Trade qualification', 'TAFE qualification', 'University qualification', and 'Postgraduate qualification'.

While the original list of occupations was deemed substantial, Lim (2011) highlighted that there was no provision for athletes or sports personnel. Given this, the list of occupations was both revised and refined to include 'Athlete/Sport', 'Clerical/Administration', 'Community/Personal services', 'Defence', 'Health/Medical', 'Manager/Professional', 'Manual/Labourer', 'Operator/Driver', 'Police/Emergency', 'Sales/Marketing', 'Student/Education', 'Technical/Trade', 'Not currently employed', and 'Other'.

Further, the list of reasons for completing the BRUMS was not comprehensive enough to "meet the needs of a wider variety of users" according to Lim (2011, p. 170). As one comment highlighted, "More reasons for participation in the test should be added to meet a wide variety of subjects". However, upon review it was decided that the list of reasons were unnecessarily specific for the purposes of the present research. To better represent a variety of motives, ‘Preparing for a presentation’, ‘Preparing for a sales pitch’, ‘Preparing for a sport competition’ and ‘Preparing for an examination’ were collapsed down into one encompassing category of ‘Preparing for a performance or task’. Each of the other reasons (i.e., ‘General interest’, ‘Not feeling my normal self’, ‘Wanting to help with research, and ‘Other’) remained unchanged.

5.3.2 Mood-performance relationship. A number of suggestions through the User Experience Survey involved requests for additional information on the mood-performance relationship. For example, “More references on how mood will impede performance”; “More options for strategies to improve specific aspects of mood for performance, more website info, especially more on the link between mood and performance”; “I’d like to read more info about moods in general and how they affect performance”. Given this, Lim (2011) proposed that additional information be provided on the ‘further reading’ page, together with corresponding hyperlinks.

In line with this recommendation, four additional journal articles were incorporated into the revision. These included *On the relative effectiveness of affect regulation strategies: A meta-analysis* by Augustine and Hemenover (2009); *Fatigue: The most critical accident risk in oil and gas construction* by Chan (2011); *A study of the lagged relationships among safety climate, safety motivation, safety behaviour, and accidents at the individual and group levels* by Neal and Griffin (2006), *Classifying affect regulation strategies* by and Parkinson and Totterdell (1999). Each article was selected on the basis of its potential relevance and interest to *In The Mood* users, as well as those populations specifically targeted for Study 3 (i.e., construction and mining employees). Additionally, hyperlinks to PDF versions of each article were provided (refer to Figure 5.6), excluding the *Revised manual for* *the Profile of Mood States* by McNair et al. (1971). In this case, a PDF was unable to be located on the Internet.

Figure 5.6. The ‘Further reading’ page on the re-developed *In The Mood*.

5.3.3 Results page. Another useful suggestion received through the open-ended responses of the User Experience Survey was to incorporate a log book facility to enable users to retrieve and compare mood responses over time (e.g., “A log book with which to save my data so I can come back and review my mood over a period of time and look at the general change, so a personal account would be nice”). Two options as provided by Lim (2011) were to create either an email or login feature. Once completed, mood assessments could be emailed and/or stored and retrieved via an account. Alternatively, a *save* option would enable users to save the results to an external device, thereby eliminating the need to provide personal details.

It was decided that incorporating a *save as PDF* option, as well as embedding the date/time in the results page, would enable users to track mood responses over time. Additionally, this change would preserve the perception of anonymity afforded by *In The Mood*, which as previously mentioned has been has been found to positively influence self-disclosure (Feigelson & Dwight, 2000; Joinson, 2001). Therefore, a PDF icon was added to the results page with *export to PDF* instructions, and the date/time of day was also clearly displayed. Additionally, the 'Please take a moment and give us your opinion about this website' hyperlink was replaced with an icon, and the printing icon was changed; reasons being for aesthetic purposes (see Figure 5.7).

Figure 5.7. An example of the three icons embedded within the 'Results' page, together with the date and time of day.

Additionally, another recommendation by Lim (2011) related to traffic light colours being incorporated into the graphical profile. As commented by one user, "On the graph it would be good if you could have traffic light highlighting to show where the results sit. It would tie the graph together with the traffic lights". Despite the merit of such an idea, Lim noted that implementing this change would require a website programming specialist, due to the limitations inherent in the current graphing program. This alteration was not included in the re-development process, as unfortunately it was beyond the expertise of those involved.

5.4 Additional Website Changes

5.4.1 Revisions for Study 3. A number of changes were made to *In The Mood* to aid data collection for Study 3. For example, the consent page was revised (see Figure 5.8), and the 'About the authors page' was updated to include a small bio on the principle researcher (see Figure 5.9). The Workplace Health and Safety Scale (WHSS; Neal, Griffin, & Hart, 2000) was also included (refer to Figure 5.10).

Figure 5.8. The 'Take the test' page.

In The Mood

An online mood assessment based on the Brunel Mood Scale (BRUMS)

home
about
take the test
leave feedback
tell a friend

about this website | about the measure | about the authors | further reading

About the Authors

Dr Peter Terry, PhD FAPS FASMF FBASES, is Professor of Psychology at the University of Southern Queensland in Australia, a registered psychologist, and formerly Psychology Coordinator at the Queensland Academy of Sport. Over the past 30 years he has provided psychological support to more than 1,000 international and professional performers, including a host of Olympic medallists. He has worked as a sport psychologist at nine Olympic Games and more than 100 other international events.

Peter is author of over 200 publications, including five books, 24 book chapters, and 60 peer-reviewed journal articles. His most recent books, Inside Sport Psychology (with Costas Karageorghis) and The New Sport and Exercise Psychology Companion (with Tony Morris), were published in 2011.

Peter is President of the Asian-South Pacific Association of Sport Psychology (ASPASP) and a Fellow of the Australian Psychological Society (APS), the Australian Sport Medicine Federation (ASMF) and the British Association of Sport and Exercise Sciences (BASES). He served as President of the APS College of Sport Psychologists from 2002-2006, and was the 2011 recipient of the APS Colleges Award of Distinction.

In the distant past, Peter played sport at representative level in rugby, soccer and track and field, competed in the national bobsled championships, and ran a three-hour marathon. He has now migrated to golf and tennis, both of which he admits to playing badly.

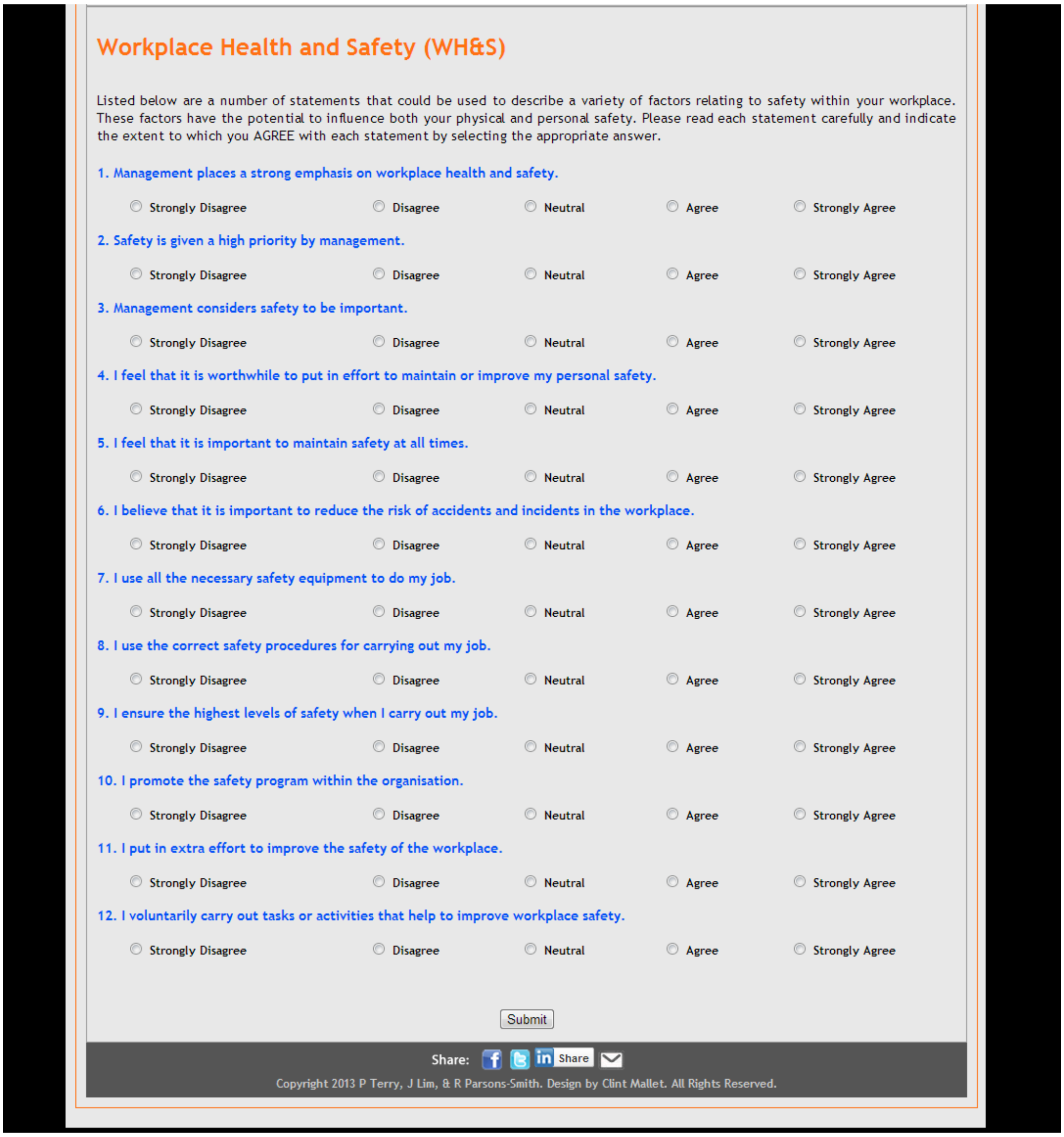
Dr Julian Lim, DPsych MAPS, has recently completed postgraduate studies in Clinical Psychology at the University of Southern Queensland and is currently in private practice. Clearly less celebrated and illustrious than his supervisor (i.e., Professor Peter Terry), he is content to leave this biography relatively short. His sole passion in life (outside of psychology) is soccer, a sport that he plays on a regular basis (both competitively and socially). Unlike Peter, Julian shamelessly admits to playing soccer relatively well, razzling and dazzling his opponents on the field (or so he likes to believe!). He is an avid and lifelong supporter of Liverpool Football Club, and it pains him to see them under-achieving for a number of years now.

Renée L. Parsons-Smith, BSc Hons (Psych) Assoc MAPS, is a Doctor of Philosophy candidate (psychology) currently completing her postgraduate studies at the University of Southern Queensland under the supervision of Professor Peter Terry. Raised on a yacht on the Great Barrier Reef, Renée has also travelled around Australia. Aside from an adventurous personality and a self-confessed passion for research, Renée enjoys more solitary sporting activities such as jogging and scuba diving. Renée is currently in the process of publishing her first journal article.

Share: in Share

Copyright 2013 P Terry, J Lim, & R Parsons-Smith. Design by Clint Mallet. All Rights Reserved.

Figure 5.9. The ‘About the authors’ page.



Workplace Health and Safety (WH&S)

Listed below are a number of statements that could be used to describe a variety of factors relating to safety within your workplace. These factors have the potential to influence both your physical and personal safety. Please read each statement carefully and indicate the extent to which you AGREE with each statement by selecting the appropriate answer.

1. Management places a strong emphasis on workplace health and safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

2. Safety is given a high priority by management.

Strongly Disagree Disagree Neutral Agree Strongly Agree

3. Management considers safety to be important.

Strongly Disagree Disagree Neutral Agree Strongly Agree

4. I feel that it is worthwhile to put in effort to maintain or improve my personal safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

5. I feel that it is important to maintain safety at all times.

Strongly Disagree Disagree Neutral Agree Strongly Agree

6. I believe that it is important to reduce the risk of accidents and incidents in the workplace.

Strongly Disagree Disagree Neutral Agree Strongly Agree

7. I use all the necessary safety equipment to do my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

8. I use the correct safety procedures for carrying out my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

9. I ensure the highest levels of safety when I carry out my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

10. I promote the safety program within the organisation.

Strongly Disagree Disagree Neutral Agree Strongly Agree

11. I put in extra effort to improve the safety of the workplace.

Strongly Disagree Disagree Neutral Agree Strongly Agree

12. I voluntarily carry out tasks or activities that help to improve workplace safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

Submit

Share: in Share

Copyright 2013 P Terry, J Lim, & R Parsons-Smith. Design by Clint Mallet. All Rights Reserved.

Figure 5.10. The WHSS.

Additionally, if a participant selected ‘Construction’ or ‘Mining’ from either the homepage or the ‘Take the test’ page, they were instantly redirected to the relevant demographic data. While the gender (Male; Female), age (18–24; 25–35; 36–45; 46–55; 65+), Ethnicity (Asian; Caucasian; African; Middle Eastern; Indigenous; Other), and highest education achieved (previously listed) categories remained, additional demographic variables were added to better explore data for potential moderating effects. These included ‘Current roster’ (Drive in/Drive out - night shift; Drive in/Drive out - day shift; Drive in/Drive out - day off; Fly in/Fly out

- night shift; Fly in/Fly out - day shift; Fly in/Fly out - on 'break'; Other), 'Where you work' (Australian Capital Territory [ACT]; New South Wales [NSW]; Northern Territory [NT]; Queensland [QLD]; South Australia [SA]; Tasmania [TAS]; Victoria [VIC]; Western Australia [WA]; Other), and 'Role'. However, the groupings for role slightly differed between the construction and mining vocations. The initial list of mining jobs was taken from the iMINCO website (http://www.iminco.net/), whereby 16 roles were simplified into 10 overarching categories (refer to Table 5.2).

Table 5.2

Comparison of Role Groupings for Mining Demographic Data

iMINCO	*In The Mood*
Catering/Cleaning/Domestic	Administration
Drill & Blast	Catering/Cleaning/Domestic
Dump Truck	Drill & Blast
Electrical	Dump Truck/Machine Operator/ Truck Driver
Environment	Environment/Health & Safety
Finance	Geology/Planning & Production
Geologist	Finance/Management
Health & Safety	Plant Maintenance/Vehicle & Freight Management
Machine Operator/All Rounder	Trades & Services
Management	Other
Mechanical/Fitter/Welder/ Boilermaker	
Planning & Production	
Plant Maintenance/Vehicle Management	
Trades & Services	
Truck Driving/Freight Management	

Similarly, the list of construction job titles was taken from the About Careers website (http://www.jobsearch.about.com). In this case, 47 specific roles were collapsed down into 10 broad categories that for comparison purposes, were analogous with those selected for mining (see Table 5.3). Further, construction also had a ‘Size of current project’ category (Less than \$5 million; \$5–\$500 million; \$500 million–\$1 billion; \$1+ billion), while mining had a ‘Type of mine’ grouping (i.e., Open-cut; Underground; Other).

Table 5.3

Comparison of Role Groupings for Mining and Construction Demographic Data

Mining	Construction
Administration	Administration
Catering/Cleaning/Domestic	Catering/Cleaning/Domestic
Drill & Blast	Superintendent/Supervisor/Foreman
Dump Truck/Machine Operator/ Truck Driver	Machine Operator/Truck Driver
Environment/Health & Safety	Environment/Health & Safety
Geology/Planning & Production	Engineering/Planning & Development
Finance/Management	Finance/Management
Plant Maintenance/Vehicle & Freight Management	Labourer/Trade Assistant
Trades & Services	Trades & Services
Other	Other

5.4.2 Expansion of mood regulation strategies. The original list of mood regulation strategies was reviewed. Although the majority of the tactics were retained, many were slightly expanded upon. For example, ‘Engage in a physical activity’ was changed to ‘Engage in a physical activity to increase energy’, and ‘Think positive’ was expanded to ‘Try to control your thoughts so they are more positive’. By providing more descriptive information, the subcomponents of the rational decision-making processes are better supported. More specifically, the weighted utility (i.e., combination of assigned value and the extent to which an option satisfies it; Westen et al., 2006) and expected utility (i.e., combination of weighted utility and expected probability of obtaining an outcome; Westen et al., 2006) relating to each action can be more accurately judged.

Further, a selection of biopsychological and cognitive-behavioural strategies were included to provide a greater number of mood regulating options. For example, a variation of ‘Eat a nutritional snack’ was added for vigour and fatigue, given that food consumption has been found to positively impact the biopsychological component of energy (Thayer et al., 1994). Indeed, vigour and fatigue may best be described as dichotomous (see Odagiri, Shimomitsu, Iwane, & Katsumura, 1996), rather than operating at either ends of a continuum. Although, it seems reasonable to conclude that each share an etiological foundation, given the interrelated and multifaceted connections that characterise the arousal system (Thayer, 2001). Additionally, the word nutritional was chosen to encourage health-related behaviours. ‘Drink a caffeinated beverage’ was also added for vigour because of its potential ergotropic effects (Lieberman, Tharion, Shukitt-Hale, Speckman, & Tulley, 2002; Thayer, 2001), as was ‘Take a shower or bath’ for the dimension of fatigue. Indeed, moderate doses of caffeine (i.e., 200mg) have been found to improve cognitive function and mood alike (see Lieberman et al., 2002).

From this physiological and health-related perspective, ‘Engage in physical activity’ was added for fatigue, depression, and anger, although the wording slightly varied according to each mood dimension. For example, ‘Engage in light physical activity or non-strenuous physical tasks’ was added for fatigue; ‘Engage in physical activity or work-related physical tasks’ was added for depression; and ‘Engage in physical activities to reduce the feelings’ was added for anger. As highlighted in Chapter 2: Section 2.5.1, a vast amount of literature has supported the anxiolytic effects associated with exercise, ranging from generalised mood improvements (see Berger & Motl, 2000) to decreases in depressive states reaching the diagnostic threshold (see Mather et al., 2002; Salmon, 2001; Sylvia et al., 2009). Additionally, positive influences on fatigue have also been identified (see Tsang, 2011).

More generally however, the ideal combination to change a *bad mood* involves relaxation, stress management, and exercise techniques, as well as incorporating a cognitive component (Thayer et al., 1994). For this reason, a selection of cognitive-behavioural strategies were also included in the revision, although the wording again slightly varied according to each mood dimension. For example, ‘Talk with others to distract yourself from your feelings’; ‘Keep busy to distract yourself from the feeling’ was added for tension and fatigue; ‘Chat with others to distract yourself from how you are feeling’ and ‘Engage in humorous conversation or activities as a feel-good distraction’ were added for depression; ‘Engage in humorous conversation or activities’ was added for vigour; and ‘Engage in humorous conversation or activities as a feel-good distraction’ was added for confusion and anger. Distraction encompasses a range of heterogeneous techniques, and similarly with cognitive reappraisal, is well recognised as having a moderate effect on various emotional states (Parkinson & Totterdell, 1999; Thayer et al., 1994). For this reason, ‘Give yourself a pep talk using upbeat self-talk’ was also added for vigour and confusion.

Additionally, ‘Listen to favourite music’ was added for tension as well as depression, anger, and fatigue, being in line with Wales’ (1985 as cited in Karageorghis, 1992) findings. However, in an effort to appeal to a diverse audience, this mood regulation strategy was worded to purposely omit detail involving tempo (i.e., fast versus slow) and feel (i.e., positive versus negative). Although the interval and harmony of music can act as strong emotional prompts (Hunter et al., 2011), there is evidence to suggest that musical preference involves a number of mitigating factors (Saarikallio & Erkkilä, 2007), including idiosyncratic inclinations towards differential subgenres (Bunt, 1994). Indeed, heavy metal music has been found to improve mood for adolescents (Arnett, 1991), while pop, rock, high brow, urban, and dance music have also been found to provide psychophysical effects (Ter Bogt et al., 2011). An aside, the mood regulation strategy for vigour remained relatively unchanged, given that fast, upbeat music has been found to positively influence this mood dimension (Terry et al., 1999).

‘Concentrate on task-related strategies to clarify what is required’ was added for confusion to reduce attentional deployment, thereby facilitating selective attention (Westen et al., 2006). Similarly, ‘Spend some time alone to consider the issues’ and ‘Write your thoughts and feelings down to clarify things’ were also added for confusion to minimise divided attention and unnecessary distraction (Westen et al., 2006). Additionally, ‘Focus on task-related strategies to minimise negative impacts on your performance’ was added for tension. Alternatively, ‘Express yourself to let your feelings out’, was added for anger to encourage an external form of emotion-expression (Gross, 2002; Spielberger, 1991; Totterdell & Parkinson, 1999). ‘Talk to someone about how you are feeling’ was also included to encourage affiliative-communicative behaviours, which have previously been identified as a popular way to eliminate negative mood states (Terry et al., 2006). Alternatively, ‘Follow your usual routine’ was added for tension to minimise potential disruptions to day-to-day activities.

‘Deal with the cause of the feelings’ was omitted from the revised list of mood regulation strategies for tension, anger, and fatigue, in recognition that daily stressors such as work commitments often negatively contribute to these feeling states. Additionally, 'Avoid the cause of the feelings' was also removed for confusion in favour of a selection of other techniques. A full list of the mood regulations strategies for the Lim and Terry (2011) and revised versions of the *In The Mood* websites can be found in Table 5.4. Additionally, a complete overview of the redeveloped *In The Mood* website can be found in Appendix D.

Table 5.4

Comparison of Mood Regulation Strategies for Versions of In The Mood

Lim and Terry (2011) Version	Re-developed Version
Tension	
Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs	Use relaxation techniques to reduce your tension
Engage in the use of imagery related to the task	Use task-related imagery to prepare you for the task ahead
Engage in a physical activity	Engage in a physical activity or work-related physical tasks
Engage in superstitious activities	Engage in religious or spiritual activities
Think positively	Give yourself a pep talk using upbeat self-talk
Deal with the cause of the feelings	---
	Follow your usual routine
	Listen to favourite music
	Focus on task-related strategies to minimise negative impacts on your performance
	Talk with others to distract yourself from your feelings
	Keep busy to distract yourself from the feeling

(Table 5.4 continues)

(Table 5.4 continued)

Lim and Terry (2011) Version	Re-developed Version
Depression	
Think positively	Try to control your thoughts so that they are more positive
Deal with the cause of the feelings	Try to address the cause of your feelings
Talk to someone about your feelings	Talk to someone about how you are feeling
Put your feelings into perspective	Put your feelings into perspective to recognise the situation in a broader context
Seek physical affection	Seek physical affection
Think about something else	Try to think about something else other than how you are feeling
	Listen to favourite music
	Chat with others to distract yourself from how you are feeling
	Engage in humorous conversation or activities as a feel-good distraction
	Engage in physical activity or work-related physical tasks
Anger	
Deal with the cause of the feelings	---
Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs	Use relaxation techniques to calm yourself
Spend some time alone	Spend time alone to think about how you can address the situation
Focus on strategies related to successfully completing the task	Focus on task-related strategies to minimise negative impacts on your performance
Put your feelings into perspective	Put your feelings into perspective to recognise the situation in a broader context
Avoid the cause of the feelings	Try to avoid the cause of your anger

(Table 5.4 continues)

(Table 5.4 continued)

Lim and Terry (2011) Version	Re-developed Version
Anger	
	Express yourself to let your feelings out
	Listen to favourite music
	Talk to someone about how you are feeling
	Engage in humorous conversation or activities as a feel-good distraction
	Engage in physical activities to reduce the feelings
Vigour	
Engage in a physical activity	Engage in a physical activity to increase energy
Think positive	Try to control your thoughts so they are more positive
Engage in the use of imagery related to the task	Use task-related imagery to help you to feel ready to perform
Listen to fast, upbeat music	Listen to favourite music with a fast, upbeat style
Focus on strategies related to successfully completing the task	Focus on task-related strategies to minimise negative impacts on your performance
Put your feelings into perspective	Put your feelings into perspective by accepting that low vigour is normal from time to time
	Engage in humorous conversation or activities
	Eat a nutritional snack
	Drink a caffeinated beverage
	Give yourself a pep talk using upbeat self-talk
Fatigue	
Use relaxation techniques such as taking slow deep breaths or listening to relaxation CDs	Use relaxation techniques to re-energise yourself
Take a shower	Splash your face with cold water

(Table 5.4 continues)

(Table 5.4 continued)

Lim and Terry (2011) Version	Re-developed Version
Fatigue	
Have a rest, take a nap or go to sleep	Have a rest, take a nap, or sleep
Put your feelings into perspective	Put your feelings into perspective by accepting that fatigue is normal from time to time
Have a massage	Have a massage
Deal with the cause of the feelings	---
	Keep busy to distract yourself from the feeling
	Listen to favourite music
	Take a shower or bath
	Eat a nutritional snack to increase energy
	Engage in light physical activity or non-strenuous physical tasks
Confusion	
Focus on strategies related to successfully completing the task	Engage in task-related imagery to identify what is required
Think positively	Try to think positively until your confusion subsides
Deal with the cause of the feelings	Try to address the cause of your confusion
Talk to someone about how you are feeling	Talk to someone about your confusion to clarify things
Mentally switch off	Mentally switch off for awhile to give yourself a break
Avoid the cause of the feelings	---
	Engage in humorous conversation or activities as a feel-good distraction
	Concentrate on task-related strategies to clarify what is required
	Give yourself a pep talk using upbeat self-talk
	Write your thoughts and feelings down to clarify things

CHAPTER 6:
Replication of Mood Profiles: Sample C

Following the re-development of *In The Mood* the website was re-released into the public domain on 1 November, 2013. A third sample from the *In The Mood* website (i.e., Sample C) was used to replicate the findings of Sample A and Sample B. Again, cluster analytic methodology was used to identify clusters of mood responses in the general population. A multiple DFA and MANOVA were used to provide support for the accuracy of the final cluster solution, and a series of chi-squared tests for goodness-of-fit were used to describe demographic characteristics of mood profiles (i.e., gender, age, and level of education).

6.1 Method

6.1.1 Participants. Participants were again recruited from the general population through the *In The Mood* website. The snowballing technique via social networking sites (i.e., Facebook, Linkedin, etc.) and e-mail were used during the data collection period from October 31, 2013 to May 1, 2014. The initial sample comprised of 61.5% males and 38.4% females. A large portion (i.e., 44.4%) were aged 18–24, and approximately one third of the population reported a ‘High school’ level of education (i.e., 32.5%). Additionally, a large percentage (26.6%) of the sample selected an occupation listed as ‘Student/Education’, and 72.0% identified as being Caucasian ethnicity. Among reasons for completing the BRUMS, 34.5% reported ‘General interest’.

6.1.2 Measures. The online version of the BRUMS on the *In The Mood* website was again used to measure mood with the standard response timeframe of ‘How do you feel right now?’

6.1.3 Procedure. The research was conducted under the previous Human Research Ethics Committee Approval No., H13REA169. Again, all analyses were performed using IBM SPSS Statistics Software Version 22.0 (2013).

6.2 Results

A total of 2,290 cases were screened for missing values, abnormal and unusual responses. No missing values were detected. However, 166 cases of nil values were identified, and subsequently deleted. A visual inspection of the dataset was undertaken, and abnormalities were detected. A subsample of 11 participants scored 16 on each dimension of mood, and 9 cases scored 0 for each dimension (suggesting these individuals did not feel anything at all). Further, 4 cases were also identified as abnormal responses. One case scored 16 on each mood dimension except fatigue, which was 0. Another case scored 16 on tension only. The last two cases scored 16 on each mood dimension except vigour, which was 0. These two cases were consecutive (i.e., case ID numbers 9263 and 9264) and logged as being completed within 1 minute of one another. Additionally, both of these cases listed as being ‘Female’, ‘25–35’, completed a ‘TAFE qualification’, involved with ‘Mining’, ‘African’, and ‘Preparing for a sport competition’. Each of the four above mentioned cases were deleted as they were judged to constitute invalid data. Additionally, a further 235 participants listing Asian as their ethnicity were also deleted for reasons previously outlined in Chapter 3: Section 3.3.

A check for multivariate outliers was conducted according to the statistical recommendations of Tabachnick and Fidell (2013). Using Mahalanobis distance, 82 outliers were found to exceed the critical value of 22.46. All cases were retained, in line with Meyers et al. (2006). The final sample of online BRUMS respondents was 1,865 (i.e., Sample C). Scores ranged from 0–16 on each of the BRUMS subscales (i.e., tension, depression, anger, vigour, fatigue, and confusion). A complete summary of the demographic composition is presented in Table 6.1.

Table 6.1

Demographic Characteristics of the BRUMS Respondents (N = 1,865)

Dependent Variable	*n*	%
Gender		
Male	1,152	61.8
Female	713	38.2
Age Group		
18–24	767	41.1
25–35	277	14.9
36–45	306	16.4
46–55	352	18.9
56–65	163	8.7
65+	0	0.0
Education		
< High School Certificate	57	3.1
High School Certificate	654	35.1
Trade Apprenticeship	46	2.5
Trade Qualification	50	2.7
TAFE Qualification	107	5.7
University Degree	571	30.6
Postgraduate Degree	380	20.4
Occupation		
Athlete/Sport	455	25.4
Clerical/Administration	16	0.9
Community/Personal Services	19	1.0
Construction	258	13.8
Defence	8	0.4
Health/Medical	22	1.2
Manager/Professional	127	6.8
Manual/Labourer	1	0.1

(Table 6.1 continues)

(Table 6.1 continued)

Dependent Variable	*n*	%
Occupation		
Mining	201	10.8
Operator/Driver	6	0.3
Police/Emergency Services	5	0.3
Sales/Marketing	19	1.0
Student/Education	487	26.1
Technical/Trade	14	0.8
Not Currently Employed	24	1.3
Other	203	10.9
Ethnicity		
African	159	8.5
Asian	0	0.0
Caucasian	1,513	81.1
Indigenous	12	0.6
Middle Eastern	23	1.2
Other	158	8.5
Reason for Completing BRUMS		
General Interest	631	33.8
Not Feeling my Normal Self	46	2.5
Preparing for a Performance or Task	174	9.3
Preparing for a Presentation	43	2.3
Preparing for a Sport Competition	139	7.5
Preparing for an Examination	45	2.4
Wanting to Help with Research	496	26.6
Other	283	15.2

6.2.1 Parametric data screening. A visual inspection of the P-P plots and histograms of the raw scores for the BRUMS subscales indicated that the frequency distribution for vigour was approximately symmetrical, with a leptokurtic shape, while fatigue was approximately normal, with a slight positive skew. The scores for tension, depression, anger, and confusion deviated from the diagonal on the P-P plots, suggesting a positive skew for each mood dimension. The shape of these frequency distributions were approximately unimodal, skewed to the left, with some outliers identified for tension, depression, anger. Additionally, outliers were also identified for confusion. As expected, departures from normal were present: tension (skewness = 1.771, kurtosis = 3.230), depression (skewness = 2.069, kurtosis = 4.690), anger (skewness = 2.068, kurtosis = 4.444), vigour (skewness = –0.046, kurtosis = –0.395), fatigue (skewness = 0.730, kurtosis = –.155), and confusion (skewness = 1.904, kurtosis = 3.907). Despite obvious deviations from normal distributions for at least five of the six BRUMS subscales, no further parametric data screening was undertaken for reasons previously outlined in Chapter 3: Section 3.3. The means, standard deviations, and 95% CI's for each mood dimension are provided in Table 6.2.

Table 6.2

Descriptive Statistics of the BRUMS Subscales (N = 1,865)

Mood Dimension	*M*	*SD*	95% CI
Tension	45.89	8.00	[45.53, 46.25]
Depression	51.12	10.82	[50.63, 51.61]
Anger	50.89	9.35	[40.47, 51.32]
Vigour	49.58	8.92	[49.18, 49.99]
Fatigue	52.17	9.38	[51.74, 52.59]
Confusion	49.48	9.54	[49.04, 49.91]

6.2.2 K-means cluster analysis. K-means clustering using random aggregation centres with a prescribed six-cluster solution was used to replicate the previous findings in Sample A and Sample B. The mean *t* scores of the final cluster centroids according to each mood dimension are presented in Table 6.3. A graphical representation superimposing the six mood profiles can be found in Figure 6.1.

Table 6.3

Cluster Centroids of the Six-cluster Solution (N = 1,865)

Mood Dimension	**C1**[c] (*n* = 541)	**C2**[c] (*n* = 307)	**C3**[c] (*n* = 44)	**C4**[c] (*n* = 276)	**C5**[c] (*n* = 174)	**C6**[c] (*n* = 523)
Tension	41.67	44.97	70.45	50.64	57.82	42.25
Depression	45.95	52.00	87.43	53.03	69.87	45.65
Anger	46.66	49.48	81.86	53.92	66.69	46.64
Vigour	44.58	42.35	45.39	52.26	46.90	58.84
Fatigue	47.02	64.10	70.00	52.92	60.91	45.69
Confusion	44.62	48.98	78.73	54.00	66.05	44.42

Note. [c] denotes clusters found within Sample C.

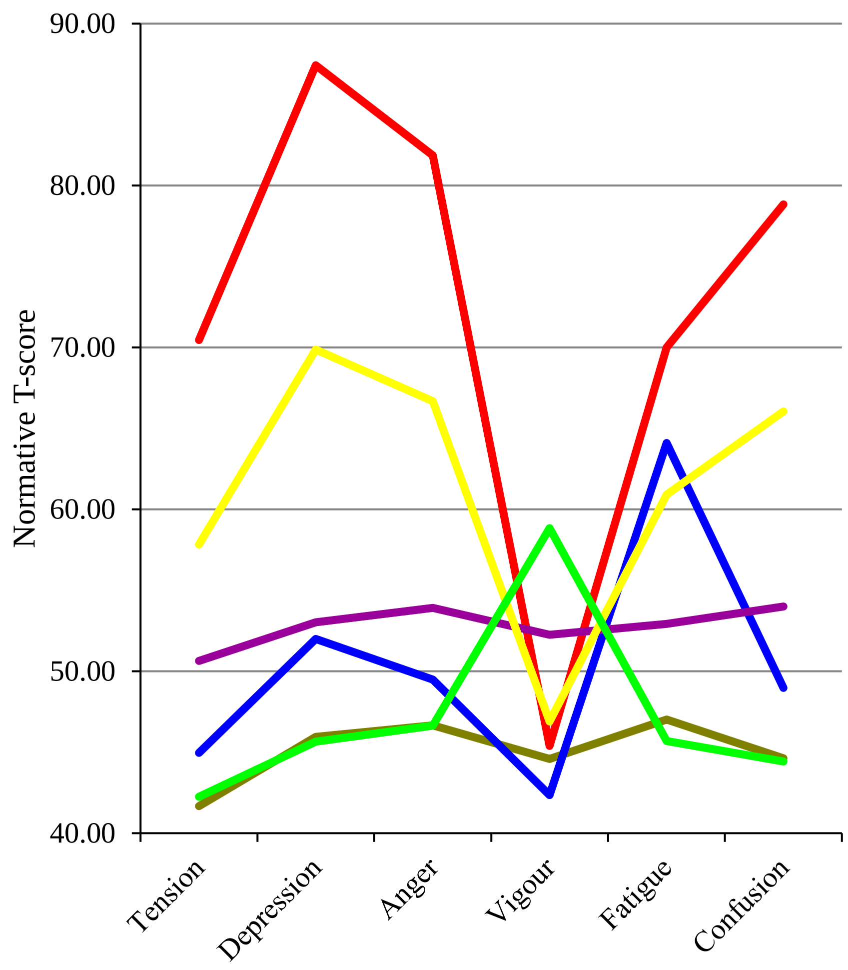


Figure 6.1. Graphical representation of the six-cluster solution (*N* = 1,865): C1^c (*n* = 541) = submerged profile, C2^c (*n* = 307) = shark fin profile, C3^c (*n* = 44) = inverse Everest profile, C4^c (*n* = 276) = surface profile, **C5^c** (*n* = 174) = inverse iceberg profile, and **C6^c** (*n* = 523) = iceberg profile.

6.2.3 Independence of clusters C1^c to C6^c. A between-groups MANOVA was performed to investigate whether the groups identified via the k-means cluster analysis differed to one another according to a combination of variables. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .034, $F(30, 1{,}865) = 326.93$, $p < .001$, partial $\eta^2 = .490$, observed power = 1.00. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for each dimension of mood: tension, $F(5, 1{,}859) = 617.96$, *p*

$< .001$, partial $\eta^2 = .624$, observed power = 1.00; depression, $F(5, 1{,}859) = 838.85$, $p < .001$, partial $\eta^2 = .693$, observed power = 1.00; anger, $F(5, 1{,}859) = 721.23$, $p < .001$, partial $\eta^2 =.660$, observed power = 1.00; vigour, $F(5, 1{,}859) = 424.30$, $p < .001$, partial $\eta^2 =.533$, observed power = 1.00; fatigue, $F(5, 1{,}859) = 718.82$, $p < .001$, partial $\eta^2 = .659$, observed power = 1.00; and confusion, $F(5, 1{,}859) = 828.67$, $p < .001$, partial $\eta^2 = .690$, observed power = 1.00.

An examination of the mean scores for each dependent variable (see Table 6.4) revealed that the magnitude of tension varied significantly between each cluster excluding $C1^c$ ($M = 41.67$, $SD = 2.84$, 95% CI [41.43, 41.91]) and $C6^c$ ($M = 42.25$, $SD = 3.20$, 95% CI [41.97, 42.52]), which were found to be at a similar level. The magnitude of depression was also found to vary significantly between each cluster excluding $C1^c$ ($M = 45.95$, $SD = 3.95$, 95% CI [45.61, 46.28]) and $C6^c$ ($M = 45.65$, $SD = 3.69$, 95% CI [45.33, 45.97]); as well as $C2^c$ ($M = 52.00$, $SD = 7.68$, 95% CI [51.14, 52.87]) and $C4^c$ ($M = 53.03$, $SD = 7.13$, 95% CI [52.18, 53.87]), which were found to be at a similar level. The magnitude of anger was found to vary significantly between each cluster excluding $C1^c$ ($M = 46.66$, $SD = 3.19$, 95% CI [46.39, 46.93]) and $C6^c$ ($M = 46.64$, $SD = 3.27$, 95% CI [46.36, 46.92]). The magnitude of vigour was found to vary significantly between each cluster excluding $C1^c$ ($M = 44.58$, $SD = 5.96$, 95% CI [44.07, 45.08]) and $C3^c$ ($M = 45.39$, $SD = 8.67$, 95% CI [42.75, 48.02]); as well as $C3^c$ ($M = 45.39$, $SD = 8.67$, 95% CI [42.75, 48.02]) and $C5^c$ ($M = 46.90$, $SD = 7.95$, 95% CI [45.71, 48.09]), which were found to be at a similar level. The magnitude of fatigue was found to vary significantly between each cluster, as was the magnitude of confusion excluding $C1^c$ ($M = 44.62$, $SD = 3.25$, 95% CI [44.35, 44.90]) and $C6^c$ ($M = 44.42$, $SD = 2.73$, 95% CI [44.19, 44.66]).

Table 6.4

Descriptive Statistics of the Six-cluster Solution (N = 1,865)

Mood Dimension	C1c (*n* = 541)			C2c (*n* = 307)			C3c (*n* = 44)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	41.67	2.84	[41.43, 41.91]	44.97	5.67	[44.33, 45.61]	70.45	7.32	[68.23, 72.68]
Depression	45.95	3.95	[45.61, 46.28]	52.00	7.68	[51.14, 52.87]	87.43	11.91	[83.81, 91.05]
Anger	46.66	3.19	[46.39, 46.93]	49.48	5.33	[48.88, 50.07]	81.86	9.86	[78.87, 84.86]
Vigour	44.58	5.96	[44.07, 45.08]	42.35	6.37	[41.63, 43.06]	45.39	8.67	[42.75, 48.02]
Fatigue	47.02	4.68	[46.62, 47.41]	64.10	6.43	[63.38, 64.82]	70.00	6.59	[68.00, 72.00]
Confusion	44.62	3.25	[44.35, 44.90]	48.98	6.35	[48.26, 49.69]	78.73	9.26	[75.91, 81.54]
Mood Dimension	C4c (*n* = 276)			C5c (*n* = 174)			C6c (*n* = 523)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	50.64	7.31	[49.77, 51.51]	57.82	6.81	[56.80, 58.84]	42.25	3.20	[41.97, 42.52]
Depression	53.03	7.13	[52.18, 53.87]	69.87	9.03	[68.52, 71.22]	45.65	3.69	[45.33, 45.97]
Anger	53.92	7.57	[53.03, 54.82]	66.69	9.40	[65.28, 68.10]	46.64	3.27	[46.36, 46.92]
Vigour	52.26	6.38	[51.50, 53.02]	46.90	7.95	[45.71, 48.09]	58.84	4.94	[58.42, 59.27]
Fatigue	52.92	5.83	[52.23, 53.61]	60.91	7.21	[59.83, 61.99]	45.69	4.72	[45.28, 46.09]
Confusion	54.00	7.16	[53.15, 54.84]	66.05	8.61	[64.76, 67.34]	44.42	2.73	[44.19, 44.66]

Note. C1c = submerged profile, C2c = shark fin profile, C3c = inverse Everest profile, C4c = surface profile, C5c = inverse iceberg profile, C6c = iceberg profile.

A *post hoc* simultaneous DFA was once again calculated. The sample was randomly drawn from the population, so the groups were considered a valid estimate of the population proportions in each group. Therefore, the best estimates of actual group sizes and the prior probabilities were not equal values, but the sample proportions. The groups were defined according to the six-cluster solution identified via the k-means cluster analysis (i.e., $C1^c$ [n = 541] = submerged profile, $C2^c$ [n = 307] = shark fin profile, $C3^c$ [n = 44] = inverse Everest profile, $C4^c$ [n = 276] = surface profile, $C5^c$ [n = 174] = inverse iceberg profile, and $C6^c$ [n = 523] = iceberg profile). The ratio of cases to independent variables was 311 to 1, which satisfied the preferred requirement of ≥ 20 to 1. The number of cases in the smallest group was 44, being larger than the number of independent variables (i.e., 6), and thus exceeded the preferred number of cases (i.e., ≥ 20) per group. The maximum number of possible discriminant functions was five, being the number of groups minus one.

The five canonical discriminant functions extracted accounted for 100% of the variance, and each function was able to predict an outcome at a significant level. As can be seen in Table 6.5, discriminant function 1 (DF^{1c}) accounted for R^2 = 87.05% of the between-group variance, Wilks' Λ = .034, $\chi^2(30, N = 1{,}865) = 6261.51$, $p < .001$. Discriminant function 2 (DF^{2c}) accounted for R^2 = 59.60% of the between-group variance, Wilks' Λ = .266, $\chi^2(20, N = 1{,}865) = 2459.64$, $p < .001$. Discriminant function 3 (DF^{3c}) accounted for R^2 = 30.47% of the between-group variance, Wilks' Λ = .659, $\chi^2(12, N = 1{,}865) = 776.21$, $p < .001$. Discriminant function 4 (DF^{4c}) accounted for R^2 = 4.84% of the between-group variance, Wilks' Λ = .947, $\chi^2(6, N = 1{,}865) = 101.80$, $p < .001$. Discriminant function 5 (DF^{5c}) accounted for R^2 = 0.53% of the between-group variance, Wilks' Λ = .995, $\chi^2(2, N = 1{,}865) = 9.96$, $p = .007$. The significance of the Wilks' lambda in the maximum number of discriminant functions supported the interpretation of a solution using five discriminant functions. Table 6.6 shows the group centroids (vector of means) on the five new canonical variables formed by applying the discriminant function weights.

Table 6.5

Eigenvalues for the Discriminant Function (N = 1,865)

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
DF^{1c}	6.739	77.4	77.4	.933
DF^{2c}	1.475	16.9	94.3	.772
DF^{3c}	0.438	5.0	99.4	.552
DF^{4c}	0.051	0.6	99.9	.220
DF^{5c}	0.005	0.1	100.0	.073

Note. ^{c} denotes canonical discriminant functions created using Sample C.

Table 6.6

Functions at Group Centroids (N = 1,865)

	Function				
Cluster	DF^{1c}	DF^{2c}	DF^{3c}	DF^{4c}	DF^{5c}
$C1^{c}$	–1.563	–0.684	–0.868	–0.025	0.012
$C2^{c}$	0.940	–2.123	0.900	–0.030	0.004
$C3^{c}$	9.727	1.288	–0.455	–0.337	0.354
$C4^{c}$	1.021	0.718	0.095	0.514	0.006
$C5^{c}$	5.055	0.650	–0.373	–0.179	–0.158
$C6^{c}$	–1.974	1.250	0.482	–0.140	0.005

Note. $C1^{c}$ (*n* = 541) = submerged profile, $C2^{c}$ (*n* = 307) = shark fin profile, $C3^{c}$ (*n* = 44) = inverse Everest profile, $C4^{c}$ (*n* = 276) = surface profile, $C5^{c}$ (*n* = 174) = inverse iceberg profile, $C6^{c}$ (*n* = 523) = iceberg profile.

Based on the structure matrix, the mood dimensions strongly associated with DF^{1c} included high levels of anger, fatigue, depression, tension, and confusion. The predictor variables strongly associated with DF^{2c} included a high level of vigour and low fatigue. The predictor variables strongly associated with DF^{3c} included high levels of fatigue and vigour. The predictor variables strongly associated with DF^{4c} included low levels of depression and high tension, while the predictor variables strongly associated with DF^{5c} included high tension and low levels of confusion. The number and composition of the dimensions of discrimination between groups can be found in Table 6.7, and the unstandardised canonical coefficients are shown in Table 6.8.

Table 6.7

Structure Matrix (N = 1,865)

Mood Dimension	Function				
	DF^{1c}	DF^{2c}	DF^{3c}	DF^{4c}	DF^{5c}
Anger	.520*	.254	–.228	–.225	.247
Vigour	–.141	.756*	.612	–.025	–.032
Fatigue	.438	–.531	.715*	.029	.001
Depression	.570	.145	–.130	–.727*	.119
Tension	.478	.257	–.075	.604*	.432
Confusion	.564	.220	–.152	.281	–.712*

Note. * Largest absolute correlation between each variable and any discriminant function.

Table 6.8

Unstandardised Canonical Coefficients (N = 1,865)

Mood Dimension	Function				
	DF^{1c}	DF^{2c}	DF^{3c}	DF^{4c}	DF^{5c}
Tension	.187	.115	–.008	.316	.355
Depression	.222	.100	.023	–.520	.082
Anger	.237	.070	–.187	.019	.134
Vigour	–.055	.312	.265	–.036	–.020
Fatigue	.189	–.236	.321	.022	.005
Confusion	.267	.105	–.090	.153	–.594

The DFA found that cluster membership was correctly classified with a high degree of accuracy. The percentage of correct classifications were: submerged profile = 98.2%, shark fin profile = 93.2%, inverse Everest profile = 93.2%, surface profile = 82.6%, inverse iceberg profile = 98.3%, and iceberg profile = 99.2%. Prior probabilities from $C1^c$ to $C6^c$ inclusive were 29.0%, 16.5%, 2.4%, 14.8%, 9.3%, 28.0% (respectively). The proportional by chance accuracy rate was computed (i.e., $0.290^2 + 0.165^2 + 0.024^2 + 0.148^2 + 0.093^2 + 0.280^2 = 0.221$). Additionally, when the discriminant functions were used to predict group membership, the hit ratio was very high. A total of 95.2% of the cases were correctly reclassified back into the original categories. This percentage was notably higher than the minimum classification accuracy rate of 47.1%. These findings suggest that the overlap of the overall distribution was small, and the function was a good discriminator between groups. Table 6.9 and Table 6.10 list the classification function coefficients and DFA classification results, respectively.

Table 6.9

Classification Function Coefficients (N = 1,865)

Mood Dimension	Cluster					
	$C1^c$	**$C2^c$**	**$C3^c$**	**$C4^c$**	**$C5^c$**	**$C6^c$**
Tension	0.189	0.472	2.548	0.994	1.468	0.285
Depression	0.314	0.769	3.223	0.771	1.997	0.506
Anger	–0.065	0.095	2.715	0.476	1.480	–0.283
Vigour	0.953	0.835	1.060	1.484	1.145	1.942
Fatigue	0.577	1.957	2.373	1.055	1.668	0.473
Confusion	0.133	0.496	3.071	0.970	2.076	0.091

Note. $C1^c$ (n = 541) = submerged profile, $C2^c$ (n = 307) = shark fin profile, $C3^c$ (n = 44) = inverse Everest profile, $C4^c$ (n = 276) = surface profile, $C5^c$ (n = 174) = inverse iceberg profile, $C6^c$ (n = 523) = iceberg profile.

Table 6.10

Classification of Results (N = 1,865)

	Predicted Group Membership						
Cluster	1	2	3	4	5	6	*n*
C1c	531	0	0	0	0	10	541
C2c	18	286	0	2	0	1	307
C3c	0	0	41	0	3	0	44
C4c	17	9	0	228	4	18	276
C5c	0	1	0	2	171	0	174
C6c	3	0	0	1	0	519	523

Note. $C1^c$ = submerged profile, $C2^c$ = shark fin profile, $C3^c$ = inverse Everest profile, $C4^c$ = surface profile, $C5^c$ = inverse iceberg profile, $C6^c$ = iceberg profile.

6.2.4 Characteristics of clusters $C1^c$ to $C6^c$. Figure 6.2 to Figure 6.7 present the graphical representations (using mean *t* scores) of the six clusters (i.e., $C1^c$, $C2^c$, $C3^c$, $C4^c$, $C5^c$, $C6^c$) derived from the K-means analysis.

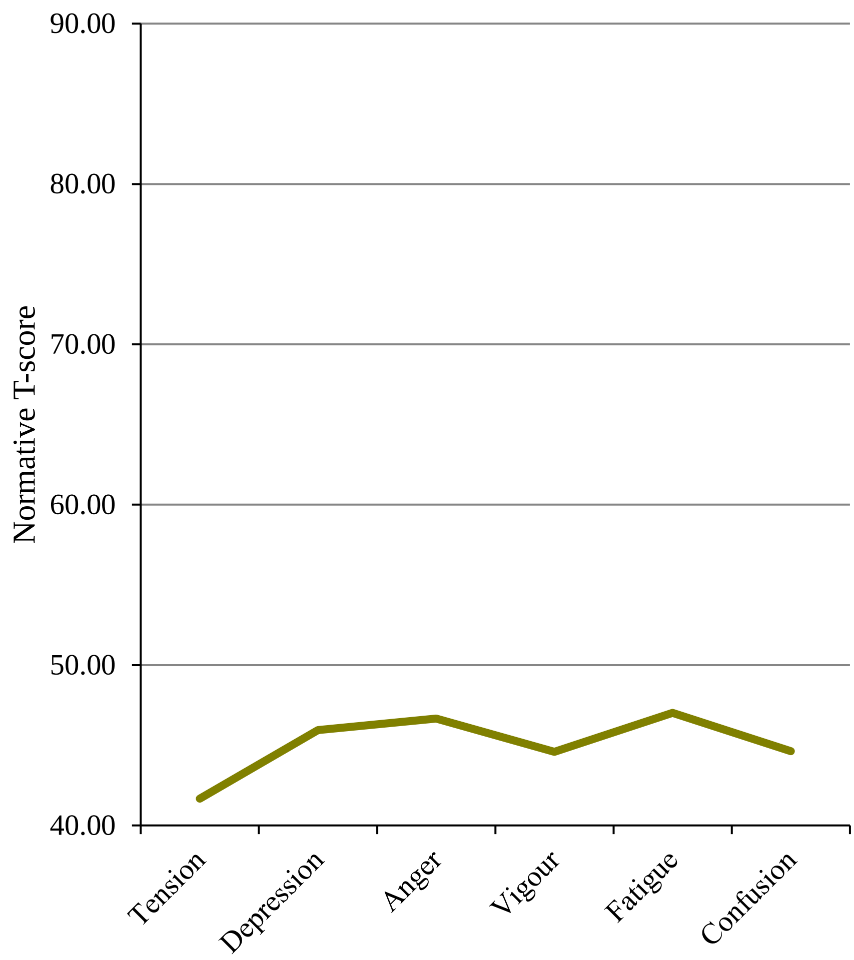


Figure 6.2. Graphical representation of C1[c] (n = 541).

C1[c] was identified as the submerged profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 41.67, SD = 2.84, 95% CI [41.26, 42.09]; depression, M = 45.95, SD = 3.95, 95% CI [45.44, 46.46]; anger, M = 46.66, SD = 3.19, 95% CI [46.20, 47.12]; vigour, M = 44.58, SD = 5.96, 95% CI [44.06, 45.09]; fatigue, M = 47.02, SD = 4.68, 95% CI [46.55, 47.48]; and confusion, M = 44.62, SD = 3.25, 95% CI [44.18, 45.07].

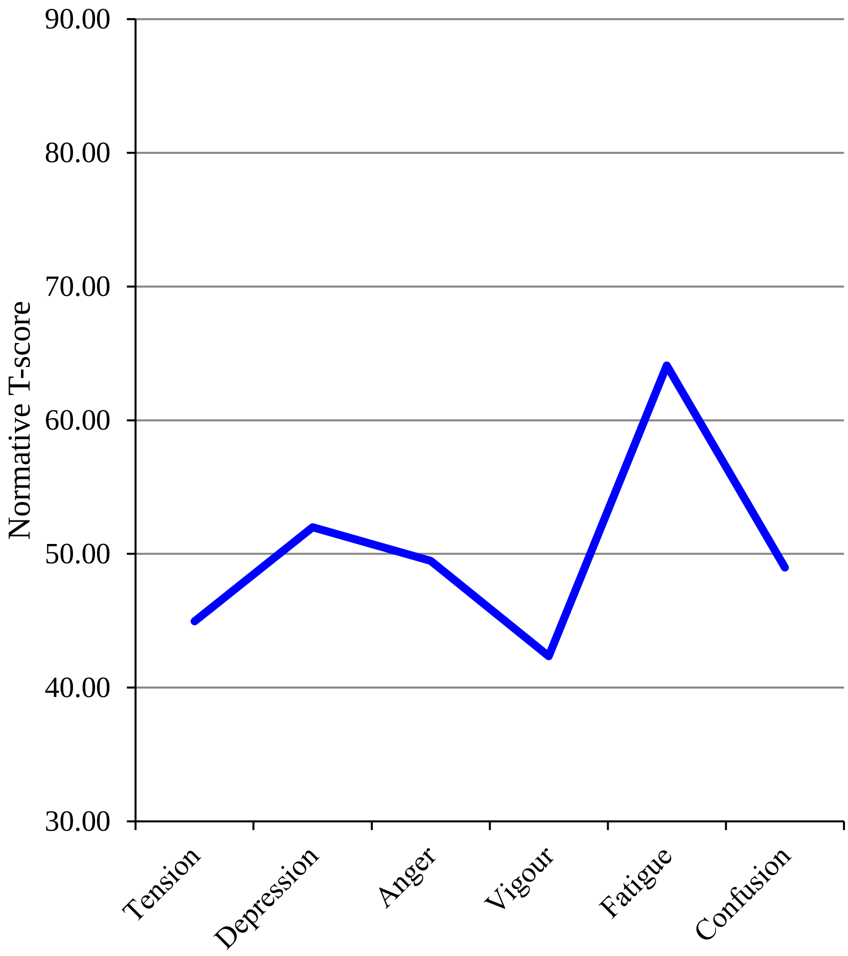


Figure 6.3. Graphical representation of C2^c (n = 307).

C2^c was identified as the shark fin profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, M = 44.97, SD = 5.67, 95% CI [44.42, 45.52]; depression, M = 52.00, SD = 7.68, 95% CI [51.33, 52.68]; anger, M = 49.48, SD = 5.33, 95% CI [48.87, 50.08]; vigour, M = 42.35, SD = 6.37, 95% CI [41.66, 43.03]; fatigue, M = 64.10, SD = 6.43, 95% CI [63.49, 64.72]; and confusion, M = 48.98, SD = 6.35, 95% CI [48.38, 49.57].

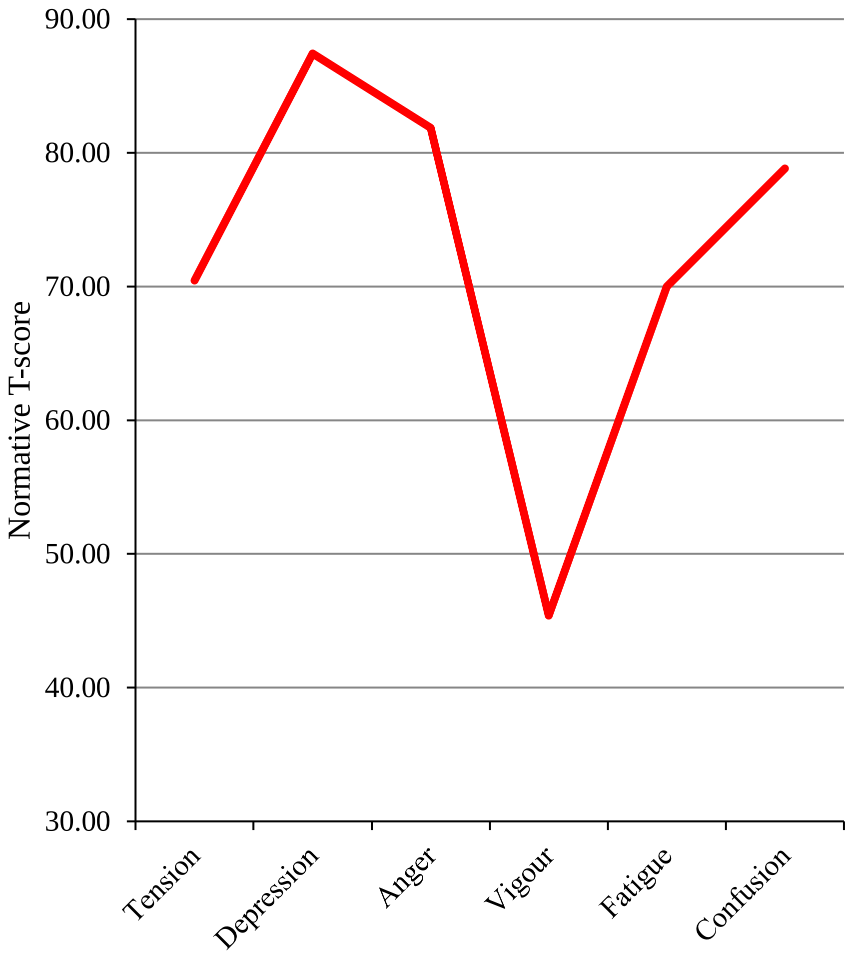


Figure 6.4. Graphical representation of C3[c] (*n* = 44).

C3[c] was identified as the inverse Everest profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 70.45, *SD* = 7.32, 95% CI [69.01, 71.90]; depression, *M* = 87.43, *SD* = 11.91, 95% CI [85.65, 89.22]; anger, *M* = 81.86, *SD* = 9.86, 95% CI [80.26, 83.47]; vigour, *M* = 45.39, *SD* = 8.67, 95% CI [43.58, 47.20]; fatigue, *M* = 70.00, *SD* = 6.59, 95% CI [68.37, 71.63]; and confusion, *M* = 78.73, *SD* = 9.26, 95% CI [77.16, 80.30].

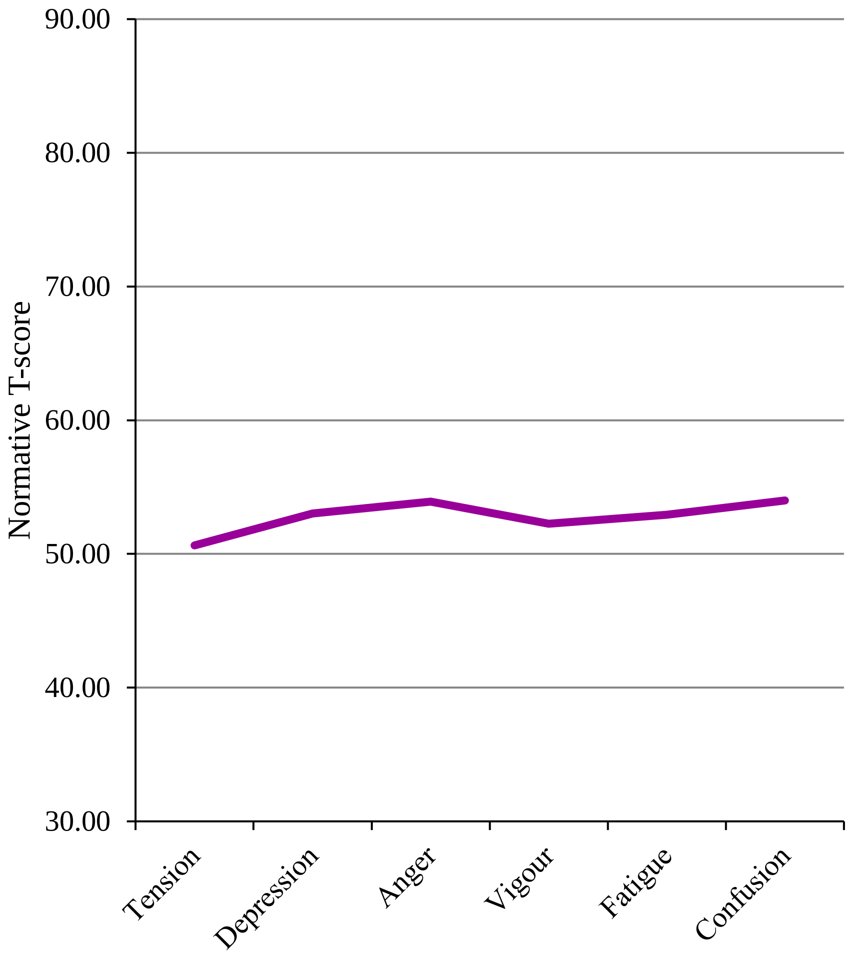


Figure 6.5. Graphical representation of C4^c (*n* = 276).

C4^c was identified as the surface profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 50.64, *SD* = 7.31, 95% CI [50.06, 51.22]; depression, *M* = 53.03, *SD* = 7.13, 95% CI [52.32, 53.74]; anger, *M* = 53.92, *SD* = 7.57, 95% CI [53.28, 54.57]; vigour, *M* = 52.26, *SD* = 6.38, 95% CI [51.54, 52.98]; fatigue, *M* = 52.92, *SD* = 5.83, 95% CI [52.27, 53.57]; and confusion, *M* = 54.00, *SD* = 7.16, 95% CI [53.37, 54.62].

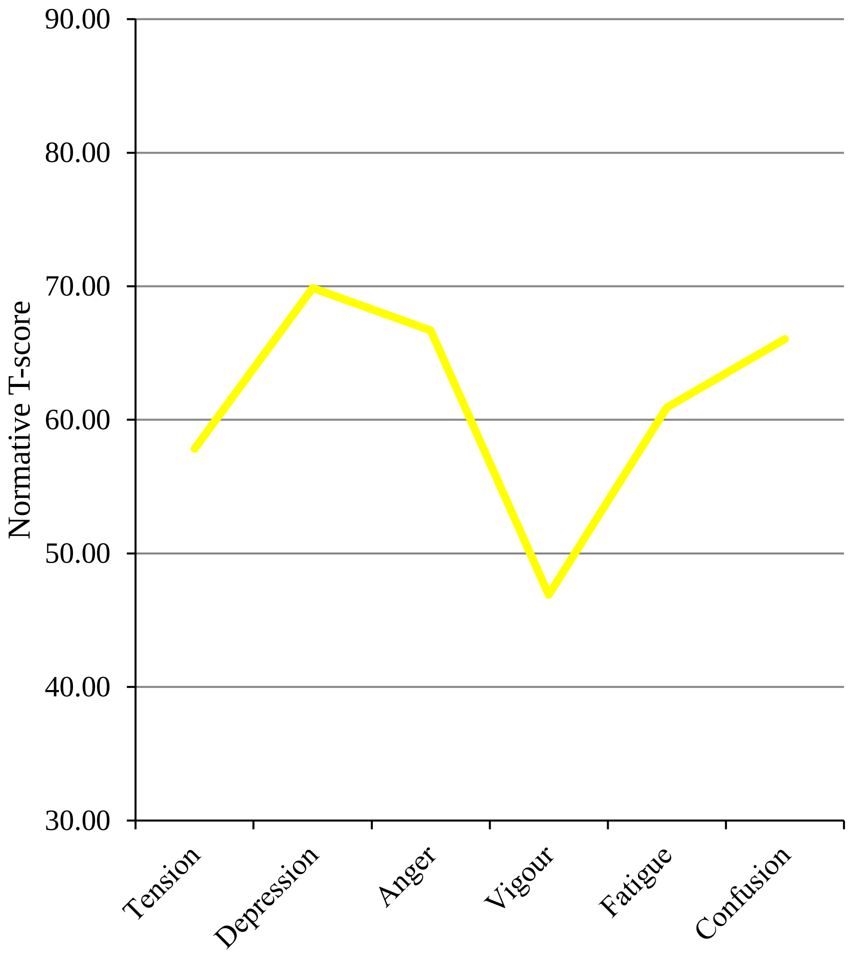


Figure 6.6. Graphical representation of **C5^c** (n = 174).

C5^c was identified as the inverse iceberg profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 57.82, *SD* = 6.81, 95% CI [57.09, 58.55]; depression, *M* = 69.87, *SD* = 9.03, 95% CI [68.97, 70.77]; anger, *M* = 66.69, *SD* = 9.40, 95% CI [65.88, 67.50]; vigour, *M* = 46.90, *SD* = 7.95, 95% CI [45.99, 47.81]; fatigue, *M* = 60.91, *SD* = 7.21, 95% CI [60.09, 61.73]; and confusion, *M* = 66.05, *SD* = 8.61, 95% CI [65.26, 66.84].

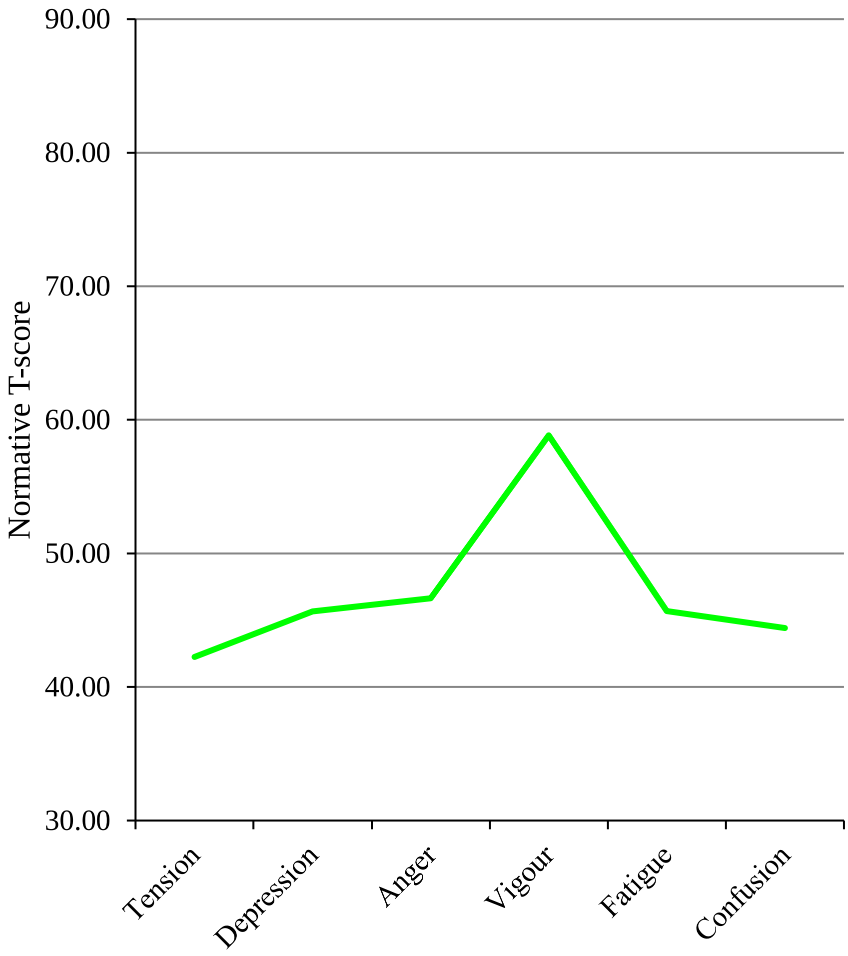


Figure 6.7. Graphical representation of **C6ᶜ** (n = 523).

C6ᶜ was identified as the iceberg profile. Mean scores, standard deviations, and 95% confidence intervals characterising this cluster were: tension, *M* = 42.25, *SD* = 3.20, 95% CI [41.83, 42.67]; depression, *M* = 45.65, *SD* = 3.67, 95% CI [45.13, 46.17]; anger, *M* = 46.64, *SD* = 3.27, 95% CI [46.17, 47.12]; vigour, *M* = 58.84, *SD* = 4.94, 95% CI [58.32, 59.37; fatigue, *M* = 45.69, *SD* = 4.72, 95% CI [45.21, 46.16]; and confusion, *M* = 44.42, *SD* = 2.73, 95% CI [43.97, 44.88].

6.2.5 Demographics of clusters C1^c to C6^c. A chi-square test of goodness-of-fit was performed to determine whether the number of participants varied across the submerged (C1^c), shark fin (C2^c), inverse Everest (C3^c), surface (C4^c), inverse iceberg (C5^c), and iceberg (C6^c) mood profiles according to gender. The overall sample consisted of an unequal distribution of males and females, being 61.8% and 38.2%, respectively. As can be seen in the bar chart (refer to Figure 6.8) and frequencies cross tabulated in Table 6.11, the distributions were significantly different from expected values, $\chi^2(5, N = 1{,}865) = 77.66$, $p < .001$, suggesting an association between gender and cluster.

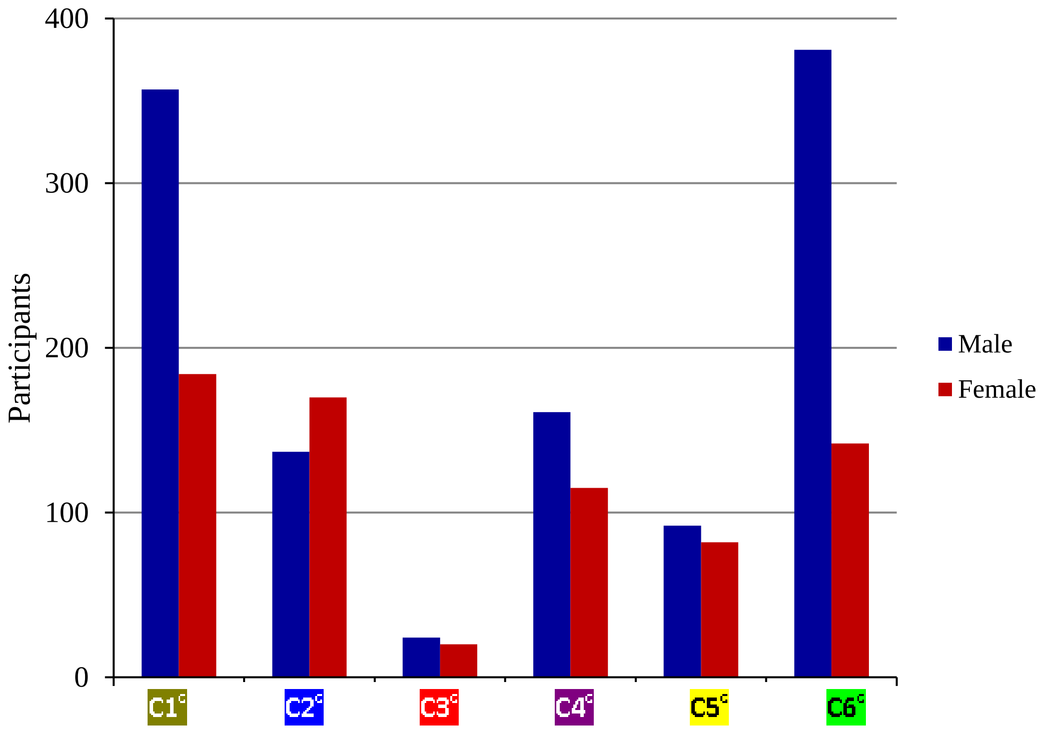


Figure 6.8. Distribution of gender across clusters ($N = 1{,}865$). Overall number of participants according to gender: male ($n = 1{,}152$), female ($n = 713$). C1^c ($n = 541$) = submerged profile, C2^c ($n = 307$) = shark fin profile, C3^c ($n = 44$) = inverse Everest profile, C4^c ($n = 276$) = surface profile, C5^c ($n = 174$) = inverse iceberg profile, and C6^c ($n = 523$) = iceberg profile.

Table 6.11

Crosstabulations of Clusters C1^c to C6^c by Gender (N = 1,865)

Gender	C1^c (*n* = 541)	C2^c (*n* = 307)	C3^c (*n* = 44)	C4^c (*n* = 276)	C5^c (*n* = 174)	C6^c (*n* = 523)
Male						
Actual	357	137	24	161	92	381
Expected	334	190	27	171	108	323
Female						
Actual	184	170	20	115	82	142
Expected	207	117	17	106	67	200

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
Male (*n* = 1,152), Female (*n* = 713).
Expected frequencies are rounded to whole numbers.

The distribution of gender within the submerged profile (C1^c) included: male = 66.0% and female = 34.0%. C1^c had an over-representation of males by 6.9% and an under-representation of females by 11.2%. The distribution of gender within the shark fin profile (C2^c) included: male = 44.6% and female = 55.4%. C2^c had an over-representation of females by 8.5% and an under-representation of males by 27.9%. The distribution of gender within the inverse Everest profile (C3^c) included: male = 54.5% and female = 45.5%. C3^c had an over-representation of females by 17.6% and an under-representation of males by 11.2%. The distribution of gender within the surface profile (C4^c) included: male = 58.3% and female = 41.7%. C4^c had an over-representation of females by 8.5% and an under-representation of males by 5.8%. The distribution of gender within the inverse iceberg profile (C5^c) included: male = 52.9% and female = 47.1%. C5^c had an over-representation of females by 22.4% and an under-representation of males by 14.8%. Finally, the distribution of gender within the iceberg profile (C6^c) included: male = 72.8% and female = 27.2%. C6^c had an over-representation of males by 18.0% and an under-representation of females by 29.0%. Table 6.12 lists the within gender percentage according to each cluster.

Table 6.12

Cluster Membership According to Within Gender Percentage (N = 1,865)

Gender	$C1^c$ (*n* = 541)	$C2^c$ (*n* = 307)	$C3^c$ (*n* = 44)	$C4^c$ (*n* = 276)	$C5^c$ (*n* = 174)	$C6^c$ (*n* = 523)
Male	31.0%	11.9%	2.1%	14.0%	8.0%	33.1%
Female	25.8%	23.8%	2.8%	16.1%	11.5%	19.9%

Note. $C1^c$ = submerged profile, $C2^c$ = shark fin profile, $C3^c$ = inverse Everest profile, $C4^c$ = surface profile, $C5^c$ = inverse iceberg profile, $C6^c$ = iceberg profile.
Male (*n* = 1,152), Female (*n* = 713).

Again, a *post hoc* review of the adjusted residuals identified which groups made the largest contributions to the significant chi-square result (refer to Table 6.13). The gender split within the shark fin ($C2^c$) and iceberg ($C6^c$) profiles were found to have made the highest contributions, with significant adjusted residuals of –6.8 = $p < .001$ (males) and 6.8 = $p < .001$ (females), and 6.1 = $p < .001$ (males) and –6.1 = $p < .001$ (females), respectively. The submerged profile ($C1^c$) was also found to have contributed to the significant chi-square result with adjusted residuals of 2.4 = $p < .05$ (males) and –2.4 = $p < .001$ (females), as did the inverse iceberg profile ($C5^c$) with adjusted residuals of –2.5 = $p < .05$ (males) and 2.5 = $p < .001$ (females). No relationship was found between gender and cluster for the inverse Everest ($C3^c$) and surface ($C4^c$) profiles.

Table 6.13

Standardised and Adjusted Residuals for Gender (N = 1,865)

Gender	$C1^c$ (n = 541)	$C2^c$ (n = 307)	$C3^c$ (n = 44)	$C4^c$ (n = 276)	$C5^c$ (n = 174)	$C6^c$ (n = 523)
Male						
Std	1.2	–3.8	–0.6	–0.7	–1.5	3.2
Adj	2.4*	–6.8***	–1.0	–1.3	–2.5*	6.1***
Female						
Std	–1.6	4.9	0.8	0.9	1.9	–4.1
Adj	–2.4*	6.8***	1.0	1.3	2.5*	–6.1***

Note. $C1^c$ = submerged profile, $C2^c$ = shark fin profile, $C3^c$ = inverse Everest profile, $C4^c$ = surface profile, $C5^c$ = inverse iceberg profile, $C6^c$ = iceberg profile.
Male (n = 1,152), Female (n = 713).
* $p < .05$, *** $p < .001$.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the submerged ($C1^c$), shark fin ($C2^c$), inverse Everest ($C3^c$), surface ($C4^c$), inverse iceberg ($C5^c$), and iceberg ($C6^c$) mood profiles according to differential age groupings. Figure 6.9 and Table 6.14 both illustrate that the frequencies were significantly different from expected values, $\chi^2(20, N = 1{,}865) = 42.82$, $p = .002$, suggesting an association between age and cluster.

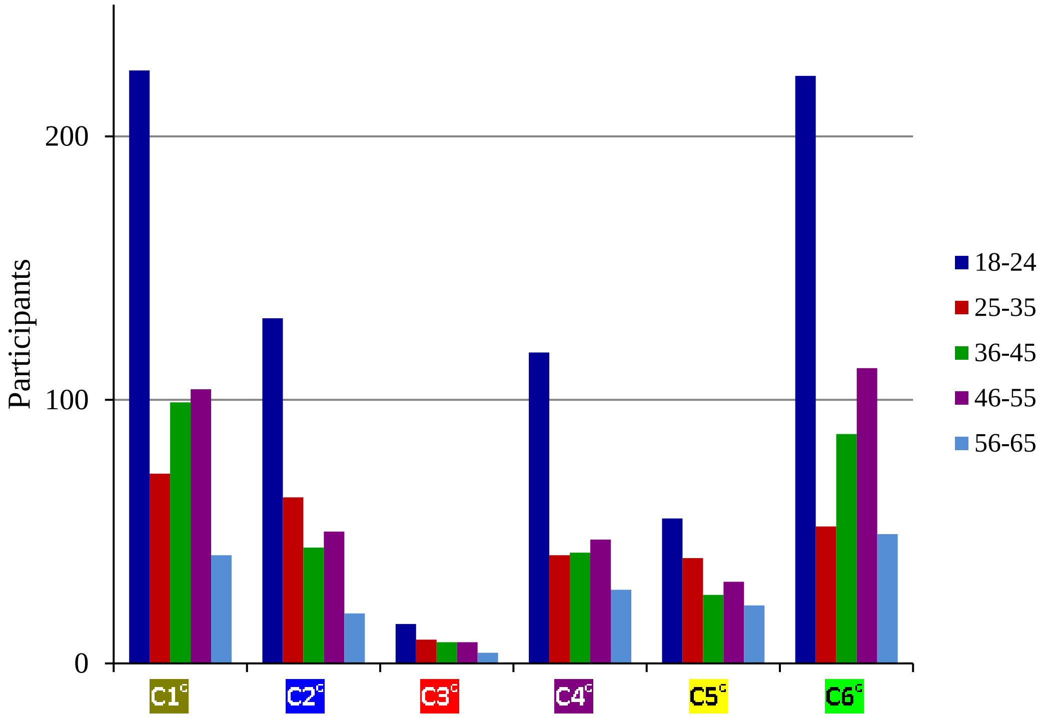


Figure 6.9. Distribution of age across clusters (*N* = 1,865). Overall number of participants according to age grouping: 18–24 (*n* = 767), 25–35 (*n* = 277), 36–45 (*n* = 306), 46–55 (*n* = 352), 56–65 (*n* = 163). $C1^c$ (*n* = 541) = submerged profile, $C2^c$ (*n* = 307) = shark fin profile, $C3^c$ (*n* = 44) = inverse Everest profile, $C4^c$ (*n* = 276) = surface profile, $C5^c$ (*n* = 174) = inverse iceberg profile, and $C6^c$ (*n* = 523) = iceberg profile.

Table 6.14

Crosstabulations of Clusters C1^c to C6^c by Age Grouping (N = 1,865)

Age	C1^c (*n* = 541)	C2^c (*n* = 307)	C3^c (*n* = 44)	C4^c (*n* = 276)	C5^c (*n* = 174)	C6^c (*n* = 523)
18–24						
Actual	225	131	15	118	55	223
Expected	223	126	18	114	72	215
25–35						
Actual	72	63	9	41	40	52
Expected	80	46	7	41	26	78
36–45						
Actual	99	44	8	42	26	87
Expected	89	50	7	45	29	86
46–55						
Actual	104	50	8	47	31	112
Expected	102	58	8	52	33	99
56–65						
Actual	41	19	4	28	22	49
Expected	47	27	4	24	15	46

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
18–24 (*n* = 767), 25–35 (*n* = 277), 36–45 (*n* = 306), 46–55 (*n* = 352), 56–65 (*n* = 163).
Expected frequencies are rounded to whole numbers.

The distribution of age within the submerged profile (C1^c) included: 18–24 = 41.6%, 25–35 = 13.3%, 36–45 = 18.3%, 46–55 = 19.2%, and 56–65 = 7.6%. C1^c had an over-representation of the 18–24, 36–45, and 46–55 age groups by 0.9%, 11.2%, and 2.0%, respectively, and an under-representation of the 25–35 and 56–65 age groups by 10.0% and 12.8%, respectively. The distribution of age within the shark fin profile (C2^c) included: 18–24 = 42.7%, 25–35 = 20.5%, 36–45 = 14.3%, 46–55 = 16.3%, and 56–65 = 6.2%. C2^c had an over-representation of the 18–24 and 25–35 age groups by 4.0% and 37.0%, respectively, and an under-representation of the 36–45, 46–55, and 56–65 age groups by 12.0%, 13.8%, and 29.6%, respectively.

The distribution of age within the inverse Everest profile ($C3^c$) included: 18–24 = 34.1%, 25–35 = 20.5%, 36–45 = 18.2%, 46–55 = 18.2%, and 56–65 = 9.1%. $C3^c$ had an over-representation of the 25–35 and 36–45 age groups by 28.6% and 14.3%, respectively, and an under-representation of the 18–24 age group by 16.7%, while the 46–55 and 56–65 age groups matched the chi-square expected count.

Further, the distribution of age within the surface profile ($C4^c$) included: 18–24 = 42.8%, 25–35 = 14.9%, 36–45 = 15.2%, 46–55 = 17.0%, and 56–65 = 10.1%. $C4^c$ had an over-representation of the 18–24 and 56–65 age groups by 3.5% and 16.7%, respectively, and an under-representation of the 36–45 and 46–55 age groups by 6.7% and 9.6%, respectively, while the 25–35 age group matched the chi-square expected count. The distribution of age within the inverse iceberg profile ($C5^c$) included: 18–24 = 31.6%, 25–35 = 23.0%, 36–45 = 14.9%, 46–55 = 17.8%, and 56–65 = 12.6%. $C5^c$ had an over-representation of the 25–35 and 56–65 age groups by 53.8% and 46.7%, respectively, and an under-representation of the 18–24, 36–45, and 46–55 age groups by 23.6%, 10.3%, and 6.1%, respectively. The distribution of age within the iceberg profile ($C6^c$) included: 18–24 = 42.6%, 25–35 = 9.9%, 36–45 = 16.6%, 46–55 = 21.4%, and 56–65 = 9.4%. $C6^c$ had an over-representation of the 18–24, 36–45, 46–55, and 56–65 age groups by 3.7%, 1.2%, 13.1%, and 6.5%, respectively, and an under-representation of the 25–35 age group by 33.4%.

The overall significant chi-square result indicated a relationship between age and mood profile. In this case, 1 of the 30 expected cell counts were < 5 (i.e., 3.4%) and none of the expected counts were < 1, suggesting the integrity of the overall chi-square test remained sound. These expected frequencies appeared to be an artefact of sample size for the inverse Everest profile ($C3^c$, $n = 44$), meaning that the subsequently affected over- and under-representations should be considered with caution. Table 6.15 lists the within age grouping percentages according to each cluster.

Table 6.15

Cluster Membership According to Within Age Group Percentage (N = 1,865)

Age	**C1c** (*n* = 541)	**C2c** (*n* = 307)	**C3c** (*n* = 44)	**C4c** (*n* = 276)	**C5c** (*n* = 174)	**C6c** (*n* = 523)
18–24	29.3%	17.1%	2.0%	15.4%	7.2%	29.1%
25–35	26.0%	22.7%	3.2%	14.8%	14.4%	18.8%
36–45	32.4%	14.4%	2.6%	13.7%	8.5%	28.4%
46–55	29.5%	14.2%	2.3%	13.4%	8.8%	31.8%
56–65	25.2%	11.7%	2.5%	17.2%	13.5%	30.1%

Note. C1c = submerged profile, C2c = shark fin profile, C3c = inverse Everest profile, C4c = surface profile, C5c = inverse iceberg profile, C6c = iceberg profile.
18–24 (*n* = 767), 25–35 (*n* = 277), 36–45 (*n* = 306), 46–55 (*n* = 352), 56–65 (*n* = 163).

Following a *post hoc* review of the adjusted residuals the shark fin (C2c), inverse iceberg (C5c), and iceberg (C6c) profiles were each found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for C2c were 3.1 = $p < .01$ (25–35 group), while the significant adjusted residuals for C5c were –2.7 = $p < .01$ (18–24 group) and 3.2 = $p < .01$ (25–35 group). Finally, the significant adjusted residuals for C6c were –3.7 = $p < .001$ (25–35 group). No relationship was found between age and cluster for the submerged (C1c), inverse Everest (C3c), and surface (C4c) profiles. Table 6.16 lists the standardised and adjusted residuals for each cluster solution.

Table 6.16

Standardised and Adjusted Residuals for Age Grouping (N = 1,865)

Age	C1^c (n = 541)	C2^c (n = 307)	C3^c (n = 44)	C4^c (n = 276)	C5^c (n = 174)	C6^c (n = 523)
18–24						
Std	0.2	0.4	–0.7	0.4	–2.0	0.5
Adj	0.3	0.6	–1.0	0.6	–2.7**	0.8
25–35						
Std	–0.9	2.6	1.0	0.0	2.8	–2.9
Adj	–1.2	3.1**	1.1	0.0	3.2**	–3.7***
36–45						
Std	1.1	–0.9	0.3	–0.5	–0.5	0.1
Adj	1.4	–1.1	0.3	–0.6	–0.5	0.2
46–55						
Std	0.2	–1.0	–0.1	–0.7	–0.3	1.3
Adj	0.2	–1.3	–0.1	–0.8	–0.4	1.8
56–65						
Std	–0.9	–1.5	-	0.8	1.7	0.5
Adj	–1.1	–1.7	-	0.9	1.9	0.6

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
18–24 (n = 767), 25–35 (n = 277), 36–45 (n = 306), 46–55 (n = 352), 56–65 (n = 163).
** p < .01, *** p < .001.
- denotes uninterpretable data.

A chi-square test of goodness-of-fit was also calculated to determine whether the number of participants varied across the submerged (C1^c), shark fin (C2^c), inverse Everest (C3^c), surface (C4^c), inverse iceberg (C5^c), and iceberg (C6^c) mood profiles according to level of education. Figure 6.10 and Table 6.17 both illustrate that the frequencies were significantly different from expected values, $\chi^2(25, N = 1{,}865) = 49.08$, $p = .003$, suggesting an association between level of education and cluster.

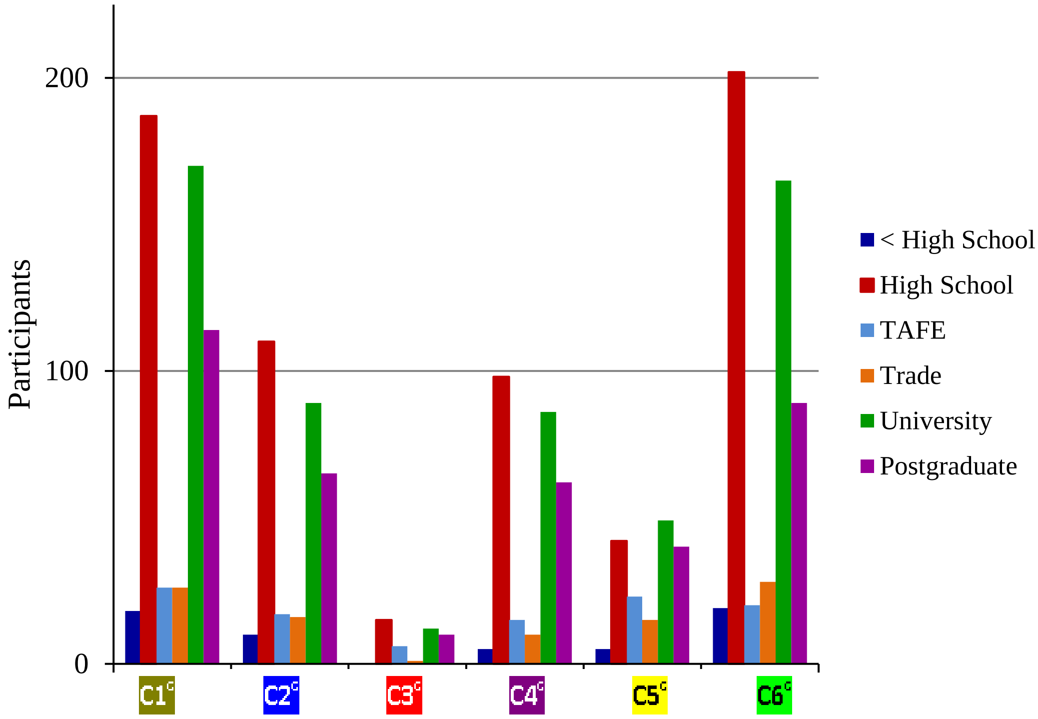


Figure 6.10. Distribution of education across clusters (*N* = 1,865). Overall number of participants according to level of education: less than high school (*n* = 57), high school (*n* = 654), TAFE (*n* = 107), trade (*n* = 96) university (*n* = 571), postgraduate (*n* = 380). C1^{c} (*n* = 541) = submerged profile, C2^{c} (*n* = 307) = shark fin profile, C3^{c} (*n* = 44) = inverse Everest profile, C4^{c} (*n* = 276) = surface profile, C5^{c} (*n* = 174) = inverse iceberg profile, and C6^{c} (*n* = 523) = iceberg profile.

Table 6.17

Crosstabulations of Clusters C1^c to C6^c by Level of Education (N = 1,865)

Education	C1^c (*n* = 541)	C2^c (*n* = 307)	C3^c (*n* = 44)	C4^c (*n* = 276)	C5^c (*n* = 174)	C6^c (*n* = 523)
< High School						
Actual	18	10	0	5	5	19
Expected	17	9	1	8	5	16
High School						
Actual	187	110	15	98	42	202
Expected	190	108	15	97	61	183
TAFE						
Actual	26	17	6	15	23	20
Expected	31	18	3	16	10	30
Trade						
Actual	26	16	1	10	15	28
Expected	28	16	2	14	9	27
University						
Actual	170	89	12	86	49	165
Expected	166	94	14	85	53	160
Postgraduate						
Actual	114	65	10	62	40	89
Expected	110	63	9	56	36	107

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
< High School (*n* = 57), High School (*n* = 654), TAFE (*n* = 107), Trade (*n* = 96), University (*n* = 571), Postgraduate (*n* = 380).
Expected frequencies are rounded to whole numbers.

The distribution of education within the submerged profile (C1^c) included: < high school = 3.3%, high school = 34.6%, TAFE = 4.8%, trade = 4.8%, university = 31.4%, and postgraduate = 21.1%. C1^c had an over-representation of those with a < high school, university, and postgraduate level of education by 5.9%, 2.4%, and 3.6%, respectively, and an under-representation of those with a high school, TAFE, and trade level of education by 1.6%, 16.1%, and 7.1%, respectively. The distribution of education within the shark fin profile ($C2^c$) included: < high school = 3.3%, high school = 35.8%, TAFE = 5.5%, trade = 5.2%, university = 29.0%, and postgraduate = 21.2%. $C2^c$ had an over-representation of those with a < high school, high school, and postgraduate level of education by 11.2%, 1.9%, and 3.2%, respectively, and an under-representation of those with a TAFE and university level of education by 5.6% and 5.3%, respectively, while those with a trade matched the chi-square expected count. The distribution of education within the inverse Everest profile ($C3^c$) included: < high school = 0.0%, high school = 34.1%, TAFE = 13.6%, trade = 2.3%, university = 27.3%, and postgraduate = 22.7%. $C3^c$ had an over-representation of those with a TAFE and postgraduate level of education by 50.0% and 11.2%, respectively, and an under-representation of those with a < high school, trade, and university level of education by 100.0%, 50.0% and 14.3%, respectively.

Further, the distribution of education within the surface profile ($C4^c$) included: < high school = 1.8%, high school = 35.5%, TAFE = 5.4%, trade = 3.6%, university = 31.2%, and postgraduate = 22.5%. $C4^c$ had an over-representation of those with a high school, university, and postgraduate level of education by 2.1%, 1.2%, and 10.7%, respectively, and an under-representation of those with a < high school, TAFE, and trade by 37.5%, 6.3%, and 28.6%, respectively. The distribution of education within the inverse iceberg ($C5^c$) profile included: < high school = 2.9%, high school = 24.1%, TAFE = 13.2%, trade = 8.6%, university = 28.2%, and postgraduate = 23.0%. $C5^c$ had an over-representation of those with a TAFE, trade, and postgraduate level of education by 130.0%, 66.7%, and 10.0%, respectively, and an under-representation of those with a high school and university level of education by 31.1% and 7.5%, respectively, while those with a < high school level of education matched the chi-square expected count. The distribution of education within the iceberg profile (C6^c) included: < high school = 3.6%, high school = 38.6%, TAFE = 3.8%, trade = 5.4%, university = 31.5%, and postgraduate = 17.0%. C6^c had an over-representation of those with a < high school, high school, trade, and university level of education by 18.8%, 10.4%, 3.7%, and 3.1%, respectively, and an under-representation of those with a TAFE and postgraduate level of education by 33.4% and 16.8%, respectively.

The overall significant chi-square result indicated a relationship between level of education and mood profile. In this case, 3 of the 36 expected cell counts were < 5 (i.e., 8.4%) and none of the expected counts were < 1, suggesting the integrity of the test remained sound. Unfortunately once again the small expected frequencies appeared to be an artefact of sample size for the inverse Everest (C3^c, n = 44) profile. Consequently, the over- and under-representations for the affected groupings should be considered with some caution. Table 6.18 lists the within level of education grouping percentages according to each cluster.

Table 6.18

Cluster Membership According to Within Education Group Percentage (N = 1,865)

Education	C1^c (n = 541)	C2^c (n = 307)	C3^c (n = 44)	C4^c (n = 276)	C5^c (n = 174)	C6^c (n = 523)
< High School	31.6%	17.5%	0.0%	8.8%	8.8%	33.3%
High School	28.6%	16.8%	2.3%	15.0%	6.4%	30.9%
TAFE	24.3%	15.9%	5.6%	14.0%	21.5%	18.7%
Trade	27.1%	16.7%	1.0%	10.4%	15.6%	29.2%
University	29.8%	15.6%	2.1%	15.1%	8.6%	28.9%
Postgraduate	30.0%	17.1%	2.6%	16.3%	10.5%	23.4%

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
< High School (n = 57), High School (n = 654), TAFE (n = 107), Trade (n = 96), University (n = 571), Postgraduate (n = 380).

A *post hoc* review of the adjusted residuals identified which groups made the largest contributions to the significant chi-square result. The inverse iceberg ($C5^c$), and iceberg ($C6^c$) profiles were each found to have contributed to the overall significant chi-squared result. The significant adjusted residuals for $C5^c$ were –3.2 = $p < .01$ (high school), 4.5 = $p < .001$ (TAFE), and 2.2 = $p < .01$ (trade). The significant adjusted residuals for $C6^c$ were 2.0 = $p < .01$ (high school), –2.2 = $p < .01$ (TAFE), and –2.2 = $p < .01$ (postgraduate). No relationship was found between level of education and cluster for the submerged ($C1^c$), shark fin ($C2^c$), and surface ($C4^c$) profiles. Table 6.19 lists the standardised and adjusted residuals for each cluster solution.

Table 6.19

Standardised and Adjusted Residuals for Level of Education (N = 1,865)

Education	C1^c (*n* = 541)	C2^c (*n* = 307)	C3^c (*n* = 44)	C4^c (*n* = 276)	C5^c (*n* = 174)	C6^c (*n* = 523)
< High School						
Std	0.4	0.2	-	–1.2	–0.1	0.8
Adj	0.4	0.2	-	–1.3	–0.1	0.9
High School						
Std	–0.2	0.2	–0.1	0.1	–2.4	1.4
Adj	–0.3	0.3	–0.1	0.2	–3.2**	2.0*
TAFE						
Std	–0.9	–0.1	-	–0.2	4.1	–1.8
Adj	–1.1	–0.2	-	–0.2	4.5***	–2.2*
Trade						
Std	–0.4	0.0	-	–1.1	2.0	0.2
Adj	–0.4	0.1	-	–1.2	2.2*	0.3
University						
Std	0.3	–0.5	–0.4	0.2	–0.6	0.4
Adj	0.5	–0.7	–0.5	0.2	–0.7	0.5
Postgraduate						
Std	0.4	0.3	0.3	0.8	0.8	–1.7
Adj	0.5	0.4	0.4	0.9	0.9	–2.2*

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.
< High School (*n* = 57), High School (*n* = 654), TAFE (*n* = 107), Trade (*n* = 96), University (*n* = 571), Postgraduate (*n* = 380).
* *p* < .05, ** *p* < .01, *** *p* < .001.
- denotes uninterpretable data.

6.3 Summary

The mood responses of 1,865 participants were analysed using a k-means iterative procedure with random seeds, and a prescribed six-cluster solution. The findings from sample A and sample B were replicated. The mood profiles identified were $C1^c$ = submerged profile, $C2^c$ = shark fin profile, $C3^c$ = inverse Everest profile, $C4^c$ = surface profile, $C5^c$ = inverse iceberg profile, and $C6^c$ = iceberg. Once again, a MANOVA showed significant differences between clusters on each dimension of mood, and a DFA indicated that cluster membership could be correctly classified with a high degree of accuracy (ranging from 82.6% to 99.2%).

As previously found, the submerged profile was characterised by slightly below average levels on each mood dimension, being tension, depression, anger, vigour, fatigue, and confusion (0.83, 0.41, 0.33, 0.54, 0.30, and 0.54 *SD* below *M* = 50.00, respectively). The shark fin profile was characterised by slightly below average levels of tension, anger, vigour, and confusion (0.50, 0.05, 0.77 and 0.10 *SD* below *M* = 50.00, respectively), and average levels of depression (0.20 *SD* above *M* = 50.00), together with a high level of fatigue (1.41 *SD* above *M* = 50.00). The inverse Everest profile was characterised by a low level of vigour (0.46 *SD* below *M* = 50.00), together with high levels of tension and fatigue (2.05, and 2.00 *SD* above *M* = 50.00), and very high levels of depression, anger, and confusion (3.74, 3.19, and 2.87 *SD* above *M* = 50.00). The surface profile was characterised by slightly above average levels of each mood dimension, being tension, depression, anger, vigour, fatigue, and confusion (0.06, 0.30, 0.39, 0.23, 0.29, and 0.40 *SD* above *M* = 50.00, respectively). The inverse iceberg profile was characterised by a low level of vigour (0.31 *SD* below *M* = 50.00), together with high levels of tension, depression, anger, fatigue, and confusion (0.78, 1.99, 1.67, 1.09, and 1.61 *SD* above *M* = 50.00, respectively). Finally, the iceberg profile was characterised by a high level of vigour (0.88 *SD* above *M* = 50.00), together with low levels of tension, depression, anger, fatigue, and confusion (0.78, 0.44, 0.34, 0.43, and 0.56 *SD* below *M* = 50.00, respectively).

Additionally, a series of chi-square tests of goodness-of-fit once again indicated that gender, age, and level of education were unequally distributed across clusters (relative to the sample size and demographic groupings). In the current sample, an estimated equal number of males and females experienced the inverse Everest and surface profiles. Males were more likely to experience the iceberg profile, while females were more likely to experience the shark fin, and inverse iceberg profiles compared with males.

An estimated equal number of individuals across all age groups experienced the submerged, inverse Everest, and surface profiles. Those aged 18–24 were less likely to experience the inverse iceberg profile, while those aged 25–35 were more likely to experience the shark fin and inverse iceberg profiles, and less likely to experience the iceberg profile. Those aged 36–45, 46–55, and 56–65 had a relatively equal distribution across clusters. However, the findings relating to the inverse Everest profile for the 56–65 age group were ultimately deemed uninterpretable due to small sample sizes.

The findings further suggested that a relatively equal number of individuals across all levels of education experienced the submerged, shark fin, and surface profiles. Additionally, those with a less than high school level of education had a relatively equal distribution across clusters, as did those with a university level of education. Those with a high school level of education were more likely to experience the iceberg profile, and less likely to experience the inverse iceberg profile. Those with a TAFE certificate were more likely to experience the inverse Everest and inverse iceberg profiles, and less likely to experience the iceberg profile. Those with a trade qualification were more likely to experience the inverse iceberg profile, while those with a postgraduate level of education were less likely to experience the iceberg profile. However, the results relating to the Everest profile for the less than high school level of education, as well as the TAFE and trade groupings were negatively affected by small sample sizes.

Overall, the k-means cluster analysis produced multivariate cluster structures that were found to be very similar to those identified in the previous two samples (i.e., sample A, and sample B). Further to this, the mood profiles found within each of the three samples also share a number of demographic similarities.

CHAPTER 7: Mood and Performance in High-Risk Vocations

7.1 Introduction

According to Brief and Weiss (2002) “it is apparent that discrete emotions are important, frequent occurring elements of everyday experience. Even at work ─ perhaps especially at work ─ people feel angry, happy, guilty, jealous, proud, etc. Neither the experiences themselves, nor their consequences, can be subsumed easily under a simple structure of positive or negative states” (p. 297). Judgments and performance-related decision-making processes are central to every workplace; however, in occupations that involve a substantial risk of harm and/or mortality, such decisions can have grave consequences. Counterintuitively perhaps, findings in the general domain of psychology suggest that mood may bias cognition more than manifest behaviours (Clore, Schwarz, & Conway, 1994; Davidson, 1994; Gross & Thompson, 2007).

In fact, many laboratory-based studies have found that experiential states influence perception and attentional networks (see Ekman & Davidson, 1994; Jiang, Scolaro, Bailey, & Chen, 2011). Decision-making processes have also been found to be manipulated by feelings. For example, according to the *affect-priming principle*, affect may indirectly influence judgments during processing through selective influence on attention, encoding, retrieval, and associative processes (Bower, 1981, 1991; Forgas & Bower, 1987). In addition, according to the *affect-as-information principle*, feelings can directly inform judgments during fast, heuristic processing, as affective states infer evaluative reactions (Schwarz & Bless, 1991; Schwarz & Clore, 1988). Such cognitive theories give evidence that decision-making processes can be influenced by mood, which can in turn can influence overt behaviour with positive or negative outcomes. Of equal importance is that levels of motivation in the context of engaging in workplace activities have also been found to be affected by mood (see George & Brief, 1996).

Injury statistics consistently classify both the construction and mining industries as high-risk vocations (refer to Figure 7.1 and Figure 7.2). Unique job stressors and differing organisational safety cultures (see Bahn & Barratt-Pugh, 2012; Lingard et al., 2010) are commonly-cited reasons behind occupational injury. Stress or *strain* has previously been identified as a primary mechanism by which occupational stressors influence psychological well-being (Clarke, 2012), which in turn can affect accident vulnerability through reduced concentration, increased distractibility, tendency toward cognitive failure, and emotional exhaustion (Fogarty & McKeon, 2006). A strong link has also been found between perceived safety climate and safety performance within construction organisations (Gillen, Baltz, Gassel, Kirsch, & Vaccaro, 2002), with proximal antecedents of safety-related behaviour identified as having the strongest influence (Lingard et al., 2010).

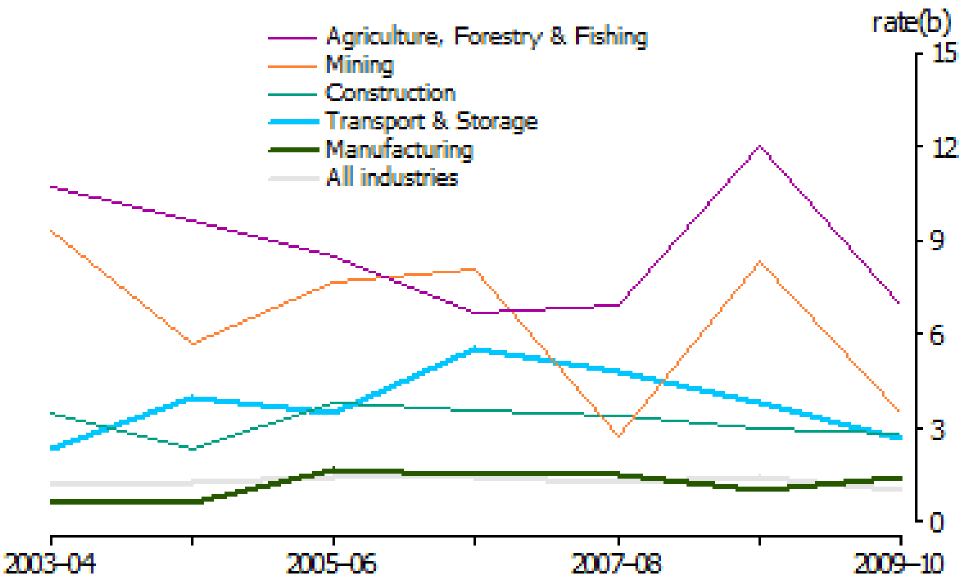


Figure 7.1. Workplace fatalities per 100,000 Australian employees by selected industries 2009/2010 (taken from the Australian Bureau of Statistics, 2011).

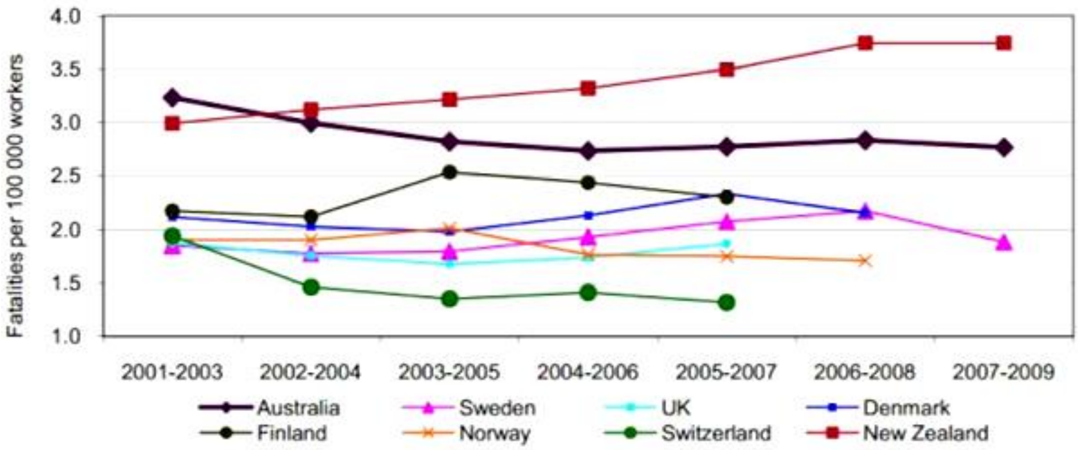


Figure 7.2. Comparison of Australia's work-related injury fatality rate with the best performing countries (taken from the Australian Bureau of Statistics, 2011).

Neal and Griffin (2006) conducted a longitudinal study to identify top-down and bottom-up effects based on the model of antecedents, determinants, and components of safety behaviour developed by Neal et al. (2000; refer to Figure 7.3). Perceptions of safety climate, motivation, and safety behaviour were investigated at two time points and further linked with prior and subsequent accidents over a 5-year period. Safety climate referred to individual perceptions of policies, procedures, and practices concerning safety in the workplace. Safety behaviour was operationalised as safety compliance (i.e., core activities that maintain workplace safety) and safety participation (i.e., behaviours that facilitate a supportive safety environment), highlighting a distinction between task and conceptual performance (Borman & Motowidlo, 1993; Neal & Griffin, 2006). Results showed that perceived safety climate (at group level) at one point predicted subsequent changes in individual safety motivation. In turn, individual safety motivation was associated with subsequent changes in self-reported safety behaviour. Further, improvements in averaged levels of safety behaviour within groups were associated with subsequent reductions in accidents (Neal & Griffin, 2006).

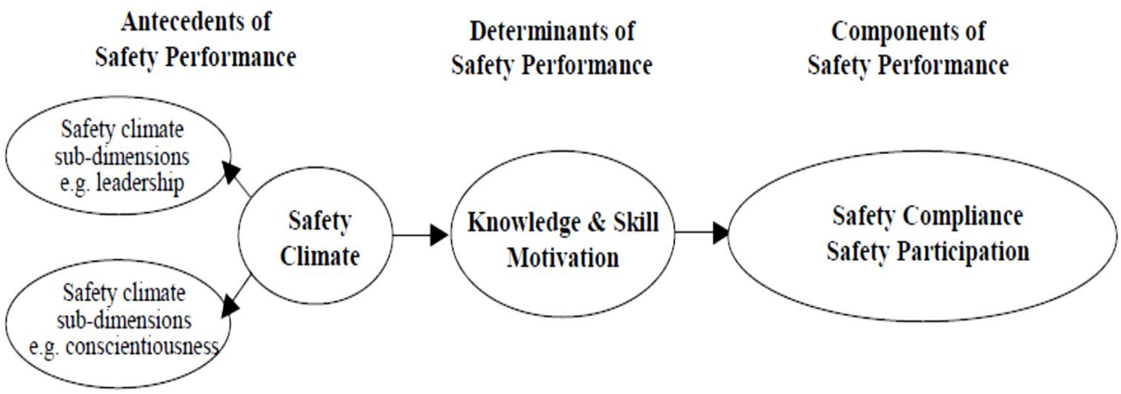


Figure 7.3. Model of relationships between antecedents, determinants, and components of safety performance taken from Neal and Griffin (2002).

In a similar vein, Clarke (2012) conducted a meta-analysis to test the relationships between occupational stressors (i.e., challenge and hindrance), safety behaviours (i.e., compliance and participation), and safety outcomes (i.e., occupational injuries and near-misses). It was hypothesised that hindrance stressors (i.e., situational constraints, hassles, role ambiguity, role and interpersonal conflict, role overload, supervisor-related stress, organisational politics, and concerns about job security) would have negative effects on both safety compliance and safety participation, and subsequently safety outcomes. Conversely, challenge stressors (i.e., high workload, time pressure, job scope, and high responsibility) would have positive effects. Results showed that hindrance stressors were associated with a reduction in both compliance and participation, and were also related to higher levels of occupational injuries/near-misses. Interestingly, hindrance stressors and occupational injuries were fully mediated by safety behaviours. However, challenge stressors had a near-zero association with compliance and occupational injuries, a small negative association with participation, and a small positive association with near-misses (refer to Figure 7.4; Clarke, 2012).

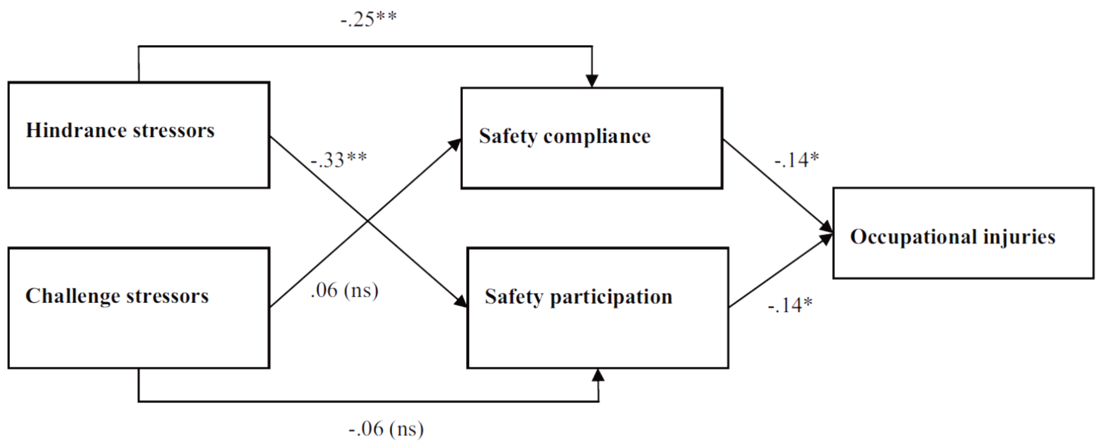


Figure 7.4. Structural Equation Model (SEM) of links between occupational stressors, safety behaviours, and occupational injuries (taken from Clarke, 2012).

Overall, general trends show a decline in injury rates for construction workers, a finding mirrored in mining industry data (see Figure 7.5 and Figure 7.6, respectively; Ruff, Coleman, & Martini, 2011). Physical and biomechanical interventions such as improving tools, equipment, and task techniques have each contributed to the change (Abbe et al., 2011; Hess, Hecker, Weinstein, & Lunger, 2004), as have reinforcing safety motivation and safety-related behaviour on an individual level (Lingard et al., 2010). However, despite this trend, the construction and mining industries remain high-risk occupations throughout the world (see Abbe et al., 2011; Ruff et al., 2011; Khanzode et al., 2011). Given this, researchers continue to try to establish links between psychological factors, occupational stress, and injury (Abbe et al., 2011; Cooper & Sutherland, 1987; Glasscock, Rasmussen, Cartensen, & Hansen, 2006; Goldenhar, Williams, & Swanson, 2003). Attempts to mediate and negate the risk of acute trauma (i.e., crush injuries, fractures, strains, and sprains) and/or mortality persist (Khanzode et al., 2011).

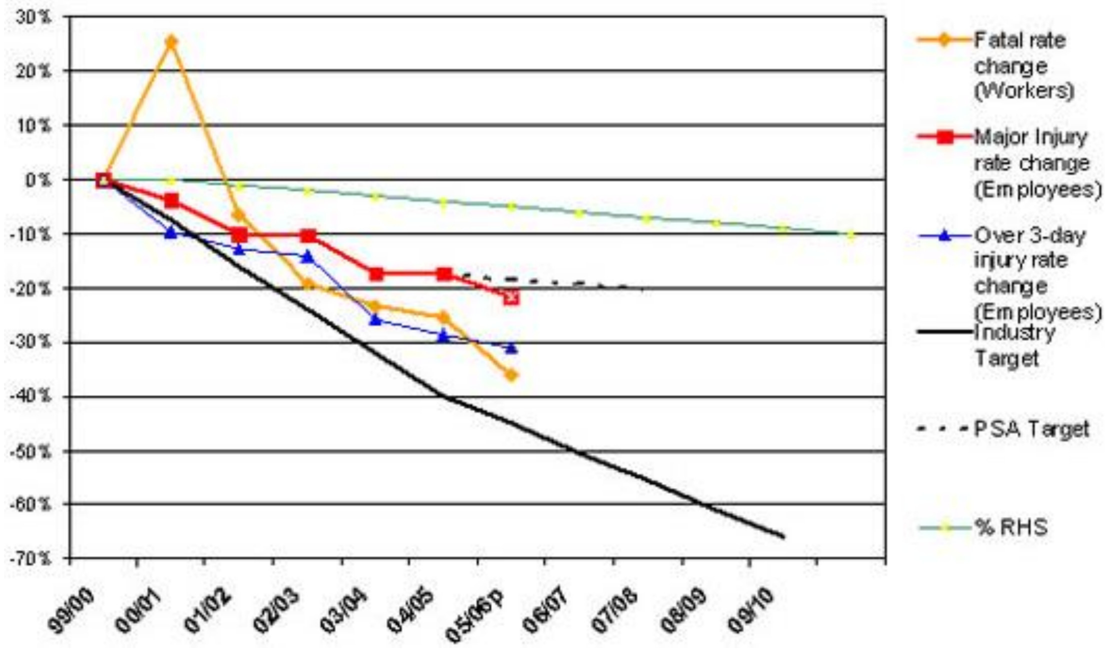


Figure 7.5. Construction injury rates in the United Kingdom since 1999/2000 (taken from Health and Safety Executive, 2006).

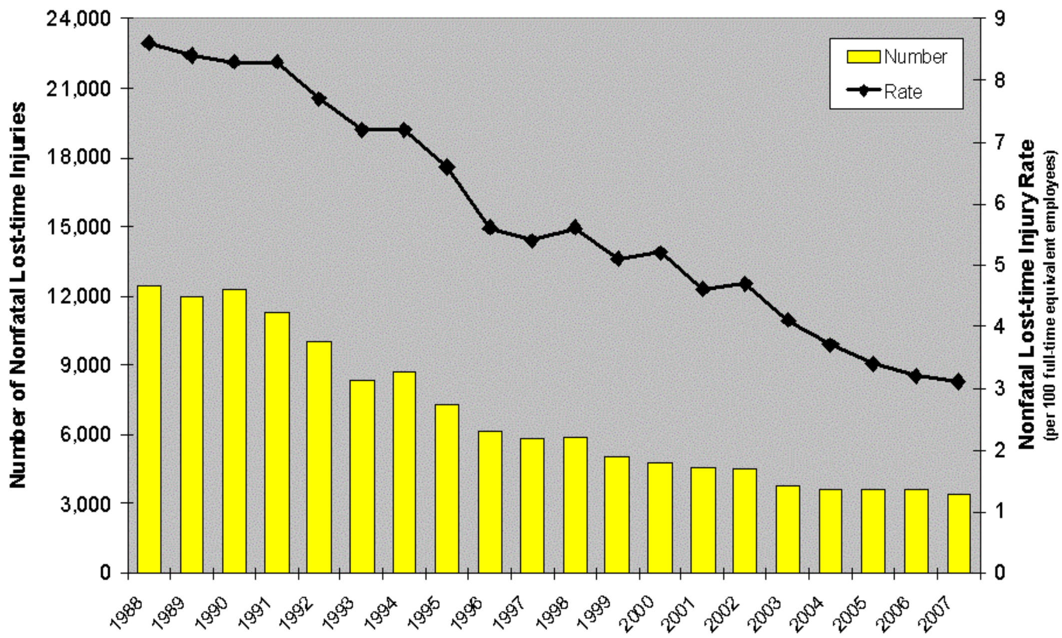


Figure 7.6. Number and rate of coal mining non-fatal lost-time injuries 1988–2007 (taken from National Institute for Occupational Safety and Health website, n.d.).

The *In The Mood* website has potential for mood profiling in performance environments where safety-related behaviour becomes especially salient. Indeed, decisions are the product of complex interactions between cognitive resources, memory processing, and decision-making strategies, and as previously mentioned mood influences all of these cognitive factors (Bower, 1981, 1991; Forgas & Bower, 1987; Schwarz & Bless, 1991; Schwarz & Clore, 1988). Additionally, it has been suggested that non-physical stressors and behaviour mechanisms should be further investigated to minimise workplace injury (Abbe et al., 2011; Clarke, 2012).

Given the relationship between mood and performance outcomes in athletes (Pieter & Pieter, 2008; Terry & Lane, 2011; Zehsaz et al., 2011), and that components of safety behaviour have been associated with reduced accidents and injuries (Clarke, 2012; Neal & Griffin, 2006), the proposed research will attempt to investigate a possible link between mood and safety performance using items taken from the Neal and Griffin (2006) questionnaire. The variables that moderate the mood-performance relationship for each of the two populations of interest will also be examined, and the standard formula for calculating tables of normative data using *t*-scores will be used where appropriate.

7.2 Method

7.2.1 Participants. The initial sample comprised of 459 construction and mining participants, parceled out from Sample C (N = 1,865). Additionally, 39 Asian construction/mining participants were re-added to the sample given that the present study used the WHSS which has previously been used by Jiang, Yu, Li, and Li (2010) in Asian samples. During the data collection period from May 1, 2014 to June 25, 2014, participants continued to be recruited from the general population through the *In The Mood* website as per the previously used snowballing technique. An additional 53 construction and 17 mining participants visited the site and were included in the analyses.

7.2.2 Measures. The online version of the BRUMS on the *In The Mood* website was again used to measure mood with the standard response timeframe of 'How do you feel right now?' Additionally, 12 items of the WHSS (Neal et al., 2000; Griffin & Neal, 2000) were included on the *In The Mood* website to measure safety climate, safety motivation, and safety behaviour (i.e., safety compliance and safety participation). Each item was assessed according to a 5-point scale ranging from 1 *(strongly disagree)* to 5 *(strongly agree)*. Total subscale scores range from 3–15. Each subscale is made up of the following items:

- Safety climate: 'Management places a strong emphasis on workplace health and safety', 'Safety is given a high priority by management', and 'Management considers safety to be important.'
- Safety motivation: 'I feel that it is worthwhile to put in the effort to maintain or improve my personal safety', 'I feel that it is important to maintain safety at all times', and 'I believe that it is important to reduce the risk of accidents and incidents in the workplace'.
- Safety compliance: 'I use all the necessary safety equipment to do my job', 'I use the correct safety procedures for carrying out my job', and 'I ensure the highest levels of safety when I carry out my job'.
- Safety participation: 'I promote the safety program within the organization', 'I put in extra effort to improve safety in the workplace', and 'I voluntarily carry out tasks or activities that help to promote workplace safety'.

Psychometric properties of the individual items were assessed via confirmatory factor analysis (CFA) by Neal and Griffin (2006). An eight-factor model comprising four constructs repeated across two years provided a good fit to the data, $\chi^2(212, N = 194) = 373.93$, $p > .05$; GFI = .87; NFI = .95; comparative fit index = .96; RMSEA = .05. Correlations between factors ranged from .08 ($p > .05$) for safety compliance in Year 2 and safety motivation in Year 4 to .68 ($p < .001$) for safety motivation in Year 2 and safety compliance in Year 2. Individual factor loadings can be found below (see Figure 7.7).

Factor Loadings for Items Assessing Safety Climate, Motivation, and Behavior

Variable and item	Year 2	Year 4
Safety climate		
1. Management places a strong emphasis on workplace health and safety	.93	.91
2. Safety is given a high priority by management	.95	.97
3. Management considers safety to be important	.95	.93
Safety motivation		
1. I feel that it is worthwhile to put in effort to maintain or improve my personal safety	.84	.68
2. I feel that it is important to maintain safety at all times	.96	.87
3. I believe that it is important to reduce the risk of accidents and incidents in the workplace	.92	.89
Safety compliance		
1. I use all the necessary safety equipment to do my job	.78	.91
2. I use the correct safety procedures for carrying out my job	.89	.94
3. I ensure the highest levels of safety when I carry out my job	.92	.87
Safety participation		
1. I promote the safety program within the organization	.85	.80
2. I put in extra effort to improve the safety of the workplace	.95	.95
3. I voluntarily carry out tasks or activities that help to improve workplace safety	.70	.71

Figure 7.7. Factor loadings of the WHSS (taken from Neal & Griffin, 2006).

Jiang et al., (2010) adopted a 6-item scale from Neal and Griffin (2006) to assess safety compliance (i.e., three items) and safety participation (i.e., three items). Using CFA, a two-factor model of safety behaviour proved a good fit, with all parameters meeting the requirements, consistent with Griffin and Neal's (2000) model. The reliability of each scale was ≥ 0.75, being an accepted level. Further, Brondino, Silva, and Pasini (2012) used an 8-item adjusted version of the scale. A model with a second-order factor (i.e., safety behaviour) and two first-order factors (i.e., safety compliance and safety participation) was estimated, and the psychometric properties were again assessed with CFA. As in the Neal and Griffin (2006) study and the Jiang et al. results, the estimated model provided a good fit to the data, $\chi^2(18, N = 964) = 47.38$, $p = .001$; TLI = .98; CFI = .99; SRMR = .023. Inter-item reliability of the scale was high ($a = .84$), and the CR and AVE for each first-order factor were acceptable: compliance (CR = .83; AV = .54) and participation (CR = .73; AVE = .40; Brondino et al., 2012).

7.2.3 Procedure. The research was conducted under the previous Human Research Ethics Committee Approval No., H13REA169. All analyses were performed using IBM SPSS Software Version 22.0 (2013).

7.3 Results

A total of 568 cases were screened for missing values, abnormal and unusual responses. One case of missing values for gender was detected. Additionally, a total of 16 cases of zero values were identified for the WHSS, and total of 2 cases of nil data were identified for the BRUMS. All cases were retained given that each could contribute to at least part of the analyses. A visual inspection of the dataset was undertaken, and no other abnormalities were detected.

A check for multivariate outliers according to the BRUMS was conducted in line with the statistical recommendations of Tabachnick and Fidell (2013). Using Mahalanobis distance, 8 outliers were found to exceed the critical value of 22.46. However, all cases were retained. The final sample of online BRUMS and WHSS respondents was N = 568. Scores ranged from 0–16 on each of the BRUMS subscales (i.e., tension, 0–16; depression, 0–16; anger, 0–16; vigour, 0–16; fatigue, 0–16; confusion, 0–16) and 4–15 on the WHSS subscales (i.e., safety climate, 5–15; safety motivation, 6–15; safety compliance, 4–15; safety participation, 4–15). A complete summary of the demographic composition is presented in Table 7.1.

Table 7.1

Demographic Characteristics of the BRUMS and WHSS Respondents (N = 568)

Dependent Variable	*n*	%
Gender		
Male	398	70.1
Female	170	29.9
Age Group		
18–24	31	5.5
25–35	111	19.5
36–45	157	27.6
46–55	175	30.8
56–65	94	16.5
65+	0	0.0
Education		
< High School Certificate	17	3.0
High School Certificate	70	12.3
Trade Qualification	75	13.2
TAFE Qualification	74	13.0
University Degree	190	33.5
Postgraduate Degree	142	25.0
Occupation		
Construction	326	57.4
Mining	242	42.6
Roster		
Drive-in/Drive-out	411	72.4
Fly-in/Fly-out	157	27.6
Ethnicity		
African	24	4.2
Asian	47	8.3
Caucasian	444	78.2
Indigenous	8	1.4
Middle Eastern	4	0.7
Other	41	7.2

(Table 7.1 continues)

(Table 7.1 continued)

Dependent Variable	*n*	%
Location		
ACT	14	2.5
NSW	30	5.3
NT	6	1.1
QLD	81	14.3
SA	18	3.2
TAS	2	0.4
VIC	5	0.9
WA	124	21.8
Other	288	50.7

Note. ACT = Australian Capital Territory; NSW = New South Wales; NT = Northern Territory; QLD = Queensland; SA = South Australia; TAS = Tasmania; VIC = Victoria; WA = Western Australia.

A visual inspection of the P-P plots and histograms of the raw scores for the BRUMS subscales indicated that the frequency distribution for vigour was approximately symmetrical, with a leptokurtic shape, while fatigue was approximately normal, with a slight positive skew. The scores for tension, depression, anger, and confusion deviated from the diagonal on the P-P plots, suggesting a positive skew for each mood dimension. The shape of frequency distributions for tension, depression, anger, and confusion were approximately unimodal, skewed to the left, with some outliers identified for depression, anger, and confusion. As expected, departures from normal were present: tension (skewness = 1.482, kurtosis = 1.960), depression (skewness = 1.434, kurtosis = 1.827), anger (skewness = 1.326, kurtosis = 1.303), vigour (skewness = –0.124, kurtosis = –0.288), fatigue (skewness = 0.600, kurtosis = –0.400), and confusion (skewness = 1.529, kurtosis = 2.223). Despite obvious deviations from normal distribution for at least five of the six BRUMS subscales, no further parametric data screening was undertaken for reasons previously outlined in Chapter 3: Section 3.3.

Further, a visual inspection of the BRUMS subscale means found them to be characteristic of standardised values (i.e., *M* = 50.00, *SD* = 10.00), suggesting that participants from the construction and mining industries reported mood scores in line with existing normative data. The means, standard deviations, and 95% CI's for each mood dimension are provided in Table 7.2.

Table 7.2

Descriptive Statistics of the BRUMS Subscales (N = 566)

Mood Dimension	*M*	*SD*	95% CI
Tension	47.25	8.59	[46.54, 47.96]
Depression	55.55	13.17	[54.47, 56.64]
Anger	54.92	11.59	[53.97, 55.88]
Vigour	50.52	8.26	[49.84, 51.20]
Fatigue	53.39	9.79	[52.58, 54.19]
Confusion	51.84	10.95	[50.93, 52.74]

A visual inspection of the P-P plots and histograms of the raw scores for the WHSS subscales indicated that the scores safety motivation, safety compliance, and safety participation deviated from the diagonal on the P-P plots, suggesting a negative skew for each variable, while safety climate was approximately symmetrical. However, the shape of each frequency distribution was approximately unimodal, skewed to the right, with some outliers identified for each. As expected, departures from normal were present: safety climate (skewness = –0.646, kurtosis = –0.064), safety motivation (skewness = –1.756, kurtosis = 3.808), safety compliance (skewness = –1.199, kurtosis = 1.845), and safety participation (skewness = –1.098, kurtosis = 0.887). Despite obvious deviations from normal distributions for each of the four WHSS subscales, no further parametric data screening was undertaken for reasons previously outlined in Chapter 3: Section 3.3.

Further, the raw scores were transformed into z scores using the standard formula represented by Equation 3.

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

Where *x* represents a raw score, μ represents the population mean of the WHSS, and σ represents the population standard deviation.

The z scores were then transformed into t scores using the standard formula represented by Equation 4.

$$t = 50 + (10 * z) \tag{4}$$

Where *t* represents the *t*-score, and *z* represents the *z*-score.

Although it is recognised that a factorial analysis of variance (ANOVA) design study could readily answer the research questions with a minimum number of analyses, unbalanced data can confound the qualitative outcome (Hector, Von Felten, & Schmid, 2010). In non-orthogonal designs, unequal cell sizes can negatively affect the ability of the test to adequately distinguish small from large groupings. This is primarily due to some variables being negatively or positively correlated with one another (Hector et al., 2010). Previous research by Lan, Lane, Roy, and Hanin (2012) identified significant inter-correlations between BRUMS subscales, being consistent with those reported by Terry et al. (1999) and Terry, Lane et al. (2003). The findings by Lan et al. revealed that tension was positively correlated with anger ($r = .62$, $p < .01$); depression was positively correlated with anger ($r = .96$, $p < .01$) and tension ($r = .64$, $p < .01$); fatigue was positively correlated with anger ($r = .79$, $p < .01$), tension ($r = .64$, $p < .01$), and depression ($r = .83$, $p < .01$); vigour was negatively correlated with anger ($r = –.24$, $p < .01$), tension ($r = –.22$, $p < .01$), depression ($r = –.33$, $p < .01$), and fatigue ($r = –.27$, $p < .01$); while confusion was positively correlated with anger ($r = .90$, $p < .01$), tension ($r = .74$, $p < .01$), depression (r = .91, p < .01), and fatigue (r = .82, p < .01), and negatively correlated with vigour (r = –.26, p < .01). For these reasons, a series of one-way MANOVA tests better matched the objectives of the analyses, and were conducted to investigate mood-performance relationships and moderating variables of the BRUMS and WHSS.

7.3.1 Mood and performance analyses. A between-groups MANOVA was performed to investigate whether perceptions of perceptions safety climate, motivation to perform safe behaviours, willingness to comply with safety procedures, and overt safety participation differed according to the groups identified via the k-means cluster analysis using Sample C. There was a significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .846, F(20, 1,457) = 3.78, p < .001, partial η^2 = .041, observed power = 1.00. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for safety climate, F(5, 442) = 6.01, p < .001, partial η^2 = .064, observed power = .995; safety motivation, F(5, 442) = 7.36, p < .001, partial η^2 = .077, observed power = .999; safety compliance, F(5, 442) = 5.55, p < .001, partial η^2 = .059, observed power = .992; and safety participation, F(5, 442) = 5.97, p < .001, partial η^2 = .063, observed power = .995.

An examination of the mean scores for each dependent variable (see Table 7.3) revealed that a significantly higher perception of safety climate was endorsed by individuals experiencing the iceberg profile ($C6^c$; M = 53.73, SD = 7.91, 95% CI [51.97, 55.49]) compared with those experiencing the shark fin ($C2^c$; M = 47.09, SD = 9.10, 95% CI [44.87, 49.31]), inverse Everest ($C3^c$; M = 45.75, SD = 12.01, 95% CI [41.85, 49.64]), and inverse iceberg ($C5^c$; M = 48.83, SD = 11.24, 95% CI [46.29, 51.38]) profiles. A significantly lower level of safety motivation was reported by individuals experiencing the inverse iceberg profile (C5[c]; *M* = 45.06, *SD* = 13.77, 95% CI [42.67, 47.45]) compared with those experiencing the submerged (C1[c]; *M* = 51.28, *SD* = 7.76, 95% CI [49.57, 52.99]), shark fin (C2[c]; *M* = 49.82, *SD* = 9.32, 95% CI [47.74, 51.91]), surface (C4[c]; *M* = 52.52, *SD* = 6.80, 95% CI [50.58, 54.46]), and iceberg (C6[c]; *M* = 52.95, *SD* = 7.27, 95% CI [51.29, 54.60]) profiles.

Further, a significantly higher level of safety compliance was reported by individuals experiencing the iceberg profile (C6[c]; *M* = 53.82, *SD* = 8.30, 95% CI [52.14, 55.50]) compared with those experiencing the shark fin (C2[c]; *M* = 48.89, *SD* = 9.46, 95% CI [46.77, 51.01]) and inverse iceberg (C5[c]; *M* = 46.63, *SD* = 13.36, 95% CI [44.20, 49.06]) profiles. Additionally, a significantly lower level of safety compliance was reported by individuals experiencing the inverse iceberg profile (C5[c]; *M* = 46.63, *SD* = 13.36, 95% CI [44.20, 49.06]) compared with those experiencing the submerged profile (C1[c]; *M* = 51.21, *SD* = 7.78, 95% CI [49.47, 52.96]). Further, a significantly higher level of safety participation was reported by individuals experiencing the iceberg profile (C6[c]; *M* = 53.74, *SD* = 8.10, 95% CI [52.01, 55.47]) compared with those experiencing the shark fin (C2[c]; *M* = 47.96, *SD* = 10.01, 95% CI [45.78, 50.14]) and inverse iceberg (C5[c]; *M* = 46.88, *SD* = 12.83, 95% CI [44.38, 49.38]) profiles. Additionally, a significantly lower level of safety participation was reported by individuals experiencing the inverse iceberg profile (C5[c]; *M* = 46.88, *SD* = 12.83, 95% CI [44.38, 49.38]) compared with those experiencing the surface profile (C4[c]; *M* = 51.98, *SD* = 7.56, 95% CI [49.95, 54.01]).

The difference between means was divided by the pooled standard deviation for each significant pairwise comparison (Rosnow & Rosenthal, 1996) and compared with Cohen's (1992) conventions (i.e., .20 = small, .50 = moderate, and .80 = large; all effect sizes were compared with these conventions hereafter). The effect sizes for the iceberg profile ($C6^c$) compared with the shark fin ($C2^c$), inverse Everest ($C3^c$), and inverse iceberg ($C5^c$) profiles for safety climate were $d = .39$ ($p < .001$), $d = .40$ ($p = .004$) and $d = .26$ ($p = .030$), respectively, indicating a small to moderate effect for each comparison. The effect sizes for the inverse iceberg profile ($C5^c$) compared with the submerged ($C1^c$), shark fin ($C2^c$), surface ($C4^c$), and iceberg ($C6^c$) profiles for safety motivation were $d = .29$ ($p = .001$), $d = .21$ ($p = .050$), $d = .36$ ($p < .001$), and $d = .38$ ($p < .001$), respectively, indicating a small to moderate effect for each comparison.

Further, the effect sizes for the iceberg profile ($C6^c$) compared with the shark fin ($C2^c$) and inverse iceberg ($C5^c$) profiles for safety compliance were $d = .28$ ($p = .006$) and $d = .33$ ($p < .001$), respectively, indicating a small to moderate effect for each comparison. Additionally, the effect size for the inverse iceberg profile ($C5^c$) compared with the submerged profile ($C1^c$) was $d = .22$ ($p = .041$), indicating a small effect. The effect sizes for the iceberg profile ($C6^c$) compared with the shark fin ($C2^c$) and inverse iceberg ($C5^c$) profiles for safety participation were $d = .32$ ($p = .001$) and $d = .33$ ($p < .001$), respectively, indicating a small to moderate effect for each comparison. Additionally, the effect size for the inverse iceberg profile ($C5^c$) compared with the surface profile ($C4^c$) was $d = .25$ ($p = .030$), indicating a small effect.

Table 7.3

Descriptive Statistics of the Six-cluster Solution by the WHSS Subscales (N = 448)

	C1^c^ (*n* = 105)			C2^c^ (*n* = 71)			C3^c^ (*n* = 23)		
Subscale	*M*	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	51.11	9.97	[49.28, 52.93]	47.09	9.10	[44.87, 49.31]	45.75	12.01	[41.85, 49.64]
Safety Motivation	51.28	7.76	[49.57, 52.99]	49.82	9.32	[47.74, 51.91]	47.15	12.12	[43.49, 50.81]
Safety Compliance	51.21	7.78	[49.47, 52.96]	48.89	9.46	[46.77, 51.01]	49.53	11.80	[45.81, 53.26]
Safety Participation	50.09	8.60	[48.30, 51.89]	47.96	10.01	[45.78, 50.14]	48.80	12.14	[44.97, 52.63]
	C4^c^ (*n* = 82)			C5^c^ (*n* = 54)			C6^c^ (*n* = 113)		
Subscale	*M*	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	50.20	9.26	[48.13, 52.26]	48.83	11.24	[46.29, 51.38]	53.73	7.91	[51.97, 55.49]
Safety Motivation	52.52	6.80	[50.58, 54.46]	45.06	13.77	[42.67, 47.45]	52.95	7.27	[51.29, 54.60]
Safety Compliance	51.20	6.78	[49.23, 53.17]	46.63	13.36	[44.20, 49.06]	53.82	8.30	[52.14, 55.50]
Safety Participation	51.98	7.56	[49.95, 54.01]	46.88	12.83	[44.38, 49.38]	53.74	8.10	[52.10, 55.47]

Note. C1^c = submerged profile, C2^c = shark fin profile, C3^c = inverse Everest profile, C4^c = surface profile, C5^c = inverse iceberg profile, C6^c = iceberg profile.

7.3.2 Moderating demographic variables analyses (BRUMS). A between-groups MANOVA was performed to investigate whether mood scores differed according to gender. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .963, $F(6, 559) = 3.57$, p = .002, partial η^2 = .037, observed power = .953. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for vigour, $F(1, 564) = 13.01$, $p < .001$, partial η^2 = .023, observed power = .951 and fatigue, $F(1, 564) = 8.55$, $p = .004$, partial η^2 = .015, observed power = .831.

An examination of the mean scores for each dependent variable (see Table 7.4) showed that males reported a significantly higher level of vigour (M = 51.33, SD = 8.17, 95% CI [50.52, 52.14]) and a significantly lower level of fatigue (M = 52.62, SD = 9.61, 95% CI [51.67, 53.57]) compared with females (M = 48.63, SD = 8.19, 95% CI [47.39, 49.87] and M = 55.18, SD = 10.00, 95% CI [53.66, 56.69], respectively). The effect sizes for males compared with females for level of vigour and fatigue were d = .17 ($p < .001$) and d = .13 (p = .004), respectively, indicating a small effect for each comparison. While a statistically significant MANOVA statistic was identified, the small effect sizes suggest that these differences were not clinically meaningful.

Table 7.4

Descriptive Statistics of the BRUMS Subscales by Gender (N = 566)

Mood Dimension	Gender					
	Male (*n* = 396)			Female (*n* = 170)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Tension	46.98	8.28	[46.16, 47.80]	47.86	9.28	[46.45, 49.26]
Depression	55.31	12.92	[54.03, 56.59]	56.12	13.75	[54.04, 58.21]
Anger	54.77	11.50	[53.63, 55.90]	55.29	11.83	[53.50, 57.08]
Vigour	51.33	8.17	[50.52, 52.14]	48.63	8.19	[47.39, 49.87]
Fatigue	52.62	9.61	[51.67, 53.57]	55.18	10.00	[53.66, 56.69]
Confusion	51.49	10.49	[50.45, 52.52]	52.65	11.96	[50.84, 54.46]

A between-groups MANOVA was performed to investigate whether mood scores differed according to age. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' $\Lambda = .845$, $F(24, 556) = 3.99$, $p < .001$, partial $\eta^2 = .041$, observed power = 1.000. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for tension, $F(4, 561) = 10.75$, $p < .001$, partial $\eta^2 = .071$, observed power = 1.000; depression, $F(4, 561) = 11.26$, $p < .001$, partial $\eta^2 = .074$, observed power = 1.000; anger, $F(4, 561) = 10.37$, $p < .001$, partial $\eta^2 = .069$, observed power = 1.000; fatigue, $F(4, 561) = 11.29$, $p < .001$, partial $\eta^2 = .0.74$, observed power = 1.000; and confusion, $F(4, 561) = 18.99$, $p < .001$, partial $\eta^2 = .119$, observed power = 1.000.

An examination of the mean scores for each dependent variable (see Table 7.5) revealed that the 18–24 age group reported a significantly higher level of tension (*M* = 55.93, *SD* = 12.83, 95% CI [51.05, 60.81]), depression (*M* = 67.59, *SD* = 17.58, 95% CI [60.90, 74.27]), anger (*M* = 66.00, *SD* = 16.80, 95% CI [59.61, 72.39]), and confusion (*M* = 65.62, *SD* = 15.81, 95% CI [59.61, 71.63]), compared with each of the other age groups. Additionally, the 18–24 age group reported a significantly higher level of fatigue (*M* = 60.79, *SD* = 9.24, 95% CI [57.28, 64.31]) compared with the 36–45 age group (*M* = 53.05, *SD* = 9.34, 95% CI [51.58, 54.52]), 46–55 age group (*M* = 51.87, *SD* = 9.18, 95% CI [50.50, 53.24]), and 56–65 age group (*M* = 50.53, *SD* = 9.28, 95% CI [48.63, 52.43]). The 25–35 age group reported a significantly higher level of tension (*M* = 48.86, *SD* = 7.84, 95% CI [47.39, 50.34]), depression (*M* = 58.80, *SD* = 11.87, 95% CI [56.57, 61.03]), anger (*M* = 57.25, *SD* = 11.10, 95% CI [55.16, 59.34]), fatigue (*M* = 56.72, *SD* = 10.23, 95% CI [54.80, 58.64]), and confusion (*M* = 55.03, *SD* = 10.86, 95% CI [52.98, 57.07]), compared with the 56–65 age group (tension, *M* = 45.38, *SD* = 7.70, 95% CI [43.81, 46.96]; depression, *M* = 51.33, *SD* = 11.41, 95% CI [48.99, 53.67]; anger, *M* = 52.56, *SD* = 9.95, 95% CI [50.53, 54.60]; fatigue, *M* = 50.53, *SD* = 9.28, 95% CI [48.63, 52.43]; confusion, *M* = 49.04, *SD* = 9.01, 95% CI [47.20, 50.89]).

Additionally, the 25–35 age group also reported a significantly higher level of depression (*M* = 58.80, *SD* = 11.87, 95% CI [56.57, 61.03]), anger (*M* = 57.25, *SD* = 11.10, 95% CI [55.16, 59.34]), fatigue (*M* = 56.72, *SD* = 10.23, 95% CI [54.80, 58.64]), and confusion (*M* = 55.03, *SD* = 10.86, 95% CI [52.98, 57.07]), compared with the 46–55 age group (depression, *M* = 54.39, *SD* = 12.72, 95% CI [52.49, 56.29]; anger, *M* = 53.34, *SD* = 11.13, 95% CI [51.68, 55.00]; fatigue, *M* = 51.87, *SD* = 9.18, 95% CI [50.50, 53.24]; confusion, *M* = 50.15, *SD* = 10.00, 95% CI [48.66, 51.65]). Fatigue and confusion were also found to differ significantly between the 25–35 age group (fatigue, *M* = 56.72, *SD* = 10.23, 95% CI [54.80, 58.64]; confusion, *M* = 55.03, *SD* = 10.86, 95% CI [52.98, 57.07]) and the 36–45 age group (fatigue, *M* = 53.05, *SD* = 9.34, 95% CI [51.58, 54.52]; confusion, *M* = 50.59, *SD* = 9.72, 95% CI [49.05, 52.12]).

Table 7.5

Descriptive Statistics of the BRUMS Subscales by Age (N = 566)

Mood Dimension	18–24 (*n* = 29)			25–35 (*n* = 111)			36–45 (*n* = 157)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	55.93	12.83	[51.05, 60.81]	48.86	7.84	[47.39, 50.34]	46.76	8.28	[45.45, 48.06]
Depression	67.59	17.58	[60.90, 74.27]	58.80	11.87	[56.57, 61.03]	54.87	12.95	[52.82, 56.91]
Anger	66.00	16.80	[59.61, 72.39]	57.25	11.10	[55.16, 59.34]	54.40	10.90	[52.68, 56.12]
Vigour	50.07	9.98	[46.27, 53.86]	49.49	8.91	[47.81, 57.16]	50.20	8.93	[48.80, 51.61]
Fatigue	60.79	9.24	[57.28, 64.31]	56.72	10.23	[54.80, 58.64]	53.05	9.34	[51.58, 54.52]
Confusion	65.62	15.81	[59.61, 71.63]	55.03	10.86	[52.98, 57.07]	50.59	9.72	[49.05, 52.12]

Mood Dimension	46–55 (*n* = 175)			56–65 (*n* = 94)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Tension	46.22	8.00	[45.02, 47.41]	45.38	7.70	[43.81, 46.96]
Depression	54.39	12.72	[52.49, 56.29]	51.33	11.41	[48.99, 53.67]
Anger	53.34	11.13	[51.68, 55.00]	52.56	9.95	[50.53, 54.60]
Vigour	50.50	7.44	[49.39, 51.61]	52.44	6.97	[51.01, 53.86]
Fatigue	51.87	9.18	[50.50, 53.24]	50.53	9.28	[48.63, 52.43]
Confusion	50.15	10.00	[48.66, 51.65]	49.04	9.01	[47.20, 50.89]

While a statistically significant MANOVA statistic was identified for tension, depression, anger, and confusion in the 18–24 age group compared with all of the other age groups, as well as fatigue in the 18–24 age group compared with the 36–45, 46–55, and the 56–65 age groups, the 18–24 age group sample size and large variance warrants due consideration. A comparison of effect sizes for the 18–24 age group can be found in Table 7.6. The effect sizes for tension, depression, anger, fatigue, and confusion in the 25–35 age group compared with the 56–65 age group were d = .22 (p = .031), d = .32 (p < .001), d = .22 (p = .027), d = .32 (p < .001), and d = .30 (p < .001), respectively, indicating a moderate effect for each comparison. The effect sizes for depression, anger, fatigue, and confusion in the 25–35 age group compared with the 46–55 age group were d = .18 (p = .049), d = .18 (p = .042), d = .25 (p < .001), and d = .23 (p = .001), respectively, indicating a small effect for each comparison. The effect sizes for fatigue and confusion in the 25–35 age group compared with the 36–45 age group were d = .19 (p = .021), and d = .22 (p = .005), indicating a small effect for each comparison. Overall, these differences could be considered clinically meaningful.

Table 7.6

Effect Size Comparisons for the 18–24 Age Group (N = 566)

	Age Group			
Mood Dimension	25–35	36–45	46–55	56–65
Tension	.34***	.43***	.47***	.51***
Depression	.30**	.42***	.44***	.56***
Anger	.31**	.42***	.45***	.50***
Vigour	-	-	-	-
Fatigue	-	.42***	.48***	.55***
Confusion	.40***	.59***	.60***	.67***

Note. 25–35 (n = 111), 36–45 (n = 157), 46–55 (n = 175), 56–65 (n = 94). ** p < .01. *** p < .001.

Given the unequal sample sizes within the education groupings (i.e., < high school, *n* = 17; high school, *n* = 70; trade, *n* = 75; TAFE, *n* = 74; university, *n* = 190; postgraduate, *n* = 142), the < high school group were combined with the high school group. A between-groups MANOVA was performed to investigate whether mood scores differed according to level of education. There was a non-significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .944, $F(24, 556) = 1.34$, $p = .125$, partial $\eta^2 = .014$, observed power = .898, suggesting that there were no differences between groups in mood scores. The means, standard deviations, and 95% CI's for each mood dimension by education are provided in Table 7.7.

Table 7.7

Descriptive Statistics of the BRUMS Subscales by Education (N = 566)

Mood Dimension	High School (n = 85)			Trade (n = 75)			TAFE (n = 74)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	49.06	10.77	[46.73, 51.38]	46.08	7.49	[44.36, 47.80]	48.62	10.25	[46.25, 51.00]
Depression	58.19	15.88	[54.76, 61.61]	53.57	11.73	[50.87, 56.27]	58.88	15.78	[55.22, 62.53]
Anger	57.96	13.42	[55.07, 60.86]	53.55	9.81	[51.29, 55.80]	57.72	14.01	[54.47, 60.96]
Vigour	50.24	8.83	[48.33, 52.14]	51.53	7.84	[49.73, 53.34]	49.65	7.64	[47.88, 51.42]
Fatigue	53.26	11.02	[50.88, 55.64]	51.69	8.95	[49.63, 53.75]	55.34	10.61	[52.88, 57.80]
Confusion	53.93	13.15	[51.09, 56.77]	50.00	7.87	[48.19, 51.81]	54.54	13.56	[51.40, 57.68]

Mood Dimension	University (n = 190)			Postgraduate (n = 142)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Tension	46.36	7.11	[45.35, 47.38]	47.24	8.39	[45.85, 48.63]
Depression	53.87	11.65	[52.21, 55.54]	55.54	12.05	[53.54, 57.54]
Anger	53.11	10.19	[51.65, 54.56]	54.80	11.16	[52.95, 56.65]
Vigour	50.48	8.80	[49.22, 51.74]	50.65	7.73	[49.37, 51.94]
Fatigue	53.19	9.31	[51.86, 54.52]	53.60	9.57	[52.01, 55.19]
Confusion	51.05	9.88	[49.63, 52.46]	51.20	10.47	[49.47, 52.94]

A between-groups MANOVA was performed to investigate whether mood scores differed according to occupation. There was a non-significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .989, F(6, 559) = 1.05, p = .391, partial η^2 = .011, observed power = .418, suggesting that there were no differences between groups in mood scores. The means, standard deviations, and 95% CI's for each mood dimension by occupation are provided in Table 7.8.

Table 7.8

Descriptive Statistics of the BRUMS Subscales by Occupation (N = 566)

Mood Dimension	Occupation					
	Construction (n = 324)			Mining (n = 242)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Tension	46.61	7.99	[45.74, 47.49]	48.09	9.29	[46.91, 49.27]
Depression	54.43	12.52	[53.06, 55.80]	57.06	13.86	[55.30, 58.81]
Anger	54.02	11.01	[52.81, 55.22]	56.14	12.24	[54.59, 57.69]
Vigour	50.81	7.92	[49.94, 51.67]	50.13	8.71	[49.03, 51.23]
Fatigue	52.83	9.35	[51.81, 53.85]	54.13	10.34	[52.82, 55.44]
Confusion	50.97	10.14	[49.86, 52.08]	53.00	11.88	[51.50, 54.50]

Given the unequal sample sizes within the project size groupings (i.e., < $5 million, n = 68; $5–$500 million, n = 143; $500–$1 billion, n = 26; $1+ billion, n = 87), the $500–$1 billion group were combined with the $1+ billion group and re-named $500+ million. A between-groups MANOVA was performed to investigate whether mood scores differed according to the size of the construction project. There was a non-significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .966, F(18, 557) = 1.08, p = .368, partial η^2 = .011, observed power = .775, suggesting that there were no differences between groups in mood scores. Additionally, a between-groups MANOVA was performed to investigate whether mood scores differed according to the type of mine. There was a non-significant multivariate main effect on a composite of the six dependent variables, Wilks' $\Lambda = .964$, $F(18, 557) = 1.14$, $p = .303$, partial $\eta^2 = .012$, observed power = .775, suggesting that there were no differences between groups in mood scores. The means, standard deviations, and 95% CI's for each mood dimension by project size and mine are provided in Table 7.9 and Table 7.10, respectively.

Table 7.9

Descriptive Statistics of the BRUMS Subscales by Project Size (N = 324)

Mood Dimension	Size of Construction Project								
	< \$5 Million (*n* = 68)			\$5–\$500 Million (*n* = 143)			\$500+ Million (*n* = 113)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	46.35	7.77	[44.47, 48.23]	47.20	8.43	[45.80, 48.59]	46.04	7.55	[44.63, 47.44]
Depression	53.09	11.89	[50.21, 55.96]	55.57	13.00	[53.42, 57.72]	53.81	12.26	[51.25, 56.09]
Anger	52.85	10.85	[50.23, 55.48]	54.10	10.79	[52.32, 55.89]	54.60	11.43	[52.47, 56.73]
Vigour	51.66	8.72	[49.55, 53.77]	50.07	7.15	[48.89, 51.25]	51.23	8.31	[49.68, 52.78]
Fatigue	50.93	9.30	[48.68, 53.18]	53.72	9.49	[52.15, 55.29]	52.85	9.09	[51.15, 54.54]
Confusion	50.28	9.85	[47.89, 52.66]	51.31	9.69	[49.71, 52.91]	50.96	10.90	[48.92, 52.99]

Table 7.10

Descriptive Statistics of the BRUMS Subscales by Mine (N = 242)

Mood Dimension	Type of Mine								
	Open-cut (n = 138)			Underground (n = 69)			Other (n = 35)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	48.17	9.33	[46.60, 49.74]	47.61	9.55	[45.31, 49.90]	48.71	8.82	[45.68, 51.74]
Depression	56.93	13.15	[54.72, 59.15]	56.72	15.01	[53.12, 60.33]	58.20	14.62	[53.18, 63.22]
Anger	55.42	11.31	[53.52, 57.32]	56.20	13.05	[53.07, 59.34]	58.83	14.01	[54.02, 63.64]
Vigour	49.62	8.69	[48.15, 51.08]	51.80	9.33	[49.56, 54.04]	48.86	7.12	[46.41, 51.30]
Fatigue	54.57	10.38	[52.82, 56.31]	52.54	10.69	[50.97, 56.10]	53.57	9.64	[50.26, 56.88]
Confusion	53.20	12.10	[51.16, 55.23]	52.22	11.71	[49.41, 55.03]	53.77	11.60	[49.79, 57.76]

A between-groups MANOVA was performed to investigate whether mood scores differed according to roster. There was a non-significant multivariate main effect on a composite of the six dependent variables, Wilks' Λ = .980, $F(6, 559)$ = 1.87, p = .083, partial η^2 = .020, observed power = .699, suggesting that there were no differences between groups in mood scores. The means, standard deviations, and 95% CI's for each mood dimension by roster are provided in Table 7.11.

Table 7.11

Descriptive Statistics of the BRUMS Subscales by Roster (N = 566)

	Roster					
	DIDO (n = 409)			FIFO (n = 157)		
Mood Dimension	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Tension	47.23	8.66	[46.39, 48.07]	47.29	8.44	[45.96, 48.62]
Depression	55.29	12.83	[54.04, 56.54]	56.24	14.03	[54.03, 58.45]
Anger	54.38	11.27	[53.28, 55.47]	56.34	12.30	[54.40, 58.28]
Vigour	50.77	8.30	[49.96, 51.57]	49.87	8.14	[48.59, 51.16]
Fatigue	52.83	9.76	[51.88, 53.77]	54.84	9.77	[53.30, 56.38]
Confusion	51.63	10.77	[50.58, 52.68]	52.38	11.43	[50.58, 54.18]

Given the unequal sample sizes within the ethnic groupings (i.e., African, n = 24; Asian, n = 45; Caucasian, n = 444; Indigenous, n = 8; Middle Eastern, n = 4; Other, n = 41), and the inherent difficulty of collapsing data further, inferential statistics were not used to investigate whether mood scores differed according to ethnicity. Similarly, given the unequal sample sizes (i.e., ACT, n = 14; NSW, n = 30; NT, n = 6; QLD, n = 81; SA, n = 18; TAS, n = 2; VIC, n = 5; WA, n = 124; Other, n = 288) inferential statistics were not used to investigate whether mood scores differed according to location of employment. Instead, groups were collapsed down according to country (i.e., Australia and Other), in line with Tabachnick and

Fidell's (2013) suggestion that equal or approximately equal size groups be maintained to better support the integrity of MANOVA.

A between-groups MANOVA was performed to investigate whether mood scores differed according to country. There was a significant multivariate main effect on a composite of the six dependent variables, Wilks' $\Lambda = .939$, $F(6, 559) = 6.06$, $p < .001$, partial $\eta^2 = .061$, observed power = .997. Using a Bonferroni adjusted alpha level of .008, significant univariate main effects were identified for anger, $F(1, 564) = 7.93$, $p = .005$, partial $\eta^2 = .014$, observed power = .803; vigour, $F(1, 564) = 17.78$, $p < .001$, partial $\eta^2 = .031$, observed power = .988; and fatigue, $F(1, 564) = 20.16$, $p < .001$, partial $\eta^2 = .035$, observed power = .994.

An examination of the mean scores for each dependent variable (see Table 7.12) revealed that Australians reported a significantly higher level anger (M = 56.34, SD = 12.82, 95% CI [54.83, 57.85]), and fatigue (M = 55.24, SD = 10.13, 95% CI [54.04, 56.43) together with a significantly lower level of vigour (M = 49.03, SD = 8.30, 95% CI [48.05, 50.01]) compared with other countries (anger, M = 53.56, SD = 10.11, 95% CI [52.38, 54.73]; vigour, M = 51.95, SD = 7.98, 95% CI [51.03, 52.88]; and fatigue, M = 51.60, SD = 9.13, 95% CI [50.54, 52.66]). The effect sizes for Australians compared with other countries for level of anger, vigour, and fatigue were $d = .12$ ($p = .005$), $d = .18$ ($p < .001$), and $d = .19$ ($p < .001$), respectively, indicating a small effect for each comparison.

Table 7.12

Descriptive Statistics of the BRUMS Subscales by Country (N = 566)

Mood Dimension	Country					
	Australia (*n* = 278)			Other (*n* = 288)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Tension	47.94	9.18	[46.86, 49.03]	46.57	7.94	[45.65, 47.49]
Depression	56.70	14.44	[54.99, 58.40]	54.45	11.73	[53.09, 55.81]
Anger	56.34	12.82	[54.83, 57.85]	53.56	10.11	[52.38, 54.73]
Vigour	49.03	8.30	[48.05, 50.01]	51.95	7.98	[51.03, 52.88]
Fatigue	55.24	10.13	[54.04, 56.43]	51.60	9.13	[50.54, 52.66]
Confusion	53.06	11.95	[51.65, 54.48]	50.65	9.77	[49.52, 51.79]

7.3.3 Moderating demographic variables analyses (WHSS). A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to gender. There was a non-significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .989, $F(4, 547) = 1.56$, $p = .185$, partial $\eta^2 = .011$, observed power = .482, suggesting that there were no differences between groups. The means, standard deviations, and 95% CI's for each dependent variable by gender are provided in Table 7.13

Table 7.13

Descriptive Statistics of the WHSS Subscales by Gender (N = 552)

Subscale	Gender					
	Male (n = 387)			Female (n = 165)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	50.05	9.88	[49.06, 51.04]	49.89	10.32	[48.30, 51.47]
Safety Motivation	49.92	9.96	[48.92, 50.91]	50.19	10.12	[48.64, 51.75]
Safety Compliance	49.80	10.31	[48.77, 50.83]	50.46	9.25	[49.04, 51.88]
Safety Participation	50.37	10.23	[49.35, 51.39]	49.13	9.42	[47.68, 50.58]

A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to level of education. There was a non-significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .955, $F(16, 544) = 1.57$, p = .069, partial η^2 = .011, observed power = .793. Despite this finding, using a Bonferroni adjusted alpha level of .008, a significant univariate main effect was identified for safety participation, $F(4, 547) = 3.50$, p = .008, partial η^2 = .025, observed power = .863.

An examination of the mean scores for each dependent variable (see Table 7.14) revealed that individuals with a high school level of education reported a significantly lower level of safety participation (M = 46.44, SD = 11.65, 95% CI [43.87, 49.02]) compared with individuals with a trade qualification (M = 50.97, SD = 10.01, 95% CI [48.61, 53.32]), TAFE certificate (M = 51.87, SD = 9.28, 95% CI

[49.71, 54.04]), and university degree (*M* = 50.37, *SD* = 9.37, 95% CI [49.02, 51.72]). The effect sizes for individuals with a high school level of education compared with a trade qualification, TAFE certificate, and university degree for level of safety participation was $d = .21$ ($p = .050$), $d = .26$ ($p = .007$), and $d = .19$ ($p = .030$), respectively, indicating a small effect for each comparison. Although the small effect sizes suggest that these differences were not practically meaningful, the lower power of the study should be taken into consideration.

Table 7.14

Descriptive Statistics of the WHSS Subscales by Education (N = 552)

Subscale	High School (n = 81)			Trade (n = 72)			TAFE (n = 73)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	49.12	11.09	[46.67, 51.57]	49.22	9.18	[47.07, 51.38]	51.64	9.84	[49.35, 53.94]
Safety Motivation	47.76	11.76	[45.16, 50.36]	50.58	9.52	[48.35, 52.82]	51.04	9.45	[48.84, 53.25]
Safety Compliance	48.14	12.08	[45.47, 50.81]	50.08	10.52	[47.60, 52.55]	50.27	9.18	[48.13, 52.41]
Safety Participation	46.44	11.65	[43.87, 49.02]	50.97	10.01	[48.61, 53.32]	51.87	9.28	[49.71, 54.04]
Subscale	University (n = 188)			Postgraduate (n = 138)					
	M	*SD*	95% CI	*M*	*SD*	95% CI			
Safety Climate	48.89	9.27	[47.55, 50.22]	51.57	10.59	[47.79, 53.35]			
Safety Motivation	49.97	9.27	[48.63, 51.30]	50.51	10.31	[48.77, 52.24]			
Safety Compliance	50.08	9.76	[48.68, 51.49]	50.80	9.09	[49.26, 52.33]			
Safety Participation	50.37	9.37	[49.02, 51.72]	50.09	9.79	[48.44, 51.74]			

A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to occupation. There was a non-significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .987, $F(4, 547) = 1.81$, $p = .125$, partial η^2 = .013, observed power = .553, suggesting that there were no differences between groups. The means, standard deviations, and 95% CI's for each dependent variable by occupation are provided in Table 7.15.

Table 7.15

Descriptive Statistics of the WHSS Subscales by Occupation (N = 552)

	Occupation					
	Construction (n = 315)			Mining (n = 237)		
Subscale	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	49.93	10.03	[48.82, 51.04]	50.09	9.98	[48.82, 51.37]
Safety Motivation	49.98	10.11	[48.86, 51.10]	50.02	9.87	[48.76, 51.29]
Safety Compliance	50.58	10.29	[49.44, 51.72]	49.22	9.56	[48.01, 50.45]
Safety Participation	50.67	9.86	[49.58, 51.77]	49.12	10.13	[47.81, 50.40]

A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to roster. There was a significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .965, $F(4, 547) = 4.89$, $p = .001$, partial $\eta^2 = .035$, observed power = .958. Using a Bonferroni adjusted alpha level of .008, a significant univariate main effect was identified for safety participation, $F(1, 550) = 9.59$, $p = .002$, partial $\eta^2 = .017$, observed power = .871.

An examination of the mean scores for each dependent variable (see Table 7.16) revealed that individuals working a FIFO roster reported a significantly lower level of safety participation ($M = 47.87$, $SD = 10.34$, 95% CI [46.21, 49.53]) compared with individuals working a DIDO roster ($M = 50.80$, $SD = 9.76$, 95% CI [49.84, 51.76]). The effect size for individuals working a FIFO roster compared with a DIDO roster for safety participation was $d = .15$ ($p = .002$), indicating a small effect.

Table 7.16

Descriptive Statistics of the WHSS Subscales by Roster (N = 552)

Subscale	Roster					
	DIDO (*n* = 401)			FIFO (*n* = 151)		
	M	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	49.74	10.23	[48.73, 50.74]	50.10	9.35	[49.20, 52.20]
Safety Motivation	50.33	9.98	[49.35, 51.31]	49.12	10.03	[47.51, 50.73]
Safety Compliance	49.97	10.37	[48.95, 50.99]	50.07	8.98	[48.63, 51.52]
Safety Participation	50.80	9.76	[49.84, 51.76]	47.87	10.34	[46.21, 49.53

Note. DIDO = Drive-in/Drive-out, FIFO = Fly-in/Fly-out.

A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to country. There was a significant multivariate main effect on a composite of the four dependent variables, Wilks' $\Lambda = .963$, $F(4, 547) = 5.23$, $p < .001$, partial $\eta^2 = .037$, observed power = .970. Using a Bonferroni adjusted alpha level of .008, a significant univariate main effect was identified for safety motivation, $F(1, 550) = 7.72$, $p = .006$, partial $\eta^2 = .014$, observed power = .792; and safety participation, $F(1, 550) = 19.67$, $p < .001$, partial $\eta^2 = .035$, observed power = .993.

An examination of the mean scores for each dependent variable (see Table 7.17) revealed that individuals working in Australia reported a significantly lower level of safety motivation (*M* = 48.80, *SD* = 11.10, 95% CI [47.47, 50.13]), and safety participation (*M* = 48.10, *SD* = 10.74, 95% CI [46.82, 49.39]), compared with individuals working in other countries (safety motivation, *M* = 51.15, *SD* = 8.68, 95% CI [50.13, 52.17]; safety participation, *M* = 51.82, *SD* = 8.88, 95% CI [50.78, 52.80]). The effect sizes for individuals working in Australia compared with other countries for safety motivation, safety compliance, and safety participation were *d* = .12 (*p* = .006), and *d* = .19 (*p* < .001), respectively, indicating a small effect for each comparison.

Table 7.17

Descriptive Statistics of the WHSS Subscales by Country (N = 552)

	Country					
	Australia (*n* = 270)			Other (*n* = 282)		
Subscale	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	49.32	9.86	[48.13, 50.50]	50.65	10.11	[49.47, 51.84]
Safety Motivation	48.80	11.10	[47.47, 50.13]	51.15	8.68	[50.13, 52.17]
Safety Compliance	49.04	10.56	[47.47, 50.30]	50.92	9.36	[49.83, 52.02]
Safety Participation	48.10	10.74	[46.82, 49.39]	51.82	8.88	[50.78, 52.80]

A between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to the size of the construction project. There was a non-significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .973, $F(12, 545)$ = 1.23, p = .256, partial η^2 = .009, observed power = .641, suggesting that there were no differences between groups. Additionally, a between-groups MANOVA was performed to investigate whether perceptions of safety climate, motivation to perform safety behaviours, willingness to comply with safety procedures, and overt safety participation differed according to the type of mine. There was a non-significant multivariate main effect on a composite of the four dependent variables, Wilks' Λ = .964, $F(12, 545)$ = 1.66, p = .070, partial η^2 = .012, observed power = .802, suggesting that there were no differences between groups. The means, standard deviations, and 95% CI's for each dependent variable by project size and mine are provided in Table 7.18 and Table 7.19, respectively.

Table 7.18

Descriptive Statistics of the WHSS Subscales by Project Size (N = 315)

Subscale	Size of Construction Project								
	< $5 Million (*n* = 67)			$5–$500 Million (*n* = 139)			$500+ Million (*n* = 109)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	48.85	9.31	[46.57, 51.12]	49.92	11.17	[48.05, 51.79]	50.61	8.89	[48.92, 52.30]
Safety Motivation	50.01	10.51	[47.45, 52.57]	49.92	10.53	[48.15, 51.68]	50.05	9.39	[48.27, 51.83]
Safety Compliance	50.58	10.15	[48.10, 53.05]	50.28	11.53	[48.35, 52.25]	50.96	8.67	[49.31, 52.61]
Safety Participation	51.88	9.92	[49.46, 54.30]	50.96	10.22	[49.24, 52.67]	49.57	9.33	[47.80, 51.34]

Table 7.19

Descriptive Statistics of the WHSS Subscales by Mine (N = 237)

Subscale	Type of Mine								
	Open-cut (n = 133)			Underground (n = 69)			Other (n = 35)		
	M	*SD*	95% CI	*M*	*SD*	95% CI	*M*	*SD*	95% CI
Safety Climate	49.76	9.68	[48.10, 51.42]	50.38	10.82	[47.78, 52.98]	50.79	9.58	[47.50, 54.07]
Safety Motivation	48.98	10.31	[47.22, 50.75]	51.49	9.82	[49.14, 53.85]	51.08	7.78	[48.41, 53.76]
Safety Compliance	48.15	9.85	[46.46, 49.84]	51.92	8.59	[49.85, 53.98]	48.03	9.48	[44.77, 51.29]
Safety Participation	47.67	10.82	[45.81, 45.52]	51.90	8.04	[49.96, 53.83]	49.07	10.23	[45.56, 52.59]

7.4 Summary

A subsample consisting of 568 cases from the construction and mining industries were parcelled out from Sample C. The responses from the BRUMS and WHSS were analysed via a series of between-groups MANOVA tests. Significant differences between clusters (i.e., $C1^c$ = submerged, $C2^c$ = shark fin, $C3^c$ = inverse Everest, $C4^c$ = surface, $C5^c$ = inverse iceberg, and $C6^c$ = iceberg profile) were found according to each of the WHSS subscales. Also, a number of variables were found to moderate the BRUMS and WHSS. Differences in mood scores were identified according to gender, age, and country. However, no moderating effects were found for level of education, occupation, size of construction project, type of mine, and roster. Additionally, level of education, roster, and country were found to moderate the WHSS, although no differences in responses were identified for gender, occupation, size of construction project, and type of mine.

More specifically, individuals experiencing the iceberg profile endorsed a higher perception of policies, procedures, and practices concerning safety in the workplace; were more motivated; and were more likely to comply with core activities that maintain workplace safety as well as practice behaviours that facilitate a supportive safety environment compared with those experiencing the shark fin and inverse iceberg profiles. Additionally, individuals experiencing the iceberg profile also endorsed a higher perception of safety climate compared with those experiencing the inverse Everest profile. Further, individuals experiencing the inverse iceberg profile were less likely to comply with core activities that maintain workplace safety as well less likely to practice behaviours that facilitate a supportive safety environment compared with those experiencing the submerged and surface profiles (respectively). Additionally, individuals experiencing the inverse iceberg profile were also less motivated to perform safety behaviours compared with those experiencing the submerged, shark fin, surface, and iceberg profiles. The effects sizes ranged from small to moderate (i.e., .21 to .40), suggesting that these findings were practically meaningful.

Males reported a higher level of vigour and lower level of fatigue compared with females, although these differences were not considered clinically meaningful. Those aged 8–24 reported a higher level of tension, depression, anger, and confusion compared with each of the other age groups, as well as a higher level of fatigue compared with those aged 36–45, 46–55, and 56–65. However, the small sample size and large variance warranted consideration. Those aged 25–35 reported a higher level of tension, depression, anger, fatigue, and confusion, compared with those aged 56–65. Additionally, those aged 25–35 also reported a higher level of depression, anger, fatigue, and confusion compared with those aged 46–55. Fatigue and confusion were also found to differ significantly between the 25–35 and 36–45 age groups. Although these differences could be considered meaningful, the effects sizes were small according to Cohen (1992). Lastly, Australian construction and mining employees reported a higher level of anger and fatigue, together with a lower level of vigour compared with those from other countries. Again small effects were identified.

In terms of the moderating effects on the WHSS subscales, individuals with a high school level of education were less likely to practice safe behaviours compared with those with a trade, TAFE certificate, and university degree. Although only small effects were identified, the lower power of the study should once again be taken into consideration. Further, individuals working a FIFO roster were less likely to practice safe behaviours compared with those working a DIDO roster, with another small effect identified. Individuals working in Australia were also less motivated to perform safe behaviours, and less likely to practice safe behaviours compared with those in other countries. However, again the effect sizes were small.

CHAPTER 8:
Recapitulations

8.1 Overview of Results

Previous research has identified three mood profiles (i.e., the iceberg, inverse iceberg, and Everest profiles) predominately within athletic samples. The purpose of the present research was to investigate if relatively consistent mood patterning could be found within the general population using a web-based delivery method. Three datasets from the BRUMS hosted through the *In The Mood* website were investigated via cluster analytic methodology. More specifically, the mood responses of Sample A (N = 2,364) were analysed using agglomerative, hierarchical cluster analysis. Six mood profiles were identified: iceberg, inverse iceberg, inverse Everest, shark fin, surface, and submerged profile. When the fate of members were traced, the submerged profile demonstrated the highest level of stability. This was followed by the surface, iceberg, inverse Everest, and shark fin profiles. Upon closer inspection, the inverse iceberg profile was formed one step before the cut. Being a bottom-up clustering technique, this suggests that this cluster had a higher variation between means.

A k-means clustering procedure with a specified six-cluster outcome was used to further refine the final multivariate structures. Both clustering techniques produced clusters that were highly correlated with one another, being strong evidence of dissimilarity between groups and similarity within groups. Further, a MANOVA found significant differences between clusters on each dimension of mood and a multiple DFA showed that cluster membership could be correctly classified with a high degree of accuracy. A series of chi-square tests of goodness-of-fit indicated that the distributions of demographic variables (i.e., gender, age, and education level) were significantly different from expected cell counts. The k-means, MANOVA, multiple DFA, and chi-square results were replicated in Sample B (*N* = 2,303) and Sample C (*N* = 1,865).

Notwithstanding some expected variation, each cluster demonstrated remarkable consistency across all three samples. For example, iceberg profile: tension (*M* range = 42.25–42.84), depression (*M* range = 44.98–45.65), anger (*M* range = 46.26–47.24), vigour (*M* range = 57.13–58.84), fatigue (*M* range = 45.11–45.72), and confusion (*M* range = 44.42–45.27). Inverse iceberg profile: tension (*M* range = 56.65–59.16), depression (*M* range = 63.86–69.87), anger (*M* range = 59.82–66.69), vigour (*M* range = 45.73–47.25), fatigue (*M* range = 60.80–61.45), and confusion (*M* range = 63.20–66.09). Inverse Everest profile: tension (*M* range = 66.76–70.45), depression (*M* range = 87.17–89.53), anger (*M* range = 79.05–81.71), vigour (*M* range = 42.50–42.71), fatigue (*M* range = 67.59–70.00), and confusion (*M* range = 78.73–80.67). Shark fin profile: tension (*M* range = 44.42–45.22), depression (*M* range = 48.97–52.00), anger (*M* range = 48.00–50.15), vigour (*M* range = 41.12–42.59), fatigue (*M* range = 64.10–65.11), and confusion (*M* range = 47.47–50.39). Surface profile: tension (*M* range = 50.64–51.90), depression (*M* range = 50.68–53.03), anger (*M* range = 52.26–54.49), vigour (*M* range = 52.26–55.66), fatigue (*M* range = 51.11–52.92), and confusion (*M* range = 54.00–55.77). Submerged profile: tension (*M* range = 41.67–43.23), depression (*M* range = 45.95–47.26), anger (*M* range = 46.50–47.26), vigour (*M* range = 42.51–44.58), fatigue (*M* range = 46.99–49.21), and confusion (*M* range = 44.62–46.55).

Additionally, group sizes were similar across all three samples: iceberg ~29.1% (range = 28.0–29.8%), inverse iceberg ~10.7% (range = 9.3–12.3%), inverse Everest ~2.9% (range = 2.4–3.6%), shark fin ~15.9% (range = 13.8–17.3%), surface

~14.9% (range = 14.8–15.0%), and submerged ~26.7% (range = 25.4–29.0%) profile. Correct classification of cluster membership also showed little variation: iceberg (range = 98.5–100%), inverse iceberg (range = 93.0–98.3%), inverse Everest (range = 93.2–98.4%), shark fin (range = 93.2–98.7%), surface (range = 82.6–95.7%), and submerged (range = 96.9–98.3%).

Interestingly, a relationship between cluster and gender was identified. An over-representation of females was found for the inverse iceberg profile, with all three samples identifying a significant difference at $p < .05$. A similar trend was identified for the shark fin profile, in that two of three samples (i.e., Sample B and Sample C) identified a significant difference at $p < .001$. Conversely, an over-representation of males was found for the iceberg profile, with all three samples identifying a significant difference at $p < .001$. Although significant differences for gender were found for the submerged profile within Sample A (over-representation of females) and Sample C (over-representation of males), no discernible trends were identified across all three samples. Further, no significant differences nor trends were identified according to the demographic variables for the surface profile (refer to Appendix E for a visual summary of the six-cluster solutions and distributions of demographic variables across samples).

Additionally, given the importance of performance in the workplace, the present research aimed to further generalise the BRUMS as well as investigate a possible mood-performance relationship in high-risk vocations. A relationship between mood and the components of safety behaviour was identified using a subsample of respondents from the construction and mining industries ($N = 568$). Overall, the iceberg profile was found to be facilitative of safety performance in that employees endorsed a higher perception of safety climate, were more likely to comply with safety procedures, and more likely to practice safe behaviours.

Further, the inverse iceberg profile was considered debilitative of safety performance in that employees were less likely to comply with safety procedures, were less motivated to perform safe behaviours, and less likely to practice safe behaviours. A number of demographic variables were found to influence the BRUMS (i.e., gender, age, and country) and the WHSS (i.e., level of education, roster, and country). However, the small effect sizes suggested that these results were likely the product of overpowered analyses, rather than meaningful differences. For this reason, only the main findings will be discussed.

8.2 Discussion of Main Findings

8.2.1 Mood-performance relationships. Characterised by a combination of an above average level of vigour (> 50%) together with below average levels of tension, depression, anger, fatigue, and confusion (< 50%), the iceberg profile is considered a positive feeling state facilitative of corporeal performance (see Morgan, 1980, 1985) and supportive of healthy cognitive functioning (the negative effects of high fatigue are discussed later). Similarly, the Everest profile (vigour > 60%; tension, depression, anger, fatigue, and confusion < 40%) has been associated with "superior" performance (Terry, 1995, p. 322), although is found considerably less frequently. Despite criticism and mixed findings (see Prapavessis, 2000 for a review), the iceberg profile has garnered the strongest support in athletic communities (see Beedie et al., 2000; Gill, 1986; Terry & Lane, 2000; Terry & Hall, 1996; etc.). In the past, researchers have highlighted its ability to distinguish athletes from non-athletes (Morgan, 1980, 1985; Rowley et al., 1995), while still others have argued even finer-grain distinctions can be made according to skill level (Nagle et al., 1975; Silva, Schultz, Haslam, Martin, & Murray, 1985).

While it is acknowledged that trends from normative samples do not always apply to individuals (Terry, 1995), and optimal-functional emotional states are likely to be somewhat individualised; empirical data suggests that the iceberg profile is a mood state typically experienced within athletic populations and has a small to moderate effect on performance (Beedie et al., 2000; Rowley et al., 1995). Indeed, given the frequency in which the psychological profile is found, Terry, Lane, and Beedie (2005) argued that sport-specific normative data should be developed to better utilise the BRUMS in this cohort. However, as previously mentioned the ability of the iceberg profile to *predict* athletic success remains questionable, with variables involving type of sport and idiosyncratic differences (e.g., physiology, personality factors, meta-beliefs on emotional states, trait emotional intelligence, etc.) each having an influence (Lane & Terry, 2011; Lane & Wilson, 2011; Rowley et al., 1995; Terry, Lane et al., 2005).

If the iceberg profile is indicative of *mental health* (Morgan, 1980), it should then follow that the inverse iceberg is representative of poor psychological functioning. Characterised by an opposite pattern of below average vigour (< 50%), together with above average levels of tension, depression, anger, fatigue, and confusion (~60%), the inverse iceberg profile is considered a negative feeling state debilitative of performance by means of mood disturbance and compromised physical functioning (Terry, 1995, 2004). Most commonly associated with overtraining symptoms (Terry, 1995) and dysfunctional athletic ability (Lahart et al., 2013), the inverse iceberg profile, like the iceberg profile, has typically been investigated within sporting communities.

According to Lemyre, Roberts, and Stray-Gundersen (2007), overtraining syndrome refers to a temporary state of incompetence, usually involving decreases or plateaus in performance ability. Intimately related to athlete burnout (a more severe manifestation of the syndrome; Gustafsson, 2007), the two conditions share a number of characteristics such as impaired performance, fatigue, exhaustion, and mood disturbance (e.g., irritability/moodiness, depression, decreased enthusiasm, decreased concentration, emotional instability, and anxiousness; Quinn, 2014). Demonstrating an obvious departure from psychological well-being, it is easy to visualise how the BRUMS subscales have the ability to detect the phenomena; as well as understand why the inverse iceberg profile is considered an important diagnostic indicator for overtraining symptoms by the British Olympic Medical Centre (Terry, 1995).

The significantly high levels of tension (> 60%), depression (> 80%), anger (~80%), fatigue (~70%), and confusion (~70%), combined with the below average level of vigour (< 50%), suggest that the inverse Everest profile would also likely impede performance efforts. Indeed, the small group sizes for the inverse iceberg (i.e., ~10.7%) and inverse Everest (~2.9%) profiles could be indicative of a form of psychopathology. The Australian Bureau of Statistics (2013) reported that in 2007 an estimated 6% of the population aged 16–85 experienced an affective condition (e.g., depression, dysthymia, bipolar affective disorder, etc.). Subsumed under the generic term *mood disorder*, many of these clinical states vary in intensity (e.g., mild, moderate, severe) and share a myriad of symptoms. For example, according to the DSM-IV-TR, major depression and dysthymic disorder are both characterised by depressed mood, insomnia (or hypersomnia), fatigue, and confusion (together with other cognitive deficits and physiological indicators; Barlow & Durand, 2009; Sarapas, Shankman, Harrow, & Goldberg, 2012).

Interestingly, many of the symptoms that depict depressive states correspond with key indicators for overtraining syndrome. As Gustafsson (2007) notes, few distinctions can be made between overtraining syndrome, athletic burnout, and depression. This lends credence to the suggestion that the BRUMS is in fact detecting incidences of clinically diagnosable mental health disturbance, represented as the inverse iceberg and inverse Everest profiles, as opposed to a more generalised and subclinical *depressed mood* (i.e., unhappiness, misery, downheartedness; Lane et al., 2001). While there are at least 12 different forms of depressive states (i.e., major depression, melancholia, psycholtic depression, antenatal/postnatal depression, bipolar disorder, cyclothymic disorder, dysthymic disorder, and seasonal affective disorder; "beyondblue", n.d.), it is impossible to ascertain if the BRUMS is detecting symptoms underlying one specific disorder, or a range of psychopathologies. This is due to two primary reasons: 1) variations in severity of mood disorders; and 2) the high likelihood of comorbidity with anxiety disorders (Barlow & Durand, 2009). Additionally, while not categorised as a mood disorder *per se*, manifestations of grief also resemble some mood disorders, and for this reason should not be discounted.

Withal, what is clear is that severity of mood disorder is experienced along a continuum, with increased symptomology corresponding with greater cognitive deficits (e.g., negative/distorted thinking, reduced concentration, distractibility, forgetfulness, reduced reaction time, memory loss, indecisiveness; Sarapas et al., 2012; Tartakovsky, 2013). Given this, it appears that the inverse Everest profile—like the inverse iceberg profile—would have a positive relationship with dysfunctional performance. This notion is further supported by Lane and Terry's (2000) conceptual framework. Although the underlying nature of the anger construct remains unknown (i.e., self-directed versus external expression), previous research suggests that an internal expression of anger usually accompanies depressed mood (Spielberger, 1991). Furthermore, an internal expression of anger is also commonly associated with suppression, self-blame (Spielberger, 1991), worry, and low self-confidence (Comunian, 1989; Lane, 2001; Lane et al., 2004), all of which have been associated with debilitating performance, and identified as contributing to the "fundamentally negative and de-motivating nature" (Lane et al., 2004, p. 135) of depressed states.

Similarly, the shark fin profile may also emulate a negative feeling state, likely to be debilitative of performance. Although the shark fin profile appears to lack the typical markers of the other negative mood profiles (i.e., high levels of tension, depression, anger, and confusion); the below average level of vigour (< 50%) together with the above average level of fatigue (> 60%) suggests otherwise. Indeed, this mood profile could be related to of sleep disturbance. There is a well-characterised connection between sleep and emotional well-being. Indeed, the relationship is so strong that sleep deprivation is considered a "stress and duress" (Allhoff, 2003, p. 106) form of psychological torture.

Even less severe forms of sleep deprivation have been found to increase levels of tension, fatigue, and confusion, as well as decrease levels of vigour (Brendel et al., 1990). Reductions in sleep quantity/quality and sleep fragmentation can also impact neurobehavioral performance, concentration, and memory (Dinges & Kribbs, 1991; Pilcher & Walters, 1997), and have also been associated with decreased confidence and effort (Lane & Terry, 2000). These findings, taken together with the reasonably robust vigour-performance relationship underlying Lane and Terry's (2000) conceptual model of performance, suggest that a low level of vigour and high level of fatigue would likely have a negative influence.

Finally, with all mood dimensions at ~50%, the surface and submerged profiles appear to be variations of the *baseline* or *waterline* test norms originally identified by Morgan (1985). Although it is not possible to isolate the underlying mechanisms nor pinpoint contributing factors, diurnal mood variations could provide some explanation for the high level of uniformity in the magnitude of each mood dimension. Biological and behavioural parameters, otherwise known as biorhythms (Adan & Sánchez-Turet, 2001) show circadian rhythmicity in response to 24-hour cycles of natural light (Westen et al., 2006). Although each parameter differs, correlation design studies and self-report measures have identified patterns of fluctuations as a function of time of day (Adan & Sánchez-Turet, 2001; Cappaert, 1999; Karageorghis, Dimitriou, & Terry, 1999; Murray et al., 2002). For example, PA has demonstrated endogenous variation that is absent in NA, and has been shown to adopt a phase-advanced position relative to circadian temperature rhythms (Murray et al., 2002). Although results were not definitive, an inspection of the plotted means showed that PA was highest at 15:00h and lowest at 24:00h, while NA displayed a linear increase across the 24-hour period. If PA varies according to regular biorhythms (i.e., decreases at night) while NA steadily increases, it seems plausible that PA and NA may vary together (e.g., from 21:00h to early morning) thereby creating a pattern of overall stability affecting each mood dimension.

In terms of performance, the slightly above average levels of tension, depression, anger, vigour, fatigue, and confusion characterising the surface profile suggest that this mood state would not promote optimal performance. While not as debilitating as the inverse iceberg profile, the slightly inflated negative mood dimensions, combined with only a slightly above average level of vigour, signals that performance would likely be compromised. Interestingly, the magnitude of confusion was higher than any other mood dimension in this cluster for each of the three samples. The only discernible difference between the iceberg profile and the submerged profile also involves the magnitude of vigour. While the slightly below average levels of tension, depression, anger, fatigue, and confusion reinforce improved performance, once again the vigour-performance relationship suggests that the submerged profile would impede performance efforts.

8.2.2 Mood profiles and gender differences. The results found that a significantly greater number of females experienced the inverse iceberg (in 3/3 samples) and shark fin (in 2/3 samples) profiles compared with males. As previously mentioned, the strongest between gender difference involves the finding that females are more likely to experience depressive states compared with males (e.g., McGrath, Keita, Strickland, & Russo, 1990; Nolen-Hoeksema, 1987). Such statistics may perhaps be related to the implementation of diverse mood regulation tactics. According to a review involving both empirical and theoretical analyses, females are more likely to use techniques such as rumination as opposed to distraction (Nolen-Hoeksema, 1991, 2001; Thomsen, Melsen, Vijdik, Summerland, & Zachariae, 2005) or positive reappraisal (Kállay et al., 2009), which are strategies often employed by males. Otherwise known as the response theory of depression, Nolen-Hoeksema (1991) suggested that the strategies differ in underlying efficiency.

For example, rumination may increase focus on current feeling states, unintentionally creating a reciprocal influence on depression (or anti-hedonic shift), whereas distraction has been demonstrated as a relatively effective mood regulation strategy (Augustine & Hemenover, 2009; Nolen-Hoeksema, 1991; Nolen-Hoeksema & Morrow, 1993; Thayer et al., 1994), as has positive reappraisal (otherwise known as *benefit finding*; see Helgeson, Reynolds, & Tomich, 2006). According to Nolen-

Hoeksema, Morrow, and Fredrickson (1993), there is an apparent link between rumination and duration of negative feeling states. Nolen-Hoeksema, Wisco, and Lyubomirsky further highlight a possible connection between rumination and onset of depression. However, it makes intuitive sense that personality tendencies (i.e., extroverts versus introverts) influencing the overt selection of strategy also require judicious consideration (Larsen, 2000; Shockley et al., 2012). Further gender differences suggest males prefer a range of strategies ranging from straightforward behaviours such as humour, sexual activity, hobbies, and thought control, to more maladaptive methods involving psychoactive substances and alcohol (Berger & Adesso, 1991; Brandon, 1994; Carmody, 1989; Khantzian, 1985). Alternatively, food consumption, shopping, expressing feelings, and social interaction are commonly employed techniques for females (Thayer et al., 1994).

From a chronobiological perspective, gender differences in affective activation patterns have also been observed (see Mecacci, Scaglione, Vitrano, 1991; van Dongen, 1998). Indeed, many mood disorders have been linked to the menstrual cycle (see Arpels, 1996; Deecher, Andree, Sloan, & Schechter, 2008; Little & Zahn, 1974; Parry, 2001; Rasgon, Bauer, Glenn, Elman, & Whybrow, 2003; etc.), as well as other reproductive-related events (i.e., postpartum, menopausal transition, etc.; Soares, 2013). Mood variability, anxiety symptoms, and sleep problems have each been associated with these “windows of vulnerability” (Soares, 2013, p. 677) which are commonly marked by dynamic hormonal changes and vasomotor symptoms (Deecher et al., 2008).

In fact, estrogen has been found to play an important mechanistic role in mood regulation (see Miller, Conney, Rasgon, Fairbanks, & Small, 2002), although the specific pathways underlying behavioural effects remain unclear (Soares, 2013).

What is clear, however, is that receptors are distributed throughout the brain, with corresponding effects observed in areas known to be associated with mood regulation (i.e., the hypothalamus, prefrontal cortex, hippocampus, and brainstem; Soares, 2013). Additionally, an estrogen-serotonin interaction has also been proposed (Joffe & Cohen, 1998). Gender differences in neural activation patterning during the process of cognitive regulation (i.e., decreased amygdala activity and control-related prefrontal activity in males, and increased ventral striatal activity in females; McRae et al., 2008) have also been identified.

Overall, alternate mood regulation strategies and dissimilar hormonal activity both provide valid arguments as to why gender differences between mood profiles may exist. The finding that females are more likely to experience depression compared with males; coupled with the over-representation of female participants for the inverse iceberg profile, together strengthen the evidence to suggest that the inverse iceberg profile could be associated with a form of clinical depression. Furthermore, the finding that males were more likely to experience the iceberg profile compared with females is not surprising given that the inverse iceberg profile is essentially a transverse replica of the iceberg profile.

If the inverse iceberg profile is indeed associated with depression, the fact that no gender differences were found for the arguably more extreme variation—the inverse Everest profile—becomes especially interesting. However, the notion that the inverse Everest profile may be related to clinical depression or some other affective psychopathology shouldn't be discounted. Importantly, individuals experiencing disturbed mood states do not exist according to one group or another, but rather experience a combination of the magnitude of each mood dimension along a fluctuating continuum. Indeed, it is the cluster analytic procedure that has made a clear distinction between groupings. Further, there are a number of mood disorders that have an equal incidence across gender (e.g., bipolar affective disorder). An aside, bipolar affective disorder affects approximately two percent of the population ("beyondblue", n.d.), while the inverse Everest profile made up ~2.9% of the sample.

8.2.3 Mood-performance relationships in high-risk vocations. Overall, the iceberg profile was deemed to be facilitative of safety performance, given that individuals experiencing this mood state endorsed a higher perception of policies, procedures, and practices concerning safety in the workplace; were more likely to comply with core activities that maintain workplace safety; and were more likely to practice behaviours that facilitate a supportive safety environment. Given the negative relationship between components of safety behaviour and safety outcomes (i.e., occupational injuries/near-misses), it appears attempts to mediate and negate the risk of acute trauma and/or mortality (Khanzode et al., 2011) are improved for individuals experiencing this mood state.

The role of mood in the formation of performance expectancies (Eccles, 1983) may provide some insight as to the underlying mechanisms. For example, Marshall and Brown (2004) posit that task difficulty moderates the connection between performance expectancies and manifest behaviour. Performance expectancies (subjective ratings and/or beliefs about behaviour on an achievement-related task) are contingent upon two factors: perceived ability and perceived task difficulty (Eccles, 1983; Marshall & Brown, 2004; Reinhard & Dickhäuser, 2009). A combination of easy task with high self-confident ability are assumed to contribute to a higher performance expectancy (Eccles, 1983; Reinhard & Dickhäuser, 2009). Dickhäuser and Reinhard (2006) as well as Reinhard and Dickhäuser (2009) note that performance expectancy formation is likely influenced by cognitive, motivational, and affective variables.

Additionally, mood and motivation also warrant some consideration. George and Brief (1996) posit that positive mood influences two forms of motivation (i.e., distal and proximal) which can be explained according to three mechanisms: mood-congruent judgment, mood-congruent recall, and mood effects on attribution. According to George and Brief, distal motivation refers to “how workers make choices about what specific job behaviours to engage in and how much initial effort to exert”, while proximal motivation is concerned with “how workers regulate their behaviours once they are engaged in the chosen task” (p. 89). Mood-congruent judgment refers to the tendency to perceive the environment according to present feeling states, whereas mood-congruent recall describes the tendency to recollect cognitive material consistent with the current mood experienced. Finally, mood effects refers to the tendency to assign more internal/stable attributions to task achievement and external attributions to failure while experiencing a positive mood (the opposite is often associated with negative mood sates).

Hence, according to the abovementioned mechanisms, performance expectancies have the ability to impact manifest behaviour. Individuals experiencing positive affective states are more likely to recognise the relationship between effort and reward, decision-make according to more positive cognitive content, as well as attribute successes to internal factors, and failures to external factors, which in turn influences beliefs about the effort-performance relationship (George & Brief, 1996). While the mood-performance relationship is considered dynamic and bi-directional (Hanin, 2003), the notion that individuals develop performance expectancies is generally agreed upon by researchers (see Atkinson, 1957; Bandura, 1997; Eccles, 1983; Reinhard & Dickhäuser, 2011; Wigfield & Eccles, 2000).

From this information-processing perspective, the above average level of vigour, coupled with below average levels of tension, depression, anger, fatigue, and confusion may have encouraged perceived task ability through mood-congruent recall, thereby facilitating distal motivation to comply with safety procedures and perform safe practices. Evidence for this lies in the significant increase in overt safety behaviour, which has consequently been associated with reductions in accidents (Neal & Griffin, 2006). Although a significant difference in safety motivation was not identified for the iceberg profile, an inspection of means highlighted an increase compared with each of the other five mood profiles. Further, the significant increase in perceptions of policies, procedures, and practices concerning safety in the workplace may in part be explained by means of mood-congruent recall increasing associations within existing knowledge structures, thereby increasing cognitive flexibility, originality, and creative problem solving (Ashby et al., 1999; Lyubomirsky, King, & Diener, 2005).

Conversely, the inverse iceberg profile was considered debilitating of safety performance in that individuals were both less motivated and less likely to comply with core activities that maintain workplace safety, as well as perform behaviours that facilitate a supportive safety environment. It is possible that the below average level of vigour, coupled with inflated levels of tension, depression, anger, fatigue, and confusion may also have negatively impacted task ability through mood-congruent recall reinforcing a negative self-schema causing a reduction in perceived coping ability (Abramson et al., 1989; Rokke, 1993). This in turn reduced distal motivation (George & Brief, 1996) to comply with safety procedures and perform safe practices, leaving these individuals at increased risk of workplace accidents. Once again, evidence for this lies in the significant decrease in components of safety behaviour as measured by the WHSS. Further, a significant decrease in safety motivation was also identified. Indeed, simply regulating the inverse iceberg profile would likely have negatively affected cognitive resources allocated to performance efforts (Muraven et al., 1998). An aside, 56.1% of the sample for the inverse Everest profile belonged to the mining and construction industry, despite making up only 26.1% of Sample C.

8.3 Strengths and Limitations

The primary strength of the current research relates to the fact that data from three large samples were consistent with two previously-identified and four previously-unidentified, theoretically meaningful mood profiles using cluster analytic methodology: namely the iceberg profile, inverse iceberg profile, inverse Everest profile, shark fin profile, surface profile, and submerged profile. The agglomerative, hierarchical cluster analysis followed by the k-means iterative technique both produced similar multivariate structures, signalling a robust method of allocation of cases. While the web-based delivery method and snowballing technique for data collection resulted in three large and heterogeneous samples, the convenience sampling method may have introduced bias in that access to the Internet was required for participation. However, replication of the six-cluster solution in each of the three independent samples is strong evidence to support the consistency of the cluster structures as well as external validity of the results.

Closer inspection of variable groupings revealed that the less than high school level of education group, and the over 65 age group both made up only a small percentage of each sample (range = 1.7%–8.9%, range = 0%–0.7%, respectively). While these percentages may correspond with population norms, it remains unknown if these participants were representative of the underlying populations of interest. Additionally, the small sample sizes negatively impacted the expected and actual cell counts for some chi-square tests of goodness-of-fit, making the results for a small number of analyses uninterpretable, and others somewhat questionable due to violations of underlying assumptions. Unfortunately, analyses involving the inverse Everest mood profile were most affected, due to the small number of participants comprising that cluster.

A further strength of this research lies in that the effects of mood on components of safety behaviour in high-risk vocations were identified. Although specific interacting relationships (e.g., between mood and challenge/hindrance stressors) and underlying mechanisms remain known, the iceberg profile was deemed facilitative of safety performance in the construction and mining industries, while the inverse iceberg profile was more likely to be associated with an increased risk of incidents, accidents, and/or mortality by means of a reduction in safety behaviour. These results were considered in line with previous studies investigating mood and performance in sport, suggesting that the iceberg and inverse iceberg profiles appear to affect performance similarly across diverse contexts and circumstances. This adds further support to the generalisation of the current findings to true-to-life settings.

8.4 Implications and Future Directions

Identification of discrete mood profile clusters will assist in the interpretation of individual affective states by applied practitioners. While the BRUMS has previously demonstrated its ability to depict *depressed mood*, the current findings suggest that the scale may have utility as a screening tool for psychopathology in non-clinical samples. It is for this reason that the psychometric sensitivity of the BRUMS to detect clinically diagnosable forms of depression should be investigated.

It should be noted that the BRUMS has previously been used as a screening tool for post-traumatic stress risk in military populations (see van Wijk, Martin, & Hans-Arendse, 2013).

Additionally, determining the therapeutic meaningfulness and predictability of mood profiles both appear to be logical directions for future research. The empirical examination of potential links between mood profiles and dimensions of personality according to the five-factor model (i.e., extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience; Costa & McCrae, 1992) may also yield beneficial findings, from both a theoretical as well as a practical standpoint. Better defining mood-performance relationships according to Lane and Terry’s (2000) framework would also prove a valuable area of study.

Further, the relationship between cluster and gender should be explored. More specifically, gender differences in the implementation of mood regulation strategies and the inverse iceberg and inverse Everest profiles should be investigated, as should a possible estrogen aetiology. Chronopsychological influences on the surface and submerged profiles also warrant consideration, as does endogenous diurnal variations of specific mood dimensions (i.e., tension, depression, anger, vigour, fatigue, and confusion). Possible links between fatigue and the shark fin profile should also be fully considered, given that severe and chronic levels of sleepiness represent “a serious, potentially life threatening condition, that affects not only sleepy individuals but also society in general” (Campos-Morales, Valencia-Flores, Castaňo-Meneses, Castaňeda-Figueiras, & Martínez-Guerroero, 2005, p. 9).

Furthermore, given that hindrance stressors have previously been associated with a decrease in safety behaviour (i.e., safety compliance and safety participation) thereby contributing to occupational injuries and negative safety outcomes, it is suggested that situational constraints, hassles, role ambiguity, role and interpersonal conflict, role overload, supervisor-related stress, organisational politics, and concerns about job security should be further examined to identify potential underlying relationships with the inverse iceberg profile. Additionally, in an effort to isolate factors that mediate safety behaviour adherence, the role of challenge stressors (i.e., high workload, time pressure, job scope, and high responsibility) in the mood-performance framework should also be considered, as should the impacts of performance expectancy formation. Also, the unusually high number of construction and mining employees experiencing the inverse Everest profile warrants an explanation.

8.5 Conclusions

In summary, this dissertation provides strong evidence to suggest that the stability and/or volatility of mood patterns may be somewhat predictable in the general population. Support for this lies in that six mood profiles were detected via cluster analytic methodology in three large, independent, and heterogeneous samples. Additionally, safety performance was found to be affected by interactions between mood dimensions. Although isolating the factors that contribute to mood profiles and identifying the mechanisms underlying mood-performance relationships are beyond the scope of this study, the results of the present research have contributed to the ideographic approach and theoretical understanding of the ephemeral mood construct, as well as offered important directions for future research.

References

Abbe, O. O., Harvey, C. M., Ikuma, L. H., & Aghazadeh, F. (2011). Modeling the relationship between occupational stressors, psychosocial/physical symptoms and injuries in the construction industry. *International Journal of Industrial Ergonomics, 41*, 106–117. doi:10.1016/j.ergon.2010.12.002

Abbott, J., Klein, B., & Ciechomski, L. (2008). Best practices in online therapy. *Journal of Technology in Human Services, 26,* 360–375. doi:10.1080/15228830802097257

Abramson, L. Y., Metalsky, F. I., & Alloy, L. B. (1989). Hopelessness depression: A theory-based subtype of depression. *Psychological Review, 96,* 358–372. doi:10.1037/0033-295X.96.2.358

Adams, F. M., & Osgood, C. E. (1973). A cross-cultural study of the affective meanings of color. *Journal of Cross-Cultural Psychology, 4,* 135–156. doi:10.1177/002202217300400201

Adan, A., & Sánchez-Turet, M. (2001). Gender differences in diurnal variations of subjective activation and mood. *Chronobiology International, 18,* 491–502. doi:10.1081/CBI-100103971

Alleman, J. R. (2002). Online counselling: The Internet and mental health treatment. *Psychotherapy: Theory, Research, Practice, Training, 39,* 199–209. doi:10.1037/0033-3204.39.2.199

Allhoff, F. (2003). Terrorism and torture. *International Journal of Applied Philosophy, 17*, 121–134. doi:10.5840/ijap200317113

Almoite, M. K., & Norasakkunkit, V. (2012). *Psychology of emotions: The implications of universality and variability.* Retrieved from http://www.mariaalmoite.com/2012/12/psychology-of-emotions-implications-of.html

Altenmüller, E., Schürmann, K., Lim, V. K., & Parlitz, D. (2002). Hits to the left, flops to the right: Different emotions during listening to music are reflected in cortical lateralisation patterns. *Neuropsychologia, 40*, 2242–2256. doi:10.1016/S0028-3932(02)00107-0

Alvidrez, J., & Azocar, F. (1999). Distressed women's clinic patients: Preferences for mental health treatments and perceived obstacles. *General Hospital Psychiatry, 21,* 340–347. doi:10.1016/S0163-8343(99)00038-9

American Counseling Association. (2005). ACA code of ethics. Retrieved from http://www.counseling.org/Resources/CodeOfEthics/TP/Home/CT2.aspx

American Psychiatric Association. (2000). *Diagnostic and statistical manual of mental disorders* (Revised 4th ed.). Washington, DC: American Psychiatric Publishing.

American Psychological Association. (2002). Ethical principles of psychologists and code of conduct. Retrieved from http://www.apa.org/ethics/code/index.aspx

Anderberg, M. R. (1973). *Cluster analysis for applications* [Abstract only]. Office of the Assistant for Study Support Kirtland. Retrieved from http://oai.dtic.mil

Anderson, R. J., & Brice, S. (2011). The mood-enhancing benefits of exercise: Memory biases augment the effect. *Psychology of Sport and Exercise, 12,* 79–82. doi:10.1016/j.psychsport.2010.08.003

Andersson, G. (2009). Using the Internet to provide cognitive behaviour therapy. *Behaviour Research and Therapy, 47*, 175–180. doi:10.1016/j.brat.2009.01.010

Andersson, G., Bergstrom, J., Hollandare, F., Carlbring, P., Kaldo, V., & Ekselius, L.

(2005). Internet-based self-help for depression: Randomised controlled trial. *The British Journal of Psychiatry, 187,* 456–461. doi:10.1192/bjp.187.5.456

Arnett, J. (1991). Adolescents and heavy-metal music: From the mouths of metalheads. *Youth & Society, 23,* 76–98. doi: 10.1177/ 0044118X91023001004

Arpels, J. C. (1996). The female brain hypoestrogenic continuum from the premenstrual syndrome to menopause: A hypothesis and review of supporting data. *Journal of Reproductive Medicine, 41*(9), 633–639. Retrieved from http://europepmc.org/abstract/med/8887186

Ashby, F. G., Isen, A. M., & Turken, A. U. (1999). A neuropsychological theory of positive affect and its influence on cognition. *Psychological Review, 106,* 529–550. doi:10.1037/0033-295X.106.3.529

Ashby, F. G., Valentin, V. V., & Turken, A. U. (2002). The effects of positive affect and arousal and working memory and executive attention: Neurobiology and computational models. In S. C. Moore & M. Oaksford (Eds.), *Emotional cognition: From brain to behaviour* (pp. 245–287). Amsterdam: John Benjamins.

Atkinson, J. W. (1957). Motivational determinants of risk taking behavior. *Psychological Review, 64,* 381–390. doi:10.1037/h0043445

Augustine, A. A., & Hemenover, S. H. (2009). On the relative effectiveness of affect regulation strategies: A meta-analysis. *Cognition and Emotion, 23,* 1181–1220. doi:10.1080/02699930802396556

Australian Bureau of Statistics. (2011). *Australian social trends.* Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/4102.0Main+Features 20Jun+2011

Australian Bureau of Statistics. (2013). *8153.0 – Internet Activity, Australia*. from http://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/8153 0Media%20Release1December%202012?opendocument&tabname=Summary&prodno=8153.0&issue=December%202012&num=&view=

Australian Psychological Society. (2008). *Online therapy beneficial in treating mental health problems* [Media release]. Retrieved from http://www.psychology.org.au/Content.aspx?ID=2345

Australian Psychological Society. (2011). APS ethical guidelines: Guidelines for providing psychological services and products using the Internet and telecommunications technologies. Retrieved from http://www.psychology.org.au/Assets/Files/EG-Internet.pdf

Australian Psychological Society. (2011, April 6). *Online treatments vital to meet mental health demand* [Media release]. Retrieved from http://www.psychology.org.au/news/media_releases/6apr2011/

Avery, R. K. (1979). Adolescents' use of the mass media. *American Behavioral Scientist, 23,* 53–70. doi:10.1177/000276427902300104

Baas, M., De Drue, C. K. W., & Nijstad, B. A. (2008). A meta-analysis of 25 years of mood-creativity research: Hedonic tone, activation, or regulatory focus? *Psychological Bulletin, 134,* 779–806. doi:10.1037/a0012815

Bagozzi, R. P. (1993). An examination of the psychometric properties of measures of negative affect in the PANAS-X scales. *Journal of Personality and Social Psychology, 65,* 836–851. doi:10.1037/0022-3514.65.4.836

Bahn, S., & Barratt-Pugh, L. (2012). Evaluation of the mandatory construction induction training program in Western Australia: Unanticipated consequences. *Evaluation and Program Planning, 35,* 337–343.

doi:10.1016/j.evalprogplan.2011.11.006

Bahrke, M. S., & Morgan, W. P. (1978). Anxiety reduction following exercise and meditation. *Cognitive Therapy and Research, 2,* 323–333. doi:10.1007/BF01172650

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York, NY: W. H. Freeman.

Baños, R. M., Botella, C., Quero, S., & García-Palacios, A. (2012). Delivering psychological treatments in the XXI century. In J. M. García-Gómez & P. Paniagua- Paniagua (Eds.), *Information and communication technologies applied to mental health* (pp. 44–47). Valencia, Spain: Editorial Universitat Politècnica de València.

Barak, A. (1999). Psychological applications on the Internet: A discipline on the threshold of a new millennium. *Applied and Preventive Psychology, 8,* 231–245. doi:10.1016/S0962-1849(05)80038-1

Barak, A., & English, N. (2002). Prospects and limitations of psychological testing on the Internet. *Journal of Technology in Human Services, 19,* 65–89. doi:10.1300/J017v19n02_06

Barak, A., Hen, L., Boniel-Nissim, M., & Shapira, N. (2008). A comprehensive review and a meta-analysis of the effectiveness of Internet-based psychotherapeutic interventions. *Journal of Technology in Human Services, 26,* 109–160. doi:10.1080/15228830802094429

Barak, A., Klein, B., & Proudfoot, J. G. (2009). Defining Internet-supported therapeutic interventions. *Annals of Behavioral Medicine, 38,* 4–17. doi:10.1007/s12160-009-9130-7

Barber, B., McKenzie, S., & Helme, R. (1997). A study of brain electrical responses to music using quantitative electroencephalography (QEEG). *International Journal of Arts Medicine, 5*(2), 12–21. Retrieved from http://psycnet.apa.org/psycinfo/1998-10127-002

Bard, P. (1929). Emotion. I. The neuro-humoral basis of emotional reactions. In C. Murchsion (Ed.), *The foundations of experimental psychology* (pp. 449–487). Worcester, MA: Clark University Press.

Barlow, D. H., & Durand, V. M. (2009). *Abnormal psychology: An integrated approach* (5th ed.). Belmount, CA: Wadsworth Cengage Learning.

Barrett, L. F., & Russell, J. A. (1998). Independence and bipolarity in the structure of current affect. *Journal of Personality and Social Psychology, 74,* 967–984. doi:10.1037/0022-3514.74.4.967

Barron, A. (1998). Designing web-based training. *British Journal of Educational Technology, 29,* 355–370. doi:10.1111/1467-8535.00081

Barsade, S. G., & Gibson, D. E. (2007).Why does affect matter in organizations? *Academy of Management Perspectives, 2,* 36–59. doi:10.5465/AMP.2007.24286163

Batson, C. D., Shaw, L. L., Oleson, K. C., & Clark, M. S. (1992). Differentiating affect, mood, and emotion: Toward functionally based conceptual distinctions. *Review of Personality and Social Psychology, 13,* 294–326. Retrieved from http://psycnet.apa.org/psycinfo/1992-97396-011

Baumeister, R. F., Vohs, K. D., DeWall, C. N., & Zhang, L. (2007). How emotion shapes behavior: Feedback, anticipation, and reflection, rather than direct causation. *Personality and Social Psychology Review, 11,* 167–203. doi:10.1177/1088868307301033

Beck, A. T., & Clark, D. A. (1988). Anxiety and depression: An information processing perspective. *Anxiety Research, 1,* 23–56. doi:10.1080/10615808808248218

Beck, A. X., Ward, C. H., Mendelson, M., Mock, J., & Erbaugh, J. (1961). An inventory for measuring depression. *Archives of General Psychiatry, 4,* 561–571. doi:10.1001/archpsyc.1961.01710120031004

Beedie, C., Terry, P., & Lane, A. (2005). Distinctions between emotion and mood. *Cognition and Emotion, 19,* 847–848. doi:10.1080/02699930541000057

Beedie, C. J. (2005, August). It's the POMS, it measures mood - doesn't it? In T. Morris (Chair), *Promoting health and performance for life: International Society of Sport Psychology (ISSP).* Symposium conducted at the meeting of the 11th World Congress of Sport, Sydney Convention and Exhibition Centre.

Beedie, C. J., Lane, A. M., & Terry, P. C. (2005). Development and Validation of the Emotion & Mood Components of Anxiety Questionnaire. In T. Morris (Chair), *Promoting health and performance for life: International Society of Sport Psychology (ISSP).* Symposium conducted at the meeting of the 11th World Congress of Sport, Sydney Convention and Exhibition Centre.

Beedie, C. J., Terry, P. C., & Lane, A. M. (2000). The profile of mood states and athletic performance: Two meta-analyses. *Journal of Applied Sport Psychology, 12,* 49–68. doi:10.1080/10413200008404213

Bell, V. (2007). Online information, extreme communities and Internet therapy: Is the Internet good for our mental health? *Journal of Mental Health, 16,* 445–457. doi:10.1080/09638230701482378

Berger, B. G. (1994). Coping with stress: The effectiveness of exercise and other techniques. *Quest, 46,* 100–119. doi:10.1080/00336297.1994.10484112

Berger, B. G. (1996). Psychological benefits of an active lifestyle: What we know and what we need to know. *Quest, 48,* 330–353. doi:10.1080/00336297.1994.10484112

Berger, B. G., & Adesso, V. J. (1991). Gender differences in using alcohol to cope with depression. *Addictive Behaviors, 16,* 315–327. doi:10.1016/0306-4603(91)90024-C

Berger, B. G., & Mackenzie, M. M. (1980). A case study of a woman jogger: A psychodynamic analysis. *Journal of Sport Behavior, 3*, 3–16. Retrieved from https://secure.sportquest.com/su.cfm?articleno=79488&title=79488

Berger, B. G., & McInman, A. (1993). Exercise and the quality of life. In R. N. Singer, M. Murphey, & L. K. Tennant (Eds.), *Handbook of research on sport psychology* (pp. 729–760). New York, NY: Macmillan Publishing.

Berger, B. G., & Motl, R. W. (2000). Exercise and mood: A selective review and synthesis of research employing the profile of mood states. *Journal of Applied Sport Psychology, 12,* 69–92. doi:10.1080/10413200008404214

Berger, B. G., & Owen, D. R. (1983). Mood alteration with swimming: Swimmers really do “feel better”. *Psychosomatic Medicine, 45*, 425–433. Retrieved from http://journals.lww.com/psychosomaticmedicine/Abstract/1983/10000/Mood_Alteration_with_Swimming_Swimmers_Really_Do.6.aspx

Berger, B. G., & Owen, D. R. (1992). Mood alteration with yoga and swimming: Aerobic exercise may not be necessary. *Perceptual and Motor Skills, 75,* 1331–1343. doi:10.2466/pms.1992.75.3f.1331

Beyond Blue. (n.d.). *Types of depression.* Retrieved from http://www.beyondblue.org.au/the-facts/depression/types-of-depression

Biddle, S. J. H. (2000). Emotion, mood and physical activity. In S. J. H. Biddle,

K. R. Fox, & S. H. Boutcher (Eds.), *Physical activity and psychological well-being* (pp. 63–87). London, UK: Routledge.

Bijnen, E. J. (1973). *Cluster analysis: Survey and evaluation of techniques*. Tilburg, Netherlands: Tilburg University Press.

Billmeyer, F. W., & Saltzman, M. (1981). *Principles of color technology*. New York, NY: John Wiley.

Blaney, P. H. (1986). Affect and memory: A review. *Psychological Bulletin, 99,* 229–246. doi:10.1037/0033-2909.99.2.229

Blashfield, R. K. (1976). Mixture model tests of cluster analysis: Accuracy of four agglomerative hierarchical models. *Psychological Bulletin, 83,* 377–388. doi:10.1037/0033-2909.83.3.377

Blashfield, R. K. (1980). Propositions regarding the use of cluster analysis in clinical research. *Journal of Consulting and Clinical Psychology, 48*(4), 456. doi:10.1037/0022-006X.48.4.456

Blashfield, R. K., & Aldenderfer, M. S. (1978). The literature on cluster analysis. *Multivariate Behavioural Research, 13,* 271–295. doi:10.1207/s15327906mbr1303_2

Bless, H. (2001). Mood and the use of general knowledge structures. In L. L. Martin & G. L. Clore (Eds.), *Theories of mood and cognition* (pp. 9–26). Mahwah, NJ: Lawrence Erlbaum.

Blood, A. J., & Zatorre, R. J. (2001). Intensely pleasurable responses to music correlate with activity in brain regions implicated in reward and emotion. *Proceedings of the National Academy of Sciences of the United States of America, 98,* 11818–11823. doi:10.1073/pnas.191355898

Bloom, J. W. (1998). The ethical practice of web counseling. *British Journal of*

Guidance and Counselling, 26, 53–59. doi:10.1080/03069889808253838

Bloom, J. W., & Walz, G. R. (2000). *Cybercounseling and cyberlearning: Strategies and resources for the millennium*. Alexandria, VA: American Counseling Association.

Boothby, D. M., & Robbins, S. J. (2011). The effects of music listening and art production on negative mood: A randomized controlled trial. *The Arts in Psychotherapy, 38,* 204–208. doi:10.1016/j.aip.2011.06.002

Borgen, F. H., & Seling, M. J. (1978). Uses of discriminant analysis following MANOVA: Multivariate statistics for multivariate purposes [Abstract]. *Journal of Applied Psychology, 63,* 689. doi:10.1037/0021-9010.63.6.689

Borman, W. C., & Motowidlo, S. J. (1993). Expanding the criterion domain include elements of contextual performance. In N. Schmitt & W. C. Borman (Eds.), *Personnel selection in organizations* (pp. 71–98). San Francisco, CA: Jossey-Bass.

Borsboom, D., Cramer, A. O. J., Kievit, R. A., Scholten, A. Z., & Franic, J. (2009). The end of construct validity. In R. W. Lissitz (Ed.), *The concept of validity: Revisions, new directions, and applications* (pp. 135–170). Charlotte, NC: Information Age Publishing.

Bouchard, C., Shephard, R. J., Stephens, T. (1994). *Physical activity, fitness, and health*. Champaign, IL: Human Kinetics.

Bourgeois, A., LeUnes, A., & Meyers, M. (2010). Full-Scale and Short-Form of the Profile of Mood States: A factor analytic comparison. *Journal of Sport Behavior, 33*(4), 355–376. Retrieved from http://www.questia.com

Bower, G. H. (1981). Mood and memory. *American Psychologist, 36,* 129–148. doi:10.1037/0003-066X.36.2.129

Bower, G. H. (1991). Mood and congruity of social judgements. In J. P. Forgas (Ed.), *Emotion and social judgments* (pp. 31–53). Elmsford, NY: Pergamon.

Boyle, G. (1987). A cross-validation of the factor structure of the Profile of Mood States: Were the factors correctly identified in the first instance? *Psychological Reports, 60,* 343–354. doi:10.2466/pr0.1987.60.2.343

Boyle, G. (1988). Central clinical states: An examination of the Profile of Mood States and the Eight State Questionnaire. *Journal of Psychopathology and Behavioral Assessment, 70,* 205–215. doi:10.1007/BF00962545

Bradburn, N. M. (1969). *The structure of psychological well-being.* Chicago, IL: Aldine.

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry, 25,* 49–59. doi:10.1016/0005-7916(94)90063-9

Bradley, S. J. (1990). Affect regulation and psychopathology: Bridging the mind-body gap. *Canadian Journal of Psychiatry, 35*(6), 540–547. Retrieved from http://europepmc.org/abstract/med/1976429

Brandon, T. H. (1994). Negative affect as motivation to smoke. *Current Directions in Psychological Science, 3*(2), 33–37. Retrieved from http://www.jstor.org/discover/10.2307/20182258?uid=2&uid=4&sid=21106124422151

Brendel, D. H., Reynolds, C. F., Jennings, J. R., Hoch, C. C., Monk, T. H., Berman, S. R., ... & Kupfer, D. J. (1990). Sleep stage physiology, mood, and vigilance responses to total sleep deprivation in healthy 80-year-olds and 20-year-olds. *Psychophysiology, 27,* 677–685. doi:10.1111/j.1469-8986.1990.tb03193.x

Brenner, B. (1975). Enjoyment as a preventive of depressive affect. *Journal of*

Community Psychology, 3, 346–357. doi: 10.1002/ 1520-6629(197510)3:4<346::AID-JCOP2290030404>3.0.CO;2-T

Breuer, J., & Freud, S. (1957). *Studies on hysteria.* (J. Strachey, Trans.). New York: Basic Books. (Original work published 1895).

Brief, A. P., & Weiss, H. M. (2002). Organizational behavior: Affect in the workplace. *Annual Review of Psychology, 53,* 279–307. doi:10.1146/ annurev.psych.53.100901.135156

Brondino, M., Silva, S. A., & Pasini, M. (2012). Multilevel approach to organizational and group safety climate and safety performance: Co-workers as the missing link. *Safety Science, 50,* 1847–1856. doi:10.1016/ j.ssci.2012.04.010

Brown, D. R., Morgan, W. P., & Raglin, J. S. (1993). Effects of exercise and rest on the state anxiety and blood pressure of physically challenged college students. *Journal of Sports Medicine and Physical Fitness, 33*(3), 300–305. Retrieved from http://europepmc.org/abstract/med/8107484

Buchanan, T. (2002). Online assessment: Desirable or dangerous? *Professional Psychology Research and Practice, 33,* 148–154. doi:10.1037// 0735-7028.33.2.148

Buchanan, T., & Smith, J. L. (1999). Using the Internet for psychological research: Personality testing on the World Wide Web. *British Journal of Psychology, 90,* 125–144. doi:10.1348/000712699161189

Buck, R. (1980). Nonverbal behavior and the theory of emotion: The facial feedback hypothesis. *Journal of Personality and Social Psychology, 38,* 811–824. doi:10.1037/0022-3514.38.5.811

Buck, R. (1999). The biological affects: A typology. *Psychological Review, 106,* 301–336. doi:10.1037/0033-295X.106.2.301

Buckworth, J., & Dishman, R. K. (2002). Affect, mood, & emotion. *Exercise Psychology*. Champaign, IL: Human Kinetics.

Bunt, L. (1994). *Music therapy: An art beyond words*. London: Routledge Chapman & Hall.

Bupa Australia (2011, February 9). *Aussies turning to cyberspace to self-diagnose* [Media release]. Retrieved from http://www.bupa.com.au/about-us/media-centre/media-releases

Cacioppo, J. T. & Berntson, G. G. (2007). Affective distinctiveness: Illusory or real? *Cognition & Emotion, 21,* 1347–1359. doi:10.1080/02699930701502262

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin, 56,* 81–105. doi:10.1037/h0046016

Campos-Morales, R. M., Valencia-Flores, M., Castaňo-Meneses, A., Castaňeda-Figueiras, S., & Martínez-Guerrero, J. (2005). Sleepiness, performance and mood state in a group of Mexican undergraduate students.*Biological Rhythm Research, 36,* 9–13. doi:10.1080/09291010400028484

Cannon, W. B. (1927). The James-Lange theory of emotions: A critical examination and an alternative theory. *American Journal of Psychology, 39*(1), 106–124. Retrieved from http://www.jstor.org/discover/10.2307/1415404?uid=2&uid=4&sid=21106124422151

Cannon, W. B. (1931). Again the James-Lange and the thalamic theories of emotion. *Psychological Review, 38,* 281–295. doi:10.1037/h0072957

Cappaert, T. A. (1999). Time of day effect on athletic performance: An update. *Journal of Strength and Conditioning Research, 13*(4), 412–421. Retrieved from http://journals.lww.com/nsca-jscr/abstract/1999/11000/time_of_day_effect_on_athletic_performance__an.19.aspx

Carlbring, P., & Andersson, G. (2006). Internet and psychological treatment: How well can they be combined? *Computers in Human Behavior, 22,* 545–553. doi:10.1016/j.chb.2004.10.009

Carmody, T. P. (1989). Affect regulation, nicotine addiction, and smoking cessation. *Journal of Psychoactive Drugs, 21,* 331–342. doi:10.1080/02791072.1989.10472175

Cella, D. F., Jacobsen, P. B., Orav, E. J., Holland, J. C., Silberfarb, P. M., & Rafla, S. (1987). A brief POMS measure of distress for cancer patients. *Journal of Chronic Diseases, 40,* 939–942. doi:10.1016/0021-9681(87)90143-3

Chan, M. (2011). Fatigue: The most critical accident risk in oil and gas construction. *Construction Management and Economics, 29,* 341–353. doi:10.1080/01446193.2010.545993

Childress, C. A. (2000). Ethical issues in providing online psychotherapeutic interventions. *Journal of Medical Internet Research, 2,* e5. doi:10.2196/jmir.2.1.e5

Childress, C. A., & Asamen, J. K. (1998). The emerging relationship of psychology and the Internet: Proposed guidelines for conducting Internet intervention research. *Ethics and Behavior, 8,* 19–35. doi:10.1207/s15327019eb0801_2

Cho, E., & Kim, Y. K. (2012). The effects of website designs, self-congruity, and flow on behavioral intention. *International Journal of Design, 6*(2), 31-39. Retreived from http://www.ijdesign.org

Christensen, H., & Griffiths, K. M. (2002). The prevention of depression using the Internet. *Medical Journal of Australia, 177,* S122–S125. Retrieved from http://europepmc.org/abstract/med/12358571

Christensen, H., Griffiths, K. M., & Jorm, A. F. (2004). Delivering interventions for depression by using the Internet: Randomised controlled trial. *British Medical Journal, 328,* 265. doi:10.1136/bmj.37945.566632.EE

Christensen, L. (2001). The effect of food intake on mood. *Clinical Nutrition, 20,* 161–166. doi:10.1054/clnu.2001.0420

Christensen, L., & Brooks, A. (2006). Changing food preference as a function of mood. *Journal of Psychology, 140,* 293–306. doi:10.3200/JRLP.140.4

Christensen, L., & Pettijohn, L. (2001). Mood and carbohydrate cravings. *Appetite, 36,* 137–145. doi:10.1006/appe.2001.0390

Clark, G., Horan, J. J., Tompkins-Bjorkman, A., Kovalski, T., & Hackett, G. (2000). Interactive career counseling on the Internet. *Journal of Career Assessment, 8,* 85–93. doi:10.1177/106907270000800107

Clark, L. A., Watson, D., & Leeka, L. (1989). Diurnal variation in the positive affects. *Motivation and Emotion, 13,* 205–234. doi:10.1007/BF00995536

Clark, M. S., & Isen, A. M. (1982). Toward understanding the relationship between feeling states and social behavior. In A. H. Hastrof & A. M. Isen (Eds.), *Cognitive social psychology* (pp. 73–108). New York, NY: Elsevier.

Clarke, R. (2004). An Internet primer. In G. Goggin (Ed.), *Virtual nation: The Internet in Australia* (pp. 13–27). Sydney, NSW: University of New South Wales.

Clarke, S. (2012). The effect of challenge and hindrance stressors on safety behavior and safety outcomes: A meta-analysis. *Journal of Occupational Health Psychology, 17,* 387–397. doi:10.1037/a0029817

Clatworthy, J., Hankins, M., Buick, D., Weinman, J., & Horne, R. (2007). Cluster analysis in illness perception research: A Monte Carlo study to identify the most appropriate method. *Psychology and Health, 22,* 123–142. doi:10.1080/ 14768320600774496

Clemes, S. R., & Dement, W. C. (1967). Effect of REM sleep deprivation on psychological functioning. *The Journal of Nervous and Mental Disease, 144*(6), 485–491. Retrieved from http://journals.lww.com/jonmd/ Citation/1967/06000/EFFECT_OF_REM_SLEEP_DEPRIVATION _ON_PSYCHOLOGICAL.6.aspx

CliffsNotes. (*nd*). *Early Theories of Emotion.* Retrieved from http://www.cliffsnotes. com/sciences/psychology/psychology/psychology-emotions/early-theories- of-emotion

Clore, G. L., Schwarz, N., & Conway, M. (1994). Affective causes and consequences of social information processing. In R. S. Wyer & T. K. Srull (Eds.), *Handbook of* s*ocial cognition* (pp. 323–417). Hillsdale, NJ: Erlbaum.

Coan, J., & Allen, J. (2007). Organizing the tools and methods of affective science. In J. Coan & J. Allen (Eds.), *Handbook of emotion elicitation and assessment* (pp. 3–6). New York, NY: Oxford University Press.

Cohen, G. E., & Kerr, B. A. (1999). Computer-mediated counseling: An empirical study of a new mental health treatment. *Computers in Human Services, 15,* 13–26. doi:10.1300/J407v15n04_02

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112,* 155–159. doi:10.1037/0033-2909.112.1.155

Cole, P. M., Martin, S. E., & Dennis, T. A. (2004). Emotion regulation as a scientific construct: Methodological challenges and directions for child development research. *Child Development, 75,* 317–333. doi:10.1111/

j.1467- 8624.2004.00673.x

Colliver, J. A., Conlee, M. J., & Verhulst, S. J. (2012). From test validity to construct validity... and back? *Medical Education in Review, 46,* 366–371. doi:10.1111/j.1365-2923.2011.04194.x

Comunian, A. L. (1989). Some characteristics of relations among depression, anxiety, and self-efficacy. *Perceptual and Motor Skills, 69,* 755–764. doi:10.2466/pms.1989.69.3.755

Cook, J. E., & Doyle, C. (2002). Working alliance in online therapy as compared to face-to-face therapy: Preliminary results. *CyberPsychology & Behavior, 5,* 95–105. doi:10.1089/109493102753770480

Cooper, C., & Sutherland, V. (1987). Job stress, mental health, and accident analysis among offshore workers in the oil and gas extraction industries. *Journal of Occupational Medicine, 29*(2), 119–125. Retrieved from http://journals.lww.com/joem/abstract/1987/29020/job_stress,_mental_health,_and_accidents_among.7.aspx

Cormack, R. M. (1971). A review of classification. *Journal of the Royal Statistical Society, 134*(3), 321–367. Retrieved from http://www.jstor.org/discover/10.2307/2344237?uid=2&uid=4&sid=21106124422151

Costa, P. T., Jr., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor (NEO-FFI) Inventory professional manual.* Odessa, FL: PAR.

Cowdry, R. W., Gardner, D. L., O'Leary, K. M., Leibenluft, E., & Rubinow, D. R. (1991). Mood variability: A study of four groups. *American Journal of Psychiatry, 148*(11), 1505–1511. Retrieved from http://psycnet.apa.org/psycinfo/1992-09161-001

Craighead, D., Privette, G., Vallianos, E, & Byrkit, D. (1986). Personality characteristics of basketball players, starters and non starters. *International Journal of Sport Psychology, 17*(2), 110–119. Retrieved from http://psycnet.apa.org/psycinfo/1987-31265-001

Crawford, J. R., & Henry, J. D. (2004). The Positive and Negative Affect Schedule (PANAS): Construct validity, measurement properties and normative data in a large non-clinical sample. *British Journal of Clinical Psychology, 43,* 245–265. doi:10.1348/0144665031752934

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52,* 281–302. doi:10.1037/h0040957

Crone, P., Knapp, M., Proudfoot, J., Ryden, C., Cavanagh, K., Shapiro, D. A., … Tylee, A. (2004). Cost-effectiveness of computerized cognitive-behavioural therapy for anxiety and depression in primary care: Randomised controlled trial. *The British Journal of Psychiatry, 185,* 55–62. doi:10.1192/ bjp.185.1.55

Crowder, R. G. (1984). Perception of the major/minor distinction: I. Historical and theoretical foundations. *Psychomusicology, 4,* 3–12. doi:10.1037/h0094207

Crowley, A. E. (1993). The two-dimensional impact of color on shopping. *Marketing Letters, 4,* 59–69. doi:10.1007/BF00994188

Curran, S. L., Andrykowski, M. A., & Studts, J. L. (1995). Short form of the Profile of Mood States (POMS-SF): Psychometric information. *Psychological Assessment, 7,* 80–83. doi:10.1037/1040-3590.7.1.80

Cyr, D., Head, M., & Larios, H. (2010). Colour appeal in website design within and across cultures: A multi-method evaluation. *International Journal of Human-Computer Studies, 68,* 1–21. doi:10.1016/j.ijhcs.2009.08.005

Daley, A. J., & Maynard, I. W. (2003). Preferred exercise mode and affective responses in physically active adults. *Psychology of Sport and Exercise, 4,* 347–356. doi:10.1016/S1469-0292(02)00018-3

Dalgleish, T. (2004). The emotional brain. *Nature Reviews Neuroscience, 5,* 583–589. doi:10.1038/nrn1432

Damasio, A. R. (1994). *Descartes' error: Emotion, reason, and the human brain*. New York, NY: G. P. Putnam.

Dana, C. L. (1921). The anatomic seat of emotions: A discussion of the James–Lange theory. *Archives of Neurology and Psychiatry, 6,* 634. doi:10.1001/archneurpsyc.1921.02190060041003

Darwin, C. (1872/1965). *The expression of the emotions in man and animals.* Chicago, IL: Chicago University Press.

Davidson, R. J. (1994). On emotion, mood, and related affective constructs. In P. Ekman & R. J. Davidson (Eds.), *The nature of emotion: Fundamental questions* (pp. 51–55). New York, NY: Oxford University Press.

Davidson, R. J. (2002). Anxiety and affective style: Role of prefrontal cortex and amygdala. *Biological Psychiatry, 51,* 68–80. doi:10.1016/S0006-3223(01)01328-2

Day, S. X., & Schneider, P. (2000). The subjective experiences of therapists in face-to-face, video and audio sessions. In J. R. Bloom & G. R. Walz (Eds.), *Cybercounseling and cyberlearning: Strategies and resources for the millennium* (pp. 203–218). Alexandria,VA: American Counseling Association.

De Castro, J. M. (1987). Circadian rhythms of the spontaneous meal pattern, macronutrient intake, and mood of humans. *Physiology & Behavior, 40,* 437–446. doi:10.1016/0031-9384(87)90028-X

de Sousa, R. (1987). *The rationality of emotions.* Cambridge, MA: The MIT Press.

Dean, J. E., Whelan, J. P., & Meyers, A. W. (1990, September). *An incredibly quick way to assess mood states: The incredibly short POMS*. Paper presented at the Annual Conference of the Association for the Advancement of Applied Sport Psychology, San Antonio, TX.

Deecher, D., Andree, T. H., Sloan, D., & Schechter, L. E. (2008). From menarche to menopause: Exploring the underlying biology of depression in women experiencing hormonal changes. *Psychoneuroendocrinology, 33,* 3–17. doi:10.1016/j.psyneuen.2007.10.006

DeLancey, C. (2006). Basic moods. *Philosophical Psychology, 19,* 527–538. doi:10.1080/09515080600806567

Demaree, H. A., Pu, J., Robinson, J. L., Schmeichel, B. J., & Everhart, D. E. (2006). Predicting facial valence to negative stimuli from resting RSA: Not a function of active emotion regulation. *Cognition and Emotion, 20,* 161–176. doi:10.1080/02699930500260427

DeNora, T. (1999). Music as a technology of the self. *Poetics, 27,* 31–56. doi:10.1016/S0304-422X(99)00017-0

Depue, R. A., & Iacono, W. G. (1989). Neurobehavioral aspects of affective disorders. *Annual Review of Psychology, 40,* 457–492. doi:10.1146/annurev.ps.40.020189.002325

Derogatis, L. R., Lipman, R. S., Rickels, K., Uhlenhuth, E. H., & Covi, L. (1974). The Hopkins Symptom Checklist (HSCL): A self-report symptom inventory. *Behavioral Science, 19,* 1–15. doi:10.1002/bs.3830190102

deVries, H. A. (1981). Tranquilizer effect of exercise: A critical review. *The*

Physician and Sports Medicine, 9, 46–55.

Dhir, A. (2004). *The digital consumer technology handbook: A comprehensive guide to devices, standards, future directions, and programmable logic solutions*. Burlington, MA: Newnes.

Dickhäuser, O., & Reinhard, M.-A. (2006). Factors underlying expectancies of success and achievement: The influential roles of need for cognition and general or specific self-concepts. *Journal of Personality and Social Psychology*, *90,* 490–500. doi:10.1037/0022-3514.90.3.490

Diener, E., & Emmons, R. A. (1984). The independence of positive and negative affect. *Journal of Personality and Social Psychology, 47*(5), 1105–1117. Retrieved from http://psycnet.apa.org

Diener, E., & Iran-Nejad, A. (1986). The relationship in experience between various types of affect. *Journal of Personality and Social Psychology, 50,* 1031–1038. doi:10.1037/0022-3514.50.5.1031

Diener, E., & Larsen, R. J. (1984). Temporal stability and cross-situational consistency of affective, behavioral, and cognitive responses. *Journal of Personality and Social Psychology*, *4,* 871–883. doi:10.1037/0022-3514.47.4.871

Diener, E., Larsen, R. J., Levine, S., & Emmons, R. A. (1985). Intensity and frequency: Dimensions underlying positive and negative affect. *Journal of Personality and Social Psychology, 48,* 1253–1265. doi:10.1037/0022-3514.48.5.1253

Diener, E., Sandvik, E., Pavot, W., & Gallagher, D. (1991). Response artifacts in the measurement of subjective well-being. *Social Indicators Research*, *24,* 35–56. doi:10.1007/BF00292649

DiGiacomo, A., & Kirby, B. J. (2006). The effect of musical mode on emotional state. *Canadian Journal of Music Therapy, 12*(1), 68–91. Retrieved from https://www.questia.com/library/journal/1P3-1254203021/the-effect-of-musical-mode-on-emotional-state-l-effet

Dingemans, A. E., Martijn, C., van Furth, E. F., & Jansen, A. T. M. (2009). Expectations, mood, and eating behavior in binge eating disorder: Beware of the bright side. *Appetite, 53,* 166–173. doi:10.1016/j.appet.2009.06.002

Dinges, D. F., & Kribbs, N. B. (1991). Performing while sleepy: Effects of experimentally-induced sleepiness. In T. H. Monk (Ed.), *Sleep, sleepiness and performance: Human performance and cognition* (pp. 97–128). Oxford, UK: John Wiley.

Eccles, J. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motives* (pp. 75–146). San Francisco, CA: Freeman.

Egloff, B., Schmukle, S. C., Burns, L. R., & Schwerdtfeger, A. (2006). Spontaneous emotion regulation during evaluated speaking tasks: Associations with negative affect, anxiety expression, memory, and physiological responding. *Emotion, 6,* 356–366. doi:10.1037/1528-3542.6.3.356

Eisen, M. B., Spellman, P. T., Brown, P. O., & Botstein, D. (1998). Cluster analysis and display of genome-wide expression patterns. *Proceedings of the National Academy of Sciences of the United States of America, 95*(25), 14863–14868. Retrieved from http://www.pnas.org/content/95/25/14863.short

Ekkekakis, P., Hall, E. E., VanLanduyt, L. M., & Petruzzello, S. J. (2000). Walking in (affective) circles: Can short walks enhance affect? *Journal of Behavioral Medicine, 2,* 245–275. doi:10.1023/A:1005558025163

Ekman, P. (1972). Universals and cultural differences in facial expressions of emotion. In J. Cole (Ed.), *Nebraska symposium on motivation, 1971* (pp. 207–283). Lincoln, NE: University of Nebraska Press.

Ekman, P. (1992). Facial expressions of emotion: New findings, new questions. *Psychological Science, 3,* 34–38. doi:10.1111/j.1467-9280.1992.tb00253.x

Ekman, P. (1994). All emotions are basic. In P. Ekman & R. Davidson (Eds.), *The nature of emotion: Fundamental questions* (pp. 15–19). New York, NY: Oxford University Press.

Ekman, P., & Cordaro, D. (2011). What is meant by calling emotions basic. *Emotion Review, 3,* 364–370. doi:10.1177/1754073911410740

Ekman, P., & Davidson, R. J. (1994). *The nature of emotion: Fundamental questions*. New York, NY: Oxford University Press.

Electromagnetic spectrum and visible light diagram. Retrieved from http://9-4fordham.wikispaces.com

Elliot, A. J., & Maier, M. A. (2007). Color and psychological functioning. *Current Directions in Psychological Science, 16,* 250–254. doi:10.1111/ j.1467-8721.2007.00514.x

El-Nasr, M. S., Yen, J., & Ioerger, T. R. (2000). Flame—fuzzy logic adaptive model of emotions. *Autonomous Agents and Multi-agent Systems, 3,* 219–257. doi:10.1023/A:1010030809960

Engen, R., Levy, N., & Schlosberg, H. (1958). The dimensional analysis of a new series of facial expressions. *Journal of Experimental Psychology, 55,* 454–458. doi:10.1037/h0047240

Erdem, S. A. (2008). Healthcare marketing on the web: Moving forward toward more interactive practices. *Health Marketing Quarterly, 24,* 35–49.

doi:10.1080/07359680802125816

Escoffery, C., McCormick, L., & Bateman, K. (2004). Development and process evaluation of a web-based smoking cessation program for college smokers: Innovative tool for education. *Patient Education and Counseling, 53,* 217–226. doi:10.1016/S0738-3991(03)00163-0

Everett, B. S. (1993). *Cluster analysis* (3rd ed.). New York, NY: Wiley.

Ewing, S., & Thomas, J. (2012). *CCi digital futures 2012: The Internet in Australia.* Retrieved from ARC Centre of Excellence for Creative Industries and Innovation, Swinburne University of Technology website www.cci.edu.au

Eysenbach, G., Powell, J., Kuss, O., & Sa, E. R. (2002). Empirical studies assessing the quality of health information for consumers on the World Wide Web. *The Journal of the American Medical Association, 287,* 2691–2700. doi:10.1001/jama.287.20.2691

Fallows, D. (2004). *The Internet and daily life: Many Americans use the Internet in everyday activities, but traditional offline habits still dominate*. Retrieved from http://www.pewinternet.org/~/media//Files/Reports/2004 /PIP_Internet_and_Daily_Life.pdf.pdf

Farb, N. A. S., Anderson, A. K., & Segal, Z. V. (2012). The mindful brain and emotion regulation in mood disorders. *Canadian Journal of Psychiatry, 57*(2), 70–77. Retrieved from http://www.ncbi.nlm.nih.gov/ pmc/articles/PMC3303604/

Fehr, F. S., & Stern, J. A. (1970). Peripheral physiological variables and emotion: The James-Lange theory revisited. *Psychological Bulletin, 74,* 411–424. doi:10.1037/h0032958

Feigelson, M. E., & Dwight, S. A. (2000). Can asking questions by computer improve the candidness of responding? A meta-analytic perspective. *Consulting Psychology Journal: Practice and Research, 52,* 248–255. doi:10.1037//1061-W87.52.4.248

Feil, E. G., Noell, J., Lichtenstein, E., Boles, S. M., & McKay, H. G. (2003). Evaluation of an Internet-based smoking cessation program: Lessons learned from a pilot study. *Nicotine and Tobacco Research, 5,* 189–194. doi:10.1080/1462220031000073694

Feldman-Barrett, L. (2006). Solving the emotion paradox: Categorization and the experience of emotion. *Personality and Social Psychology Review, 10,* 20–46. doi:10.1207/s15327957pspr1001_2

Fernandez, C. A., Fernandez, E. M. A., & Pesqueira, G. S. (2000). Spanish adaptation of the Profile of Mood States (POMS). *Psicothema, 12,* 47–51.

Fernstrom, J. D., & Wurtman, R. J. (1971). Brain serotonin content: Increase following ingestion of carbohydrate diet. *Science*, *174*(4013), 1023–1025. doi:10.1126/science.174.4013.1023

Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). London, UK: Sage.

Fillingim, R. B., Roth, D. L., & Haley, W. E. (1989). The effects of distraction on the perception of exercise-induced symptoms. *Journal of Psychosomatic Research, 33,* 241–248. doi:10.1016/0022-3999(89)90052-4

Fogarty, G. J., & McKeon, C. M. (2006). Patient safety during medication administration: The influence of organizational and individual variables on unsafe work practices and medication errors. *Ergonomics, 49,* 444–456. doi:10.1080/00140130600568410

Ford, B. D. (1994). Ethical and professional issues in computer-assisted therapy. *Computers in Human Behavior, 9,* 387–400. doi:10.1016/

0747-5632(93)90030-V

Fordyce, M. W. (1977). Development of a program to increase personal happiness. *Journal of Counseling Psychology, 24,* 511–520. doi:10.1037/0022-0167.24.6.511

Fordyce, M. W. (1983). A program to increase happiness: Further studies. *Journal of Counseling Psychology, 30,* 483–498. doi:10.1037/0022-0167.30.4.483

Forgas, J. P., & Bower, G. H. (1987). Mood effects on person-perception judgments. *Journal of Personality and Social Psychology, 53,* 53–60. doi:10.1037/0022-3514.53.1.53

Fotheringham, M. J., Owies, D., Leslie, E., & Owen, N. (2000). Interactive health communication in preventive medicine: Internet-based strategies in teaching and research. *American Journal of Preventive Medicine, 19,* 113–120. doi:10.1016/S0749-3797(00)00188-4

Fovell, R. G., & Fovell, M. Y. C. (1993). Climate zones of the conterminous United States defined using cluster analysis. *Journal of Climate, 6,* 2103–2135. doi:10.1175/1520-0442(1993)006<2103:CZOTCU>2.0.CO;2

Freud, S. (1946). *The ego and the mechanisms of defense.* New York: International Universities Press.

Freud, S. (1961). *Civilization and its discontents* (J. Strachey, Trans.). New York: WW Norton & Company.

Friedman, B. H. (2009). Feelings and the body: The Jamesian perspective on autonomic specificity of emotion. *Biological Psychology, 84,* 383–393. doi:10.1016/j.biopsycho.2009.10.006

Frijda, N. H. (1986). *The emotions.* Cambridge, England: Cambridge University Press.

Gainotti, G., Caltagirone, C., & Zoccolotti, P. (1993). Left /right and cortical/subcortical dichotomies in the neuropsychological study of human emotions. *Cognition & Emotion, 7,* 71–93. doi:10.1080/02699939308409178

Gamon, D., & Bragdon, A. D. (2003). *Building mental muscle: Conditioning exercises for the six intelligence zones* (2nd ed.). Walker & Company.

Gati, I., & Saka, N. (2001). Internet-based versus paper-and-pencil assessment: Measuring career decision-making difficulties. *Journal of Career Assessment, 9,* 397–416. doi:10.1177/106907270100900406

Gaye, L., Holmquist, L. E., Behrendt, F., & Tanaka, A. (2006, June). Mobile music technology: Report on an emerging community. *Proceedings of the 2006 Conference on New Interfaces for Musical Expression* (pp. 22–25). IRCAM—Centre Pompidou.

Geen, R. G., & Quanty, M. B. (1977). The catharsis of aggression: An evaluation of a hypothesis. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 10, pp. 1–37). New York, NY: Academic Press.

George, J. M., & Brief, A. P. (1996). Motivational agendas in the workplace: The effects of feelings on focus of attention and work motivation. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior, Vol 18* (pp. 75–109). Greenwich, CT: JAI Press.

Gill, D. L. (1986). *Psychological dynamics of sport.* Champaign, IL: Human Kinetics.

Gillen, M., Baltz, D., Gassel, M., Kirsch, L., & Vaccaro, D. (2002). Perceived safety climate, job demands, and coworker support among union and non-union injured construction workers. *Journal of Safety Research, 33,* 33–51. doi:10.1037/1076-8998.11.4.315

Glass, G. V., Peckham, P. D., & Sanders, J. R. (1972). Consequences of failure to meet assumptions underlying the fixed effects analyses of variance and covariance. *Review of Educational Research, 42*, 237–288. Retrieved from http://www.jstor.org/discover/10.2307/1169991?uid=2&uid=4&sid=21106124897241

Glasscock, D., Rasmussen, K., Cartensen, O., & Hansen, O. (2006). Psychosocial factors and safety behaviour as predictors of accidental work injuries in farming. *Work and Stress, 20,* 173–189. doi:10.1080/02678370600879724

Goggin, G. (2004). *Virtual nation: The Internet in Australia*. Sydney, NSW: University of New South Wales.

Gold, A. E., MacLeod, K. M., Deary, I. J., & Frier, B. M. (1995). Changes in mood during acute hypoglycemia in healthy subjects. *Journal of Personality and Social Psychology, 68,* 498–504. doi:10.1037/0022-3514.68.3.498

Goldenhar, L., Williams, L., & Swanson, N. (2003). Modeling the relationship between job stressors and injury and near-miss outcomes for construction labourers. *Work and Stress, 17,* 218–240. doi:10.1080/02678370310001616144

Goldin, P. R., McRae, K., Ramel, W., & Gross, J. J. (2008). The neural bases of emotion regulation: Reappraisal and suppression of negative emotion. *Biological Psychiatry, 63,* 577. doi:10.1016/j.biopsych.2007.05.031

Goldstein, E. (2010). *Sensation and perception* (8th ed.). Canada: Cengage Learning.

Goldstein, K. (1939). *The organism: A holistic approach to biology derived from pathological data in man.* Salt Lake City, UT: American Book Publishing.

Gonder-Frederick, L. A., Cox, D. J., Bobbitt, S. A., & Pennebaker, J. W. (1989). Mood changes associated with blood glucose fluctuations in insulin-dependent diabetes mellitus. *Health Psychology, 8,* 45–59. doi:10.1037/0278-6133.8.1.45

Gottschalk, L. (1974). Quantification and psychological indicators of emotion: The content analysis of speech and other objective measures of psychological states. *The International Journal of Psychiatry of Medicine, 5,* 587–596. doi:10.2190/QQGE-5WPK-DJQR-2M5V

Gray, E. K., & Watson, D. (2007). Assessing positive and negative affect via self-report. In J. Coan & J. Allen (Eds.), *Handbook of emotion elicitation and assessment*, (pp. 171–183). New York, NY: Oxford University Press.

Green, D. P., & Citrin, J. (1994). Measurement error and the structure of attitudes: Are positive and negative judgments opposites? *American Journal of Political Science, 38*(1), 256–281. Retrieved from http://www.jstor.org/discover/10.2307/2111344?uid=2&uid=4&sid=21106124897241

Green, D. P., Goldman, S. L., & Salovey, P. (1993). Measurement error masks bipolarity in affect ratings. *Journal of Personality and Social Psychology, 64,* 1029. doi:10.1037/0022-3514.64.6.1029

Green, D. P., & Salovey, P. (1999). In what sense are positive and negative affect independent? A reply to Tellegen, Watson, and Clark. *Psychological Science, 10,* 304–306. doi:10.1111/1467-9280.00158

Greene, T. R., & Noice, H. (1988). Influence of positive affect upon creative thinking and problem solving in children. *Psychological Reports, 63,* 895–898. doi:10.2466/pr0.1988.63.3.895

Greenspan, S. I., & Porges, S. W. (1984). Psychopathology in infancy and early childhood: Clinical perspectives on the organization of sensory and affective-thematic experience. *Child Development, 55*(1), 49–70. Retrieved from http://www.jstor.org/discover/10.2307/1129834?uid=2&uid=4&sid=21106124897241

Griffin, M. A., & Neal, A. (2000). Perceptions of safety at work: A framework for linking safety climate to safety performance, knowledge, and motivation. *Journal of Occupational Health Psychology, 5,* 347–358. doi:10.1037//1076-8998.5.3.347

Griffiths, F., Lindenmeyer, A., Powell, J., Lowe, P., & Thorogood, M. (2006). Why are health care interventions delivered over the Internet? A systematic review of the published literature. *Journal of Medical Internet Research, 8,* e10. doi:10.2196/jmir.8.2.e10

Griffiths, K. M., & Christensen, H. (2002). The quality and accessibility of Australian depression sites on the World Wide Web. *Medical Journal of Australia, 176*(10), S97. Retreived from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.151.2170&rep=rep1&type=pdf

Griffiths, P. (1989). Folk, functional, and neurochemical aspects of mood. *Philosophical Psychology, 2,* 17–30. doi:10.1080/09515088908572957

Griffiths, P. (1997). *What emotions really are.* Chicago, IL: Chicago University Press.

Grohol, J. H. (1999). *Best practices in e-therapy: Definition and scope of e-therapy.* Retrieved from http://www.psychcentral.com/best/best3.htm

Grohol, J. H. (2001). *Best practices in e-therapy: Clarifying the definition.* Retrieved from http://www.psychcentral.com/best/best5.htm

Gross, J. J. (1998a). Antecedent- and response-focused emotion regulation: Divergent consequences for experience, expression, and physiology. *Journal of Personality and Social Psychology, 74,* 224–237. doi:10.1037/

0022-3514.74.1.224

Gross, J. J. (1998b). The emerging field of emotion regulation: An integrative review. *Review of General Psychology, 2,* 271–299. doi:10.1037/1089-2680.2.3.271

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology, 39,* 281–291. doi:10.1017/S0048577201393198

Gross, J. J., & Muñoz, R. F. (1995). Emotion regulation and mental health. *Clinical Psychology: Science and Practice, 2,* 151–164. doi:10.1111/j.1468-2850.1995.tb00036.x

Gross, J. J., & Thompson, R. A. (2007). Emotion regulation: Conceptual foundations. In J. J. Gross (Ed.), *Handbook of emotion regulation* (pp. 3–26). New York, NY: The Guilford Press.

Grove, J. R., & Prapavessis, H. (1992). Preliminary evidence for the reliability and validity of an abbreviated Profile of Mood States. *International Journal of Sport Psychology, 23*(2), 93–109. Retrieved from http://psycnet.apa.org/psycinfo/1993-15924-001

Guilford, J. P. (1940). There is system in color preferences. *Journal of the Optical Society of America, 30,* 455–459. doi:10.1364/JOSA.30.000455.

Gundlach, R. H. (1935). Factors determining the characterization of musical phrases. *The American Journal of Psychology, 47*(4), 624–643. Retrieved from http://www.jstor.org/discover/10.2307/1416007?uid=2&uid=4&sid=21106124897241

Gustafsson, H. (2007). *Burnout in competitive and elite athletes*. Retrieved from http://www.diva-portal.org/smash/

record.jsf?pid=diva2%3A135387&dswid=8694

Guszkowska, M., & Sionek, S. (2009). Changes in mood states and selected personality traits in women participating in a 12-week exercise program. *Human Movement, 10,* 163–169, doi:10.2478/v10038-009-0014-2

Hall, R., & Hanna, P. (2004). The impact of web page text-background color combinations on readability, retention, aesthetics, and behavioral intention. *Behaviour and Information Technology, 23,* 183–195. doi:10.1080/01449290410001669932

Hallaq, I. Y. (1969). Neuroanatomic pathways associated with emotions. *Journal of the American Osteopathic Association, 68*(7), 719–726.

Hanin, Y. L. (1993, June). Optimal performance emotions in top athletes. *Sport psychology: An integrated approach: Proceedings of the 8th World Congress of Sport Psychology* (pp. 229–232). Lisbon, Portugal: International Society of Sport Psychology.

Hanin, Y. L. (1997). Emotions and athletic performance: Individual zones of optimal functioning model. *European Yearbook of Sport Psychology, 1,* 29–72.

Hanin, Y. L. (2003). Performance related emotional states in sport: A qualitative analysis. *Forum: Qualitative Social Research, 4,* Art 5. Retrieved from http://www.qualitativeresearch.net/fqs-texte/1-03/1-03hanin-e.html

Hanin, Y., & Syrjä, P. (1995a). Performance affect in junior ice hockey players: An application of the individual zones of optimal functioning model. *The Sport Psychologist, 9*(2), 169–187. Retrieved from http://psycnet.apa.org/psycinfo/1996-00983-001

Hanin, Y., & Syrjä, P. (1995b). Performance affect in soccer players: An application of the IZOF model. *International Journal of Sports Medicine, 16,* 260–

265. doi:10.1055/s-2007-973002

Hardy, C. J., & Rejeski, W. J. (1989). Not what but how one feels: The measurement of affect during exercise. *Journal of Sport and Exercise Psychology, 11*, 304–307. Retrieved from http://journals.humankinetics.com/AcuCustom/ Sitename/Documents/DocumentItem/9312.pdf

Harmon-Jones, E., & Sigelman, J. (2001). State anger and prefrontal brain activity: Evidence that insultrelated relative left-prefrontal activation is associated with experienced anger and aggression. *Journal of Personality and Social Psychology, 80,* 797–803. doi:10.1037/0022-3514.80.5.797

Harris Poll. (2010, August 4). *"Cyberchondriacs" on the rise? Those who go online for healthcare information continues to increase*. Retrieved from http://www.harrisinteractive.com/NewsRoom/HarrisPolls/tabid/447/mid/1508 /articleId/448/ctl/ReadCustom%20Default/Default.aspx

Hashim, H. A., Zulkifli, E. Z., & Yusof, H. A. (2010). Factorial validation of Malaysian adapted Brunel Mood Scale in an adolescent sample. *Asian Journal of Sports Medicine, 1*, 185–194. Retrieved from http://journals. tums.ac.ir/abs/17098

Hassmén, P. Koivula, N., & Uutela, A. (2000). Physical exercise and psychological well-being: A population study in Finland. *Preventative Medicine, 30,* 17–25. doi:10.1006/pmed.1999.0597

Health and Safety Executive (2006). *Construction statistics 2005/06: Falls down, slips up* (HSE Publication No. E109:06). Retrieved from http://www.hse.gov. uk/press/2006/e06109.htm

Healthy Sleep (2007). *Under the brain's control.* Retrieved from http://healthysleep. med.harvard.edu/healthy/science/how/neurophysiology

Hector, A., Von Felten, S., & Schmid, B. (2010). Analysis of variance with unbalanced data: An update for ecology and evolution. *Journal of Animal Ecology, 79,* 308–316. doi:10.1111/j.1365-2656.2009.01634.x

Hedges, S. M., Jandorf, L., & Stone, A. A. (1985). Meaning of daily mood assessments. *Journal of Personality and Social Psychology, 48*, 428–434. doi:10.1037/0022-3514.48.2.428

Heinlen, K. T., Welfel, E. R., Richmond, E. N., & O'Donnell, M. S. (2003). The nature, scope, and ethics of psychologists' e-therapy web sites: What consumers find when surfing the web. *Psychotherapy: Theory, Research, Practice, Training, 40,* 112–124. doi:10.1037/0033-3204.40.1/2.112

Helgeson, V. S., Reynolds, K. A., & Tomich, P. L. (2006). A meta-analytic review of benefit finding and growth. *Journal of Consulting and Clinical Psychology, 74*, 797–816. doi:10.1037/0022-006X.74.5.797

Heller, W. (1993). Neuropsychological mechanisms of individual differences in emotion, personality, and arousal. *Neuropsychology, 7,* 476. doi:10.1037/0894-4105.7.4.476

Hemple, C. G. (1952). *Fundamental of concept formation in empirical science*. Chicago, IL: University of Chicago Press.

Hendy, H. M. (2012). Which comes first in food-mood relationships, foods or moods? *Appetite, 58,* 771–775. doi:10.1016/j.appet.2011.11.014

Hepworth, R., Mogg, K., Brignell, C., & Bradley, B. P. (2010). Negative mood increases selective attention to food cues and subjective appetite. *Appetite, 54,* 134–142. doi:10.1016/j.appet.2009.09.019

Herr, P. M., Page, C. M., Pfeiffer, B. E., & Davis, D. F. (2012). Affective influences on evaluative processing. *Journal of Consumer Research, 38,* 833–845.

doi:10.1086/660844

Herrera, J. M., Norwalk, C. A., Okonek, A., Parent, M., & Roy, S. (1988). MMPI subtypes for chronic phencyclidine (PCP) abusers. *Journal of Substance Abuse Treatment, 5,* 178–193. doi:10.1016/0740-5472(88)90009-8

Hess, J. A., Hecker, S., Weinstein, M., & Lunger, M. (2004). A participatory ergonomics intervention to reduce risk factors for low-back disorders in concrete laborers. *Applied Ergonomics, 35,* 427–441. doi:10.1016/j.apergo.2004.04.003

Heuchert, J. P., & McNair, D. M. (2012). *Profile of mood states, POMS-2.* North Tonawanda, NY: Multi-Health Systems Inc.

Hill, A., & Scharff, L. V. (1997). Readability of websites with various foreground/background color combinations, font types and word styles. *Proceedings of the 11th National Conference in Undergraduate Research* (Vol. 2, pp. 742–746). Nacogdoches, TX: Austin State Univesity.

Hirt, E. R., Melton, R. J., McDonald, H. E., & Harackiewics, J. M. (1996). Processing goals, task interest, and the mood-performance relationship: A mediational analysis. *Journal of Personality and Social Psychology, 71,* 245–261. doi:10.1037/0022-3514.71.2.245

Hobson, J. A. (1999). Dreaming as delirium: How the brain goes out of its mind. Cambridge, MA: MIT Press.

Hoffman, J. R., Bar-Eli, M., & Tenenbaum, G. (1999). An examination of mood changes and performance in a professional basketball team. *Journal of Sports Medicine and Physical Fitness, 39*(1), 74–79. Retrieved from http://europepmc.org/abstract/med/10230174

Höglund, L., Macevičiūtė, E., & Wilson, T. D. (2004). Trust in healthcare: An information perspective. *Health Informatics Journal, 10,* 37–48. doi:10.1177/1460458204040667

Houser, B. B. (2004). An investigation of the correlation between hormonal levels in males and mood, behavior and physical discomfort. *Hormones and Behavior, 12,* 185–197. doi:10.1016/0018-506X(79)90020-5

Houston, T. K., Cooper, L. A., & Ford, D. E. (2002). Internet support groups for depression: A 1-year prospective cohort study. *American Journal of Psychiatry, 159,* 2062–2068. doi:10.1176/appi.ajp.159.12.2062

Hunt, J. M., Cole, M. W., & Reis, E. E. (1958). Situational cues distinguishing anger, fear, and sorrow. *American Journal of Psychology, 71,* 136–151. doi:10.2307/1419202

Hunter, P. G., & Schellenberg, E. G. (2010). Music and emotion. In M. R. Jones, R. R. Fay, & A. N. Popper (Eds.), *Music perception* (pp. 129–164). New York: Springer.

Hunter, P. G., Schellenberg, E. G., & Griffith, A. T. (2011). Misery loves company: Mood-congruent emotional responding to music. *American Psychological Association, 5,* 1068–1072. doi:10.1037/a0023749

Hunter, P. G., Schellenberg, E. G., & Schimmack. U. (2008). Mixed affective responses to music with conflicting cues. *Cognition and Emotion, 22,* 327–352. doi:10.1080/02699930701438145

Hunter, P. G., Schellenberg, E. G., & Schimmack, U. (2010). Feelings and perceptions of happiness and sadness induced by music: Similarities, differences, and mixed emotions. *Psychology of Aesthetics, Creativity, and the Arts, 4,* 47–56. doi:10.1037/a0016873

iMINCO. (2015). *List of mining jobs.* Retrieved from http://iminco.net/

International Society of Sport Psychology. (1992). Physical activity and psychological benefits: A position statement from the International Society of Sport Psychology. *Journal of Applied Sport Psychology, 4,* 94–98.

Ioakimidis, I., Zandian, M., Ulbl, F., Bergh, C., Leon, M., & Södersten, P. (2011). *Physiology & Behavior*, *103,* 290–294. doi:10.1016/j.physbeh.2011.01.025

Irons, D. (1894). Professor James's theory of emotion. *Mind, 3,* 78.

Isaacson, R. L. (1974). *Limbic system*. New York, NY: John Wiley.

Izard, C. E. (1984). Emotion-cognition relationships and human development. In C. E. Izard & R. B. Zajonc (Eds.), *Emotions, cognition, and behavior* (pp. 17–37). New York, NY: Cambridge University Press.

Izard, C. E. (2011). Forms and functions of emotions: Matters of emotion–cognition interactions. *Emotion Review, 3,* 371–378. doi:10.1177/1754073911410737

Jacobs, M. H., Fehres, P., & Campbell, M. (2012). Measuring emotions toward wildlife: A review of generic methods and instruments. *Human Dimensions of Wildlife, 17,* 233–247. doi:10.1080/10871209.2012.680175

Jacobs, M. K., Christensen, A., Snibbe, J. R., Dolezalwood, S., Huber, A., & Polterok, A. (2001). A comparison of computer-based versus traditional individual psychotherapy. *Professional Psychology: Research and Practice, 32,* 92–96. doi:10.1037/0735-7028.32.1.92

James, W. (1884). What is an emotion? *Mind, 9,* 188–205. doi:10.1093/mind/os-IX.34.188

Jameson, J. P., & Blank, M. B. (2007). The role of clinical psychology in rural mental health services: Defining problems and developing solutions. *Clinical Psychology: Science and Practice, 14,* 283–298. doi:10.1111/j.1468-2850.2007.00089.x

Janover, M. A., & Terry, P. C. (2002). Relationships between pre-competition mood and swimming performance: Test of a conceptual model with an emphasis on depressed mood [Abstract]. *Australian Journal of Psychology, 54,* S36–37.

Jedlicka, D., & Jennings, G. (2001, July). Marital therapy on the Internet. *Journal of Technology in Counseling, 2*. Retrieved from http://jtc.colstate.edu/ vol2_1/Marital.htm

Jerome, L. W., DeLeon, P. H., James, L. C., Folen, R., Earles, J., & Gedney, J. J. (2000). The coming age of telecommunications in psychological research and practice. *American Psychologist, 55,* 407–421. doi:10.1037// 0003-066X.55,4.407

Jiang, J., Scolaro, A. J., Bailey, K., & Chen, A. (2011). The effect of music-induced mood on attentional networks. *International Journal of Psychology, 46,* 214–222. doi:10.1080/00207594.2010.541255

Jiang, L., Yu, G., Li, Y., & Li, F. (2010). Perceived colleagues' safety knowledge/behavior and safety performance: Safety climate as a moderator in a multilevel study. *Accident Analysis and Prevention, 42,* 1468–1476. doi:10.1016/j.aap.2009.08.017

Jin, P. (1992). Efficacy of Tai Chi, brisk walking, meditation, and reading in reducing mental and emotional stress. *Journal of Psychosomatic Research, 36,* 361–370. doi:10.1016/0022-3999(92)90072-A

Joffe, H., & Cohen, L. S. (1998). Estrogen, serotonin, and mood disturbance: Where is the therapeutic bridge? *Biological Psychiatry, 44,* 798–811. doi:10.1016/S0006-3223(98)00169-3

Joinson, A. N. (2001). Self-disclosure in computer-mediated communication: The role of self-awareness and visual anonymity. *European Journal of Social*

Psychology, 31, 177–192. doi:10.1002/ejsp.36

Jokela, M., & Hanin, Y. L. (1999). Does the individual zones of optimal functioning model discriminate between successful and less successful athletes? A meta-analysis. *Journal of Sports Sciences, 17,* 873–887. doi:10.1080/026404199365434

Jones, J. D. (2006). The use of control groups in music therapy research: A content analysis of articles in the Journal of Music Therapy. *Journal of Music Therapy, 43,* 334–355. doi:10.1093/jmt/43.4.334

Judd, C. M., & McClelland, G. H. (1998). Measurement. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology* (Vol. 1, pp. 180–232). New York, NY: McGraw-Hill.

Juslin, P. N. (1997). Perceived emotional expression in synthesized performances of a short melody: Capturing the listener's judgment policy. *Musicae Scientiae, 1,* 225–256. doi:10.1177/102986499700100205

Juslin, P. N., & Västfjäll, D. (2008). Emotional responses to music: The need to consider underlying mechanisms. *Behavioral and Brain Sciences, 31,* 559–621. doi:10.1017/S0140525X08005529

Kállay, E., Ţincaş, I., & Benga, O. (2009). Emotion regulation, mood states, and quality of mental life. *Cognition, Brain, and Behavior, 1,* 31–48. Retrieved from http://www.ascred.ro/images/attach/Emotion%20regulation.pdf

Kammann, R., Christie, D., Irwin, R., & Dixon, G. (1979). Properties of an inventory to measure happiness (and psychological health). *New Zealand Psychologist, 8*(1), 1–9. Retrieved from http://www.psychology.org.nz/wp-content/uploads/PSYCH-Vol81-1979-1-Kammann.pdf

Kandel, E. R., Schwartz, J. H., & Jessel, T. M. (1995). *Essentials of neural science* *and behavior.* Norwalk, CT: Appletone & Lange.

Kane, M. T. (2001). Current concerns in validity theory. *Journal of Education Measurement, 38,* 319–342. doi:10.1111/j.1745-3984.2001.tb01130.x

Kaplan, A. (1946). Definition and specification of meaning. *Journal of Philosophy, 143,* 281–288. Retrieved from http://www.jstor.org/discover/10.2307/2019221?uid=2&uid=4&sid=21106124897241

Karageorghis, C. I. (1992). *The psychophysical effects of music in sport and exercise: A meta-analysis.* Unpublished master's thesis, United States Sports Academy, Daphne, AL.

Karageorghis, C. I., Dimitriou, L. A., & Terry, P. C. (1999). Effects of circadian rhythms on mood among athletes [Abstract]. *Journal of Sports Sciences, 17,* 56–57.

Karageorghis C. I., Priest, D. L., Terry, P. C., Chatzisarantis, N. L. D., & Lane, A. M. (2006). Redesign and initial validation of an instrument to assess the motivational qualities of music in exercise: The Brunel Music Rating Inventory-2. *Journal of Sports Sciences, 24,* 899–909. doi:10.1080/02640410500298107

Karageorghis, C. I., Terry, P. C., & Lane, A. M. (1999). Development and initial validation of an instrument to assess the motivational qualities of music in exercise and sport: The Brunel Music Rating Inventory. *Journal of Sports Sciences, 17,* 713–724. doi:10.1080/026404199365579

Kaya, N., & Epps, H. H. (2004). Relationship between color and emotion: A study of college students. *College Student Journal, 38,* 396. Retrieved from http://eric.ed.gov/?id=EJ706686

Kenardy, J., McCafferty, K., & Rosa, V. (2003). Internet-delivered indicated prevention for anxiety disorders: A randomized controlled trial. *Behavioural and Cognitive Psychotherapy, 31,* 279–289. doi:10.1017/S1352465803003047

Kenardy, J., McCafferty, K., & Rosa, V. (2006). Internet-delivered indicated prevention for anxiety disorders: Six-month follow up. *Clinical Psychologist, 10,* 39–42. doi:10.1080/13284200500378746

Ketai, R. (1975). Affect, mood, emotion, and feeling: Semantic considerations. *American Journal of Psychiatry, 132,* 1215–1217. Retrieved from http://psycnet.apa.org/psycinfo/1976-11837-001

Khantzian, E. J. (1985). The self-medication hypothesis of addictive disorders: Focus on heroin and cocaine dependence. *American Journal of Psychiatry, 142,* 1259–1264. doi:10.1007/978-1-4613-1837-8_7

Khanzode, V. V., Maiti, J., & Ray, P. K. (2011). Injury count model for quantification of risk of occupational injury. *International Journal of Injury Control and Safety Promotion, 18,* 151–162. doi:10.1080/17457300.2010.540332

Kiley, R. (2002). Does the Internet harm health?: Some evidence exists that the Internet does harm health. *British Medical Journal*, *324*(7331), 238. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1122149/

Klein, B. (2010). e-Interventions and psychology: Time to log on. *InPsych, 31*(1), 20–22.

Klein, B., & Richards, J. C. (2001). A brief Internet-based treatment for panic disorder. *Behavioural and Cognitive Psychotherapy, 29,* 113–117. doi:10.1017/S1352465801001138

Klein, B., Richards, J. C., & Austin, D. W. (2006). Efficacy of Internet therapy for panic disorder. *Journal of Behavior Therapy and Experimental Psychiatry, 37,* 213–238. doi:10.1016/j.jbtep.2005.07.001

Kline, P. (1993). *Personality: The psychometric view.* London, UK: Routledge.

Knaevelsrud, C., & Maercker, A. (2007). Internet-based treatment for PTSD reduces distress and facilitates the development of a strong therapeutic alliance: A randomized controlled clinical trial. *BMC Psychiatry, 7,* 13. doi:10.1186/1471-244X-7-13

Kobayashi, S. (1981). The aim and method of the color image scale. *Color Research & Application, 6,* 93–107. doi:10.1002/col.5080060210

Kolata, G. (2000, March 6). Web research transforms visit to the doctor. *The New York Times.* Retrieved from http://www.nytimes.com

Konečni, V. J. (2008). Does music induce emotion? A theoretical and methodological analysis. *Psychology of Aesthetics, Creativity, and the Arts, 2,* 115–129. doi:10.1037/1931-3896.2.2.115

Kos, A. J., & Psenicka, C. (2000). Measuring cluster similarity across methods. *Psychological Reports, 86,* 858–862. doi:10.2466/pr0.2000.86.3.858

Krumhansl, C. L. (2000). Rhythm and pitch in music cognition. *Psychological Bulletin, 126,* 159–179. doi:10.1037//0033-2909.126.1.159

Kummervold, P. E., Gammon, D., Bergvik, S., Johnsen, J. K., Hasvold, T., & Rosenvinge, J. H. (2002). Social support in a wired world: Use of online mental health forums in Norway. *Nordic Journal of Psychiatry, 56,* 59–65. doi:10.1080/08039480252803945

Kupersmith, J. (1992). Technostress and the reference librarian. *Reference Services Review, 20,* 7–50. doi:10.1108/eb049150

Lahart, I. M., Lane, A. M., Hulton, A., Williams, K., Godfrey, R., Pedlar, C., ... &

Whyte, G. P. (2013). Challenges in maintaining emotion regulation in a sleep and energy deprived state induced by the 4800km Ultra-Endurance Bicycle Race: The Race across AMerica (RAAM). *Journal of Sports Science and Medicine, 12,* 481.

Lambousis, E., Politis, A., Markidis, M., & Christodoulou, G. N. (2002). Development and use of online mental health services in Greece. *Journal of Telemedicine and Telecare, 8,* 51–52. doi:10.1258/135763302320302000

Lan, M. F., Lane, A. M., Roy, J., & Hanin, N. A. (2012). Validity of the Brunel Mood Scale for use with Malaysian athletes. *Journal of Sports Science and Medicine, 11*(1), 131. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3737843/

Landers, D. M. (1991). Optimizing individual performance. In D. Druckman & R. A. Bjork (Eds.), *In the mind's eye: Enhancing human performance* (pp. 193–246). Washington, DC: National Academy Press.

Landy, F. J. (1986). Stamp collecting versus science: Validation as hypothesis testing. *American Psychologist, 41,* 1183–1192. doi:10.1037/0003-066X.41.11.1183

Lane, A. M. (2001). Relationship between perceptions of performance expectations and mood among distance runners: The moderating effect of depressed mood. *Journal of Science and Medicine in Sport, 4,* 116–128. doi:10.1016/S1440-2440(01)80013-X

Lane, A. M., & Chappell, R. C. (2001). Mood and performance relationships among players at the World Student Games basketball competition. *Journal of Sport Behaviour, 24*(2), 182–196. Retrieved from http://www.cabdirect.org/abstracts/20013074611.html;jsessionid=122CC87E74E4BDDB28A53B864D

B01CEF

Lane, A. M., Crone-Grant, D., & Lane, H. (2002). Mood changes following exercise. *Perceptual & Motor Skills, 94,* 732. doi:10.2466/pms.2002.94.3.732

Lane, A. M., Davis, P. A., & Devonport, T. J. (2011). Effects of music interventions on emotional states and running performance. *Journal of Sports Science and Medicine*, *10*(11), 400–407. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3761862/

Lane, A. M., Hewston, R., Redding, E., & Whyte, G. P. (2003). Mood changes following modern-dance classes. *Social Behavior and Personality, 31,* 453–460. doi:10.2224/sbp.2003.31.5.453

Lane, A. M., Milton, K. E., & Terry, P. C. (2005). Personality does not influence exercise-induced mood enhancement among female exercisers. *Journal of Sports Science and Medicine, 4,* 223–228. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3887324/

Lane, A. M., Soos, I., Leibinger, E., Karsai, I., & Hamar, P. (2007). Validity of the Brunel Mood Scale for use with UK, Italian and Hungarian athletes. In A. M. Lane (Ed.), *Mood and human performance: Conceptual, measurement, and applied issues* (pp. 119–130). Hauppauge, NY: Nova Science.

Lane, A. M., & Terry, P. C. (1998). The conceptual independence of tension and depression. In A. J. Sargeant & H. Siddons (Eds.), *From community health to elite sport: Proceedings of the 3rd Annual Congress of the European College of Sport Science Congress* (p. 146). Liverpool, UK: Health Care Development.

Lane, A. M., & Terry, P. C. (2000). The nature of mood: Development of a conceptual model with a focus on depression. *Journal of Applied Sport*

Psychology, 12, 16–33. doi:10.1080/10413200008404211

Lane, A. M., & Terry, P. C. (2005). Test of a conceptual model of mood-performance relationships with a focus on depression: A review and synthesis five years on. In T. Morris, P. Terry, et al. (Eds.), *Promoting health and performance for life: Proceedings of the International Society of Sport Psychology (ISSP) 11th World Congress of Sport Psychology* [CD-ROM]. Sydney, NSW: International Society of Sport Psychology.

Lane, A. M., Terry, P. C., Beedie, C. J., Curry, D. A., & Clark, N. (2001). Mood and performance: Test of a conceptual model with a focus on depressed mood. *Psychology of Sport and Exercise, 2,* 157–172. doi:10.1016/S1469-0292(01)00007-3

Lane, A. M., Terry, P. C., Beedie, C. J., & Stevens, M. (2004). Mood and concentration grid performance: The moderating effect of depressed mood. *International Journal of Sport and Exercise Psychology, 2,* 133–145. doi:10.1080/1612197X.2004.9671737

Lane, A. M., Thelwell, R., & Devonport, T. (2009). Emotional intelligence and mood states associated with optimal performance. *E-Journal of Applied Psychology, 5*(1), 67–73. Retrieved from http://sensoria.swinburne.edu.au/index.php/sensoria/article/view/123

Lane, A. M., & Wilson, M. (2011). Emotions and trait emotional intelligence among ultra-endurance runners. *Journal of Science and Medicine in Sport, 14,* 358–362. doi:10.1016/j.jsams.2011.03.001

Lang, P. J. (1979). A bio-informational theory of emotional imagery. *Psychophysiology, 16,* 495–512. doi:10.1111/j.1469-8986.1979.tb01511.x

Lang, P. J. (1994). The varieties of emotional experience: A mediation on James-

Lange theory. *Psychological Review, 101,* 211–221. doi:10.1037/0033-295x.101.2.211

Lange, A., van de Ven, J. P., & Schrieken, B. (2003). Interapy: Treatment of post-traumatic stress via the Internet. *Cognitive Behaviour Therapy, 32,* 110–124. doi:10.1080/16506070302317

Lange, C. G. (1912). The mechanisms of the emotions (C. Lange, Trans). In B. Rand (Ed.), *The classical psychologists* (pp. 672–684). Houghton Mifflin, Boston. (Reprinted from Lange's Om indsbevaegelser [1885] from Lange's Ueber Gemüthsbewegungen. Eine psycho-physiologische studie [1887])

Larsen, R. J. (2000). Toward a science of mood regulation. *Psychological Inquiry, 11,* 129–141. doi:10.1207/S15327965PLI1103_01

Larsen, R. J., & Fredrickson, B. L. (1999). Measurement issues in emotion research. In D. Kahneman, E. Diener, & N. Schwarz (Eds.). *Well-being: The foundations of hedonic psychology* (pp. 40–60). New York, NY: Russell Sage Foundation publications.

Larsen, R. J., Kasimatis, M., & Frey, K. (1992). Facilitating the furrowed brow: An unobtrusive test of the facial feedback hypothesis applied to unpleasant affect. *Cognition & Emotion, 6,* 321–338. doi:10.1080/02699939208409689

Larsen, R. J., & Prizmic, Z. (2004). Affect regulation. In R. F. Baumeister & K. D. Vohs (Eds), *Handbook of self-regulation: Research, theory, and applications* (pp. 40–61). New York, NY: Guilford Press.

Larson, R. (1995). Secrets in the bedroom: Adolescents' private use of media. *Journal of Youth and Adolescence, 24,* 535–550. doi:10.1007/BF01537055

Laszlo, J. V., Esterman, G., & Zabko, S. (1999). Therapy over the Internet? Theory, research, and finances. *CyberPsychology & Behavior, 2,* 293–307.

doi:10.1089/cpb.1999.2.293

Lazar, J. (2001). *User-centered web development.* Sudburg: Jones & Bartlett Publishers.

Lazarus, R. S. (1984). On the primacy of cognition. *American Psychologist, 39,* 124–129. doi:10.1037/0003-066X.39.2.124

Lazarus, R. S. (1991). Progress on a cognitive-motivational-relational theory of emotion. *American Psychologist, 46,* 819–834. doi:10.1037/0003-066X.46.8.819

Lazarus, R. S., & Cohen-Charash, Y. (2001). Discrete emotions in organizational life. In R. L. Payne & G. L. Cooper (Eds.), *Emotions at work: Theory, research and applications for management* (pp. 45–81). Chichester, England: Wiley.

Lazarus, R. S., Kanner, A. D., & Folkman, S. (1980). Emotions: A cognitive-phenomenological analysis. In R. Plutchik & H. Kellerman (Eds.), *Theories of emotion* (pp. 189–217). New York, NY: Academic Press.

LeDoux, J. (1996). *The emotional brain: The mysterious underpinnings of emotional life*. New York, NY: Touchstone.

LeDoux, J. E. (1986). Sensory systems and emotion: A model of affective processing. *Integrative Psychiatry, 4*(4), 237–243. Retrieved from http://psycnet.apa.org/psycinfo/1988-09889-001

LeDoux, J. E. (1992). Emotion and the amygdala. In J. P. Aggleton (Ed.), *The amygdala: Neurobiological aspects of emotion, memory, and mental dysfunction* (pp. 339–355). New York, NY: Wiley-Liss.

Leibenluft, E., Fiero, P., Bartko, J. J., Moul, D. E., & Rosenthal, N. E. (1993). Depressive symptoms and the self-reported use of alcohol, caffeine, and carbohydrates in normal volunteers and four groups of psychiatric outpatients. *American Journal of Psychiatry, 150*, 294–301. Retrieved from http://ajp.psychiatryonline.org/doi/abs/10.1176/ajp.150.2.294

Lemyre, P. N., Roberts, G. C., & Stray-Gundersen, J. (2007). Motivation, overtraining, and burnout: Can self-determined motivation predict overtraining and burnout in elite athletes? *European Journal of Sport Science, 7,* 115–126. doi:10.1080/17461390701302607

LeUnes, A., & Burger, J. (2000). Profile of mood states research in sport and exercise psychology: Past, present, and future. *Journal of Applied Sport Psychology, 12,* 5–15. doi:10.1080/10413200008404210

Leung, L. (2008). Internet embeddedness: Links with online health information seeking, expectancy value/quality of health information websites, and Internet usage patterns. *CyberPsychology and Behavior, 11,* 565–569. doi:10.1089/cpb.2007.0189

Levenson, R. W. (1994). Human emotion: A functional view. In P. Ekman & R. J. Davidson (Eds.), *The nature of emotion: Fundamental questions* (pp. 123–126). New York, NY: Oxford University Press.

Levenson, R. W. (2011). Basic emotion questions. *Emotion Review, 3,* 379–386. doi:10.1177 /1754073911410743

Levy, B. I. (1984). Research into the psychological meaning of color. *American Journal of Art Therapy, 23,* 58–62. Retrieved from http://psycnet.apa.org/psycinfo/1986-23642-001

Lewis, J., Coursol, D., & Herting, W. (2004). Researching the cybercounseling process: A study of the client and counselor experience. In J. W. Bloom & G. R. Walz (Eds.), *Cybercounseling & cyberlearning: An encore* (pp. 307–325).

Alexandria, VA: American Counseling Association.

Leykin, Y., Muñoz, R. F., & Contreras, O. (2012). Are consumers of Internet health information "Cyberchondriacs"? Characteristics of 24,965 users of a depression screening site. *Depression and Anxiety, 29,* 71–77. doi:10.1002/da.20848

Lieberman, H. R., Tharion, W. J., Shukitt-Hale, B., Speckman, K. L., & Tulley, R. (2002). Effects of caffeine, sleep loss, and stress on cognitive performance and mood during US Navy SEAL training. *Psychopharmacology, 164,* 250–261. doi:10.1007/s00213-002-1217-9

Lim, J. (2011). *The development and subsequent evaluation of a website to assess and to provide mood regulation strategies based on the pattern of responses to the Brunel Mood Scale (BRUMS).* Unpublished doctoral thesis, University of Southern Queensland, Toowoomba, QLD.

Lim, J., & Terry, P. C. (2011, March 15). *In The Mood.* Retrieved from http://www.moodprofiling.com

Lindgaard, G., Fernandes, G., Dudek, C. & Brown, J. (2006). Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & Information Technology, 25,* 115–126. doi:10.1080/01449290500330448

Lindgren, K. N., Masten, V. L., Tiburzi, M. J., Ford, D. P., & Bleeker, M. L. (1999). The factor structure of the profile of mood states (POMS) and its relationship to occupational lead exposure. *Journal of Occupational and Environmental Medicine, 41*(1), 3–10. Retrieved from http://journals.lww.com/joem/Abstract/1999/01000/The_Factor_Structure_of_the_Profile_of_Mood_States.2.aspx

Lindsley, D. B. (1951). Emotion. In S. S. Stevens (Ed.), *Handbook of experimental psychology* (pp. 473–516). New York, NY: Wiley.

Lingard, H. C., Cooke, T., & Blismas, N. (2010). Properties of group safety climate in construction: The development and evaluation of a typology. *Construction Management and Economics, 28,* 1099–1112. doi:10.1080/01446193.2010.501807

Little, B. C., & Zahn, T. P. (1974). Changes in mood and autonomic functioning during the menstrual cycle. *Psychophysiology, 11,* 579–590. doi:10.1111/j.1469-8986.1974.tb01118.x

Lorence, D., & Park, H. (2006). Web-based consumer health information: Public access, digital division, and remainders. *Medscape General Medicine, 8,* 4. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1785207/

Lormand, E. (1985). Toward a theory of moods. *Philosophical Studies, 47,* 385–407. doi:10.1007/BF00355211

Loxton, N. J., Dawe, S., & Cahill, A. (2011). Does negative mood drive the urge to eat? The contribution of negative mood, exposure to food cues and eating style. *Appetite, 56,* 368–374. doi:10.1016/j.appet.2011.01.011

Lucas, R. E., Diener, E., & Larsen, R. J. (2003). Measuring positive emotions. In S. J. Lopez & C. R. Snyder (Eds.), *Positive psychological assessment: A handbook of models and measures* (pp. 201–218). Washington, DC: American Psychological Association.

Lyman, B. (1989). *A psychology of food, more than a matter of taste.* New York: Van Nostrand Reinhold.

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin, 131,* 803–

855. doi:10.1037/0033-2909.131.6.803

Macht, M., & Dettmer, D. (2006). Everyday mood and emotions after eating a chocolate bar or an apple. *Appetite, 46,* 332–336. doi:10.1016/j.appet.2006.01.014

MacLean, P. D. (1949). Psychosomatic disease and the “visceral brain”: Recent developments bearing on the Papez theory of emotion. *Psychosomatic Medicine, 11*(6), 338–353. Retrieved from http://journals.lww.com/psychosomaticmedicine/Citation/1949/11000/Psychosomatic_Disease_and_the__Visceral_Brain__.3.aspx

MacLean, P. D. (1952). Some psychiatric implications of physiological studies on frontotemporal portion of limbic system (visceral brain). *Electroencephalography and Clinical Neurophysiology, 4,* 407–418. doi:10.1016/0013-4694(52)90073-4

Maheu, M. M., & Gordon, B. L. (2000). Counseling and therapy on the Internet. *Professional Psychology Research and Practice, 31,* 484–489. doi:10.1037/0735-7028.31.5.484

Mahnke, F. H. (1996). *Color, environment, and human response: An interdisciplinary understanding of color and its use as a beneficial element in the design of the architectural environment*. New York, NY: John Wiley.

Maier, S. F., Watkins, L. R., & Fleshner, M. (1994). Psychoneuroimmunology: The interface between behavior, brain, and immunity. *American Psychologist, 49,* 1004. doi:10.1037/0003-066X.49.12.1004

Manhal-Baugus, M. (2001). E-therapy: Practical, ethical, and legal issues. *CyberPsychology & Behavior, 4,* 551–563. doi:10.1089/109493101753235142

Maroulakis, E., & Zervas, Y. (1993). Effects of aerobic exercise on mood of adult women. *Perceptual and Motor Skills, 76,* 795–801. doi:10.2466/pms.1993.76.3.795

Marshall, M. A., & Brown, J. D. (2004). Expectations and realizations: The role of expectancies in achievement settings. *Motivation and Emotion, 28,* 347–361. doi:10.1007/s11031-004-2388-y

Massart, D. L., & Kaufman, L. (1983). *The interpretation of analytical chemical data by the use of cluster analysis*. New York, NY: Wiley.

Mather, A. S., Rodriguez, C., Guthrie, M. F., McHarg, A. M., Reid, I. C. & McMurdo, M. E. T. (2002). Effects of exercise on depressive symptoms in older adults with poorly responsive depressive disorder: Randomised controlled trial. *British Journal of Psychiatry, 180,* 411–415. doi:10.1192/bjp.180.5.411

Mauss, I. B., Cook, C. L., Cheng, J. Y., & Gross, J. J. (2007). Individual differences in cognitive reappraisal: Experiential and physiological responses to an anger provocation. *International Journal of Psychophysiology, 66,* 116–124. doi:10.1016/j.ijpsycho.2007.03.017

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition and Emotion, 23,* 209–237. doi:10.1080/02699930802204677

McAdams, D. P., & Constantian, C. A. (1983). Intimacy and affiliation motives in daily living: An experience sampling analysis. *Journal of Personality and Social Psychology, 45,* 851–861. doi:10.1037/0022-3514.45.4.851

McAuley, E., Blissmer, B., Katula, J., Duncan, T. E., & Mihalko, S. L. (2000). Physical activity, self-esteem, and self-efficacy relationships in older adults: A randomized controlled trial. *Annals of Behavioral Medicine, 22,* 131–139.

doi:10.1007/BF02895777

McEllistrem, J. E. (2004). Affective and predatory violence: A bimodal classification system of human aggression and violence. *Aggression and Violent Behavior, 10,* 1–30. doi:10.1016/j.avb.2003.06.002

McGrath, E., Keita, G. P., Strickland, B. R., & Russo, N. F. (1990). *Women and depression: Risk factors and treatment issues.* Washington, DC: American Psychological Association.

McNair, D. M., Lorr, M., & Droppelman, L. F. (1971). *Manual for the Profile of Mood States.* San Diego, CA: Educational and Industrial Testing Services.

McNair, D. M., Lorr, M., & Droppelman, L. F. (1992). *Revised manual for the Profile of Mood States.* San Diego, CA: Educational and Industrial Testing Services.

McRae, K., Ochsner, K. N., Mauss, I. B., Gabrieli, J. J., & Gross, J. J. (2008). Gender differences in emotion regulation: An fMRI study of cognitive reappraisal. *Group Processes and Intergroup Relations, 11,* 143–162. doi:10.1177/1368430207088035

Mecacci, L., Scaglione, M. R., & Vitrano, I. (1991). Diurnal and monthly variations of temperature and self-reported activation in relation to sex and circadian typology. *Personality and Individual Differences, 12,* 819–824. doi:10.1016/0191-8869(91)90148-5

Meehl, P. E. (1995). Bootstraps taxometrics: Solving the classification problem in psychopathology. *American Psychologist, 50,* 266–275. doi:10.1037/0003-066X.50.4.266

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology* (Vol. 11). Cambridge, MA: MIT press.

Menon, V., & Levitin, D. J. (2005). The rewards of music listening: Response and physiological connectivity of the mesolimbic system. *Neuroimage, 28,* 175–184. doi:10.1016/j.neuroimage.2005.05.053

Messick, S. (1989). Validity. In R. L. Linn (Ed.), *Educational measurement* (3rd ed.) (pp. 13–103). New York, NY: American Council on Education/Macmillan.

Metanoia. (2001). *E-therapy history and survey*. Retrieved from http://www.metanoia.org/imhs/history.htm

Meyer, L. B. (1956). *Emotion and meaning in music.* Chicago: Chicago University Press.

Meyers, L. S., Gamst, G., & Guarino, A. J. (2006). *Applied multivariate research: Design and interpretation*. London, UK: Sage.

Microsoft Corporation. (1998). *Recommended fonts.* Retrieved from http://www.microsoft.com/typography/web/fonts/default.htm

Miller, K. J., Conney, J. C., Rasgon, N. L., Fairbanks, L. A., & Small, G. W. (2002). Mood symptoms and cognitive performance in women estrogen users and nonusers and men. *Journal of the American Geriatrics Society, 50,* 1826–1830. doi:10.1046/j.1532-5415.2002.50511.x

Milligan, G. W. (1981). A review of Monte Carlo tests of cluster analysis. *Multivariate Behavioral Research, 16,* 379–407. doi:10.1207/s15327906mbr1603_7

Miniwatts Marketing Group. (2012). *Internet world stats: Usage and population statistics*. Retrieved from http://www.internetworldstats.com/stats.htm

Mitchelson, M. (2014). *Online mood profiling of Asian athletes preparing for a sport competition: Based on the Brunel Mood Scale (BRUMS).* Unpublished master’s thesis, University of Southern Queensland, Toowoomba, QLD.

Mohammadi, S. A., & Prasanna, B. M. (2003). Analysis of genetic diversity in crop plants: Salient statistical tools and considerations. *Crop Science, 43,* 1235–1248. doi:10.2135/cropsci2003.1235

Mohammadi-Nezhad, M. (2011). An overview of hypotheses of antidepressant effects of exercise, part 1: Biological mechanisms. *Iranian Journal of Health and Physical activity, 2*(2). Retrieved from http://profdoc.um.ac.ir/paper-abstract-1026071.html

Mohr, D. C., Hart, S. L., Howard, I., Julian, L., Vella, L., Catledge, C., & Feldman, M. D. (2006). Barriers to psychotherapy among depressed and nondepressed primary care patients. *Annals of Behavioral Medicine, 32,* 254–258. doi:10.1207/s15324796abm3203_12

Mooi, E. A., & Sarstedt, M. (2011). *A concise guide to market research: The process, data, and methods using IBM SPSS statistics*. Berlin: Springer Science & Business media.

Moos, R. (1987). *Coping with life crises: An integrated approach*. New York: Springer Science & Business media.

Morgan, W. P. (1974). Selected psychological considerations in sport. *Research Quarterly, 45*, 374–390. doi:10.1080/10671315.1974.10615285

Morgan, W. P. (1980). Test of champions: The iceberg profile. *Psychology Today, 14*(2), 92–99.

Morgan, W. P. (1985). Selected psychological factors limiting performance: A mental health model. In D. H. Clarke & H. M. Eckert (Eds.), *Limits of human performance* (pp. 70–80). Champaign, IL: Human Kinetics,

Morgan, W. P., & Johnson, R. W. (1978). Personality characteristics of successful and unsuccessful oarsmen. *International Journal of Sport Psychology, 9*(2), 119–133. Retrieved from http://psycnet.apa.org/psycinfo/1980-11996-001

Morgan, W. P., & Pollock, M. L. (1977). Psychologic characterization of the elite distance runner. *Annals of the New York Academy of Sciences, 301,* 383–403. doi:10.1111/j.1749-6632.1977.tb38215.x

Morris, W. N. (1992). A functional analysis of the role of mood in affective systems. In M. S. Clarke (Ed.), *Emotion: Review of personality and social psychology* (pp. 257–293). Newbury Park, CA: Sage.

Morris, M., & Salmon, P. (1994). Qualitative and quantitative effects of running on mood. *The Journal of Sports Medicine and Physical Fitness, 34*(3), 284–291. Retrieved from http://europepmc.org/abstract/med/7830393

Moskowitz, D. S. (1986). Comparison of self-reports, reports by knowledgeable informants, and behavioural observation data. *Journal of Personality, 54,* 294–317. doi:10.1111/j.1467-6494.1986.tb00396.x

Motl, R. W., Berger, B. G., & Leuschen, P. S. (2000). The role of enjoyment in the exercise-mood relationship. *International Journal of Sport Psychology, 31*(3), 347–363. Retrieved from http://www.cabdirect.org/abstracts/20013073648.html

Mowrer, O. H. (1960). *Learning theory and behavior.* New York, USA: Wiley.

Muraven, M., Tice, D. M., & Baumeister, R. F. (1998). Self-control as a limited resource: Regulatory depletion patterns. *Journal of Personality and Social Psychology, 74,* 774–789. doi:10.1037/0022-3514.74.3.774

Murphy, F. C., Nimmo-Smith, I., & Lawrence, A. D. (2003). Functional neuroanatomy of emotions: A meta-analysis. *Cognitive, Affective and Behavioral Neuroscience, 3,* 207–233. doi:10.3758/CABN.3.3.207

Murray, E., Lo, B., Pollack, L., Donelan, K., Catania, J., Lee, K., Zapert, K., &

Turner, R. (2003). The impact of health information on the Internet on health care and the physician-patient relationship: National US survey among 1,050 US physicians. *Journal of Medical Internet Research*, *5,* e17. doi:10.2196/jmir.5.3.e17

Murray, G., Allen, N. B., & Trinder, J. (2002). Mood and the circadian system: Investigation of a circadian component in positive affect. *Chronobiology International, 19,* 1151–196. doi:10.1081/CBI-120015956

Musch, J., & Reips, U. D. (2000). A brief history of Web experimenting. In J. Musch, U. Reips & M. Birnbaum (Eds.) *Psychological experiments on the Internet* (pp. 61–87). San Diego, CA: Academic Press.

Nadler, R. T., Rabi, R., & Minda, J. P. (2010). Better mood and better performance: Learning rule-described categories is enhanced by positive mood. *Psychological Science*, *21,* 1770–1776. doi:10.1177/0956797610387441

Nagle, R. J., Morgan, W. P., Hellickson, R. O., Serfass, R. C., & Alexander J. F. (1975). Spotting success traits in Olympic contenders. *The Physician and Sports Medicine, 3*(12), 31–34.

National Institute for Occupational Safety and Health. (n.d.). Retrieved from http://www.cdc.gov/niosh/mining/statistics/injuries.htm

Neal, A., & Griffin, M. A. (2002). Safety climate and safety behaviour. *Australian Journal of Management, 27,* 67–75. doi:10.1177/031289620202701S08

Neal, A., & Griffin, M. A. (2006). A study of the lagged relationships among safety climate, safety motivation, safety behavior, and accidents at the individual and group levels. *Journal of Applied Psychology, 91,* 946–953. doi:10.1037/0021-9010.91.4.946

Neal, A., Griffin, M. A., & Hart, P. M. (2000). The impact of organizational climate on safety climate and individual behavior. *Safety Science, 34,* 99–109. doi:10.1016/S0925-7535(00)00008-4

Nelson, J. G., Pelech, M. T., & Foster, S. F. (1984). Color preference and stimulation seeking. *Perceptual and Motor skills, 59,* 913–914. doi:10.2466/ pms.1984.59.3.913

Nelson, R. J. (2005). *An introduction to behavioral endocrinology* (3rd ed.). Sunderland, MA: Sinauer Associates.

Newby, R. W. & Simpson, S. (1994). Basketball performance as a function of scores on Profile of Mood States. *Perceptual and Motor Skills, 78,* 1142–1142. doi:10.2466/pms.1994.78.3c.1142

Newman, E. B., Perkins, F. T., & Wheeler, R. H. (1930). Cannon’s theory of emotion: A critique. *Psychological Review, 37,* 305–326. doi:10.1037/ h0074972

Nickelson, D. W. (1996). Behavioral telehealth: Emerging practice, research, and policy opportunities. *Behavioral Sciences and the Law, 14,* 443–457. doi:10.1002/(SICI)1099-0798(199623)14:4<443::AID-BSL256>3.0.CO;2-G

Nielsen, J. (2000). *Designing web usability: The practice of simplicity.* Indianapolis: New Riders.

Nisbett, R. E., & Ross, L. (1980). *Human Inference: Strategies and shortcomings of social judgment.* Englewood Cliffs, NJ: Prentice-Hall.

Nisbett, R. E., & DeCamp Wilson, T. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review, 84,* 231–259. doi:10.1037/0033-295X.84.3.231

Nolen-Hoeksema, S. (1987). Sex differences in unipolar depression: Evidence and theory. *Psychological Bulletin, 101,* 259–282. doi:10.1037/

0033-2909.101.2.259

Nolen-Hoeksema, S. (1991). Responses to depression and their effects on the duration of depressive episodes. *Journal of Abnormal Psychology, 100,* 569–82. doi:10.1037/0021-843X.100.4.569

Nolen-Hoeksema, S. (2001). Gender differences in depression. *Current Directions in Psychological Science, 10,* 173–176. doi:10.1111/1467-8721.00142

Nolen-Hoeksema, S., & Morrow, J. (1993). Effects of rumination and distraction on naturally occurring depressed mood. *Cognition and Emotion, 7,* 561–570. doi:10.1080/02699939308409206

Nolen-Hoeksema, S., Morrow, J., & Fredrickson, B. L. (1993). Response styles and the duration of episodes of depressed mood. *Journal of Abnormal Psychology, 102,* 20. doi:10.1037/0021-843X.102.1.20

Nolen-Hoeksema, S., Wisco, B. E., & Lyubomirsky, S. (2008). Rethinking rumination. *Perspectives on Psychological Science, 3,* 400–424. doi:10.1111/j.1745-6924.2008.00088.

Norcross, J., Guadagnoli, E., & Prochaska, J. (1984). Factor structure of the Profile of Mood States (POMS): Two partial replications. *Journal of Clinical Psychology, 40,* 1270–1277. doi:10.1002/1097-4679(198409)40:5<1270::AID-JCLP2270400526>3.0.CO;2-7

Norman, S. (2006). The use of telemedicine in psychiatry. *Journal of Psychiatric and Mental Health Nursing, 13,* 771–777. doi:10.1111/j.1365-2850.2006.01033.x

North, T. C., McCullagh, P., & Tran, Z. V. (1990). Effect of exercise on depression. *Exercise and Sport Science Review, 18,* 379–415. Retrieved from http://journals.lww.com/acsm-essr/Citation/1990/01000/Effect_of_Exercise_on_Depression_.16.aspx

Northoff, G. (2012). Are our emotional feelings rational? A neurophilosophical investigation of the James-Lange theory. *Phenomenology and the Cognitive Sciences, 101,* 1–27.

Nowlis, V. (1965). Research with the mood adjective check list. In S. S. Tomkins, & C. E. Izard (Eds.), *Affect, cognition, and personality* (pp. 352–389). New York, NY: Springer.

Oatley, K., & Johnson-Laird, P. N. (1987). Towards a cognitive theory of emotions. *Cognition and Emotion, 1,* 29–50. doi:10.1080/02699938708408362

Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in Cognitive Sciences, 9,* 242–249. doi:10.1016/j.tics.2005.03.010

Odagiri, Y., Shimomitsu, T., Iwane, H., & Katsumura, T. (1996). Relationships between exhaustive mood state and changes in stress hormones following an ultraendurance race. *International Journal of Sports Medicine, 17,* 325–331. doi:10.1055/s-2007-972855

Oh, E., Jorm, A. F., & Wright, A. (2009). Perceived helpfulness of websites for mental health information. *Social Psychiatry and Psychiatric Epidemiology, 44,* 293–299. doi:10.1007/s00127-008-0443-9

Oliver, G., & Wardle, J. (1999). Perceived effects of stress on food choice. *Physiology and Behavior, 66,* 511–515. doi:10.1016/S0031-9384(98)00322-9

Oliver, L. W., & Whiston, S. C. (2000). Internet career assessment for the new millennium. *Journal of Career Assessment, 8,* 361–369. doi:10.1177/106907270000800405

Ortony, A., & Clore, G. L. (1981). Disentangling the affective lexicon.

Proceedings of the 3rd Annual Conference of the Cognitive Science Society (Vol. 3, pp. 90–95). Berkeley, California.

Ortony, A., & Turner, T. J. (1990). What's basic about basic emotions? *Psychological Review, 97,* 315. doi:10.1037/0033-295X.97.3.315

Osgood, C. E., Suci, G., & Tannenbaum, P. H. (1957). *The measurement of meaning*. Urbana: University of Illinois Press.

Palencik, J. T. (2007). William James and the psychology of emotion: From 1884 to the present. *Transactions of the Charles S. Peirce Society, 43,* 769–786. doi:10.1353/csp.2007.0050

Panksepp, J., & Watt, D. (2011). What is basic about basic emotions? Lasting lessons from affective neuroscience. *Emotion Review, 3,* 387–396. doi:10.1177/1754073911410741

Pallant, J. (2009). *SPSS survival manual: A step by step guide to data analysis using SPSS* (3rd ed.). Australia: McGraw-Hill International.

Pap, A. (1953). Reduction-sentences and open concepts. *Methodos, 5,* 3–30.

Parkinson, B., & Totterdell, P. (1999). Classifying affect regulation strategies. *Cognition and Emotion, 13,* 277–303. doi:10.1080/026999399379285

Parkinson, B., Totterdell, P., Briner, R. B., & Reynolds, S. (1996). *Changing moods: The psychology of mood and mood regulation*. London, UK: Longman.

Parrot, W. G., & Sabini, J. (1990). Mood and memory under natural conditions: Evidence for mood congruent recall. *Journal of Personality and Social Psychology, 59,* 321–336. doi:10.1037/0022-3514.59.2.321

Parry, B. L. (2001). The role of central serotonergic dysfunction in the aetiology of premenstrual dysphoric disorder: Therapeutic implications. *CNS Drugs, 15,* 277–85. doi:10.2165/00023210-200115040-00003

Paulhus, D. L., & Vazire, S. (2007). The self-report method. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 224–239). London, UK: The Guilford Press.

Paykel, E. S. (1971). Classification of depressed patients: A cluster-analysis-derived grouping. *British Journal of Psychiatry, 118,* 275–288. doi:10.1192/bjp.118.544.275

Paykel, E. S., & Rassaby, E. (1978). Classification of suicide attempters by cluster analysis. *British Journal of Psychiatry, 133,* 45–52. doi:10.1192/bjp.133.1.45

Pelletier, C. L. (2004). The effect of music on decreasing arousal due to stress: A meta-analysis. *Journal of Music Therapy, 4,* 192–214. doi:10.1093/jmt/41.3.192

Penner, L. A., Shiffman, S., Paty, J. A., & Fritzsche, B. A. (1994). Individual differences in intraperson variability in mood. *Journal of Personality and Social Psychology, 59,* 321–336. doi:10.1037/0022-3514.66.4.712

Peretz, I. (1990). Processing of local and global musical information by unilateral brain-damaged patients. *Brain, 113,* 1185–1205. doi:10.1093/brain/113.4.1185

Petruzzello, S. J., Landers, D. M., Hatfield, B. D., Kubitz, K. A., & Salazar, W. (1991). A meta-analysis on the anxiety-reducing effects of acute and chronic exercise. *Sports Medicine, 11,* 143–182. doi:10.2165/00007256-199111030-00002

Picker Institute. (2006, November). *Assessing the quality of information to support people in making decisions about their health and healthcare.* Retrieved from http://www.pickereurope.org/Filestore/PIE_reports/project_reports/Health-information-quality-web-version-FINAL.pdf

Pier, C., Klein, B., Austin, D., Mitchell, J., Kiropoulos, L., & Ryan, P. (2006). Reflections on Internet-therapy: Past, present and beyond. *InPsych, 28,* 14–17.

Pieter, W., & Pieter, M. S. (2008). Mood and performance in aikido athletes. *Acta Kinesiologiae Universitatis Tartuensis, 13,* 107–116. doi:10.12697/akut.2008.13.09

Pilcher, J. J., & Walters, A. S. (1997). How sleep deprivation affects psychological variables related to college students' cognitive performance. *Journal of American College Health, 46,* 121–126. doi:10.1080/07448489709595597

Platel, H., Price, C., Baron, J. C., Wise, R., Lambert, J., Frackowiak, R. S., ... & Eustache, F. (1997). The structural components of music perception: A functional anatomical study. *Brain, 120,* 229–243. doi:10.1093/brain/120.2.229

Plutchik, R. (1980). *Emotion, a psychoevolutionary synthesis.* New York: Harper & Row.

Poels, K., & Dewitte, S. (2006). How to capture the heart? Reviewing 20 years of emotion measurement in advertising. *Journal of Advertising Research, 46,* 18–37. doi:10.2139/ssrn.944401

Polivy, J., & Herman, P. C. (1985). Dieting and bingeing: A causal analysis. *American Psychologist, 40,* 193–201. doi:10.1037/0003-066X.40.2.193

Popper, K. R., Eccles, J. C., John, C., & Carew, J. (1977). *The self and its brain.* Berlin: Springer International.

Prapavessis, H. (2000). The POMS and sports performance: A review. *Journal of Applied Sport Psychology, 12,* 34–48. doi:10.1080/10413200008404212

Prapavessis, H., & Grove, R. (1991). Precompetitive emotions and shooting performance: The mental health zone of optimal function models. *The Sport Psychologist, 5*(3), 223–234. Retrieved from http://journals.humankinetics.com/tsp-back-issues/ tspvolume5issue3september/precompetitiveemotionsandshootingperformance thementalhealthandzoneofoptimalfunctionmodels

Proudfoot, J., Goldberg, D., Mann, A., Everitt, B., Marks, I., & Gray, J. A. (2003). Computerized, interactive, multimedia cognitive-behavioural program for anxiety and depression in general practice. *Psychological Medicine, 33,* 217–227. doi:10.1017/S0033291702007225

Proudfoot, J., Ryden, C., Everitt, B., Shapiro, D. A., Goldberg, D., Mann, A., … Gray, J. A. (2004). Clinical efficacy of computerized cognitive-behavioural therapy for anxiety and depression in primary care: Randomised controlled trial. *British Journal of Psychiatry, 185,* 46–54. doi:10.1192/bjp.185.1.46

Ptacek, J. T., Smith, R. E., Espe, K., & Raffety, B. (1994). Limited correspondence between daily reports and retrospective coping recall. *Psychological Assessment, 6,* 41–49. doi:10.1037/1040-3590.6.1.41

Pullmann, M. D., VanHooser, S., Hoffman, C., & Heflinger, C. A. (2010). Barriers to and supports of family participation in a rural system of care for children with serious emotional problems. *Community Mental Health Journal, 46,* 211–220. doi:10.1007/s10597-009-9208-5

Quinn, E. (2014). *Overtraining syndrome and athletes.* Retrieved from http://sportsmedicine.about.com/cs/overtraining/a/aa062499a.htm

Rabasca, L. (2000, April). Taking telehealth to the next step. *APA Monitor, 31,* 36–37.

Randall, D. M., & Fernandes, M. F. (1991). The social desirability response bias in ethics research. *Journal of Business Ethics, 10,* 805–817. doi:10.1007/BF00383696

Rasgon, N., Bauer, M., Glenn, T., Elman, S., & Whybrow, P. C. (2003). Menstrual cycle related mood changes in women with bipolar disorder. *Bipolar Disorders, 5,* 48–52. doi:10.1034/j.1399-5618.2003.00010.x

Rasmussen, P. R., Jeffrey, A. C., Willingham, J. K., & Glover, T. L. (1994). Implications of the true score model in assessment of mood state. *Journal of Social Behavior and Personality, 9,* 107–118. Retrieved from http://psycnet.apa.org/psycinfo/1994-31942-001

Ray, R. D., & Zald, D. H. (2011). Anatomical insights into the interaction of emotion and cognition in the prefrontal cortex. *Neuroscience and Biobehavioral Reviews, 36,* 479–501. doi:10.1016/j.neubiorev.2011.08.005

Reddon, J., Marceau, R., & Holden, R. (1985). A confirmatory evaluation of the Profile of Mood States: Convergent and discriminant item validity. *Journal of Psychopathology and Behavioral Assessment, 7,* 243–259. doi:10.1007/BF00960756

Reed, J. (2005). Acute physical activity and self-reported affect: A review. In A. V. Clark (Ed.), *Causes, role, and influence of mood states* (pp. 91–113). New York, NY: Nova.

Reed, J., & Ones, D. S. (2006). The effect of acute aerobic exercise on positive activated affect: A meta-analysis. *Psychology of Sport and Exercise, 7,* 477–514. doi:10.1016/j.psychsport.2005.11.003

Reeves, D. L., Levinson, D. M., Justesen, D. R., & Lubin, B. (1984). Endogenous hyperthermia in normal human subjects: Experimental study of emotional states (II). *International Journal of Psychosomatics: Official Publication of* *the International Psychosomatics Institute, 32*(4), 18–23. Retreived from http://europepmc.org/abstract/med/3865910

Regier, D. A., Narrow, W. E., Rae, D. S., & Manderscheid, R. W. (1993). The de facto US mental and addictive disorders service system: Epidemiologic catchment area prospective 1-year prevalence rates of disorders and services. *Archives of General Psychiatry, 50,* 85–94. doi:10.1001/ archpsyc.1993.01820140007001

Reinhard, M-A., & Dickhäuser, O. (2009). Need for cognition, task difficulty and the formation of performance expectancies. *Journal of Personality and Social Psychology, 96,* 1062–1076. doi:10.1037/a0014927

Reinhard, M.-A., & Dickhäuser, O. (2011). How affective states, task difficulty, and self-concepts influence the formation of consequences of performance expectancies. *Cognition and Emotion, 25,* 220–228. doi:10.1080/ 02699931003802640

Reisenzein, R. (2007). What is a definition of emotion? And are emotions mental-behavioral processes? *Social Science Information, 46*(3), 424. Retreived from http://philpapers.org/rec/REIWIA-2

Renger, R. (1993). A review of the Profile of Mood States (POMS) in the prediction of athletic success. *Journal of Applied Sport Psychology, 5,* 78–84. doi:10.1080/10413209308411306

Rey, B., & Alcañiz, M. (2012). Virtual reality and serious games: Applications in mental health. In J. M. García-Gómez & P. Paniagua-Paniagua (Eds.), *Information and communication technologies applied to mental health* (pp. 6–10). Valencia, Spain: Editorial Universitat Politècnica de València.

Richards, J. C., & Alvarenga, M. E. (2002). Extension and replication of an Internet-based treatment program for panic disorder. *Cognitive Behaviour Therapy, 31,* 41–47. doi:10.1080/16506070252823652

Ritterband, L. M., Gonder-Frederick, L. A., Cox, D. J., Clifton, A. D., West, R. W., & Borowitz, S. M. (2003). Internet interventions: In review, in use, and into the future. *Professional Psychology: Research and Practice, 34,* 527–534. doi:10.1037/0735-7028.34.5.527

Riva, G., Teruzzi, T., & Anolli, L. (2003). The use of the Internet in psychological research: Comparison of online and offline questionnaires. *CyberPsychology and Behavior, 6,* 73–80. doi:10.1089/109493103321167983

Robinson, M. D., & Clore, G. L. (2002). Episodic and semantic knowledge in emotional self-report: Evidence for two judgment processes. *Journal of Personality and Social Psychology, 83,* 198. doi:10.1037/ 0022-3514.83.1.198

Rochlen, A. B., Zack, J. S., & Speyer, C. (2004). Online therapy: Review of relevant definitions, debates, and current empirical support. *Journal of Clinical Psychology, 60,* 269–283. doi:10.1002/jclp.10263

Rohlfs, I. C. P. de M., Terry, P. C., de Carvalho, T., Krebs, R. J., Andrade, A., Rotta, T. M. et al. (2008). Development and initial validation of the Brazil Mood Scale. In N. Voudouris & V. Mrowinski (Eds.), *Psychology leading change: Proceedings of the 42nd Annual Conference of the Australian Psychological Society* (pp. 269–273). Melbourne, VIC: Australian Psychological Society.

Rokka, S., Mavridis, G., & Kouli, O. (2010). The impact of exercise intensity on mood state of participants in dance aerobic programs. *Studies in Physical Culture and Tourism, 17*(3), 241–245. Retrieved from http://www.wbc.poznan.pl/Content/147546/05_Rokka_%20REV.pdf

Rokke, P. D. (1993). Social context and perceived task difficulty as mediators of depressive self-evaluation. *Emotion and Motivation, 17,* 23–40. doi:10.1007/BF00995205

Rosnow, R. L., & Rosenthal, R. (1996). Computing contrasts, effect sizes, and counternulls on other people's published data: General procedures for research consumers. *Psychological Methods, 1,* 331–340. doi:10.1037/1082-989X.1.4.331

Rothert, K., Strecher, V. J., Doyle, L. A., Caplan, W. M., Joyce, J. S., Jimison, H. B., … Roth, M. A. (2006). Web-based weight management programs in an integrated health-care setting: A randomized controlled trial. *Obesity, 14,* 266–272. doi:10.1038/oby.2006.34

Rotter, J. B. (1954). *Social learning and clinical psychology*. Englewood Cliffs, NJ: Prentice-Hall. Retrieved from http://psycnet.apa.org/psycinfo/2005-06617-000/

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20,* 53–65. doi:10.1016/0377-0427(87)90125-7

Rouveix, M., Duclos, M., Gouarne, C., Beauvieux, M. C., & Filaire, E. (2006). The 24h urinary cortisol/cortisone ratio and epinephrine/norepinephrine ratio for monitoring training in young female tennis players. *International Journal of Sports Medicine, 27,* 856–863. doi:10.1055/s-2006-923778

Rowley, A., Landers, D., Kyllo, L., & Etnier, J. (1995). Does the iceberg profile discriminate between successful and less successful athletes? A meta-analysis. *Journal of Sport and Exercise Psychology, 17,* 185–199. Retrieved from http://www.humankinetics.com/acucustom/sitename/Documents/

DocumentItem/9003.pdf

Ruckmick, C. A. (1936). *The psychology of feeling and emotion.* New York, NY: McGraw-Hill.

Ruff, T., Coleman, P., & Martini, L. (2011). Machine-related injuries in the US mining industry and priorities for safety research. *International Journal of Injury Control and Safety Promotion, 18,* 11–20. doi:10.1080/ 17457300.2010.487154

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39,* 1161–1178. doi:10.1037/h0077714

Russell, J. A., & Barrett, L. F. (1999). Core affect, prototypical emotional episodes, and other things called emotion: Dissecting the elephant. *Journal of Personality and Social Psychology, 76,* 805–819. doi:10.1037/ 0022-3514.76.5.805

Russell, J. A., & Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. *Journal of Research in Personality, 11,* 273–294. doi:10.1016/ 0092-6566(77)90037-X

Russell, W., & Cox, R. (2000). A laboratory investigation of positive and negative affect within individual zones of optimal functioning theory. *Journal of Sport Behaviour, 23*(2), 164–180. Retrieved from https://secure.sportquest.com/ su.cfm?articleno=S-657019&title=S-657019

Saarikallio, S., & Erkkilä, J. (2007). The role of music in adolescents' mood regulation. *Psychology of Music, 35,* 88–109. doi:10.1177/ 0305735607068889

Salas, C. E., Radovic, D., & Turnbull, O. H. (2011). Inside-out: Comparing internally generated and externally generated basic emotions. *Emotion.*

Advance online publication. doi:10.1037 /a0025811

Salmon, P. (2001). Effects of physical exercise on anxiety, depression, and sensitivity to stress: A unifying theory. *Clinical Psychology Review, 21,* 33–61. doi:10.1016/S0272-7358(99)00032-X

Sarapas, C., Shankman, S. A., Harrow, M., & Goldberg, J. F. (2012). Parsing trait and state effects of depression severity on neurocognition: Evidence from a 26-year longitudinal study. *Journal of Abnormal Psychology, 121,* 830. doi:10.1037/a0028141

Scarantino, A., & Griffiths, P. (2011). Don't give up on basic emotions. *Emotion Review, 3,* 444–454. doi:10.1177/1754073911410745

Schachter, S., & Singer, J. E. (1962). Cognitive, social, and physiological determinants of emotional state. *Psychological Review, 69,* 379–399. doi:10.1037/h0046234

Scheibler, D., & Schneider, W. (1985). Monte Carlo tests of the accuracy of cluster analysis algorithms: A comparison of hierarchical and nonhierarchical methods. *Multivariate Behavioral Research, 20,* 283–304. doi:10.1207/ s15327906mbr2003_4

Scherer, K. R. (2004). Which emotions can be induced by music? What are the underlying mechanisms? And how can we measure them? *Journal of New Music Research, 33,* 239–251. doi:10.1080/0929821042000317822

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information, 44,* 695–729. doi:10.1177/0539018405058216

Scherer, K. R., Schorr, A., & Johnstone, T. (2001). *Appraisal processes in emotion: Theory, methods, and research.* Canary, NC: Oxford University Press.

Schmidt, L. A., & Trainor, L. J. (2001). Frontal brain electrical activity (EEG) distinguishes valence and intensity of musical emotions. *Cognition and Emotion, 15,* 487–500. doi:10.1080/02699930126048

Schmidt, W. C. (1997). World-Wide Web survey research: Benefits, potential problems, and solutions. *Behavior Research Methods, Instruments, and Computers, 29*, 274–279. doi:10.3758/BF03204826

Schwarz, N. (1990). Feelings as information: Informational and motivational functions of affective states. In E. T. Higgins & R. M. Sorrentino (Eds.), *Handbook of motivation and cognition: Foundations of social behavior* (Vol. 2, pp. 527–561). New York, NY: Guilford Press.

Schwarz, N. (1999). Self-reports: How the questions shape the answers. *American Psychologist, 54,* 93–105. doi:10.1037/0003-066X.54.2.93

Schwarz, N., & Bless, H. (1991). Happy and mindless, but sad and smart? The impact of affective states on analytic reasoning. In J. P. Forgas (Ed.), *Emotion and social judgements* (pp. 55–71). London, UK: Pergamon Press.

Schwarz, N., & Clore, G. L. (1988). How do I feel about it? The informative function of affective states. In K. Fiedler & J. P. Forgas (Eds.), *Affect, cognition and social behavior* (pp. 44–62). Gottingen, Germany: Hogrefe.

Shacham, S. (1983). A shortened version of the Profile of Mood States. *Journal of Personality Assessment, 47,* 305–306. doi:10.1207/s15327752jpa4703_14

Shapiro, D. E., & Schulman, C. E. (1996). Ethical and legal issues in e-mail therapy. *Ethics and Behaviour, 6,* 107–124. doi:10.1207/s15327019eb0602_3

Shephard, R. J. (1995). Physical activity, fitness, and health: The current consensus. *Quest, 47,* 288–303. doi:10.1080/00336297.1995.10484158

Shinoda, T. (2001). Music therapy in terminal care. *Japan Medical Association Journal, 44*(10), 457–460. Retrieved from http://211.121.197.24/english/

journal/pdf/jmaj/v44no10.pdf#page=33

Shockley, K. M., Ispas, D., Rossi, M. E., & Levine, E. L. (2012). A meta-analytic investigation of the relationship between state affect, discrete emotions, and job performance. *Human Performance, 25,* 377–411. doi:10.1080/08959285.2012.721832

Silberman, E. K., & Weingartner, H. (1986). Hemispheric lateralization of functions related to emotion. *Brain and Cognition, 5,* 322–353. doi:10.1016/0278-2626(86)90035-7

Silva, J. M., Shultz, B. B., Haslam, R. W., Martin, T. P., & Murray, D. F. (1985). Discriminating characteristics of contestants at the United States Olympic wrestling trials. *International Journal of Sport Psychology, 16,* 79–102. Retrieved from http://psycnet.apa.org/psycinfo/1986-23154-001

Simon, A., McGowan, C. R., Epstein, L. H., Kupfer, D. J., & Robertson, R. J. (1985). Exercise as a treatment for depression: An update. *Clinical Psychology Review, 5,* 553–568. doi:10.1016/0272-7358(85)90034-0

Sinclair, R. C, & Mark, M. M. (1992). The influence of mood state on judgment and action: Effects on persuasion, categorization, social justice, person perception, and judgmental accuracy. In L. L. Martin & A. Tesser (Eds.), *The construction of social judgments* (pp. 165–193). Hillsdale, NJ: Erlbaum.

Sizer, L. (2000). Towards a computational theory of mood. *British Journal of the Philosophy of Science, 51,* 743–769. doi:10.1093/bjps/51.4.743

Sloman, A. (2004, March). What are emotion theories about? In *Architectures for modeling emotions: Cross-disciplinary foundations.* Symposium conducted at the meeting of AAAI Spring Symposium, Stanford.

Smith, P. K., Fox, A. T., Davies, P., & Hamidi-Manesh, L. (2006).

Cyberchondriacs. *International Journal of Adolescent Medicine and Health, 18,* 209–214. doi:10.1515/IJAMH.2006.18.2.209

Smith, R. E., Leffingwell, T. R., & Ptacek, J. T. (1999). Can people remember how they coped? Factors associated with discordance between same-day and retrospective reports. *Journal of Personality and Social Psychology, 76,* 1050–1061. doi:10.1037/0022-3514.76.6.1050

Soares, C. N. (2013). Depression in peri-and postmenopausal women: Prevalence, pathophysiology and pharmacological management. *Drugs and Aging, 30,* 677–685. doi:10.1007/s40266-013-0100-1

Solanki, D., & Lane, A. M. (2010). Relationships between exercise as a mood regulation strategy and trait emotional intelligence. *Asian Journal of Sports Medicine, 1*(4), 195–200. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3289183/

Sommerfield, A. J., Deary, I. J., & Frier, B. M. (2004). Acute hyperglycemia alters mood state and impairs cognitive performance in people with type 2 diabetes. *Diabetes Care, 27,* 2335–2340. doi:10.2337/diacare.27.10.2335

Sotres-Bayon, F., Cain, C. K., & LeDoux, J. E. (2006). Brain mechanisms of fear extinction: Historical perspectives on the contribution of prefrontal cortex. *Biological Psychiatry, 60,* 329–336. doi:10.1016/j.biopsych.2005.10.012

Spielberger, C. D. (1991). *Manual of the State-Trait Anger Expression Inventory*. Odessa, FL: Psychological Assessment Resources.

Spielberger, C. D., Gorsuch, R. L., & Lushene, R. E. (1970). *Manual for the State-Trait Anxiety Inventory*. Palo Alto, CA: Consulting Psychologists Press.

Statistical Package for Social Scientists Graduate Pack (Version 21.0) [Computer software]. Chicago, IL: SPSS Inc.

Steer, R. A., Clark, D. A., Kumar, G., & Beck, A. T. (2008). Common and specific dimensions of self-reported anxiety and depression in adolescent outpatients. *Journal of Psychopathology and Behavioral Assessment, 30,* 163–170, doi:10.1007/s10862-007-9060-2

Steinberg, H., & Sykes, E. A. (1985). Introduction to symposium on endorphins and behavioural processes: Review of literature on endorphins and exercise. *Pharmacology Biochemistry and Behavior, 23,* 857–862. doi:10.1016/0091-3057(85)90083-8

Stemmler, G. (1992). The vagueness of specificity: Models of peripheral physiological emotion specificity in emotion theories and their experimental discriminability. *Journal of Psychophysiology, 6,* 17–28. Retrieved from http://psycnet.apa.org/psycinfo/1993-12111-001

Stephens, C. L., Christie, I. C., & Friedman, B. H. (2010). Autonomic specificity of basic emotions: Evidence from pattern classification and cluster analysis. *Biological Psychology, 84,* 463–473. doi:10.1016/j.biopsycho.2010.03.014

Stevens, M., & Lane, A. M. (2000). Mood-regulating strategies used by athletes [Abstract]. *Journal of Sports Sciences, 18,* 58–59. doi:10.1080/026404100365289

Stevens, M., Lane, A. M., & Terry, P. C. (2001). The impact of response set on measures of mood [Abstract]. *Journal of Sports Sciences, 19,* 82.

Stevens, M. J. (2007). A transactional model of mood. In A. M. Lane (Ed.), *Mood and human performance: Conceptual, measurement, and applied issues* (pp. 89–118). Hauppauge, NY: Nova Science.

Stevens, M. J., Lane, A. M., & Terry, P. C. (2006). Mood profiling during Olympic qualifying Judo competition: A case study testing transactional relationships.

Journal of Sports Science and Medicine, 5, 143–151. Retrieved from http://www.jssm.org/combat/1/19/v5combat-19.pdf

Stone, A. A. (1987). Event content in a daily survey is differentially associated with concurrent mood. *Journal of Personality and Social Psychology, 52,* 56–58. doi:10.1037/0022-3514.52.1.56

Stone, A. A., Hedges, S. M., Neale, J. M., & Satin, M. S. (1985). Prospective and cross-sectional mood reports offer no evidence of a "Blue Monday" phenomenon. *Journal of Personality and Social Psychology, 49,* 129–134. doi:10.1037/0022-3514.49.1.129

Strachan, M. W., Deary, I. J., Ewing, F. M., & Frier, B. M. (2000). Recovery of cognitive function and mood after severe hypoglycemia in adults with insulin-treated diabetes. *Diabetes Care, 23,* 305–312. doi:10.2337/ diacare.23.3.305

Stricker, G. (1996). Psychotherapy in cyberspace. *Ethics and Behaviour, 6,* 175–177. doi:10.1207/s15327019eb0602_12

Strom, L., Pettersson, R., & Andersson, G. (2000). A controlled trial of self-help treatment of recurrent headaches conducted via the Internet. *Journal of Consulting and Clinical Psychology, 68,* 722–727. doi:10.1037// 0022-006X.68.4.722

Sturn, A., Quackenbush, J., & Trajanoski, Z. (2002). Genesis: Cluster analysis of microarray data. *Bioinformatics, 18,* 207–208. doi:10.1093/ bioinformatics/18.1.207

Suchy, Y. (2011). *Clinical neuropsychology of emotion.* New York, NY: Guildford Press.

Suler, J. (2002). The online disinhibition effect. In The psychology of cyberspace.

Retrieved from http://www.rider.edu/suler/psycyber/disinhibit.html

Suler, J. B. (2000). Psychotherapy in cyberspace: A 5-dimensional model of online and computer-mediated psychotherapy. *CyberPsychology and Behavior, 3,* 151–159. doi:10.1089/109493100315996

Sylvia, L. G., Kopeski, L. M., Mulrooney, C., Reid, J., Jacob, K., & Neuhaus, E. C. (2009). Does exercise impact mood? Exercise patterns of patients in a psychiatric partial hospital program. *Journal of Psychiatric Practice, 15,* 70–78. doi:10.1097/01.pra.0000344923.81898.53

Tabachnick, B. L., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Boston, MA: Pearson Education.

Tantam, D. (2006). Opportunities and risks in e-therapy. *Advances in Psychiatric Treatment, 12,* 368–374. doi:10.1192/apt.12.5.368

Tartakovsky, M. (2013). *The cognitive symptoms of depression.* Retrieved from http://psychcentral.com/lib/the-cognitive-symptoms-of-depression/00016214

Tate, D. F., Finkelstein, E. A., Khavjou, O., & Gustafson, A. (2009). Cost effectiveness of Internet interventions: Review and recommendations. *Annals of Behavioral Medicine, 38,* 40–45. doi:10.1007/s12160-009-9131-6

Taylor, H. (1999). *Explosive growth of a new breed of "Cyberchondriacs".* Retrieved from http://www.harrisinteractive.com/Insights/HarrisVault.aspx

Taylor, H. (2002). *Cyberchondriacs update.* Retrieved from http://www.harrisinteractive.com/vault/Harris-Interactive-Poll-Research-Cyberchondriacs-Update-2002-05.pdf

Tellegen, A., Tuma, A. H., & Maser, J. D. (1985). Structures of mood and personality and their relevance to assessing anxiety, with an emphasis on self-report. In A. H. Tuma & J. D. Maser (Eds.), *Anxiety and the anxiety disorders* (pp. 681–706). Hillsdale, NJ: Erlbaum.

Tellegen, A., Watson, D., & Clark, L. A. (1999). On the dimensional and hierarchical structure of affect. *Psychological Science, 10,* 297–303. doi:10.1111/1467-9280.00157

Ter Bogt, T. F. M., Mulder, J., Raaijmakers, Q. A. W., & Gabhainn, S. N. (2011). Moved by music: A typology of music listeners. *Psychology of Music, 39,* 147–163. doi:10.1177/0305735610370223

Terry, P. C. (1995). The efficacy of mood state profiling among elite performers: A review and synthesis. *The Sport Psychologist, 9,* 309–324.

Terry, P. C. (2004). Mood and emotion in sport. In T. Morris & S. J. Summers (Eds.), *Sport psychology: Theory, application, and issues* (pp. 48–73). Brisbane, QLD: Wiley.

Terry, P. C. (2005). In the mood: Mood profiling applications and mood regulation strategies. In T. Morris (Chair), *Promoting health and performance for life: International Society of Sport Psychology (ISSP).* Symposium conducted at the meeting of the 11th World Congress of Sport, Sydney Convention and Exhibition Centre.

Terry, P. C., Dinsdale, S. L., Karageorghis, C. I., & Lane, A. M. (2006). Use and perceived effectiveness of pre-competition mood regulation strategies among athletes. In M. Katsikitis (Ed.), *Psychology bridging the Tasman: Science, culture and practice: Proceedings of the 2006 Joint Conference of the Australian Psychological Society and the New Zealand Psychological Society* (pp. 420–424). Melbourne, VIC: Australian Psychological Society.

Terry, P. C., & Hall, A. (1996). Development of normative data for the Profile of Mood States for use with athletic samples. *Journal of Sports Sciences, 14,* 47–48. doi:10.1080/10413200008404215

Terry, P. C., Janover, M. A., & Diment, G. M. (2004). Making a splash: Mood responses and swimming performance. *Australian Journal of Psychology, 56*, S227–228. Retrieved from http://eprints.usq.edu.au/id/eprint/4421

Terry, P. C., & Karageorghis, C. I. (2006). Psychophysical effects of music in sport and exercise: An update on theory, research and application. In M. Katsikitis (Ed.), *Psychology bridging the Tasman: Science, culture and practice: Proceedings of the 2006 Joint Conference of the Australian Psychological Society and the New Zealand Psychological Society* (pp. 415–419). Melbourne, VIC: Australian Psychological Society.

Terry, P. C., & Karageorghis, C. I. (2011). Music in sport and exercise. In T. Morris & P. C. Terry (Eds.), *The new sport and exercise psychology companion* (pp. 359–380). Morgantown, WV: Fitness Information Technology.

Terry, P. C., Karageorghis, C. I., Saha, A. M., & D' Auria, S. (2012). Effects of synchronous music on treadmill running among elite triathletes. *Journal of Science and Medicine in Sport, 15,* 52–57. doi:10.1016/j.jsams.2011.06.003

Terry, P. C., Keohane, L., & Lane, H. J. (1996). Development and validation of a shortened version of the Profile of Mood States suitable for use with young athletes. *Journal of Sports Sciences, 14,* 49.

Terry, P. C., & Lane, A. M. (2000). Development of normative data for the Profile of Mood States for use with athletic samples. *Journal of Applied Sport Psychology, 12,* 69–85.

Terry, P. C., & Lane, A. M. (2010). *User guide for the Brunel Mood Scale.* Toowoomba, QLD: Peter Terry Consultants.

Terry, P. C., & Lane, A. M. (2011). Moods and emotions. In T. Morris & P. C.

Terry (Eds.), *The new sport and exercise psychology companion* (pp. 63–87). Morgantown, WV: Fitness Information Technology.

Terry, P. C., Lane, A. M., & Beedie, C. J. (2005, August). The iceberg has melted: Theoretical, measurement and applied developments in the area of mood and physical activity. In T. Morris (Chair), *Promoting health and performance for life: International Society of Sport Psychology (ISSP).* Symposium conducted at the meeting of the 11th World Congress of Sport, Sydney Convention and Exhibition Centre.

Terry, P. C., Lane, A. M., & Fogarty, G. J. (2003). Construct validity of the Profile of Mood States-Adolescents for use with adults. *Psychology of Sport and Exercise, 4,* 125–139. doi:10.1016/S1469-0292(01)00035-8

Terry, P. C., Lane, A. M., Lane, H. J., & Keohane, L. (1999). Development and validation of a mood measure for adolescents. *Journal of Sports Sciences, 17,* 861–872. doi:10.1080/026404199365425

Terry, P. C., Malekshahi, M., & Delva, H. (2012). Development and initial validation of the Farsi Mood Scale. *International Journal of Sport and Exercise Psychology.* Advance online publication. doi:10.1080/1612197X.2012.645133

Terry, P. C., Potgieter, J. R., & Fogarty, G, J. (2003). The Stellenbosch Mood Scale: A dual-language measure of mood. *International Journal of Sport and Exercise Psychology, 1,* 231–245. doi:10.1080/1612197X.2003.9671716

Terry, P. C., & Slade, A. (1995). Discriminant effectiveness of psychological state measures in predicting performance outcome in karate competition. *Perceptual and Motor Skills, 81,* 275–286. doi:10.2466/pms.1995.81.1.275

Terry, P. C., Stevens, M. J., & Lane, A. M. (2005). Influence of response timeframe on mood assessment. *Anxiety, Stress, and Coping, 18,* 279–285. doi:10.1080/10615800500134688

Tettamanti, M., Rognoni, E., Cafiero, R., Costa, T., Galati, D., & Perani, D. (2012). Distinct pathways of neural coupling for different basic emotions. *NeuroImage, 59,* 1804–1817. doi:10.1016/j.neuroimage.2011.08.018

Thayer, R. E. (1987). Problem perception, optimism, and related states as a function of time of day (diurnal rhythm) and moderate exercise: Two arousal systems in interaction. *Motivation and Emotion, 11,* 19–36. doi:10.1007/BF00992211

Thayer, R. E. (1989). *The biopsychology of mood and arousal*. New York: Oxford University Press.

Thayer, R. E. (2001). *Calm energy: How people regulate mood with food and exercise.* New York, NY: Oxford University Press.

Thayer, R. E., Newman, J. R., & McClain, T. M. (1994). Self-regulation of mood: Strategies for changing a bad mood, raising energy, and reducing tension. *Journal of Personality and Social Psychology, 67,* 910–925. doi:10.1037/0022-3514.67.5.910

Thayer, R. E., Peters, D. P., III., Takahaski, P. J., & Birkhead-Flight, A. M. (1993). Mood and behaviour (smoking and sugar snacking) following moderate exercise: A partial test of self-regulation theory. *Personality and Individual Differences, 14,* 97–104. doi:10.1016/0191-8869(93)90178-6

Thompson, R. A. (1994). Emotion regulation: A theme in search of definition. In N. A. Fox (Ed.), *The development of emotion regulation: Biological and behavioral considerations* (Monographs of the Society for Research in Child Development) (Vol. 59, pp. 25–52).

Thompson, W. F., Schellenberg, E. G., & Husain, G. (2001). Arousal, mood, and the

Mozart Effect. *Psychological Science, 12*, 248–251. doi:10.1111/ 1467-9280.00345

Thomsen, D. K., Melsen, M. Y., Vijdik, A., Summerlund, B., & Zachariae, R. (2005). Age and gender differences in negative affect: Is there a role for emotion regulation? *Personality and Individual Differences, 38,* 1935–1946. doi:10.1016/j.paid.2004.12.001

Thorén, P., Floras, F. S., Hoffman, P., & Seals, D. R. (1990). Endorphins and exercise: Physiological mechanisms and clinical implications. *Medicine and Science in Sports and Exercise, 22*(4), 417–428. Retrieved from http://psycnet.apa.org/psycinfo/1991-00542-001

Thuné-Boyle, I. C., Stygall, J. A., Keshtgar, M. R., & Newman, S. P. (2006). Do religious/spiritual coping strategies affect illness adjustment in patients with cancer? A systematic review of the literature. *Social Science and Medicine, 63,* 151–164. doi:10.1016/j.socscimed.2005.11.055

Titchner, E. B. (1910). The past decade in experimental psychology. *American Journal of Psychology, 21*, 404–410. Retrieved from http://www.jstor.org/stable/1413349?seq=1#page_scan_tab_contents

Tolman, E. C. (1932). *Purposive behavior in animals and men*. University of California Press.

Torre, J. (2011, April). Emotional control: Strategies we use for regulating our emotions. *Psychology in Action.* Advance online publication. Retrieved from http://www.psychologyinaction.org/2011/04/08/ emotional-control-strategies-we-use-for-regulating-our-emotions/

Totterdell, P. (1999). Mood scores: Mood and performance in professional cricketers. *British Journal of Psychology, 90,* 317–332. doi:10.1348/

000712699161422

Totterdell, P., & Parkinson, B. (1999). Use and effectiveness of self-regulation strategies for improving mood in a group of trainee teachers. *Journal of Occupational Health Psychotherapy, 4,* 219–232. doi:10.1037/ 1076-8998.4.3.219

Tracy, J. L., & Randles, D. (2011). Four models of basic emotions: A review of Ekman and Cordaro, Izard, Levenson, and Panksepp and Watt. *Emotion Review, 3,* 397–405. doi:10.1177/1754073911410747er.sagepub.com

Tsang, E. C. K. (2011). A comparison on the effect of doing exercise, listening to music and taking quiet rest on mood changes. *Asian Journal of Physical Education and Recreation, 17,* 37–44.

Tye, M. (1995). *Ten problems of consciousness: A representational theory of the phenomenal mind.* Cambridge, MA: MIT Press.

Valdez, P., & Mehrabian, A. (1994). Effects of color on emotions. *Journal of Experimental Psychology: General, 123,* 394–409. doi:10.1037/ 0096-3445.123.4.394

Valdimarsdottir, H. B., & Bovbjerg, D. H. (1997). Positive and negative mood: Association with natural killer cell activity. *Psychology & Health, 12,* 319–327. doi:10.1080/08870449708406710

Vallerand, R. J., & Blanchard, C. M. (2000). The study of emotion in sport and exercise: Historical, definitional, and conceptual perspectives. In Y. L. Hanin (Ed.), *Emotions in sport* (pp. 3–38). Champaign, IL: Human Kinetics.

van Dongen, H. P. A. (1998). *Inter- and intra-individual differences in circadian phase*. Leiden, Netherlands: Leiden University, Department of Physiology.

van Praag, H. M. (1990). Two-tier diagnosing in psychiatry. *Psychiatry Research, 34,* 1–11. doi:10.1016/0165-1781(90)90053-8

van Wijk, C. H., Martin, J. H., & Hans-Arendse, C. (2013). Clinical utility of the Brunel Mood Scale in screening for post-traumatic stress risk in a Military population. *Military Medicine, 178,* 372–376. Retrieved from http://dx.doi.org/10.7205/MILMED-D-12-00422

Victorian Department of Health. (2011). *Health information on the Internet* [Fact sheet]. Retrieved from http://www.betterhealth.vic.gov.au/bhcv2/bhcarticles.nsf/pages/Health_information_on_the_internet?open

Visual pathways of the brain diagram. Retrieved from http://thalamus.wustl.edu

Vuoskoski, J. K., & Eerola, T. (2011). The role of mood and personality in the perception of emotions represented by music. *Cortex, 47,* 1099–1106. doi: 10.1016/j.cortex.2011.04.011

Vytal, K., & Hamann, S. (2010). Neuroimaging support for discrete neural correlates of basic emotions: A voxel-based meta-analysis. *Journal of Cognitive Neuroscience, 22,* 2864–2885. doi:10.1162/jocn.2009.21366

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association, 58,* 236–244. doi:10.1080/01621459.1963.10500845

Warr, P., Barter, J., & Brownbridge, G. (1983). On the independence of positive and negative affect. *Journal of Personality and Social Psychology, 44,* 644–651. doi:10.1037/0022-3514.44.3.644

Wassmann, C. (2010). Reflections on the ‘body loop’: Carl Georg Lange’s theory of emotion. *Cognition and Emotion, 24,* 970–990. doi:10.1080/02699930903052744

Watson, D. (1988a). Intraindividual and interindividual analyses of positive and negative affect: Their relation to health complaints, perceived stress, and daily activities. *Journal of Personality and Social Psychology, 54,* 1020–1030. doi:10.1037/0022-3514.54.6.1020

Watson, D. (1988b). The vicissitudes of mood measurement: Effects of varying descriptors, time frames, and response formats on measures of positive and negative affect. *Journal of Personality and Social Psychology, 55,* 128. doi:10.1037/0022-3514.55.1.128

Watson, D., & Clark, L. (1992a). On traits and temperament: General and specific factors of emotional experience and their relation to the five-factor model. *Journal of Personality, 60,* 441–476. doi:10.1111/j.1467-6494.1992.tb00980.x

Watson, D., & Clark, L. (1997). Measurement and mis-measurement of mood: Recurrent and emergent issues. *Journal of Personality Assessment, 68,* 267–296. doi:10.1207/s15327752jpa6802_4

Watson, D., & Clark, L. A. (1992b). Affects separable and inseparable: On the hierarchical arrangement of the negative affects. *Journal of Personality and Social Psychology, 62,* 489. doi:10.1037/0022-3514.62.3.489

Watson, D., & Clark, L. A. (1994). The Panas-X. *Manual for the positive and negative affect schedule–expanded form*.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54,* 1063–1070. doi:10.1037/0022-3514.54.6.1063

Watson, D., Wiese, D., Vaidya, J., & Tellegen, A. (1999). The two general activation systems of affect: Structural findings, evolutionary considerations, and psychobiological evidence. *Journal of Personality and Social Psychology, 76,* 820–838. doi:10.1037/0022-3514.76.5.820

Webb, T. L., Miles, E., & Sheeran, P. (2012). Dealing with feeling: A meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. *Psychological Bulletin, 138,* 775–808. doi:10.1037/a0027600

Webster, G. D., & Weir, C. G. (2005). Perceptions of emotion in music: Interactive effects of mode, texture, and tempo. *Motivation and Emotion, 29,* 19–39.

Wedin, L. (1972). A multidimensional study of perceptual-emotional qualities in music. *Scandinavian Journal of Psychology, 13,* 241–257. doi:10.1111/j.1467-9450.1972.tb00072.x

Weinger, K., Jacobson, A. M., Draelos, M. T., Finkelstein, D. M., & Simonson, D. C. (1995). Blood glucose estimation and symptoms during hyperglycemia and hypoglycemia in patients with insulin-dependent diabetes mellitus. *The American Journal of Medicine, 98,* 22–31. doi:10.1016/S0002-9343(99)80077-1

Welte, J. W., & Russell, M. (1993). Influence of socially desirable responding in a study of stress and substance abuse. *Alcoholism: Clinical and Experimental Research, 17,* 758–761. doi:10.1111/j.1530-0277.1993.tb00836.x

Westen, D., Burton, L., & Kowalski, R. (2006). *Psychology: Australia and New Zealand edition.* Milton, QLD: John Wiley.

Westen, D., & Rosenthal, R. (2005). Improving construct validity: Cronbach, Meehl, and Neurath's Ship. *Psychological Assessment, 17,* 409–412. doi:10.1037/1040-3590.17.4.409

Wexner, L. B. (1954). The degree to which colors (hues) are associated with mood-tones. *Journal of Applied Psychology, 38,* 432. doi:10.1037/h0062181

White, A., Kavanagh, D., Stallman, H., Klein, B., Kay-Lambkin, F., Proudfoot, J., … Young. R. (2010). Online alcohol interventions: A systematic review. *Journal of Medical Internet Research, 12,* e62. doi:10.2196/jmir.1479

Whitfield, T. W. A., & Wiltshire, T. J. (1990). Colour psychology: A critical review. *Genetic, Social and General Psychology Monographs, 116*(4), 385–411. Retreived from http://psycnet.apa.org/psycinfo/1991-11694-001

Whitwell, J. L., Przybelski, S. A., Weigand, S. D., Ivnik, R. J., Vemuri, P., Gunter, J. L., ... Josephs, K. A. (2009). Distinct anatomical subtypes of the behavioural variant of frontotemporal dementia: A cluster analysis study. *Brain: A Journal of Neurology, 132,* 2932–2946. doi:10.1093/brain/awp232

Wieck, A. (1996). Ovarian hormones, mood and neurotransmitters. *International Review of Psychiatry, 8,* 17–25. doi:10.3109/09540269609037814

Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 5,* 68–81. doi:10.1006/ceps.1999.1015

Wims, E., Titov, N., & Andrews, G. (2008). The climate panic program of Internet-based treatment for panic disorder: A pilot study. *E-Journal of Applied Psychology, 4*(2), 26–31. Retrieved from http://ojs.lib.swin.edu.au/index.php/ejap

Winkielman, P., Knäuper, B., & Schwarz, N. (1998). Looking back at anger: Reference periods change the interpretation of emotion frequency questions. *Journal of Personality and Social Psychology, 75,* 719–728. doi:10.1037/0022-3514.75.3.719

Wood, D., Winston-Salem, N. C., & Nye, C. D. (2010). Identification and measurement of a more comprehensive set of person-descriptive trait markers from the English lexicon. *Journal of Research in Personality, 44,* 258–272. doi:10.1016/j.jrp.2010.02.003

Woodworth, R. S., & Schlosberg, H. (1958). *Experimental psychology*. New York: Holt.

Worcester, W. L. (1893). Observations on some points in James's psychology. II. Emotion. *The Monist, 3,* 287. doi:10.5840/monist18934138

Wundt, W. (1891). Zur Lehre von den Gemüthsbewegungen (On emotions). *Philosophische Studien, 6,* 335–393.

Wundt, W. (1902). *Gründziige der physiologischen psychologie* (5th ed.). Leipzig: Engelmann.

Wurtman, R. J., & Wurtman, J. J. (1995). Brain serotonin, carbohydrate-craving, obesity and depression. *Obesity Research*, *3*(S4), 477S–480S. doi:10.1002/j.1550-8528.1995.tb00215.x

Wurtz, R. H., McAlonan, K., Cavanaugh, J., & Berman, R. A. (2011). Thalamic pathways for active vision. *Trends in Cognitive Sciences*, *15,* 177–184. doi:10.1016/j.tics.2011.02.004

Wyatt, J. C. (2000). Information for patients. *Journal of the Royal Society of Medicine*, *93*(9), 467–471. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1298103/

Yates, D., Moore, D., & McCabe, G. (1999). *The practice of statistics* (1st ed.). New York, NY: Freeman.

Ybarra, M. L., & Eaton, W. W. (2005). Internet-based mental health interventions. *Mental Health Services Research*, *7,* 75–87. doi:10.1007/s11020-005-3779-8

Yeung, R. R. (1996). The acute effects of exercise on mood state. *Journal of Psychosomatic Research, 40,* 123–141. doi:10.1016/0022-3999(95)00554-4

Yildirim, K., Hidayetoglu, M. L., & Capanoglu, A. (2011). Effects of interior colours on mood and preference: Comparisons of two living rooms. *Perceptual and Motor Skills, 112,* 509–524. doi:10.2466/24.27.PMS.112.2.509-524

Yu, J. C., Kuo, L. H., Chen, L. M., Yang, H. J., Yang, H. H., & Hu, W. C. (2009). Assessing and managing mobile technostress. *WSEAS Transactions on Communications, 8,* 416–425. Retreived from http://dl.acm.org

Yuen, K. S. L., & Lee, T. M. C. (2003). Could mood state affect risk-taking decisions? *Journal of Affective Disorders, 75,* 11–18. doi:10.1016/ S0164- 0327(02)00022-8

Zabinski, M. F., Celio, A. A., Wilfley, D. E., & Taylor, C. B. (2003). Prevention of eating disorders and obesity via the Internet. *Cognitive Behaviour Therapy, 32,* 137–150. doi:10.1080/16506070310000939

Zajonc, R. B. (1984). On the primacy of affect. *American Psychologist, 39,* 117–123. doi:10.1037/0003-066X.39.2.117

Zehsaz, F., Azarbaijani, M. A., Farhangimaleki, N., Tiidus, P. (2011). Effect of tapering period on plasma hormone concentrations, mood state, and performance of elite male cyclists. *European Journal of Sport Science, 11,* 183–190. doi:10.1080/17461391.2010.499976

Zentner, M., Grandjean, D., & Scherer, K. R. (2008). Emotions evoked by the sound of music: Characterization, classification, and measurement. *Emotion, 8,* 494–521. doi:10.1037/1528-3542.8.4.494

Zervas, Y., Ekkekakis, P., Emmanuel, C., Psychoudaki, M. & Kakkos, V. (1993). The acute effects of increasing levels of aerobic exercise intensity on mood states. In S. Serpa, J. Alves, V. Ferreira, & A. Paulo-Brito (Eds.), *Proceedings of the 8th World Congress of Sport Psychology*. Lisbon, Portugal: International Society of Sport Psychology.

Zevon, M. A., & Tellegen, A. (1982). The structure of mood change: An idiographic/nomothetic analysis. *Journal of Personality and Social Psychology, 43,* 111–122. doi:10.1037/0022-3514.43.1.111

Zigmond, A. S., & Snaith, R. P. (1983). The Hospital Anxiety and Depression Scale. *Acta Psychiatrica Scandinavica, 67,* 361–370. doi:10.1111/ j.1600-0447.1983.tb09716.x

Appendix A

Human Ethics Approval

University of Southern Queensland

TOOWOOMBA QUEENSLAND 4350
AUSTRALIA
TELEPHONE +61 7 4631 2300

CRICOS: QLD 00244B NSW 02225M

www.usq.edu.au

OFFICE OF RESEARCH AND HIGHER DEGREES
Ethics Committee Support Officer
PHONE (07) 4631 2690 | FAX (07) 4631 1995
EMAIL ethics@usq.edu.au

31 July 2013

Ms Renee Parsons-Smith

Dear Renee

The Chair of the USQ Fast Track Human Research Ethics Committee (FTHREC) recently reviewed your responses to the FTHREC's conditions placed upon the ethical approval for the below project. Your proposal now meets the requirements of the *National Statement on Ethical Conduct in Human Research (2007)* and full ethics approval has been granted.

Approval No.	**H13REA169**
Project Title	Online mood profiling and safety behaviour
Approval date	1 August 2013
Expiry date	31 July 2015
FTHREC Decision	**Approved**

The standard conditions of this approval are:

(a) conduct the project strictly in accordance with the proposal submitted and granted ethics approval, including any amendments made to the proposal required by the HREC
(b) advise (email: ethics@usq.edu.au) immediately of any complaints or other issues in relation to the project which may warrant review of the ethical approval of the project
(c) make submission for approval of amendments to the approved project before implementing such changes
(d) provide a 'progress report' for every year of approval
(e) provide a 'final report' when the project is complete
(f) advise in writing if the project has been discontinued.

For (c) to (e) forms are available on the USQ ethics website: http://www.usq.edu.au/research/ethicsbio/human

Please note that failure to comply with the conditions of approval and the *National Statement (2007)* may result in withdrawal of approval for the project.

You may now commence your project. I wish you all the best for the conduct of the project.

Ethics Committee Support Officer

Copies to: renee.parsons-smith@usq.edu.au
peter.terry@usq.edu.au

Toowoomba • Springfield • Fraser Coast usq.edu.au

Appendix B

2010 BRUMS Normative Data (*N* = 3,912)

BRUMS Raw Score	Equivalent T-Score					
	Tension	Depression	Anger	Vigour	Fatigue	Confusion
0	40	44	45	31	40	43
1	42	48	48	33	42	46
2	45	52	51	36	45	50
3	48	56	55	38	47	53
4	50	60	58	41	50	57
5	53	63	61	43	52	60
6	56	67	65	46	54	64
7	58	71	68	48	57	67
8	61	75	72	51	59	71
9	64	79	75	53	62	74
10	67	83	78	56	64	78
11	69	86	82	58	67	81
12	72	90	85	61	69	85
13	75	94	88	63	72	88
14	77	98	92	66	74	92
15	80	102	95	68	77	95
16	83	106	98	71	79	99

Appendix C

Table C.1

Fate of Members for Hierarchical Clusters Step 2 to Step 15 (N = 2,364)

Solution	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15
2	977	1387													
3	868	**109**	1387												
4	**394**	**109**	**474**	1387											
5	**394**	**109**	**474**	757	**630**										
6	**394**	**109**	**474**	**455**	**302**	**630**									
7	284	110	**109**	**474**	**455**	**302**	**630**								
8	284	110	**109**	106	**455**	368	**302**	**630**							
9	284	110	**109**	106	**455**	105	**302**	263	**630**						
10	143	110	**109**	141	106	**455**	105	**302**	263	**630**					
11	143	110	53	56	141	106	**455**	105	**302**	263	**630**				
12	143	110	53	56	141	106	**455**	105	**302**	263	207	423			
13	143	110	53	56	141	106	189	266	105	**302**	263	207	423		
14	143	110	53	56	141	106	189	103	105	163	**302**	263	207	423	
15	143	110	53	56	141	106	189	103	105	163	**302**	263	207	202	221

Note. H1, H2, ... H6 denotes a hierarchical cluster found within Sample A. Underlining according to colour highlights immediate member contributions.

Appendix D

Overview of the Re-Developed *In The Mood* Website

Screenshots of Website Pages from *In The Mood*

Figure D.1. The revised *In The Mood* homepage.

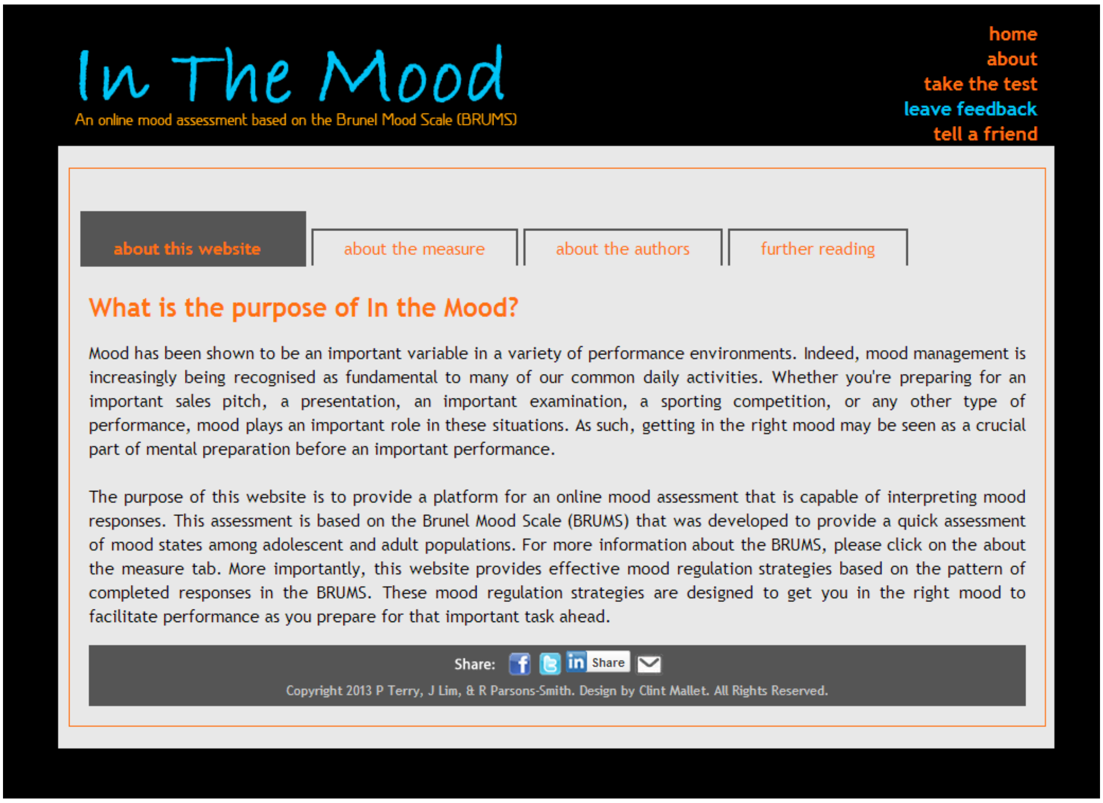


Figure D.2. The revised *In The Mood* ‘About this website’ page.

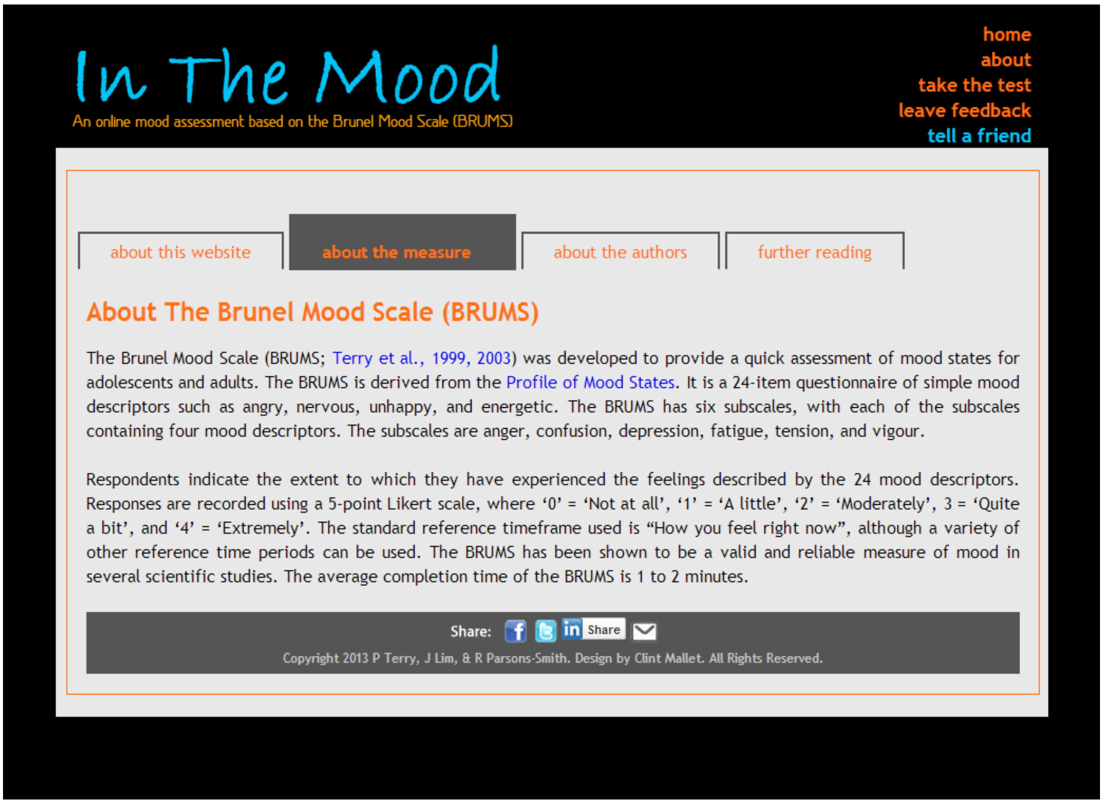


Figure D.3. The revised *In The Mood* 'About the measure' page.

home
about
take the test
leave feedback
tell a friend

In The Mood

An online mood assessment based on the Brunel Mood Scale (BRUMS)

about this website | about the measure | **about the authors** | further reading

About the Authors

Dr Peter Terry, PhD FAPS FASMF FBASES, is Professor of Psychology at the University of Southern Queensland in Australia, a registered psychologist, and formerly Psychology Coordinator at the Queensland Academy of Sport. Over the past 30 years he has provided psychological support to more than 1,000 international and professional performers, including a host of Olympic medallists. He has worked as a sport psychologist at nine Olympic Games and more than 100 other international events.

Peter is author of over 200 publications, including five books, 24 book chapters, and 60 peer-reviewed journal articles. His most recent books, Inside Sport Psychology (with Costas Karageorghis) and The New Sport and Exercise Psychology Companion (with Tony Morris), were published in 2011.

Peter is President of the Asian-South Pacific Association of Sport Psychology (ASPASP) and a Fellow of the Australian Psychological Society (APS), the Australian Sport Medicine Federation (ASMF) and the British Association of Sport and Exercise Sciences (BASES). He served as President of the APS College of Sport Psychologists from 2002-2006, and was the 2011 recipient of the APS Colleges Award of Distinction.

In the distant past, Peter played sport at representative level in rugby, soccer and track and field, competed in the national bobsled championships, and ran a three-hour marathon. He has now migrated to golf and tennis, both of which he admits to playing badly.

Dr Julian Lim, DPsych MAPS, has recently completed postgraduate studies in Clinical Psychology at the University of Southern Queensland and is currently in private practice. Clearly less celebrated and illustrious than his supervisor (i.e., Professor Peter Terry), he is content to leave this biography relatively short. His sole passion in life (outside of psychology) is soccer, a sport that he plays on a regular basis (both competitively and socially). Unlike Peter, Julian shamelessly admits to playing soccer relatively well, razzling and dazzling his opponents on the field (or so he likes to believe!). He is an avid and lifelong supporter of Liverpool Football Club, and it pains him to see them under-achieving for a number of years now.

Renée L. Parsons-Smith, BSc Hons (Psych) Assoc MAPS, is a Doctor of Philosophy candidate (psychology) currently completing her postgraduate studies at the University of Southern Queensland under the supervision of Professor Peter Terry. Raised on a yacht on the Great Barrier Reef, Renée has also travelled around Australia. Aside from an adventurous personality and a self-confessed passion for research, Renée enjoys more solitary sporting activities such as jogging and scuba diving. Renée is currently in the process of publishing her first journal article.

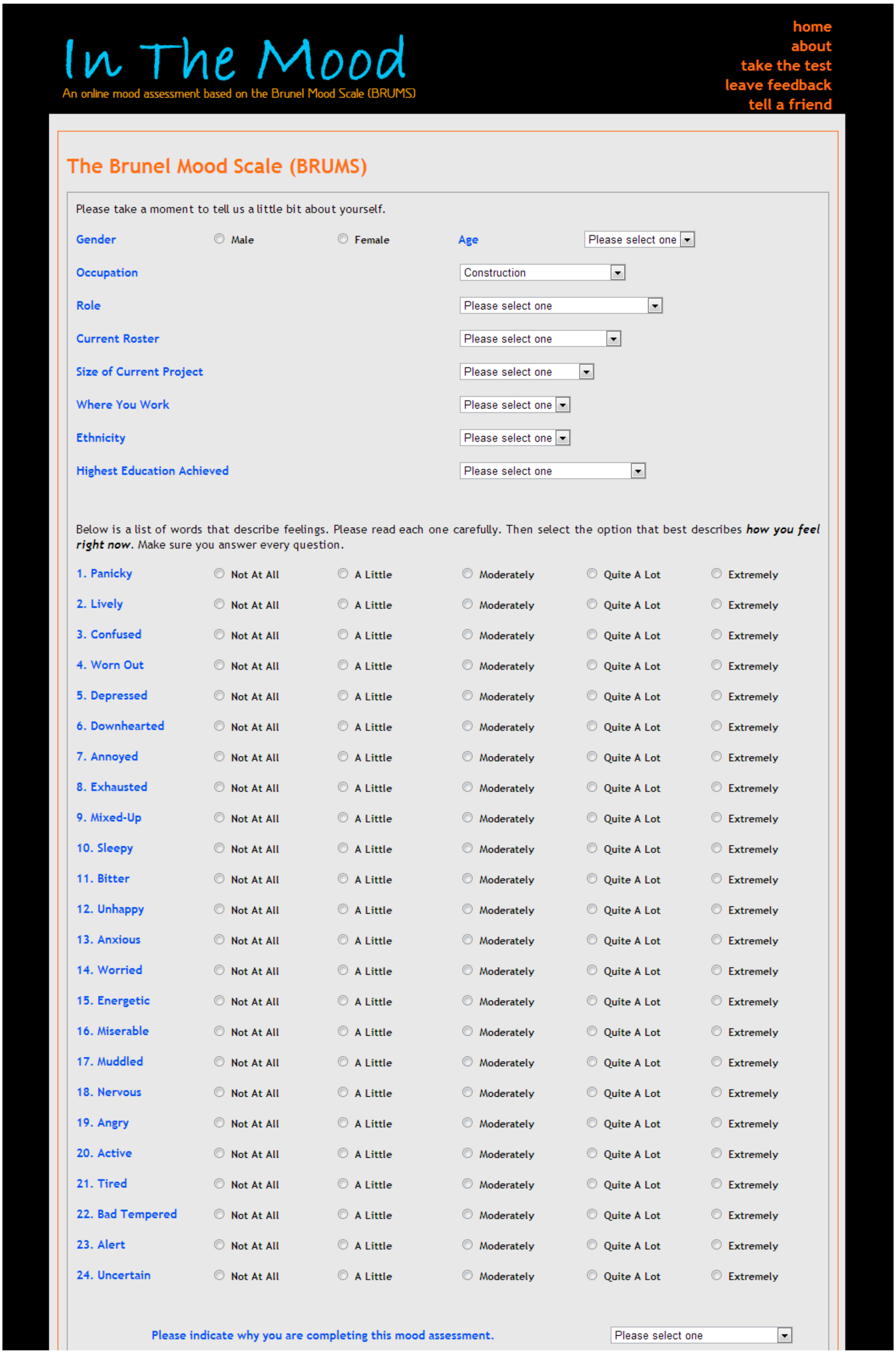
Share: Share

Copyright 2013 P Terry, J Lim, & R Parsons-Smith. Design by Clint Mallet. All Rights Reserved.

Figure D.4. The revised *In The Mood* 'About the authors' page.

Figure D.5. The revised *In The Mood* ‘Further reading’ page.

Figure D.6. The revised *In The Mood* ‘Take the test’ page.


In The Mood
An online mood assessment based on the Brunel Mood Scale (BRUMS)

home
about
take the test
leave feedback
tell a friend

The Brunel Mood Scale (BRUMS)

Please take a moment to tell us a little bit about yourself.

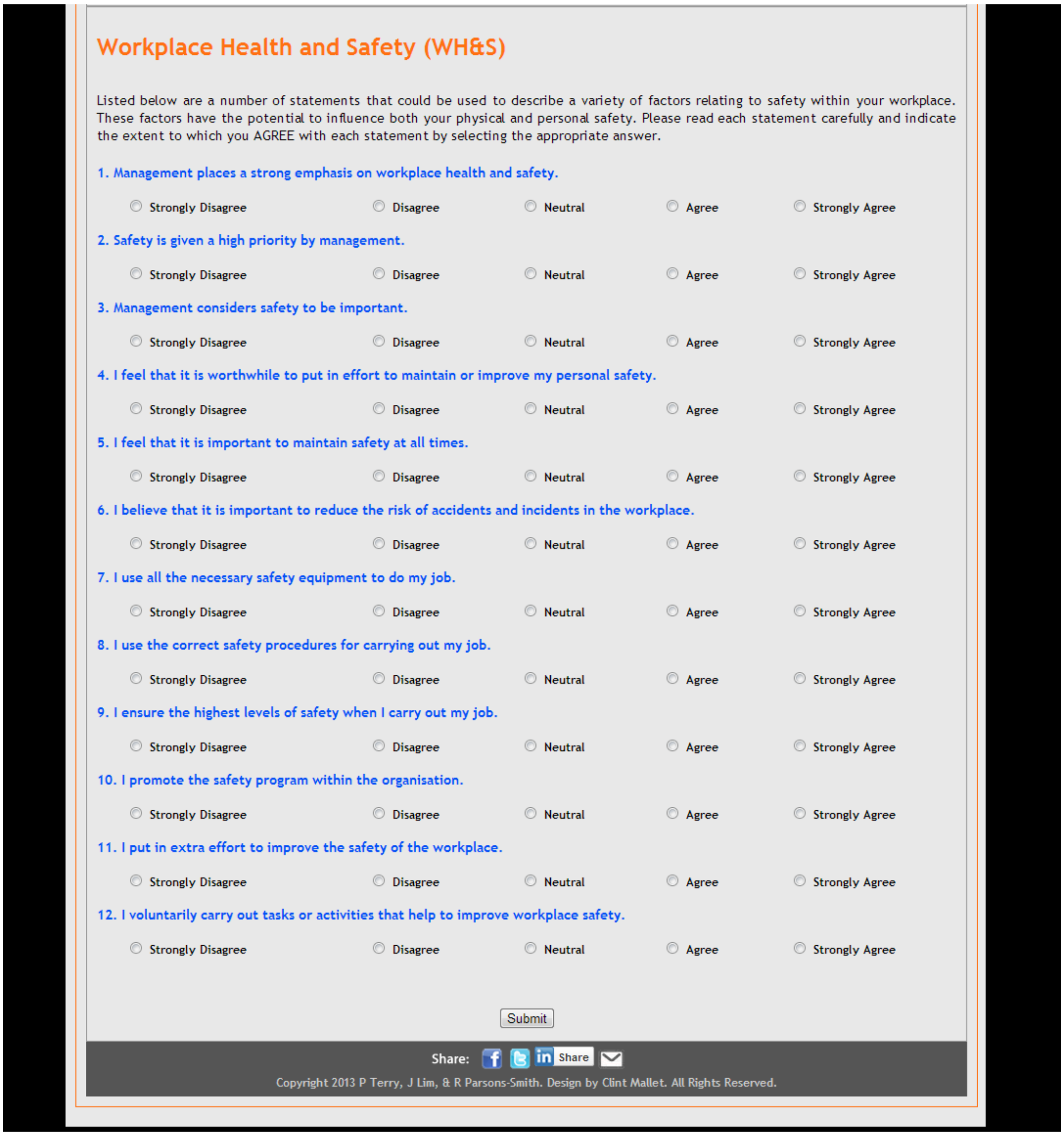
Gender	Male	Female	Age	Please select one
Occupation			Construction	
Role			Please select one	
Current Roster			Please select one	
Size of Current Project			Please select one	
Where You Work			Please select one	
Ethnicity			Please select one	
Highest Education Achieved			Please select one	

Below is a list of words that describe feelings. Please read each one carefully. Then select the option that best describes ***how you feel right now***. Make sure you answer every question.

1. Panicky	Not At All	A Little	Moderately	Quite A Lot	Extremely
2. Lively	Not At All	A Little	Moderately	Quite A Lot	Extremely
3. Confused	Not At All	A Little	Moderately	Quite A Lot	Extremely
4. Worn Out	Not At All	A Little	Moderately	Quite A Lot	Extremely
5. Depressed	Not At All	A Little	Moderately	Quite A Lot	Extremely
6. Downhearted	Not At All	A Little	Moderately	Quite A Lot	Extremely
7. Annoyed	Not At All	A Little	Moderately	Quite A Lot	Extremely
8. Exhausted	Not At All	A Little	Moderately	Quite A Lot	Extremely
9. Mixed-Up	Not At All	A Little	Moderately	Quite A Lot	Extremely
10. Sleepy	Not At All	A Little	Moderately	Quite A Lot	Extremely
11. Bitter	Not At All	A Little	Moderately	Quite A Lot	Extremely
12. Unhappy	Not At All	A Little	Moderately	Quite A Lot	Extremely
13. Anxious	Not At All	A Little	Moderately	Quite A Lot	Extremely
14. Worried	Not At All	A Little	Moderately	Quite A Lot	Extremely
15. Energetic	Not At All	A Little	Moderately	Quite A Lot	Extremely
16. Miserable	Not At All	A Little	Moderately	Quite A Lot	Extremely
17. Muddled	Not At All	A Little	Moderately	Quite A Lot	Extremely
18. Nervous	Not At All	A Little	Moderately	Quite A Lot	Extremely
19. Angry	Not At All	A Little	Moderately	Quite A Lot	Extremely
20. Active	Not At All	A Little	Moderately	Quite A Lot	Extremely
21. Tired	Not At All	A Little	Moderately	Quite A Lot	Extremely
22. Bad Tempered	Not At All	A Little	Moderately	Quite A Lot	Extremely
23. Alert	Not At All	A Little	Moderately	Quite A Lot	Extremely
24. Uncertain	Not At All	A Little	Moderately	Quite A Lot	Extremely

Please indicate why you are completing this mood assessment. Please select one

Figure D.7. The BRUMS questionnaire.



Workplace Health and Safety (WH&S)

Listed below are a number of statements that could be used to describe a variety of factors relating to safety within your workplace. These factors have the potential to influence both your physical and personal safety. Please read each statement carefully and indicate the extent to which you AGREE with each statement by selecting the appropriate answer.

1. Management places a strong emphasis on workplace health and safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

2. Safety is given a high priority by management.

Strongly Disagree Disagree Neutral Agree Strongly Agree

3. Management considers safety to be important.

Strongly Disagree Disagree Neutral Agree Strongly Agree

4. I feel that it is worthwhile to put in effort to maintain or improve my personal safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

5. I feel that it is important to maintain safety at all times.

Strongly Disagree Disagree Neutral Agree Strongly Agree

6. I believe that it is important to reduce the risk of accidents and incidents in the workplace.

Strongly Disagree Disagree Neutral Agree Strongly Agree

7. I use all the necessary safety equipment to do my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

8. I use the correct safety procedures for carrying out my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

9. I ensure the highest levels of safety when I carry out my job.

Strongly Disagree Disagree Neutral Agree Strongly Agree

10. I promote the safety program within the organisation.

Strongly Disagree Disagree Neutral Agree Strongly Agree

11. I put in extra effort to improve the safety of the workplace.

Strongly Disagree Disagree Neutral Agree Strongly Agree

12. I voluntarily carry out tasks or activities that help to improve workplace safety.

Strongly Disagree Disagree Neutral Agree Strongly Agree

Submit

Share: in Share

Copyright 2013 P Terry, J Lim, & R Parsons-Smith. Design by Clint Mallet. All Rights Reserved.

Figure D.8. The WHSS.

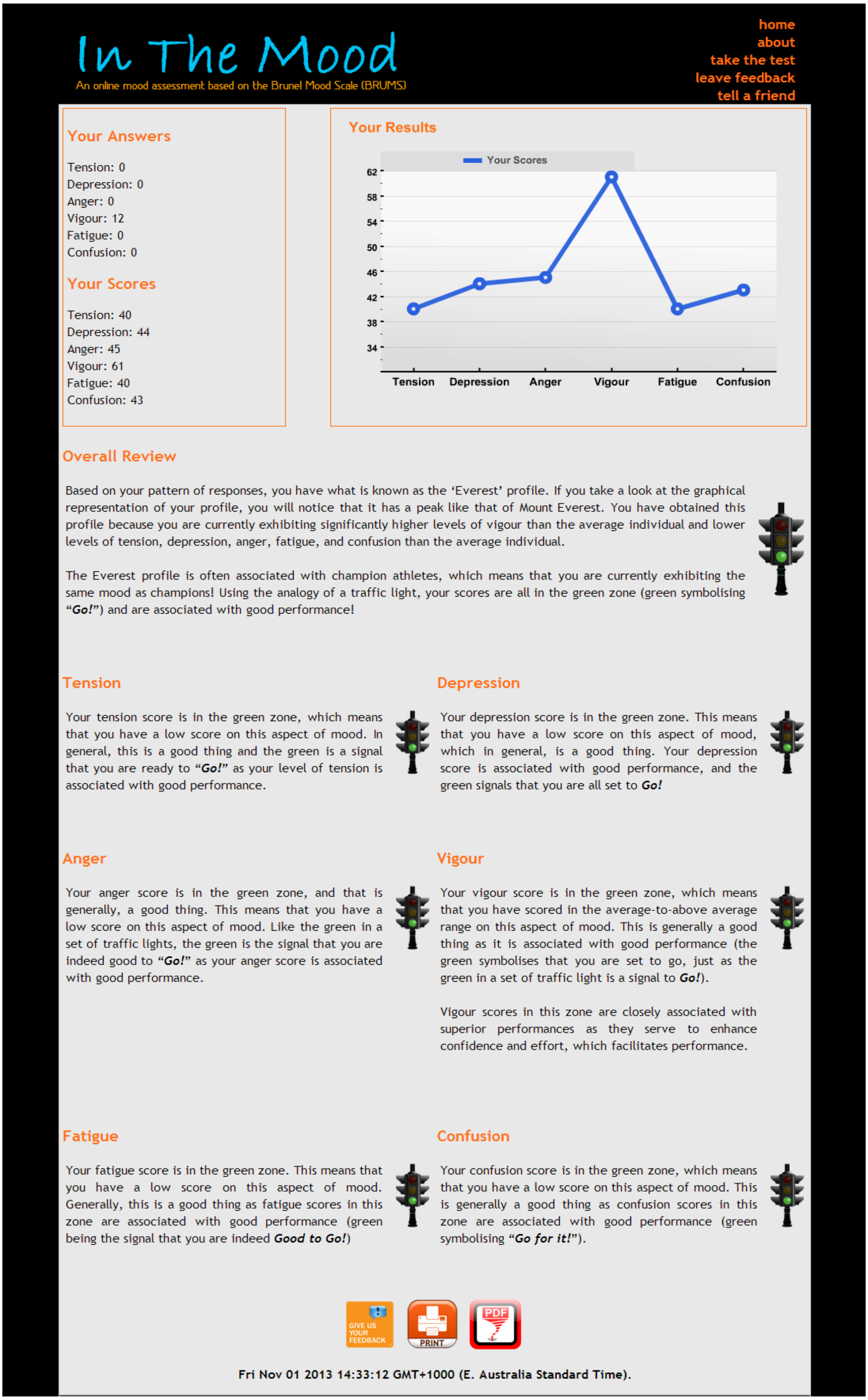
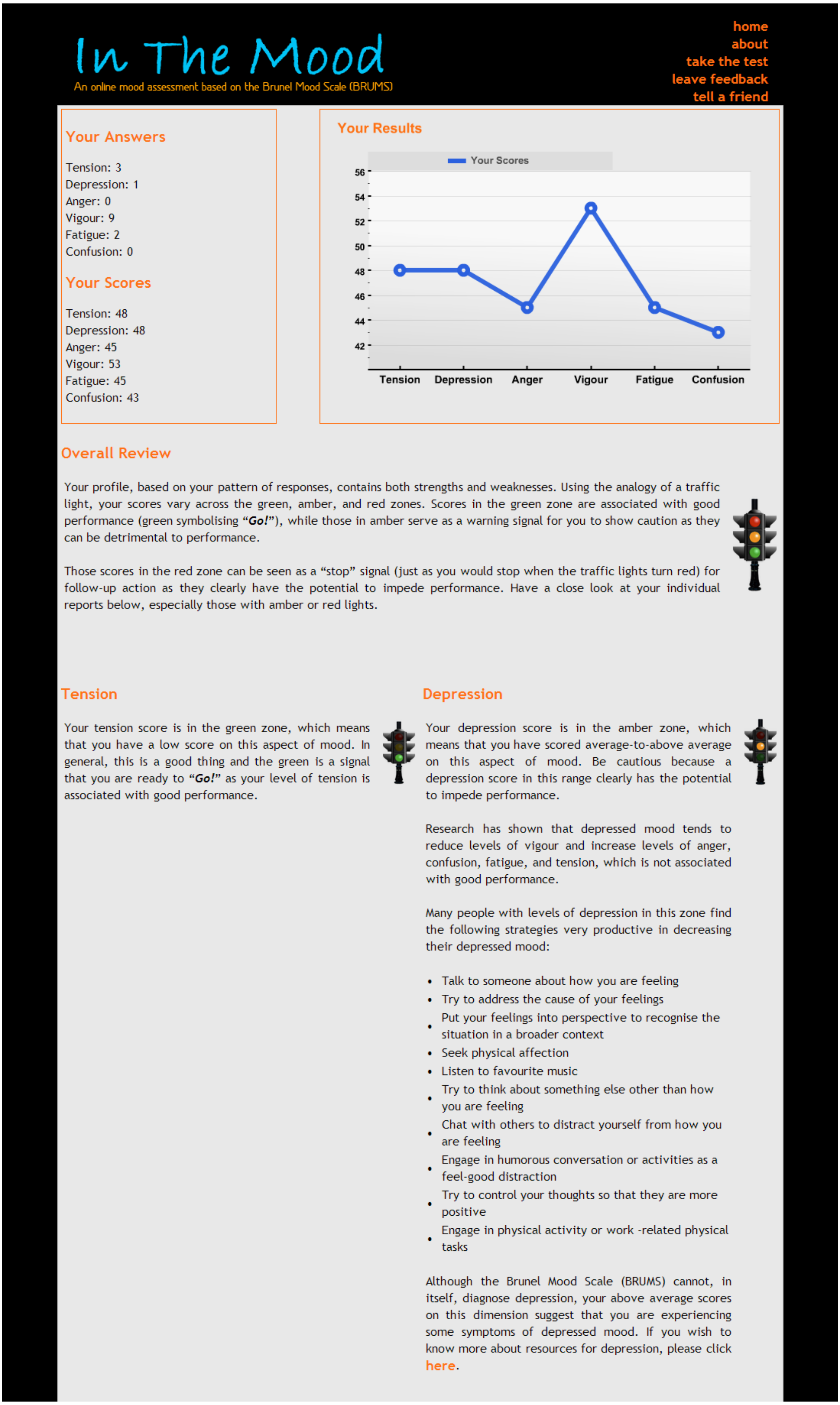


Figure D.9. An example the 'Everest profile' results page.



In The Mood

An online mood assessment based on the Brunel Mood Scale (BRUMS)

home
about
take the test
leave feedback
tell a friend

Your Answers

Tension: 3
Depression: 1
Anger: 0
Vigour: 9
Fatigue: 2
Confusion: 0

Your Scores

Tension: 48
Depression: 48
Anger: 45
Vigour: 53
Fatigue: 45
Confusion: 43

Your Results

Overall Review

Your profile, based on your pattern of responses, contains both strengths and weaknesses. Using the analogy of a traffic light, your scores vary across the green, amber, and red zones. Scores in the green zone are associated with good performance (green symbolising ***"Go!"***), while those in amber serve as a warning signal for you to show caution as they can be detrimental to performance.

Those scores in the red zone can be seen as a "stop" signal (just as you would stop when the traffic lights turn red) for follow-up action as they clearly have the potential to impede performance. Have a close look at your individual reports below, especially those with amber or red lights.

Tension

Your tension score is in the green zone, which means that you have a low score on this aspect of mood. In general, this is a good thing and the green is a signal that you are ready to ***"Go!"*** as your level of tension is associated with good performance.

Depression

Your depression score is in the amber zone, which means that you have scored average-to-above average on this aspect of mood. Be cautious because a depression score in this range clearly has the potential to impede performance.

Research has shown that depressed mood tends to reduce levels of vigour and increase levels of anger, confusion, fatigue, and tension, which is not associated with good performance.

Many people with levels of depression in this zone find the following strategies very productive in decreasing their depressed mood:

- Talk to someone about how you are feeling
- Try to address the cause of your feelings
- Put your feelings into perspective to recognise the situation in a broader context
- Seek physical affection
- Listen to favourite music
- Try to think about something else other than how you are feeling
- Chat with others to distract yourself from how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Try to control your thoughts so that they are more positive
- Engage in physical activity or work -related physical tasks

Although the Brunel Mood Scale (BRUMS) cannot, in itself, diagnose depression, your above average scores on this dimension suggest that you are experiencing some symptoms of depressed mood. If you wish to know more about resources for depression, please click **here**.

Figure D.10. An example of an 'Other profile' results page.

Figure D.11. The revised *In The Mood* ‘Leave feedback’ page.

Figure D.12. Page acknowledging receipt of user feedback.

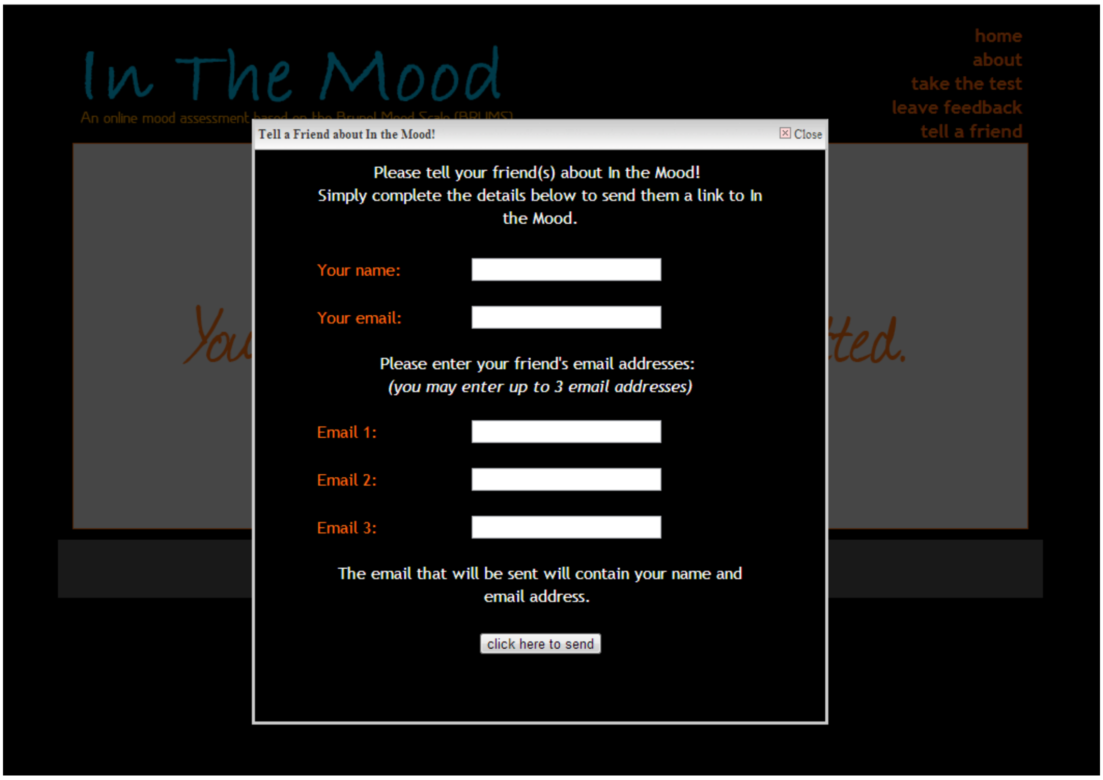


Figure D.13. The revised *In The Mood* 'Tell-a-Friend' feature.

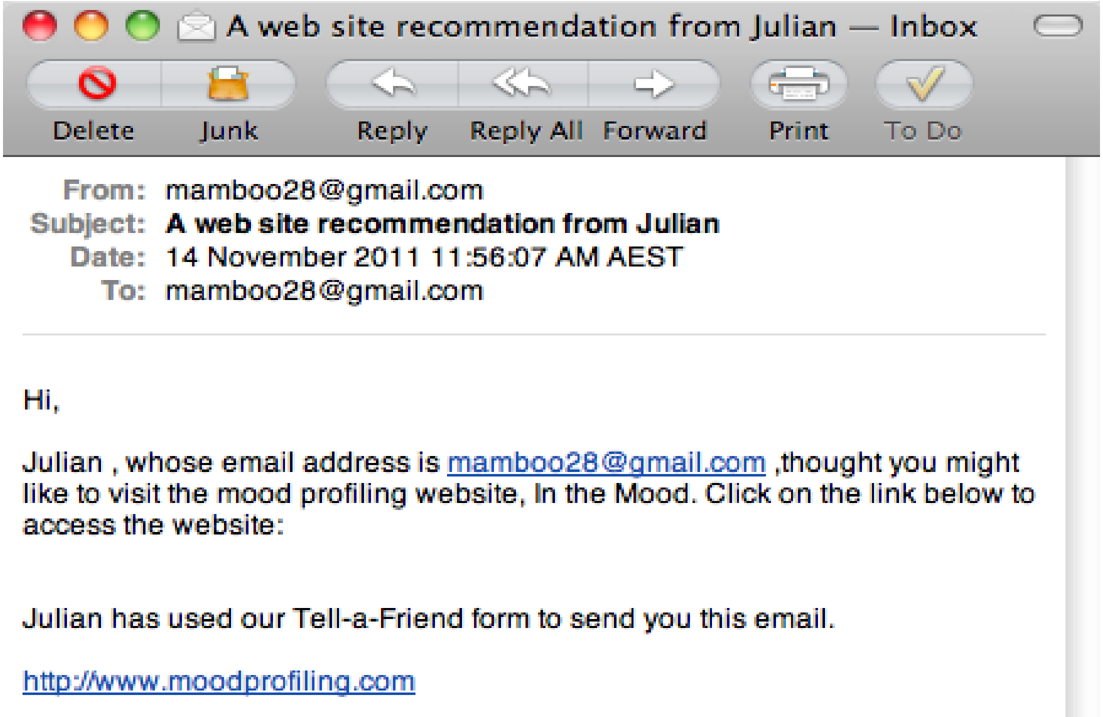


Figure D.14. Sample e-mail invitation.

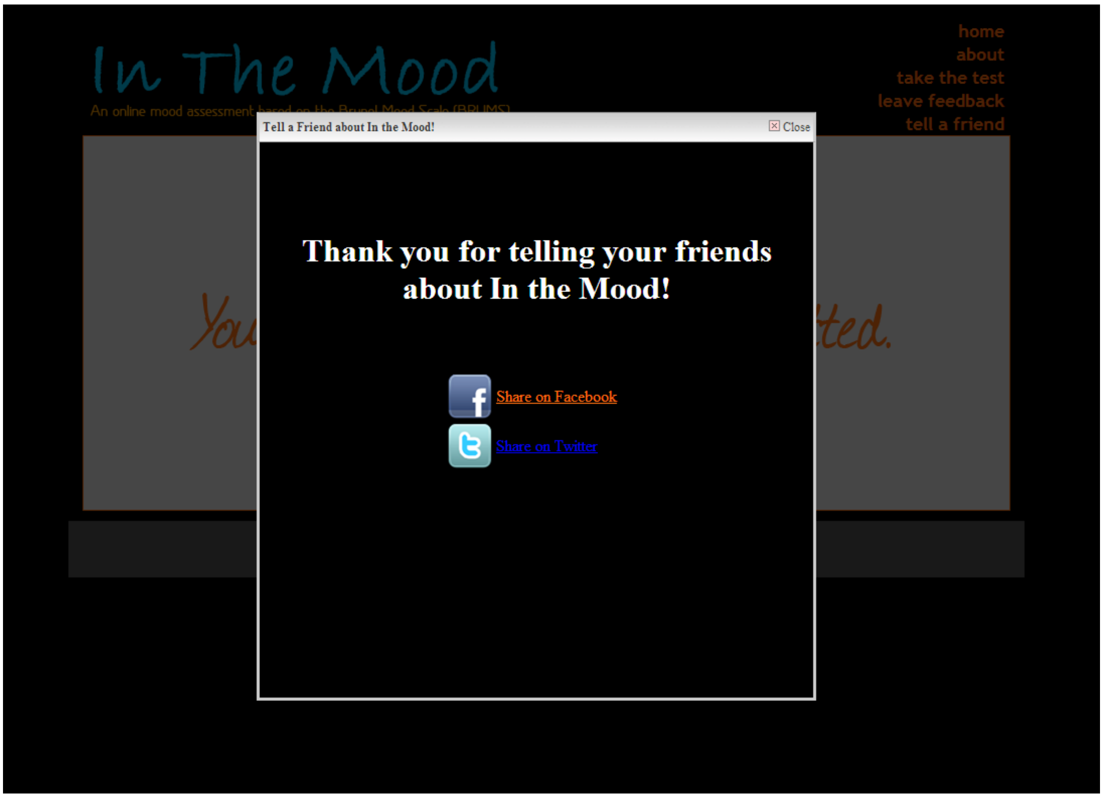


Figure D.15. Acknowledgment of successful submission of the ‘Tell-a-Friend’ form.

Verbatim Profile Summary Reports from *In The Mood*

Everest profile. Based on your pattern of responses, you have what is known as the Everest profile. If you take a look at the graphical representation of your profile, you will notice that it has a peak like that of Mount Everest. You have obtained this profile because you are currently exhibiting significantly higher levels of vigour than the average individual and lower levels of tension, depression, anger, fatigue, and confusion than the average individual. The Everest profile is often associated with champion athletes, which means that you are currently exhibiting the same mood as champions! Using the analogy of a traffic light, your scores are all in the green zone (green symbolising Go!) and are associated with good performance!

Iceberg profile. Based on your pattern of responses, you have what is known as the Iceberg profile. If you take a look at the graphical representation, you will notice that your profile has the shape of an iceberg, hence its name. This profile is characterised by higher levels of vigour and lower levels of tension, depression, anger, fatigue, and confusion than the average individual. The Iceberg profile is often associated with elite athletes, which means that you are currently exhibiting the same mood as an elite athlete. Using the analogy of a traffic light, your scores are all in the green zone (green symbolising Go!) and are associated with good performance!

Inverse iceberg profile. You are clearly not feeling your best at the moment! Your profile, based on your pattern of responses, is known as the Inverse Iceberg. If you have a look at the graphical representation, you will notice how your profile has the shape of an inverted iceberg. The inverse iceberg profile is characterised by a lower level of vigour, and higher levels of tension, depression, anger, fatigue, and confusion than the average individual. This type of mood profile is associated with a poor state of physical and mental functioning. Using the analogy of a traffic light, your scores are all in the amber or red zones. Those in the amber zone serve as a warning signal for you to slow down or prepare to stop and to pay close attention to them, as they can be detrimental to performance. Those scores in the red zone act as a signal (just as you would stop when the traffic lights turn red) for follow-up action as they clearly have the potential to impede performance. Have a look at some of the reports below, particularly those with red lights.

‘Other’ profile. Your profile, based on your pattern of responses, contains both strengths and weaknesses. Using the analogy of a traffic light, your scores vary across the green, amber, and red zones. Scores in the green zone are associated with good performance (green symbolising Go!), while those in amber serve as a warning signal for you to show caution, as they can be detrimental to performance. Those scores in the red zone can be seen as a stop signal (just as you would stop when the traffic lights turn red) for follow-up action as they clearly have the potential to impede performance. Have a close look at your individual reports below, especially those with amber or red lights.

Verbatim Profile Summary Reports According to Mood Dimension

Tension dimension of mood.

Green category: Your tension score is in the green zone, which means that you have a low score on this aspect of mood. In general, this is a good thing and the green is a signal that you are ready to Go! as your level of tension is associated with good performance.

Amber category: Your tension score is in the amber range. This means that you have scored average-to-above average on this aspect of mood, which is generally a good thing as it is associated with good performance. A level of tension in this range can increase alertness and narrow attention to focus on task-relevant cues, leading to a readiness to perform that facilitates performance. However, be cautious because a further increase in tension may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques to reduce your tension
- Follow your usual routine
- Use task-related imagery to prepare you for the task ahead
- Listen to favourite music
- Engage in a physical activity or work-related physical tasks
- Engage in religious or spiritual activities
- Focus on task-related strategies to minimise negative impacts on your performance
- Give yourself a pep talk using upbeat self-talk
- Talk with others to distract yourself from your feelings
- Keep busy to distract yourself from the feeling

Red category: Your tension score is in the red zone and means that you have scored well above average on this aspect of mood. The red light serves as a signal for you to stop (just as you would stop at a set of red traffic lights) as they clearly have the potential to impede performance. Be aware that a level of tension in this range signals the likelihood that performance will be affected unless some form of action is taken, such as increasing effort or concentration. Be aware too that a further increase in tension can lead to being over-alert, which may inhibit attention and cause performance-relevant cues to be missed, potentially interfering with performance. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques to reduce your tension
- Follow your usual routine
- Use task-related imagery to prepare you for the task ahead
- Listen to favourite music
- Engage in a physical activity or work-related physical tasks
- Engage in religious or spiritual activities
- Focus on task-related strategies to minimise negative impacts on your performance
- Give yourself a pep talk using upbeat self-talk
- Talk with others to distract yourself from your feelings
- Keep busy to distract yourself from the feeling

Depression dimension of mood.

Green category: Your depression score is in the green zone. This means that you have a low score on this aspect of mood, which in general, is a good thing. Your depression score is associated with good performance, and the green signals that you are all set to Go!

Amber category: Your depression score is in the amber zone, which means that you have scored average-to-above average on this aspect of mood. Be cautious because a depression score in this range clearly has the potential to impede performance. Research has shown that depressed mood tends to reduce levels of vigour and increase levels of anger, confusion, fatigue, and tension, which is not associated with good performance. Many people with levels of depression in this zone find the following strategies very productive in decreasing their depressed mood:

- Talk to someone about how you are feeling
- Try to address the cause of your feelings
- Put your feelings into perspective to recognise the situation in a broader context
- Seek physical affection
- Listen to favourite music
- Try to think about something else other than how you are feeling
- Chat with others to distract yourself from how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Try to control your thoughts so that they are more positive
- Engage in physical activity or work-related physical tasks

Although the Brunel Mood Scale (BRUMS) cannot, in itself, diagnose depression, your above average scores on this dimension suggest that you are experiencing some symptoms of depressed mood. If you wish to know more about resources for depression, please see below.

Sometimes, when people fill out mood questionnaires, they become more aware of their own negative feelings. If this happens to you, and if you are concerned about your mood or are feeling depressed, it is recommended that you consider seeking help either from your General Practitioner or seek useful resources from one of the local institutes listed below:

- Lifeline Australia 13 11 14
- Beyond Blue 1300 22 4636
- Black Dog Institute

Red category: Your depression score is in the red zone. This means that you have scored well above average on this aspect of mood, and this is generally not a good thing. A depression score in this range clearly has the potential to interfere with performance and thus, like the red in a traffic light, the red here serves as a signal for you to stop and take follow-up action. Research has shown that depressed mood tends to reduce levels of vigour, and increase levels of anger, confusion, fatigue, and tension, which is not associated with good performance. Many people with levels of depression in this zone find the following strategies very productive in decreasing their feelings of depressed mood:

- Talk to someone about how you are feeling
- Try to address the cause of your feelings
- Put your feelings into perspective to recognise the situation in a broader context
- Seek physical affection
- Listen to favourite music
- Try to think about something else other than how you are feeling
- Chat with others to distract yourself from how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Try to control your thoughts so that they are more positive
- Engage in physical activity or work-related physical tasks

Although the Brunel Mood Scale (BRUMS) cannot, in itself, diagnose depression, your above average scores on this dimension suggest that you are experiencing some symptoms of depressed mood. If you wish to know more about resources for depression, please see below.

Sometimes, when people fill out mood questionnaires, they become more aware of their own negative feelings. If this happens to you, and if you are concerned about your mood or are feeling depressed, it is recommended that you consider seeking help either from your General Practitioner or seek useful resources from one of the local institutes listed below:

- Lifeline Australia 13 11 14
- Beyond Blue 1300 22 4636
- Black Dog Institute

Anger dimension of mood.

Green category: Your anger score is in the green zone, and that is generally, a good thing. This means that you have a low score on this aspect of mood. Like the green in a set of traffic lights, the green is the signal that you are indeed good to Go! as your anger score is associated with good performance.

Amber category: Your anger score is in the amber zone, which means that you have scored average-to-above average on this aspect of mood. That is generally a good thing as anger levels in this range is generally associated with good performance. A level of anger in this range can be channeled productively into determination to succeed. The result is an increase in effort, which facilitates performance. However, do be cautious because a further increase in anger may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Use relaxation techniques to calm yourself
- Spend time alone to think about how you can address the situation
- Try to avoid the cause of your anger
- Listen to favourite music
- Focus on task-related strategies to minimise negative impacts on your

performance

- Put your feelings into perspective to recognise the situation in a broader context
- Express yourself to let your feelings out
- Talk to someone about how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Engage in physical activities to reduce the feelings

Red category: Your anger score is in the red zone. This means that you have scored well above average on this aspect of mood. Like the red light you would encounter at a set of traffic lights, this serves as an indication for you to stop because scores in this zone clearly have the potential to interfere with performance. While anger can be channeled productively into determination to succeed, be aware that a level of anger in this range can result in being over-alert. This can inhibit attention and cause performance-relevant cues to be missed, which may lead to a decline in performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Use relaxation techniques to calm yourself
- Spend time alone to think about how you can address the situation
- Try to avoid the cause of your anger
- Listen to favourite music
- Focus on task-related strategies to minimise negative impacts on your performance
- Put your feelings into perspective to recognise the situation in a broader context

- Express yourself to let your feelings out
- Talk to someone about how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Engage in physical activities to reduce the feelings

Vigour dimension of mood.

Green category: Your vigour score is in the green zone, which means that you have scored well above average on this aspect of mood. This is generally a good thing as it is associated with good performance (the green symbolises that you are set to go, just as the green in a set of traffic light is a signal to Go!). Vigour scores in this zone are closely associated with superior performances as they serve to enhance confidence and effort, which facilitates performance.

Amber category: Your vigour score is in the amber zone, which means that you have scored in the average-to-above average range on this aspect of mood. Generally speaking, this is not associated with good performance. Do proceed with caution because a level of vigour in this range can cause a decrease in confidence and effort, which can potentially interfere with performance. Some of the most effective strategies demonstrated by research to increase feelings of vigour are:

- Engage in physical activity to increase energy
- Try to control your thoughts so that they are more positive
- Use task-related imagery to help you to feel ready to perform
- Listen to favourite music with a fast, upbeat style
- Focus on task-related strategies to minimise negative impacts on your performance
- Put your feelings into perspective by accepting that low vigour is

normal from time to time

- Engage in humorous conversation or activities
- Eat a nutritional snack
- Drink a caffeinated beverage
- Give yourself a pep talk using upbeat self-talk

Red category: Your vigour score is in the red zone, which means that you have a low score on this aspect of mood. Generally speaking, this is not associated with good performance. A level of vigour in this range can lead to a reduction in effort and confidence, and thus, like a set of traffic lights, the red is a signal for you to stop as your level of vigour clearly has the potential to impede performance. Some of the most effective strategies demonstrated by research to increase feelings of vigour are:

- Engage in physical activity to increase energy
- Try to control your thoughts so that they are more positive
- Use task-related imagery to help you to feel ready to perform
- Listen to favourite music with a fast, upbeat style
- Focus on task-related strategies to minimise negative impacts on your performance
- Put your feelings into perspective by accepting that low vigour is normal from time to time
- Engage in humorous conversation or activities
- Eat a nutritional snack
- Drink a caffeinated beverage
- Give yourself a pep talk using upbeat self-talk

Fatigue dimension of mood.

Green category: Your fatigue score is in the green zone. This means that you have a low score on this aspect of mood. Generally, this is a good thing as fatigue scores in this zone are associated with good performance (green being the signal that you are indeed Good to Go!).

Amber category: Your fatigue score is in the amber zone. This means that you have scored average-to-above average on this aspect of mood, and is in general, not associated with good performance. Do be cautious because a level of fatigue in this range can lead to a reduction in confidence and effort, which may cause performance to decline. Some of the most effective strategies demonstrated by research to decrease feelings of fatigue are:

- Use relaxation techniques to re-energise yourself
- Have a rest, take a nap, or sleep
- Put your feelings into perspective by accepting that fatigue is normal from time to time
- Have a massage
- Listen to favourite music
- Splash your face with cold water
- Take a shower or bath
- Eat a nutritional snack to increase energy
- Engage in light physical activity or non-strenuous physical tasks
- Keep busy to distract yourself from the feeling

Red category: Your fatigue score is in the red zone, which means that you have scored well above average on this aspect of mood. Scores in the red zone serve as a stop signal as they clearly have the potential to impede performance. A level of fatigue in this range can lead to a reduction in effort and confidence, which can interfere with performance. Some of the most effective strategies demonstrated by research to decrease feelings of fatigue are:

- Use relaxation techniques to re-energise yourself
- Have a rest, take a nap, or sleep
- Put your feelings into perspective by accepting that fatigue is normal from time to time
- Have a massage
- Listen to favourite music
- Splash your face with cold water
- Take a shower or bath
- Eat a nutritional snack to increase energy
- Engage in light physical activity or non-strenuous physical tasks
- Keep busy to distract yourself from the feeling

Confusion dimension of mood.

Green category: Your confusion score is in the green zone, which means that you have a low score on this aspect of mood. This is generally a good thing as confusion scores in this zone are associated with good performance (green symbolising Go for it!).

Amber category: Your confusion score is in the amber zone. This means that you have scored average-to-above average on this aspect of mood, which is generally not associated with good performance. Proceed with caution because a confusion score in this range may lead to difficulties with attention and concentration, which can impede performance. Some of the most effective strategies demonstrated by research to decrease feelings of confusion are:

- Try to address the cause of your confusion
- Concentrate on task-related strategies to clarify what is required
- Try to think positively until your confusion subsides
- Talk to someone about your confusion to clarify things
- Mentally switch off for awhile to give yourself a break
- Give yourself a pep talk using upbeat self-talk
- Engage in humorous conversation or activities as a feel-good distraction
- Spend some time alone to consider the issues
- Write your thoughts and feelings down to clarify things
- Engage in task-related imagery to identify what is required

Red category: Your confusion score is in the red zone, which means that you have scored well above average on this aspect of mood. Scores in this zone serve as a stop signal for follow-up action as they clearly have the potential to impede performance. A level of confusion in this range can lead to difficulties with attention and concentration, which can interfere with performance. Some of the most effective strategies demonstrated by research to decrease feelings of confusion are:

- Try to address the cause of your confusion
- Concentrate on task-related strategies to clarify what is required
- Try to think positively until your confusion subsides
- Talk to someone about your confusion to clarify things
- Mentally switch off for awhile to give yourself a break
- Give yourself a pep talk using upbeat self-talk
- Engage in humorous conversation of activities as a feel-good distraction

- Spend some time alone to consider the issues
- Write your thoughts and feelings down to clarify things
- Engage in task-related imagery to identify what is required

Verbatim Profile Summary Reports for the Moderating Effects of Depression on Tension and Anger

Tension dimension of mood.

Amber category: Your tension score is in the amber zone, which means that you have scored in the average-to-above average range on this aspect of mood. In general, this is not associated with good performance. A level of tension in this range can intensify the negative symptoms of depressed mood that you have reported (see Depression aspect), and raise feelings of threat and worry which can impede performance. Increasing levels of tension may also lead to being over-alert, which can impair attention and result in important performance-relevant cues being missed. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques to reduce your tension
- Follow your usual routine
- Use task-related imagery to prepare you for the task ahead
- Listen to favourite music
- Engage in a physical activity or work-related physical tasks
- Engage in religious or spiritual activities
- Focus on task-related strategies to minimise negative impacts on your performance
- Give yourself a pep talk using upbeat self-talk
- Talk with others to distract yourself from your feelings

- Keep busy to distract yourself from the feeling

Red category: Your tension score is in the red zone. This means that you have scored well above average on this aspect of mood. The red serves as a signal for you to stop (just as you would stop at a set of red traffic lights) because a level of tension in this range clearly has the potential to impede performance. Given that you have reported some symptoms of depressed mood (see Depression aspect), a level of tension in this range can interfere with performance by increasing negative self-thoughts and promote feelings of threat and worry. A further increase in tension may also lead to being over-alert, which can inhibit attention and cause important performance-relevant cues to be missed. Some of the most effective strategies demonstrated by research to decrease feelings of tension are:

- Use relaxation techniques to reduce your tension
- Follow your usual routine
- Use task-related imagery to prepare you for the task ahead
- Listen to favourite music
- Engage in a physical activity or work-related physical tasks
- Engage in religious or spiritual activities
- Focus on task-related strategies to minimise negative impacts on your performance
- Give yourself a pep talk using upbeat self-talk
- Talk with others to distract yourself from your feelings
- Keep busy to distract yourself from the feeling

Anger dimension of mood.

Amber category: Your anger score is in the amber range, which means that you have scored average-to-above average on this aspect of mood. Scores in this range are usually not associated with good performance. As you have reported some symptoms of depressed mood (see Depression aspect), there is likelihood that you will turn this anger on yourself. This can intensify feelings of frustration, hopelessness, and/or self-blame, which can impede performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Use relaxation techniques to calm yourself
- Spend time alone to think about how you can address the situation
- Try to avoid the cause of your anger
- Listen to favourite music
- Focus on task-related strategies to minimise negative impacts on your performance
- Put your feelings into perspective to recognise the situation in a broader context
- Express yourself to let your feelings out
- Talk to someone about how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Engage in physical activities to reduce the feelings

Red category: Your anger score is in the red zone. This means that you have scored well above average on this aspect of mood. Very much like how you would stop at the red lights along a traffic junction, the red here serves as a signal for you to stop because a level of anger in this range clearly has the potential to interfere with performance. Given that you have reported some symptoms of depressed mood (see Depression aspect), this can lead to a reduction in self-confidence. There is also a possibility that you may turn this anger on yourself, which may subsequently intensify feelings of frustration, hopelessness, and/or self-blame. This can lead to a reduction in motivation that is detrimental to performance. Some of the most effective strategies demonstrated by research to decrease feelings of anger are:

- Use relaxation techniques to calm yourself
- Spend time alone to think about how you can address the situation
- Try to avoid the cause of your anger
- Listen to favourite music
- Focus on task-related strategies to minimise negative impacts on your performance
- Put your feelings into perspective to recognise the situation in a broader context
- Express yourself to let your feelings out
- Talk to someone about how you are feeling
- Engage in humorous conversation or activities as a feel-good distraction
- Engage in physical activities to reduce the feelings

Appendix E

Visual Summary of the Six-Cluster Solution Across Samples

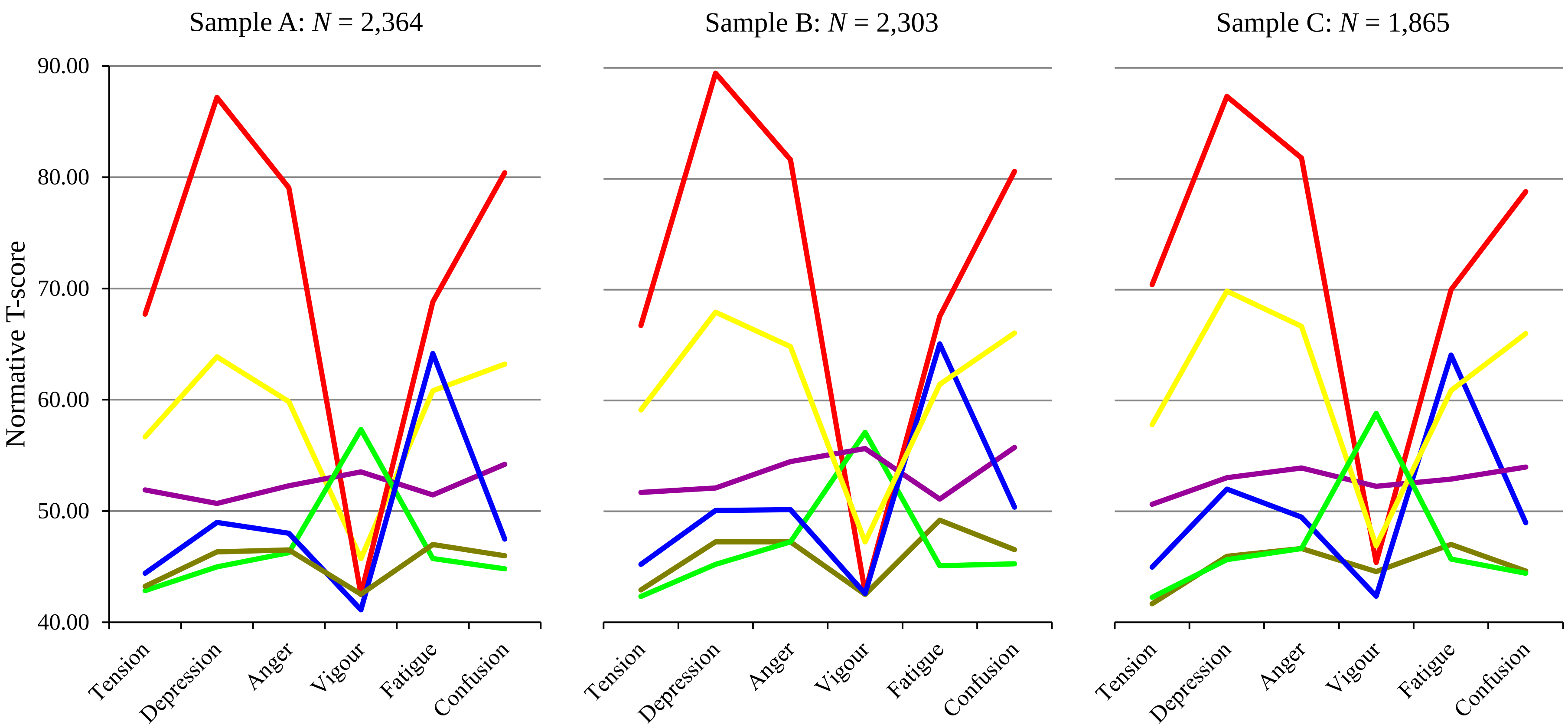


Figure E.1. Comparisons of mood profiles according to sample.

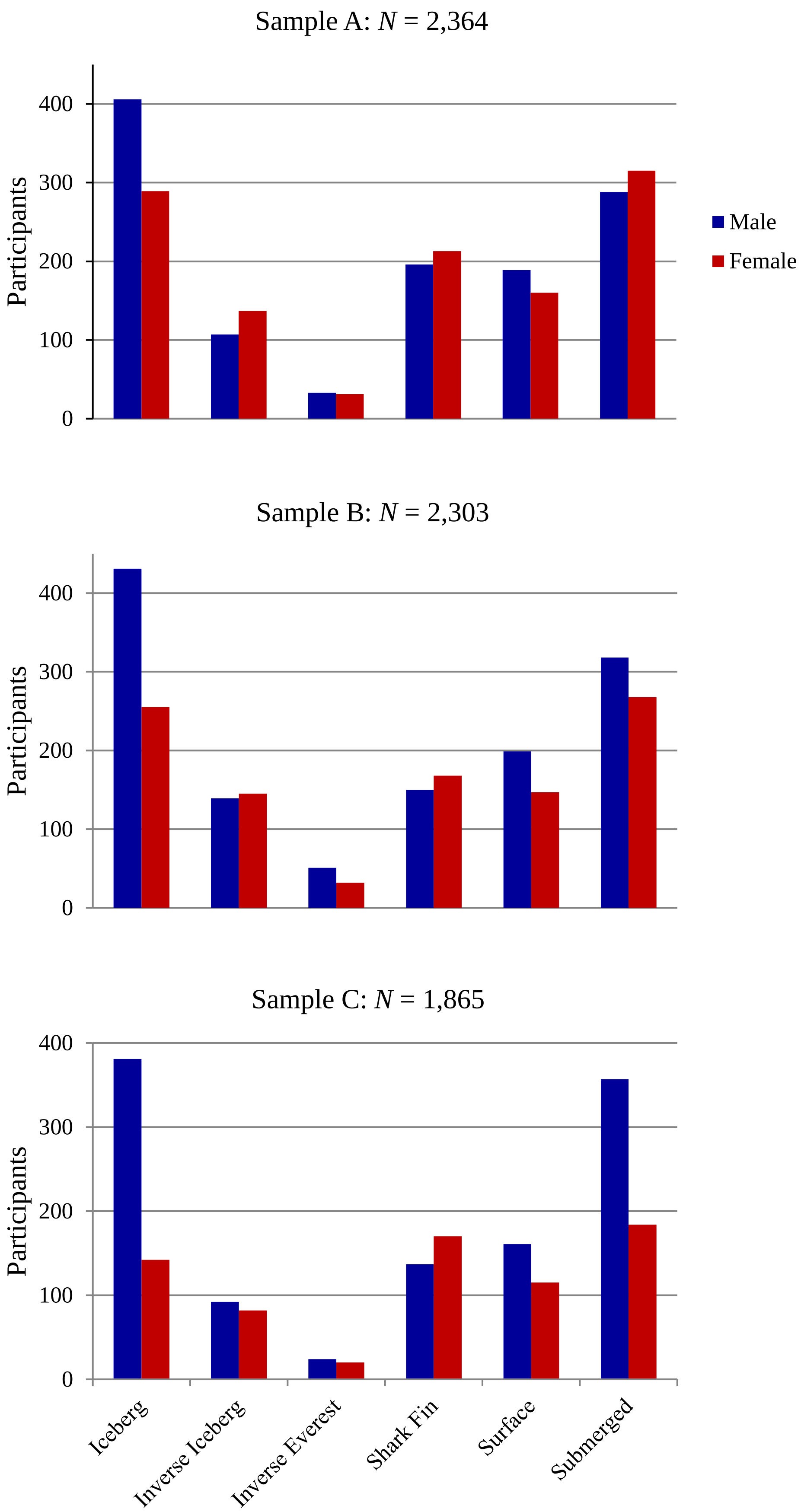


Figure E.2. Comparisons for gender according to designated cluster order.

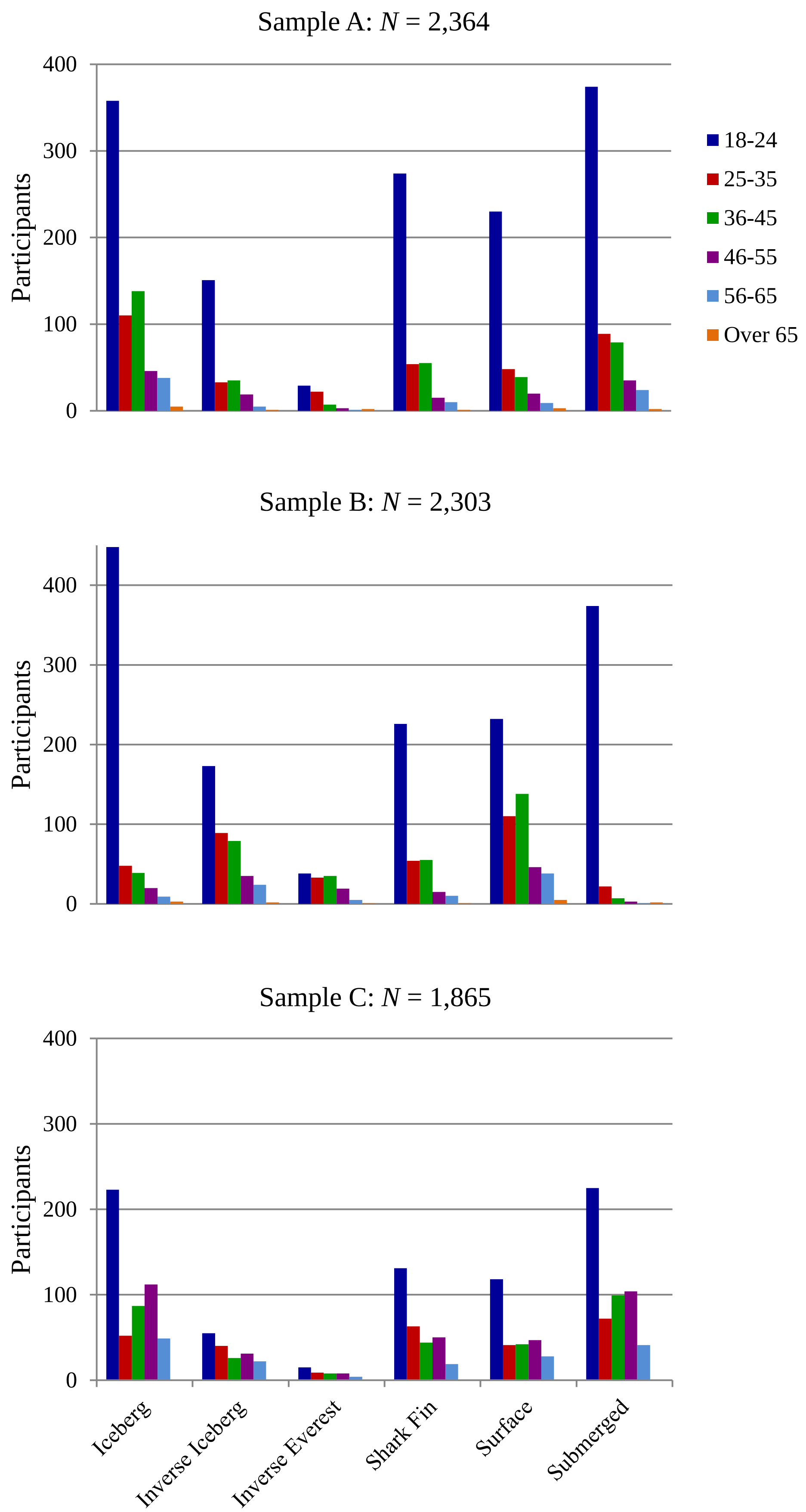


Figure E.3. Comparisons for age according to designated cluster order.

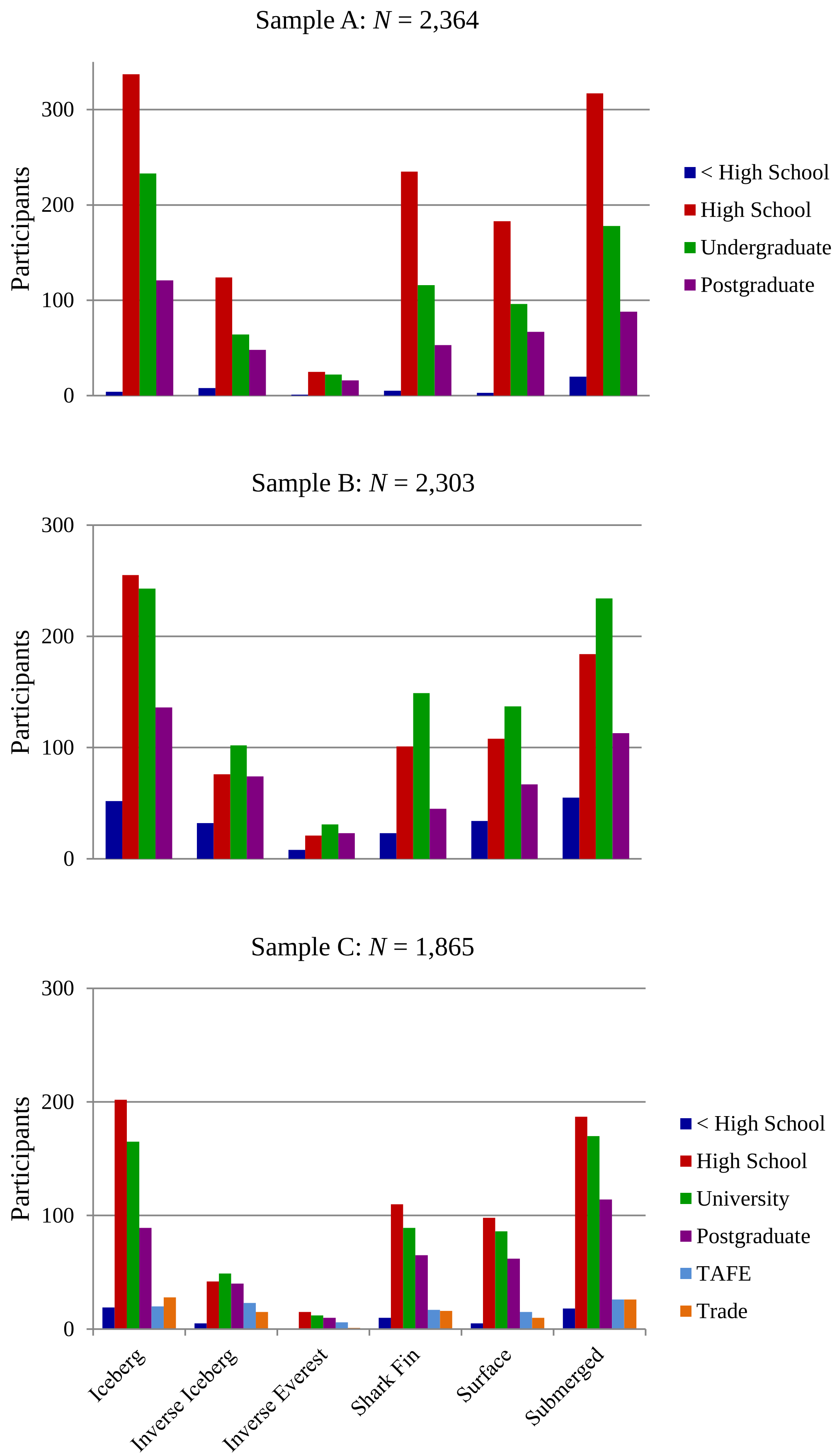


Figure E.4. Comparisons for education according to designated cluster order.