Subjective Wellbeing: An Assessment of Competing Theories

By

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Submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

Deakin University

June 2008

I certify that the thesis entitled: Subjective Wellbeing: An Assessment of Competing Theories

submitted for the degree of: Doctor of Philosophy

is the result of my own work and that where reference is made to the work of others, due acknowledgment is given.

I also certify that any material in the thesis which has been accepted for a degree or diploma by any university or institution is identified in the text.

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Acknowledgements

First and foremost I would like to thank my supervisor, Professor Mark Stokes. Mark, through your supervision you provided me the challenges and stimulation I needed and desired for intellectual growth. For this I am incredibly grateful. The value of your guidance, both professional and personal, is incalculable. Also to my mum, Angela, thank you; not only for your sacrifices that have helped bring me to this point, but also for your love and support. To my dad, Graeme, your encouragement and belief in my abilities helped keep me going when the motivation fell. Thank you for your love and support. To my brother John and my sister Rosa, thank you for your love, care, friendship, and understanding. Thanks also to my extended family for your encouragement and love. To my fellow Deakin "dungeon" crew, thanks for your friendship; especially to my fellow PhD's, Ardy, Johann, and Matt. I have no doubt the friendships we have forged will last a lifetime. A special thanks also go to my best friend, Caline. We've had an incredible relationship over the past few years; I sincerely appreciate and value the care and support you have given me. Thanks also to my close mate John and the rest of "team globe", our bodyboarding adventures helped keep me sane throughout this thesis. To the other Tomyn brothers, Justin and Luke, thanks for your fantastic friendship. To Greg, Claire, Rob, and Terry, you're incredible generosity helped build a space for me to study and live, without which this thesis would have been a little more difficult to say the least. Also thanks to Frank O'Dea whose encouragement and support was invaluable in the latter years of my high school education. Lastly, to my grandad Ernie, you pulled through and I owe you a completed thesis. Here it is.

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GLOSSARY

%SM: percentage of scale maximum

AIC: Akaike's Information Criterion

AGFI: Adjusted Goodness of Fit Index

ANEW: Affective Norms for English Words

AUWBI 8: Eighth survey of the Australian Unity Wellbeing Index

BDI: Beck Depression Inventory

BAWLC: Balanced Affective Word List Creation

CFI: Comparative Fit Index

DASS: Depression, Anxiety, and Stress Scale

Df: Degrees freedom

DV: Dependent Variable

ESM: Experience Sampling Methodology

FDR: False Discovery Rate procedure

GDP: Gross Domestic Product

GNP: Gross National Product

GT: Global Trait measurement

L-AUWBI 5: Fifth longitudinal survey of the Australian Unity Wellbeing Index

L-AUWBI 6: Sixth longitudinal survey of the Australian Unity Wellbeing Index

L-AUWBI 7: Seventh longitudinal survey of the Australian Unity Wellbeing Index

LDT: Lexical Decision Task

LOT-R: Life Orientation Test – Revised

LS: Life Satisfaction

M: Mean

MDT: Multiple Discrepancies Theory

MLM: Multi-Level Model(ling)

MR: Multiple Regression

MS*:* Mean State measurement

ms: Milliseconds

NA: Negative Affect

NEO-PI-R: NEO Personality Inventory, Revised

NFI: Normed Fit Index

NoP: No Priming

NP: Negative Priming

NvN: Negative versus Neutral task

P-A: Pleasant-Activated affect

PA: Positive Affect

PACA: Pleasant-Activated Core Affect

PANAS: Positive and Negative Affect Schedule

PDA: Personal Data Assistant

PLS: Plain Language Statement

PMAT: Purdue Momentary Assessment Tool

PP: Positive Priming

PvN: Positive versus Neutral task

PWI: Personal Wellbeing Index

QOL: Quality of Life

R: Recalled measurement

ResNvN: Residualised Reaction Time for Negative versus Neutral Task

ResPvN: Residualised Reaction Time for Positive versus Neutral Task

RMSEA: Root Mean Squared Error of Approximation

RSE: Rosenberg Self-Esteem scale

RT: Reaction Time

SD: Standard Deviation

SEM: Structural Equation Model(ling)

SMC: Squared Multiple Correlation

SWB: Subjective Wellbeing

SWLS: Satisfaction with Life Scale

TIPI: Ten Item Personality Inventory

VIT: Valence Identification Task

CHAPTER 3: STUDY 1

Section 3.1: INTRODUCTION AND METHODOLOGY

Introduction

Homeostatic theory, MDT, and affective-cognitive theory represent three divergent yet plausible explanations of SWB. Each theory posits a different mechanism by which SWB is driven. For homeostatic theory, SWB is predominantly driven by extroversion and neuroticism and the operation of a cognitive buffer system, comprised of the variables self-esteem, optimism, and perceived control. In contrast, MDT posits SWB to be directly influenced by a set of perceived discrepancies relating to an individual's circumstances. Finally in the affective-cognitive model of SWB, affect both directly, and indirectly (through personality and MDT), influences SWB. Together these three theories provide important advancements to an understanding of the influences and processes that operate in forming judgements of SWB. However, homeostatic theory, MDT, and affective-cognitive theory have yet to be empirically contrasted to each other, and as such, no strong conclusions can be drawn as to the efficacy of any of these models. It may be entirely possible that all three are important and contribute unique variance, or it may be that one or two of the theories are inadequate relative to the others. Therefore, the aim of the current study was to contrast the three theoretical models of SWB. In accordance with previous research, it was hypothesised that MDT would account for unique variance in SWB but that this effect would be small relative to homeostatic theory. In addition, it was hypothesised that a model specified from homeostatic theory would provide a superior fit to the data than an affective-cognitive model.

Participants

The subjective wellbeing of the Australian population is sampled quarterly by the Australian Unity Wellbeing Index (Cummins, Davern, Okerstrom, Lo, & Eckersley, 2005). Each sample comprises 2,000 Australians proportionally representative of the geographic distribution of the national population aged 18 and over. Individuals were contacted through randomly selected telephone numbers within the defined geographic region. Upon completion of the telephone interview, participants were asked if they would be willing to join the longitudinal wellbeing project.

This sample comprised the 38% of individuals that responded to the fifth longitudinal survey of the Australian Unity Wellbeing Index (April, 2005; henceforth L-AUWBI 5). In total, 577 surveys were mailed to participants and 387 were returned, yielding a 67% response rate. Of the 387 participants, 45% were male and 55% female. Participants ranged in age from 19 to 85 years old, with a mean age of 56.5 years (*SD*=14.72).

Materials

Subjective Wellbeing

The questionnaire included two measures of SWB. The first measure was a global evaluation of life satisfaction, believed to be a necessary characteristic of SWB (Diener, 1984). This item asked participants to rate "How satisfied are you with your life as a whole?" on a 0 (very dissatisfied) to 10 (completely satisfied) bipolar scale. It has been argued that this global evaluation is problematic in that responses are often influenced by a variety of heuristic strategies (such as current mood) due to the abstract nature of the question (Schwarz & Strack, 1999). As such, the second measure of SWB implemented in the current study (the Personal Wellbeing Index, PWI: International Wellbeing Group, 2005) assessed SWB via a domain-based approach. This approach, in contrast to the global approach, involves well-defined criteria. Specifically, the individual is restricted to considering only events and judgements associated with a particular domain. This restriction is thought to reduce the influence of heuristics by diminishing the level of abstraction required to answer the question (Schwarz & Strack, 1999; Schwarz et al., 1987).

The PWI was developed to represent the first level deconstruction of "life as a whole" and includes only those domains that contribute unique variance when regressed against "satisfaction with life as a whole" (International Wellbeing Group, 2005). Scores across seven domains; standard of living, health, achieving in life, relationships, safety, community connectedness, and future security, are aggregated and averaged to form the PWI (see Appendix A). This index has shown remarkable stability across 12 separate geographically representative surveys of the Australian population (each survey $N \approx 2,000$), with a maximum variation in mean scores of only 3.1% (Cummins et al., 2005).

The index has sound psychometric properties as documented by Cummins, Eckersley, Lo, Okerstrom, Hunter, and Davern (2004). These authors found that the combination of the domains of the PWI, across nine surveys, predicted between 48 and 52% of variance in satisfaction with life as a whole. The stability in the PWI was also evident at the domain level, with a maximum variation in beta-weights for each domain predicting LS of 11%. The maximum change in unique variance that each domain accounted for in LS was 4.4%. In addition, the within domain variation in satisfaction scores for the most volatile domain was only 4.0% across the nine surveys. Thus the PWI is a stable and strong predictor of variance in LS. Previous research conducted by Cummins, Eckersley, Pallant, Van Vugt, and Misajon (2003) on 2,000 Australians supports this conclusion. In this research each domain of the PWI was found to contribute significant unique variance to the prediction of LS (*mean* sr^2=.02) with the exception of the domain *safety* (sr^2=.00). Together, the seven domains predicted 53% of variance in LS. Similar results were found by Tiliouine, Cummins, and Davern (2006) in a sample of 1,417 Algerians. Each domain of the PWI contributed significant unique variance to the prediction of LS (*mean* sr^2=.02), with the exception of *safety* (sr^2=.00). Together the seven domains predicted 57% of the variance in LS.

The reliability of the PWI has been found to be adequate in two recent studies of Australian and Hong Kong participants (Lau, Cummins, & McPherson, 2005) and Algerian participants (Tiliouine et al., 2006). In the study conducted by Lau et al. the Cronbach's alpha for the PWI in 180 Australian participants was .73, whilst the Cronbach's alpha for the PWI in 180 Hong Kong participants was .80. In the study conducted by Tiliouine et al. the Cronbach's alpha for 1,417 Algerian participants was .85. In addition, the reliability of the PWI was found to be adequate in the current sample, as evidenced by a Cronbach's alpha of .86.

The PWI is scored on a 0 (very dissatisfied) to 10 (completely satisfied) bipolar scale with scores on each domain summed and averaged to form an overall PWI score. In an article investigating the utility of Likert–type scales, Cummins and Gullone (2000) demonstrate that 11-point end-defined (Jones & Thurstone, 1955) scales are far superior for measuring subjective quality of life compared with reduced choice Likert scales. This is due to a number of factors. Firstly, Cummins (1995, 1998) has demonstrated that SWB is not free to vary over its entire theoretical range, as most people report positive SWB. Thus, for a majority of individuals, only the positive half of the scale is used when making judgments of SWB. This reduction in scale sensitivity can be illustrated by considering a hypothetical 5-point SWB scale. In this hypothetical scale, individuals are asked how satisfied they are with their life as a whole. Responses can be 0-very dissatisfied, 1-dissatisfied, 2-mixed, 3-satisfied, or 4-very satisfied. For the majority of individuals who report positive SWB, response choice is restricted to two alternatives, 3 (satisfied) and 4 (very satisfied). Converting these scores to %SM reveals that individuals are restricted to reporting 75% satisfaction or 100% satisfaction. Such a scale would be unable to capture meaningful differences in SWB. In addition, most individuals are capable of discriminating between more than two options when reporting on their level of SWB. Thus, increasing the number of response alternatives (i.e., using an 11-point scale) increases the sensitivity of the scale to identify meaningful changes in SWB.

Cummins and Gullone (2000) also note that the assumption of interval categories for Likert-type scales is often violated. This is because Likert-type scales are frequently scored using sequential numbering in combination with category labels (i.e, the aforementioned hypothetical SWB scale). However, as Cummins and Gullone note, individuals often differ in their interpretation of such labels. For instance, Davern (2004) found that ordering of the category labels in the delighted-terrible scale of LS used by Andrews and Withey (1976) did not correspond with individual's ratings of these same labels. Specifically the anchors used by Andrews and Withey, in order of magnitude, were "delighted, pleased, mostly satisfied, mixed, mostly dissatisfied, unhappy, and terrible". However, Davern found that when individuals were asked to indicate how the affective descriptor described their feelings when they thought about their life in general (0-not at all to 10-extremely), individuals recorded the highest ratings for satisfied, followed by pleased, and delighted. Thus, in contrast to the scale developed by Andrews and Withey (1976), *satisfied* was rated as higher than *pleased,* and *pleased* was rated as higher than *delighted*.

The research conducted by Cummins and Gullone (2000) and Davern (2004) highlights the inadequacies of using reduced-choice Likert-type scales to measure SWB. As such, the PWI, an 11-point end-defined scale, represents a superior measurement of SWB that seeks to maintain the interval nature of the scale whilst also increasing scale sensitivity to capture meaningful changes in SWB.

Depression, Anxiety, Stress Scale (DASS)

The DASS was initially developed as a self-report screening measure of depression and anxiety that covered the full range of symptoms, whilst at the same time providing maximum discrimination between the constructs. During scale testing, Lovibond and Lovibond (1995) found a new factor that emerged from the non-discriminating anxiety and depression items. These items referred to difficulty relaxing, nervous tension, agitation and irritability, and together formed a new scale labelled 'Stress'. In a test of the convergent and discriminant validity of the DASS, Lovibond and Lovibond administered the Beck Depression Inventory (BDI), the Beck Anxiety Inventory (BAI), and the DASS to a large student population (N=717). The DASS depression scale was strongly correlated with the BDI (r=.74), and substantially less correlated with the BAI (r=.54). Similarly, the DASS anxiety scale was strongly correlated with the BAI (r=.81) and considerably less correlated with the BDI (r=.58). This pattern of correlations was replicated by Antony, Bieling, Cox, Enns, and Swinson (1998) in a clinical sample. These results suggest the DASS has good convergent and discriminant validity. In addition, several factor-analytic studies in both clinical (Antony et al., 1998) and non-clinical (Crawford & Henry, 2003; Lovibond & Lovibond) samples have consistently demonstrated that the DASS can be reliably grouped into three scales.

The Depression Anxiety Stress Scale 21 (DASS-21) is a short version of the 42-item DASS. The full version DASS comprised multiple similar items; in the short version, these similar items were removed, reducing each subscale from 14-items to 7-items. Consequently the DASS-21 is considered to encompass the full range of symptoms measured by the original DASS (Henry & Crawford, 2005). The psychometric properties of the DASS-21 have been tested in both clinical (Antony et al., 1998) and non-clinical (Henry & Crawford, 2005) samples. Antony et al. found, in comparison with the full DASS, that the 21-item version had a cleaner factor structure and smaller interfactor correlations, and as such, was preferable to the full version. The same conclusion was reached by Henry and Crawford following a test of the DASS-21 in a large non-clinical sample (N=1,794). As such, the DASS-21 was used in the current study.

The DASS-21 has been found to demonstrate adequate convergent and discriminant validity and reliability in two separate studies of clinical (Antony et al., 1998) and non-clinical participants (Henry & Crawford, 2005). In the study conducted by Antony et al. the Cronbach's alpha's for each subscale were .94 (depression), .87 (anxiety), and .91 (stress). The Cronbach's alpha's for each subscale in the study conducted by Henry and Crawford were .88 (depression), .82 (anxiety), and .90 (stress). Antony et al. correlated each subscale of the DASS-21 with other well-validated measures of depression, anxiety, and stress. These were the Beck Depression Inventory (BDI), the Beck Anxiety Inventory (BAI), and the Spielberger State-Trait Anxiety Inventory-Trait (STAI-T). The correlations are presented in Table 3.1.

Table 3.1: Correlations between DASS-21, BDI, BAI and STAI-T as reported in Antony et al. (1998; n=85).

Variable	1. DASS-21 Depression	2. DASS-21 Anxiety	3. DASS-21 Stress
1. DASS-21 Depression	-		
2. DASS-21 Anxiety	.46	-	
3. DASS-21 Stress	.57	.72	-
4. BDI	.79	.65	.69
5. BAI	.51	.85	.70
6. STAI-T	.71	.55	.68

Note: Correlations between BDI, BAI, and STAI-T were not reported by Antony et al.

The correlations presented in Table 3.1 indicate the DASS-21 demonstrates adequate discriminant and convergent validity. Lovibond and Lovibond (1995) give characteristic descriptions of each scale of the DASS. The depression scale is characteristic of loss of self-esteem and incentive, and associated with a low probability of attaining significant life goals. The items used to measure depression include, "I couldn't seem to experience any positive feeling at all", and "I felt I wasn't worth much as a person". For all DASS-21 items, participants respond by indicating how much the statement applied to them over the past week.

The anxiety scale is described as emphasising the link between enduring anxiety and acute fear response. It addresses situational anxiety in addition to somatic and subjective symptoms. Items include, "I was aware of dryness of my mouth", and "I felt scared without any good reason". The stress scale is characteristic of "persistent arousal and tension with a low threshold for becoming upset or frustrated" (Lovibond & Lovibond, 1995, p. 342). Items include, "I found it difficult to relax", and "I tended to over-react to situations". Cronbach's alphas for the DASS-21 in the current study were .91 for depression; .84 for anxiety; and .90 for stress. The DASS-21 was scored on an 11-point end-defined scale (0-not at all to 10-Extremely). Scale summary scores were computed and converted to represent scores on the original 5-point scale used by Lovibond and Lovibond (1995). This was done to enable meaningful comparisons with normative scores for each DASS subscale provided by Lovibond and Lovibond. A copy of the DASS-21 is included in Appendix B.

Personality

The personality dimensions of extroversion and neuroticism (reverse scored as emotional stability) were measured using the Ten-Item-Personality-Inventory (TIPI; Gosling, Rentfrow & Swann Jr., 2003). Only the items measuring extroversion and neuroticism were included as previous research has demonstrated that of the five factors, these two dimensions are most strongly related to SWB (Davern, 2004; DeNeve & Cooper, 1998). The TIPI was designed as a brief psychometrically valid measure of the five factors of personality (Gosling et al., 2003). Gosling et al. found the TIPI demonstrated adequate test-retest reliability over six weeks (correlations ranged from .62 to .77, M=.72, N=180). In addition, the convergent correlations between extroversion and stability and the 44-item Big Five Inventory (BFI-44; John &

Srivastava, 1999) measure of these same dimensions were .87 and .81 respectively (N=1,813). The convergent validity of the TIPI dimensions of extroversion and stability with the BFI-44 was also tested by Woods and Hampson (2005). These authors found, across 292 participants in three samples, a mean correlation between the TIPI measure of extroversion and the BFI-44 measure of extroversion of .79. The mean correlation between the TIPI measure of stability and the BFI-44 measure of this same dimension was .67. In addition, these authors examined the convergent validity of the TIPI dimensions of extroversion and stability with an additional measure of these dimensions, the Trait Descriptive Adjectives-35 (TDA-35; Goldberg, 1992). Woods and Hampson found a mean correlation between the TIPI measure of extroversion and the TDA-35 measure of this dimension of .74 (N=140). The mean correlation between the TIPI measure of stability and the TDA-35 measure of this dimension was .57 (N=140). Woods and Hampson also report adequate reliability of the TIPI dimensions of extroversion and stability with Cronbach's alpha's of .61 and .72 respectively. In the current sample, the Cronbach's alpha for extroversion and stability were .66 and .67 respectively. The TIPI was scored on an 11-point end-defined scale (0-strongly disagree, 5-neutral, 10-strongly agree). The first stability item and the second extroversion item were reverse coded. Scores were then summed across the two items measuring each dimension to form scale scores. A copy of the TIPI is given in Appendix C.

Buffer System

The buffer system component of homeostatic theory consists of the variables self-esteem, optimism, and perceived control. Consequently, scales were included to measure each of these variables.

Self-esteem

Self-esteem was measured using Rosenberg's self-esteem scale (RSE; Rosenberg, 1989). This scale is the most popular and widely used measure of global self-esteem (Gana, Alaphilippe, & Bailly, 2005). The scale consists of 10-items which are designed to measure global self-esteem (e.g., "On the whole I am satisfied with myself"). Participants indicate strength of agreement to each statement on an 11-point (0-strongly disagree, 10-strongly agree) end-defined response scale. Five items are reverse coded prior to each item being summed to arrive at an overall scale score.

The RSE has been found to demonstrate adequate reliability, with Vispoel, Boo, and Bleiler (2001) reporting a Cronbach's alpha of .92 across 224 participants. Similar high reliability estimates were found by Robins, Hendia, and Trzesniewski (2001) in three separate studies. In the first study (N=508) the authors reported a Cronbach's alpha of .88. In Study 2, using a 5-point scale (N=139) and a 7-point scale (N=69) did not alter the reliability of the RSE. The Cronbach's alpha's for both scale formats were .89 and .93 respectively. In Study 3 (N=66) Cronbach's alpha for the RSE was .86. The RSE also demonstrated adequate test-retest reliability over six years, with an average correlation of .69. The Cronbach's alpha of the RSE in the current study was .91.

In the research conducted by Robins et al. (2001), the RSE was also found to exhibit adequate discriminant validity. Specifically, the RSE was correlated with the NEO-Five Factor Inventory (NEO-FFI; Costa & McCrae, 1992) in addition to measures of optimism (Life Orientation Test-Revised; LOT-R; Scheier, Carver & Bridges, 1994), perceived stress (Perceived Stress Scale; Cohen, Kamarck,& Mermelstein, 1983) and depression (Center for Epidemiological Studies Depression Scale; CES-D; Radloff, 1977). The correlations between the RSE and the NEO-FFI were -.70 for neuroticism, .41 for extroversion, .23 for agreeableness, .28 for conscientiousness, and .16 for openness to experience. The RSE correlated with perceived stress at -.39, depression at -.34, and optimism at .48. Robins et al. (2001) also found that the RSE demonstrated adequate convergent validity with the Single Item Self-Esteem Scale (SISE). Across six separate assessments (*N*=508) the correlations between the RSE and the SISE ranged from .89 to .94 with a median of .93. A copy of the RSE is provided in Appendix D.

Optimism

The Revised Life Orientation Test (LOT-R; Scheier, Carver, & Bridges, 1994) is a 10-item (4 filler items) measure of dispositional optimism and pessimism and has been found to correlate .95 with the original LOT (Scheier et al., 1994). Recent research has indicated support for a bi-dimensional model of optimism and pessimism (Chang, Maydeu-Olivares, & D'Zurilla, 1997; Cheng & Hamid, 1997; Herzberg, Glaesmer, & Hoyer, 2006). Specifically, in a large scale study of 46,133 participants, Herzberg et al. found that a two-factor solution provided a substantially better fit to the data (CFI=.99; TLI=.99; RMSEA=.04) than a one-factor solution (CFI=.62; TLI=.62, RMSEA=.21). Vautier, Raufaste, and Cariou (2003) also argue that there is no empirical necessity to split the dispositional optimism construct into optimism plus pessimism. To reflect this, only the three items representing the optimism dimension were included in the present study.

The reliability and validity of the optimism dimension of the LOT-R has been investigated in a number of studies (Cheng & Hamid, 1997; Herzberg et al., 2006; Reilley, Geers, Lindsay, Deronde & Dember, 2005). Cheng and Hamid reported a

Cronbach's alpha of .91 in 318 college students and .75 in 306 adults. Herzberg et al. reported a Cronbach's alpha of .71 in 46,133 participants, whilst Reilley et al. reported Cronbach's alpha's of .82 and .83 in two separate studies of 273 and 204 participants respectively.

The discriminant and convergent validity of the optimism dimension of the LOT-R was also investigated in the studies conducted by Cheng and Hamid (1997), Herzberg et al. (2006), and Reilley et al. (2005). Cheng and Hamid reported correlations of optimism with extroversion, r=.26; neuroticism, r=-.41; PA, r=.29; NA, r=-.27; physical symptoms, r=-.21; and psychological symptoms, r=-.29. Herzberg et al. found optimism significantly predicted depression (β=-.47, R^2 not provided) and correlated at -.15 with pessimism. Reilley et al. reported a correlation between LOT-R optimism and the optimism dimension of the Optimism Pessimism Instrument (OPI; Dember, Martin, Hummer, Howe, & Melton, 1989) of .58. In addition, the LOT-R optimism dimension correlated at -.32 with the BDI.

In the current study optimism was rated on an 11-point end-defined scale (0-strongly disagree, 10-strongly agree). The scale score was computed by summing the three optimism items. The Cronbach's alpha for the optimism scale in the current study was .86. A copy of the optimism scale is provided in Appendix E.

Perceived Control

Perceived control has been defined as behaving in ways to maximise good outcomes and minimise bad outcomes (Peterson, 1999). Perceived control was measured using a scale developed by Chambers (2004) for the Australian Unity Wellbeing Project. This scale comprises a combination of items drawn from Cousins (2001) and Hollway (2003) to reflect primary, secondary, and relinquished control strategies. This combination yielded a 9-item (three-items for each dimension) scale, rated on an 11-point end-defined scale (0-strongly disagree, 10-strongly agree). Previous research has investigated the reliability and validity of this scale (Davey, 2004; Lake, 2004; Chambers, Hollway, Parsons, & Wallage, 2003). Lake found Cronbach's alpha's of .56 for primary control, .80 for secondary control, and .22 for relinquished control in a sample of 556 participants. In addition, primary control and secondary control were both found to predict 6% of unique variance in PWI. For the prediction of LS, primary control added a significant 4% unique variance whilst secondary control added a significant 5% unique variance. In a study of 562 participants, Davey reported a Cronbach's alpha of .60 for the perceived control scale. Davey also reported correlations of perceived control with LS of r=.40; PWI, r=.45; depression, r=-.38; stability, r=.03; extroversion, r=.12; self-esteem, r=.52; and optimism, r=.53. Chambers et al. reported Cronbach's alpha's of .88 for primary control, .90 for secondary control and .70 for relinquished control (number of participants unknown). The differences in the Cronbach's alpha's reported by Chambers et al. and Lake suggests a low degree of overall stability and reliability.

Each subscale of the perceived control scale was computed by summing the three items measuring each dimension. Cronbach's alphas in the present study for the primary control, secondary control, and relinquished control scales were .56, .79, and .30 respectively. As the relinquished control scale did not demonstrate adequate reliability, it was excluded from all analyses. A copy of the perceived control scale is given in Appendix F.

Trait Affect

Items used to measure trait affect were chosen to represent the two dimensions of the circumplex model of affect (pleasant-unpleasant, activated-deactivated; Russell, 2003). The circumplex model of affect proposes that affects can be organised in a circular pattern around two principal bipolar axes; pleasantness-unpleasantness and activation-deactivation. The circumplex model of affect was first proposed by Schlosberg (1954) and has since been revised by Russell (1980, 2003).

Inclusion of items was based on convergence between Yik et al.'s (1999) and Davern's (2004) studies into the structure of affect. The best markers of each dimension of the circumplex were judged to be those that were located closest on the circumplex to each of the quadrant poles (0°, 90°, 180°, 270°), and those that contributed the greatest amount of unique variance to the prediction of LS.

The application of these criteria resulted in 10 items being chosen to represent the valence and activation dimensions. Happy (7°), satisfied (347°), and content (356°) represent the pleasant quadrant; discontent (184°) and unhappy (182°) represent the unpleasant quadrant; active (65°), alert (41°), and excited (24°) represent the activated quadrant and sleepy (207°) and quiet (256°) represent the deactivated quadrant. The angles of each item were taken from Davern (2004). Participants rated items on an 11-point end-defined unipolar scale (0-not at all, 10-extremely). As this scale was constructed for the current study, validity has not yet been assessed. In addition, Cronbach's alpha was not used to test the reliability of this scale as the items measure different dimensions of the circumplex model of emotion. A copy of this scale is included in Appendix G.

Multiple Discrepancies Theory

The items chosen to represent Multiple Discrepancies Theory (MDT) were a revision of the original items supplied by Michalos (1985; personal communication, April 15, 2005). This enabled a test of the theory using the most current items. The items are a measure of the perceived discrepancy between: what one has and wants (self-wants); what relevant others have (self-other); the best one has had in the past (self-best); expected to have 3 years ago (self-progress); expects to have after 5 years (self-future); deserves (self-deserves) and needs (self-needs). The original seven-item MDT scale has demonstrated adequate reliability as reported by Davern (2004; Cronbach's alpha =.89). In addition, Davern found that this seven-item MDT scale predicted 36% of the variance in depression (as measured by the DASS) and 55% of the variance in LS. The original MDT items have also been found to be related to, but discriminant from self-esteem (Staasen & Staats, 1988). Staasen and Staats reported an average correlation between the MDT items and self-esteem of r=.25. The correlations ranged between .13 (for self-deserves and self-future) to .43 (for self-other). The reliability of the revised MDT scale used in the current study was adequate, with a Cronbach's alpha of .88. A copy of this scale is included in Appendix H.

Procedure

Following approval from the Deakin University Human Research Ethics Committee (DUHREC) a questionnaire packet was mailed to participants. This packet included a plain language statement describing the research project and a reply-paid self-addressed envelope that was used to return the completed questionnaires. Participants were instructed that by completing the questionnaire they were consenting to take part in the research as explained in the plain language statement. Each questionnaire was printed with a unique number that corresponded to contact information contained in an electronic file. This file was kept separate from the data file at all times, thus responses to questionnaires were considered confidential.

Each scale that comprised the questionnaire was prefaced with instructions as to how to complete the scale. The order of the scales remained constant for each participant. For the PWI scale, participants received the following instruction, “Thinking about your own life and personal circumstances, please circle the number that best represents how satisfied you feel with your life. How satisfied are you with…” For the trait affect scale, participants were instructed to, “Please indicate how each of the following describes your feelings when you think about your life in general.” For the DASS, participants received the instruction, “How much did these statements apply to you over the past week? 0 is not at all, and 10 is extremely.” The instructions for the perceived control scale were, “When bad things happen to you how do you cope with them? How much do you agree that when something bad happens…” The instruction for the RSE, the TIPI, and the LOT-R was, “How much do you agree with the following statements?” Each MDT item was prefaced with the instruction, “Considering your life as a whole…” The subsequent wording for each item was provided by the author of the scale (Michalos, 2005). Once the questionnaires were returned, the responses were entered directly into SPSS for Windows (12.0; SPSS, Inc., Chicago, Il).

Section 3.2: RESULTS

Data Preparation

All LS scores are presented as percentage of scale maximum (%SM) scores (see Equation 3.1). Converting scores to a common scale allows an easy comparison to be made of constructs that are scaled differently.

$$\%SM = \frac{x - k^{Min}}{k^{Max} - k^{Min}} \times 100 \qquad \text{(Eqn 3.1)}$$

where x = the score to be converted
where k^{Min} = the minimum score possible on the scale
where k^{Max} = the maximum score possible on the scale

The data was analysed using SPSS for Windows (12.0; SPSS, Inc., Chicago, Il) and AMOS (5.0; Smallwaters Corp, Chicago, Il). Prior to analysis data were screened for multivariate and univariate outliers and missing values. Twenty-nine cases were identified by Mahalanobis distance as multivariate outliers, $p<.001$. Upon examination, these outliers were considered to constitute normal and expected responses. Furthermore, an examination of residuals indicated no difference with outliers deleted. For these reasons, cases were retained. Univariate outliers were assessed through the computation of z-scores for each variable. Scores were considered univariate outliers if z-score > 4, $p<.001$ (Tabachnick & Fiddell, 2001). Application of this analysis indicated scores exceeding four on 12 items (life satisfaction; contentment; happiness; PWI domain of standard of living; PWI domain of safety; item 3 and 4 of RSE; items 2, 3, and 5 of perceived control scale; and self-wants MDT discrepancy item). However for all 12 items, less than four cases recorded z-scores exceeding four and no cases recorded z-scores exceeding five. Upon inspection of the data, scores were considered to constitute normal and expected responses. For these reasons the cases were retained.

A missing values analysis indicated the maximum percentage of missing data on any variable to be 2.1% of cases (for the affect unhappy). In addition, only three other variables had missing data of more than 1.5% of cases. As Tabachnick and Fiddell (2001) suggest that missing data of 5% or less can be ignored, the data was judged to be suitable for regression replacement (Tabachnick & Fiddell, 2001). This technique is a more sophisticated technique of data replacement than mean substitution and more objective than using prior knowledge (Tabachnick & Fidell).

The assumption of normality was not violated as assessed through inspection of expected normal probability plots of standardised residuals. In addition, raw scores of skew and kurtosis were analysed for each variable. Following extensive Monte Carlo testing of the effects of skew and kurtosis, Curran, West, and Finch (1996) concluded that raw skewness scores of less than 2.0 and kurtosis scores of less than 7.0 are not likely to distort the results. An analysis of skewness raw scores revealed four items exceeded a score of 2.0. These items were contained within the DASS and consisted of *trembling in hands* (skewness=2.46, *SE*=.12), *close to panic* (skewness=2.35, *SE*=.12), *scared for no good reason* (skewness=2.51, *SE*=.12), and *life felt meaningless* (skewness=2.34, *SE*=.12). However, these departures from strict normality were not in variables central to any of the hypotheses to be explored. As such, transformations would be of little value. Inspection of histograms also revealed these variables exhibited positive skew. Thus, a number of individuals scored at very low levels on these items.

This tendency towards lower scores for these items is to be expected in a sample of the general population. In addition, the similar shape of distribution on each item mitigates the potential distorting effect of mild skew (Bradley, 1980). Moreover, the skewness values for each scale summary score on the DASS equalled 1.78 for anxiety, .94 for stress and 1.5 for depression. No excessive kurtosis was found in any variable as evidenced by a maximum kurtosis value of 5.92 (*scared for no good reason).* Thus it was concluded that the data did not violate the assumption of normality.

Means, Standard Deviations, and Correlations between Variables

The means, standard deviations, and correlations between the PWI, LS, DASS, trait affect, cognitive buffer variables, personality variables, and MDT items are presented in Table 3.2.

Table 3.2: Correlations between PWI, LS, DASS, trait affect, cognitive buffers, personality, and MDT items.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.
1.PWI																																		
2.Std Living	.72																																	
3.Health	.65	.33																																
4.Achieving	.78	.55	.50																															
5.Relationships	.71	.46	.40	.53																														
6.Safety	.69	.40	.33	.37	.32																													
7.Community	.75	.40	.34	.50	.42	.53																												
8.Security	.81	.59	.37	.51	.45	.61	.62																											
9.Life Sat	.77	.58	.52	.75	.67	.39	.48	.52																										
10.Happy	.74	.55	.48	.66	.61	.47	.50	.52	.76																									
11.Content	.76	.54	.48	.70	.61	.49	.54	.56	.79	.87																								
12.Satisfied	.78	.57	.49	.72	.60	.50	.53	.57	.80	.85	.92																							
13.Unhappy	-.46	-.28	-.24	-.42	-.37	-.34	-.35	-.38	-.46	-.52	-.52	-.52																						
14.Discontent	-.46	-.31	-.23	-.40	-.38	-.34	-.34	-.38	-.46	-.50	-.55	-.53	.82																					
15.Active	.47	.29	.44	.37	.33	.29	.36	.31	.40	.49	.42	.43	-.22	-.19																				
16.Alert	.48	.33	.33	.44	.34	.31	.36	.34	.42	.53	.46	.45	-.30	-.30	.62																			
17.Excited	.54	.34	.35	.51	.42	.35	.41	.38	.54	.67	.60	.61	-.28	-.27	.48	.50																		
18.Sleepy	-.14	-.04	-.11	-.07	-.11	-.17	-.09	-.09	-.09	-.11	-.09	-.10	.22	.22	-.19	-.20	-.13																	
19.Quiet	-.06	.00	-.01	-.06	.00	-.10	-.09	-.06	-.07	-.06	-.05	-.06	.20	.19	-.08	-.06	-.12	.29																
20.Self-Esteem	.55	.39	.33	.57	.44	.32	.39	.35	.57	.63	.61	.60	-.44	-.47	.35	.54	.55	-.15	-.15															
21.P. Control	.33	.08	.14	.22	.10	.08	.17	.10	.33	.41	.40	.40	-.25	-.27	.29	.36	.46	-.05	-.02	.46														
22.Optimism	.49	.36	.33	.47	.36	.28	.35	.33	.43	.53	.51	.51	-.37	-.36	.33	.43	.48	-.07	.04	.56	.39													
23.Extroversion	.22	.17	.18	.26	.14	.08	.17	.13	.25	.28	.26	.28	-.14	-.17	.14	.19	.34	-.03	-.26	.32	.29	.35												
24.Stability	.47	.26	.35	.42	.36	.30	.37	.32	.46	.51	.49	.49	-.39	-.37	.31	.37	.35	-.17	.06	.27	.05	.51	.18											
25.DASS Anx.	-.52	-.25	-.51	-.41	-.35	-.39	-.40	-.34	-.44	-.46	-.50	-.49	.44	.44	-.32	-.42	-.28	.20	.13	-.51	-.19	-.31	-.15	-.52										
26.DASS St.	-.51	-.30	-.43	-.39	-.35	-.37	-.39	-.35	-.44	-.46	-.50	-.50	.48	.50	-.29	-.37	-.24	.22	.08	-.49	-.17	-.32	-.09	-.59	.76									
27.DASS Dep.	-.61	-.36	-.48	-.59	-.43	-.40	-.43	-.44	-.61	-.62	-.65	-.62	.56	.54	-.37	-.45	-.43	.20	.23	-.65	-.29	-.44	-.22	-.52	.75	.73								
28.Self-Wants	.60	.51	.36	.61	.45	.29	.43	.43	.62	.55	.61	.62	-.48	-.45	.27	.31	.40	-.09	.00	.49	.35	.41	.20	.38	-.42	-.41	-.48							
29.Self-Other	.56	.47	.34	.51	.42	.29	.39	.44	.52	.43	.50	.49	-.39	-.39	.21	.23	.27	-.06	.00	.46	.19	.39	.19	.37	-.39	-.34	-.44	.58						
30.Self-Deser.	.45	.42	.21	.35	.36	.28	.32	.39	.43	.37	.43	.42	-.29	-.32	.15	.19	.22	-.08	-.04	.29	.19	.30	.17	.25	-.27	-.25	-.32	.54	.52					
31.Self-Needs	.50	.45	.24	.47	.42	.26	.31	.40	.50	.44	.48	.49	-.34	-.35	.17	.23	.28	-.05	-.03	.34	.18	.29	.16	.24	-.28	-.22	-.38	.60	.55	.72				
32.Self-Prog.	.49	.38	.25	.50	.34	.29	.36	.39	.48	.45	.48	.51	-.33	-.38	.21	.27	.34	-.04	-.02	.39	.26	.37	.12	.32	-.33	-.32	-.42	.52	.49	.60	.62			
33.Self-Future	.40	.25	.28	.38	.28	.30	.25	.32	.36	.38	.41	.43	-.26	-.24	.19	.23	.33	-.07	-.07	.35	.29	.42	.20	.36	-.32	-.25	-.37	.35	.40	.39	.35	.54		
34.Self-Best	.46	.32	.28	.46	.32	.31	.31	.32	.48	.49	.50	.51	-.35	-.37	.24	.22	.33	-.02	-.12	.40	.27	.32	.19	.31	-.38	-.35	-.43	.47	.43	.45	.54	.63	.52	
M	72.45	77.13	70.3	69.5	75.2	77.6	68.8	69.6	76.2	7.4	7.3	7.2	2.8	2.9	6.6	7.3	6.3	4.8	5.5	76.2	42.4	20.7	10.7	14.3	6.1	10.5	7.9	72.5	65.5	59.3	57.2	57.7	59.7	53.9
SD	14.95	18.01	21.6	20.4	21.5	18.6	21.3	21.3	17.2	1.8	1.8	1.8	2.0	2.1	2.0	1.7	1.9	2.4	2.0	17.3	8.4	5.4	4.9	4.2	7.1	8.7	8.5	16.7	19.5	19.4	20.4	20.9	20.2	22.1

The data presented in Table 3.2 indicate the three strongest correlations observed were between the trait affects of satisfied and content, content and happy, and satisfied and happy. The correlations between the PWI and trait satisfaction, contentment, and happiness, and LS and trait satisfaction, contentment, and happiness were also amongst the strongest correlations observed. These correlations indicate that PWI and LS are strongly related to trait pleasant affectivity (satisfied, content, happy). In comparison, PWI and LS are only moderately positively related to trait pleasant-activated affect (active, alert, excited), self-esteem, optimism, and stability, and moderately negatively related with trait unpleasant affect (unhappy, discontent), depression, anxiety, and stress (see Table 3.2).

The data contained in Table 3.2 also reveal a very similar pattern of correlations between trait affect and the cognitive buffer system, personality, MDT, and depression, anxiety, and stress. Specifically, pleasant affect (satisfied, content, happy) exhibits the strongest correlations with the cognitive buffers, personality, MDT and the DASS (see Table 3.2) whilst only moderate correlations are recorded between these variables and pleasant-activated affect (active, alert, excited), and unpleasant affect (unhappy, discontent). In contrast, deactivated affect (sleepy, quiet) is consistently weakly related to these constructs. Interestingly, stability was consistently more strongly related to positive and negative trait affect than extroversion (with the exception of *quiet* and *excited).* Stability was also more strongly positively related with MDT than extroversion. The items comprising MDT were moderately positively correlated with the system of cognitive buffers and moderately negatively related with depression, anxiety, and stress.

The mean scores for each MDT item presented in Table 3.2 indicate that the largest discrepancy reported in the current sample was for "what one has now versus the best one has had in previous experience". However, a value of '50' on this item corresponds to 'equals previous best', indicating the absence of a perceived discrepancy. Values below 50 for all perceived discrepancy items (with the exception of self-wants) correspond to larger perceived discrepancies, whereas values of 50 and above indicate an absence of perceived discrepancies. As the mean discrepancy rating across all seven items is 60.8, in this sample there was a relative absence of perceived discrepancies.

The mean domain scores for the PWI presented in Table 3.2 indicate that participants reported the highest satisfaction in the domain of safety, followed by standard of living, and personal relationships. The mean PWI score of 72.45 is within the expected normal range of 70 to 80%SM, and is similar to the mean PWI score of 74.93 (*SD*=.75) for the previous 16 Australian Unity Wellbeing surveys (*N*=30,613; Cummins et al., 2006). In addition, the mean LS score of 76.23 is similar to the mean LS score of 77.48 (*SD*=.96) for the previous 16 Australian Unity Wellbeing surveys (*N*=31,534). The mean PWI scores for each of the previous 16 Australian Unity Wellbeing survey's are plotted in Figure 3.1.

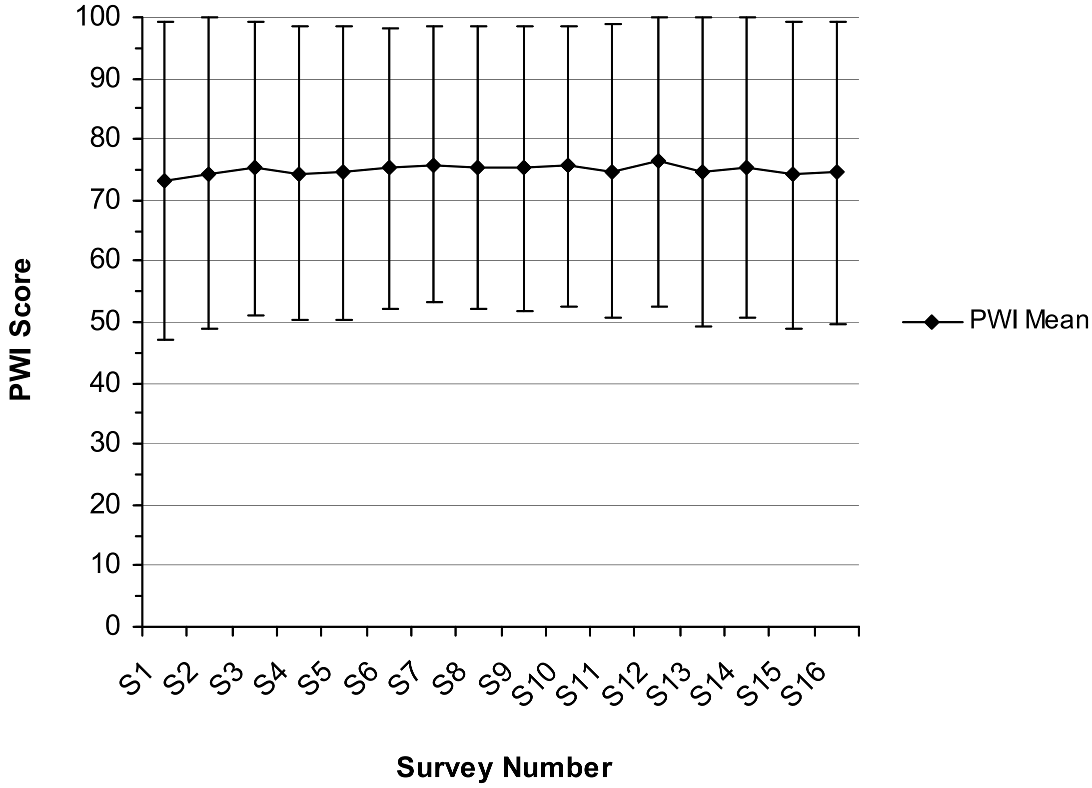


Figure 3.1: PWI mean scores according to survey number (N=30,613). The ordinate reveals mean PWI survey score ranging from 0 to 100, and the abscissa represents the survey number. Error bars represent the range of scores for 95% of the sample in each survey.

The data contained in Figure 3.1 illustrate the extremely low variability of PWI (*SD* of means=.75) across 30,613 participants. However as the data are cross-sectional no inferences about the stability of PWI over time can be made.

Testing proceeded by examining the relation between PWI and depression. Depression severity categories for normative DASS data are provided by Lovibond and Lovibond (1995). Depression scores ranging from zero to nine are considered normal, 10 to 13 mild, 14 to 20 moderate, 21 to 27 severe, and 28+ extremely severe. Frequencies for the depression categories and corresponding means and standard deviations for the PWI are presented in Table 3.3.

Table 3.3: PWI mean scores within DASS depression categories (N=387).

Depression Scores	**Depression Category**	**% of Total *N***	**PWI *M***	**PWI *SD***	***N***
0-9	Normal	68.5	77.41	10.74	265
10-13	Mild	11.9	67.05	14.39	46
14-20	Moderate	10.6	65.82	14.05	41
21-27	Severe	3.6	61.53	18.16	14
28+	Extremely Severe	5.4	41.91	13.04	21

The data contained in Table 3.3 indicate that approximately 68% of the sample report normal depression scores. The relation between PWI and depression is negative, with PWI scores falling by 10.4 points from normal to mild depression, and 35.5 points from normal to severe depression. PWI scores for all participants reporting mild to extremely severe depression fall below the level of SWB considered normal for populations (70 to 80%SM). A one-way between-groups analysis of variance was conducted to determine whether PWI scores differed significantly across depression categories. Due to cell sample size variation across groups, the assumption of equal variances was violated. As such, the Welch statistic was used in place of the F statistic. This analysis indicated a statistically significant difference in PWI scores across the six depression groups (Welch (4, 382)=44.51, R^2=.32, p<.001). Post-hoc comparisons using the Dunnett T3 indicated that participants who reported an extremely severe depression score significantly differed on PWI from all other depression categories (p<.05 for severe category, p<.001 for all other categories). In addition, participants who reported depression scores ranging from zero to nine (normal) significantly differed from all other depression categories on their PWI, with the exception of the severe category (p=.05). This anomalous result is likely due to the low sample size for the severe category, as the difference in PWI scores is 15.9 points. Participants in the mild, moderate, and severe depression categories did not significantly differ on their PWI scores. The negative relationship between PWI and depression is evident in Figure 3.2.

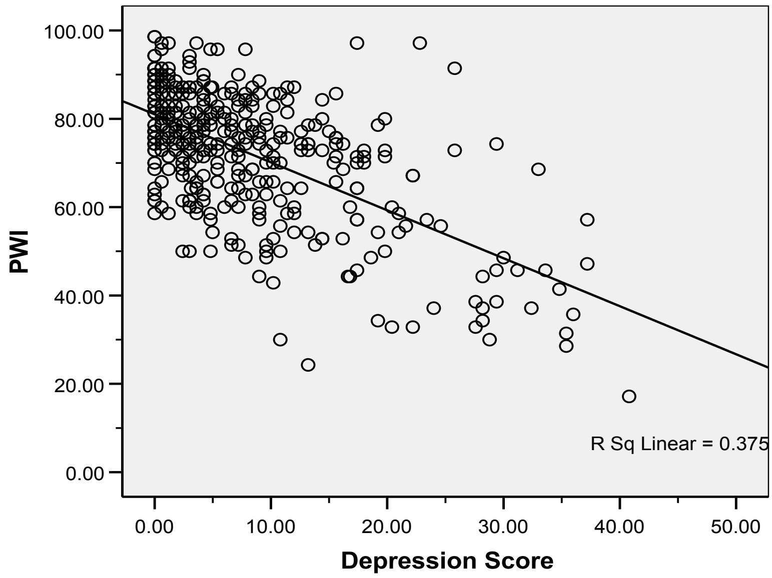


Figure 3.2: XY-plot of individual depression and PWI scores (N=387). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

The data contained in Figure 3.2 indicate that most cases had low depression and high PWI scores. However, as depression increases there is a clear reduction in PWI scores. The correlation between depression and PWI, as given previously in Table 3.1, is -.61. The R^2 linear statistic indicates that 37.5% of variance in PWI is accounted for by scores on depression.

To further investigate the relationship between SWB and depression, two PWI groups were created. The groups correspond to PWI scores below 65 (reflecting below normal levels of SWB), and PWI scores above 65 (reflecting normal levels of SWB). Homeostatic theory would predict that the relationship between below normal levels of SWB and depression would be stronger than the relationship between normal levels of

SWB and depression. This prediction was investigated through xy-plots of PWI and depression scores. The prediction was also investigated by explicitly comparing the difference between correlations for both groups. The xy-plot between depression and PWI for the PWI<65 group is presented in Figure 3.3. The xy-plot between depression and PWI for the PWI>65 group is presented in Figure 3.4.

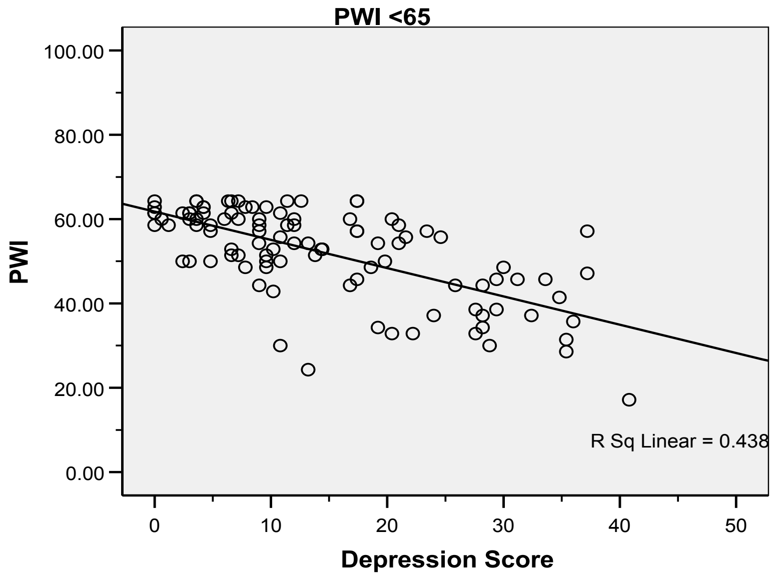


Figure 3.3 XY-plot of individual PWI and depression scores for individuals with below normal SWB (PWI<65; n=102). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

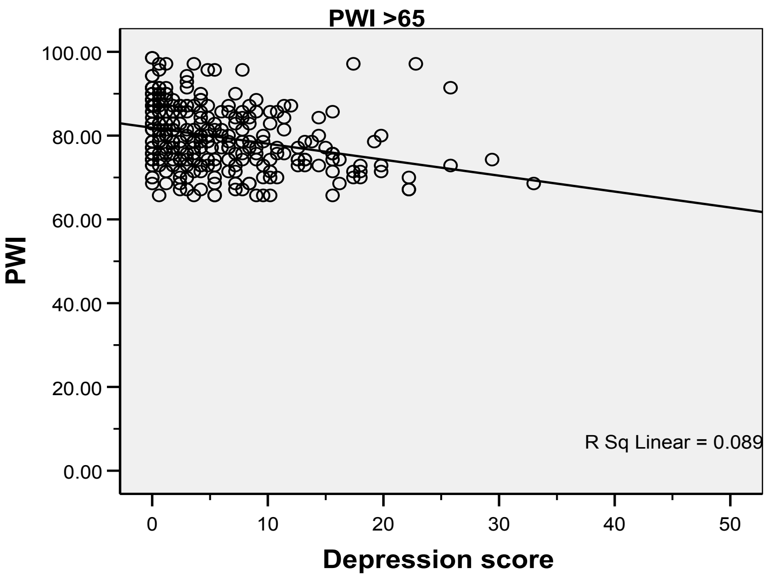


Figure 3.4: XY-plot of individual PWI and depression scores for individuals with normal SWB (PWI>65; n=285). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

The xy-plots in Figure 3.3 and Figure 3.4 indicate a stronger negative relationship between PWI and depression for individuals with PWI<65 than for individuals with PWI in the normal range. A comparison of the R^2 statistics reveals that approximately 44% of variance in PWI is accounted for by the depression scores of individual's with below normal levels of SWB, whilst for individuals with normal SWB, only 9% of variance in PWI is accounted for by their depression score. This asymmetrical relationship between PWI and depression in the two groups is reflected in the correlations for both groups. The correlation between PWI and depression in the below normal PWI group is -.66, whilst the correlation in the normal PWI group is -.30. The difference between these correlations was computed by converting Pearson r into a z-score by Fisher's z transformation, and comparing the difference in z-scores. This computation yielded a difference of z=-4.14, p<.001. Thus the relationship between

PWI and depression was significantly different in the below normal and normal PWI groups.

Theoretical Modelling Introduction

Structural Equation Modelling (SEM) was utilised to determine the relative ability of each of the three theories under investigation (homeostatic theory, MDT, and affective-cognitive theory) to adequately describe the data. This examination was conducted by specifying and testing SEMs according to the premises of each theory.

When assessing the fit of structural equation models to the data it is important to highlight the inappropriate reliance on the chi-square statistic. Chi-square is sensitive to sample size, and as a result large sample sizes will obtain significance even though differences between data and model may be trivial (Kline, 2005). This is particularly the case when using misspecified models. Misspecified models are models which do not reflect reality. For example, the specification of an unrelated variable or a spurious relationship between variables that does not reflect reality consumes variance. Conversely, by excluding a required variable or an actual relationship between variables, variance is not consumed. In both circumstances, the misspecification leads to a reduced fit between the model and the data. One technique that is often used to reduce sensitivity of chi-square to sample size is the division of chi-square by degrees freedom (χ^2/df; Kline). As such, χ^2/df will be interpreted along with absolute and incremental fit indices.

It should also be noted that when a model is found to fit, as measured by χ^2, it is considered to have demonstrated absolute fit regardless of the sample size. Better fitting models are considered superior only when parsimony is improved. Parsimony was measured herein as Akaike's Information Criterion (AIC). The formula for computation of AIC is: χ^2 + 2*number of estimated parameters (AIC=χ^2+2q). Improved parsimony results in a smaller AIC.

Kline (2005) notes that the indices reported often change depending on the researcher, but suggests a minimal set which includes χ^2/df; an index describing overall proportion of explained variance (Comparative Fit Index; CFI), and an index based on standardised residuals (Root Mean Squared Error of Approximation; RMSEA). Hu and Bentler (1999) also suggest a minimum two-index presentation strategy consisting of an index based on standardised residuals, and supplementing this with either the Normed Fit Index (NFI) or the CFI.

When assessing how well a SEM fits the data, Kline (2005) has advised that relative and absolute fit indices should be considered together as they reflect different facets of model fit. For instance, the CFI and NFI reflect the fit of a model relative to a baseline, or independence model in which all measured variables are perfectly uncorrelated (a value of .80 for the NFI indicates that the specified model provides an overall fit that is 80% better than the independence model with the same data; Kline). In comparison, the chi-square statistic reflects how well the predicted covariances (derived from the parameter estimates) match with the observed values in the particular sample. When this match is good, chi-square will be non-significant. However, as mentioned previously, chi-square is overly sensitive to sample size. Other researchers have also recommended consulting several fit indices when assessing model fit (Thompson, 2004). Using a combination of fit indices to determine the degree of agreement between results helps to avoid circumstances in which reliance on only one index leads to erroneous conclusions. For instance, relying on one index to determine the degree of model fit may lead a researcher to conclude he or she has a good fitting model, when in actuality, a consideration of that one index in combination with other indices would lead the researcher to reject that particular model.

Thompson (2004) and Kline (2005) provide rough guides for the values of indices considered to reflect adequate fitting models. For chi-square, a non-significant result is desirable. In addition, the ratio of chi-square to degrees freedom should ideally be less than three, however Kline points out that in small samples it is possible to obtain a value of less than three even if the model fit is poor. Values of above .90 for NFI and CFI are acceptable, however values above .95 are desirable. An RMSEA of less than .06 is also considered to reflect a good fit. It is also important to note that a model of sufficient complexity will always provide a good fit to the data (Thompson, 2004). Thus, a model that provides a good fit, and is parsimonious, is considered superior to a more complex model.

While fit indices are an important part of structural equation modelling, Thompson (2004) notes that a good fit does not indicate that the model specified is correct, or that it is "proven". It is possible, and perhaps probable, that several alternative models fit a given data set. In order for strong conclusions to be drawn regarding the utility of a particular model, the researcher must specify and test plausible alternative models. If after this testing, the preferred model remains the only model with an adequate fit, then the researcher can make a stronger claim regarding the model's efficacy. In addition, the fit of a model is considered more impressive when it is disconfirmable (Thompson); that is, when there are degrees of freedom remaining such that other relationships between the variables may be specified and tested.

Using maximum likelihood estimation, structural equation models were specified according to the three theories under investigation, homeostatic theory, MDT, and affective-cognitive theory. Measurement models for all three theories were constructed and assessed. Inspection of these models revealed all assumptions had been met, as evidenced by absence of negative variances, and absence of multi-collinearity. In all models, the indicators of constructs were allowed to covary to reflect their common measurement error. As these are not theoretically relevant, with the exception of trait positive affect (henceforth trait PA), they are not presented in the Figures. However all correlations between constructs are presented.

Homeostatic Model of Subjective Wellbeing

According to the homeostatic model of SWB given by Cummins et al. (2002) and Cummins (personal communication, March 10, 2006), PWI is influenced directly and indirectly by the two personality dimensions of extroversion and neuroticism (reverse coded as stability). In the direct effect, an individual with high levels of extroversion and stability is proposed to experience high levels of PWI. In the indirect effect, extroversion and stability are proposed as predictors of the cognitive buffers (comprised of perceived control, self-esteem, and optimism), which in turn, directly influence PWI.

Thus, an individual with high levels of extroversion and stability has a stronger buffer system, which protects against threats to PWI (see Figure 2.3, Chapter 2).

It is hypothesised that the homeostatic model will provide an adequate explanation of the data, as evidenced by an absolute and relative fit of a SEM specified according to this theory. A SEM specified according to the homeostatic theory of SWB is given in Figure 3.5. In this figure, the standardised regression paths are provided in addition to Squared Multiple Correlations (SMCs; in italics), and correlations. The unstandardised values for this model, and the standard errors (in parentheses), are provided in Figure 3.6.

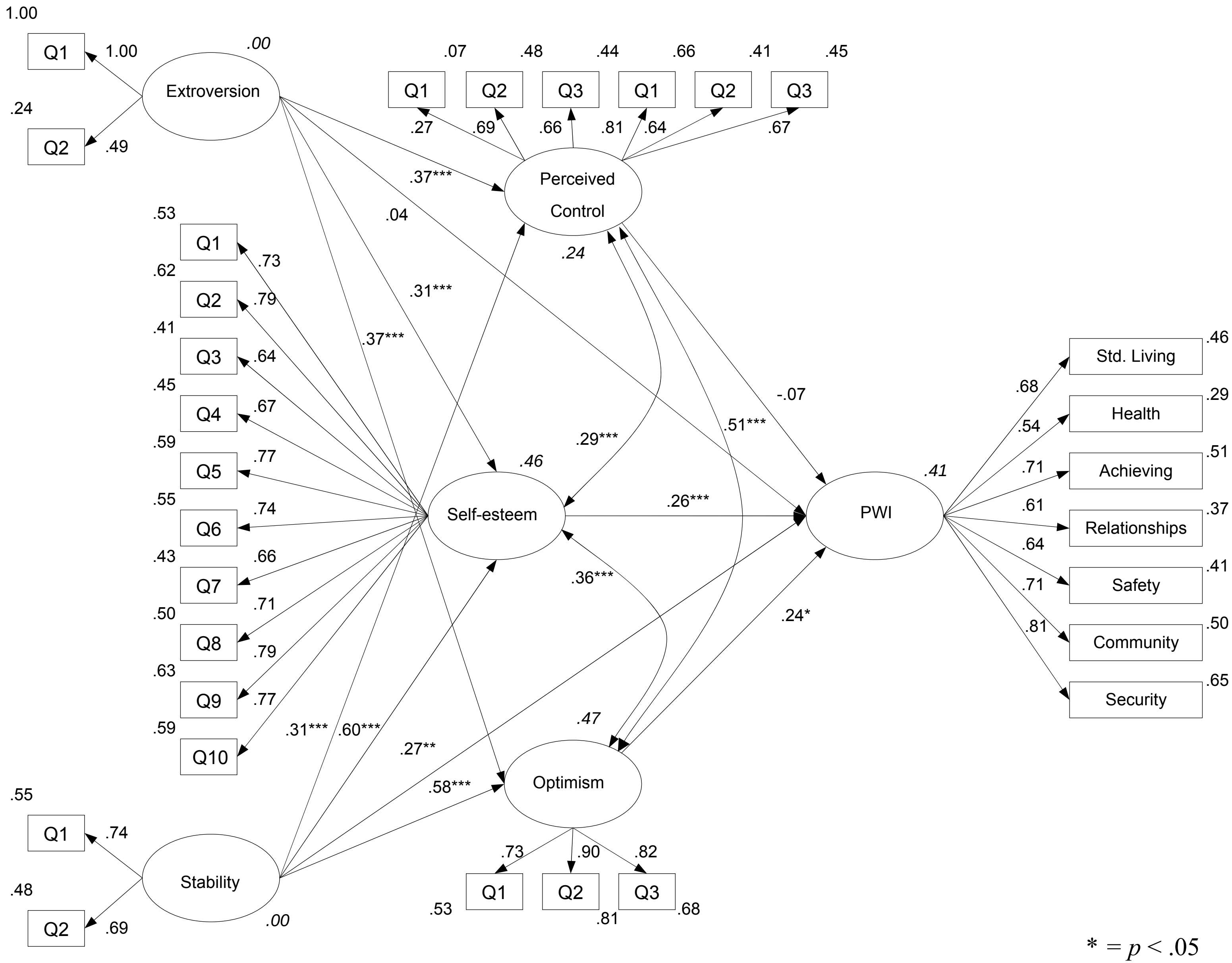


Figure 3.5: Homeostatic model of Subjective Wellbeing (Standardised, N=387).

* = $p < .05$
** = $p < .01$
*** = $p < .001$

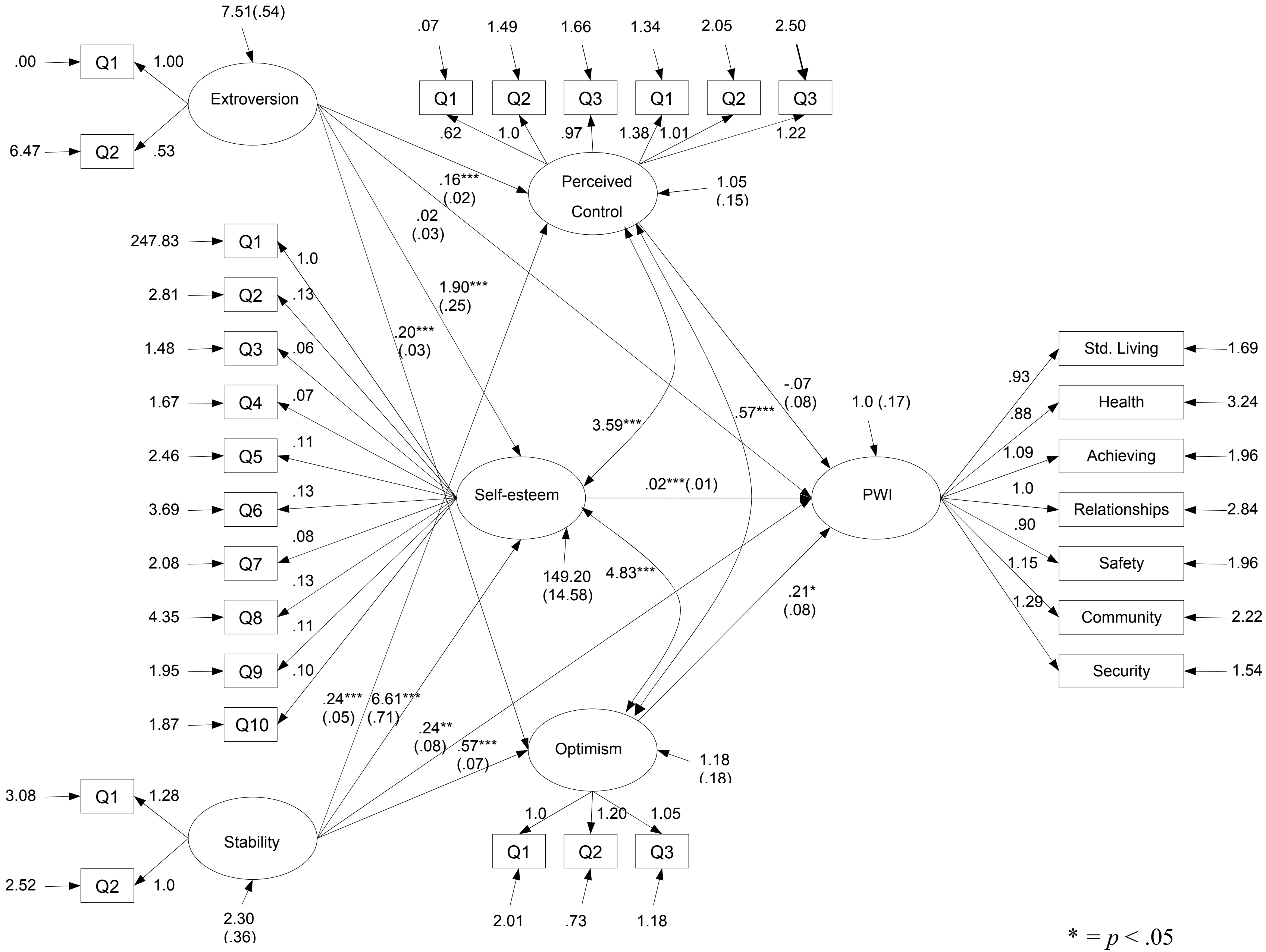


Figure 3.6: Homeostatic model of Subjective Wellbeing (Unstandardised).

* = $p < .05$
** = $p < .01$
*** = $p < .001$

The absolute and relative fit indices of the homeostatic model of SWB are provided in Table 3.4.

Table 3.4: Absolute and relative fit indices of homeostatic model of SWB.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	4,682.97	4,536.97	423	<.001	10.73	.50	.52	.16	.41
Saturated	992.0	.000	0	-	-	1.0	1.0	-	-
Independence	9,069.51	9,007.51	465	<.001	19.37	.00	.00	.21	.00

The fit indices provided in Table 3.4 indicate that the homeostatic model does not provide an absolute fit, or an adequate relative fit to the data. The low values of the relative fit indices indicate that the specified homeostatic model provides a slightly better fit than the independence model, which specifies no relationships between the variables.

The standardised and unstandardised regression paths and SMCs provided in Figure 3.5 and Figure 3.6 indicate that stability significantly influenced PWI (β=.27, B=.24, p<.01) whereas extroversion was not a significant predictor of PWI (β=.04, B=.02, p>.05). As hypothesised, extroversion and stability exerted a moderate and significant influence on all three components of the buffer system (β-weights ranged from .31 to .60), accounting for between 23 and 46% of variance in these components. Only two of the three components of the buffer system significantly predicted PWI (self-esteem, β=.26, B=.02, p<.001; optimism, β=.24, B=.21, p<.001). Although self-esteem was a significant predictor of PWI, a one unit increase in self-esteem resulted in an increase in PWI of only .02 points. Together, the combination of personality and the buffer system in the homeostatic model predicted 41% of the variance in PWI.

Testing then proceeded to determine whether any component of the buffer system mediated the relationship between extroversion and PWI, or stability and PWI. The B-weights, z-scores, and significance levels for each of the mediation paths are provided in Table 3.5.

Table 3.5: B-weights, z-scores, and significance levels of each mediation path in the homeostatic model of SWB.

Mediation Path	***B***	***z-score***	***P***
Stability → Self-esteem → PWI	.13	3.12	<.001
Stability → Optimism → PWI	.12	2.48	<.01
Stability → Perceived control → PWI	-.02	-.89	>.05
Extroversion → Self-esteem → PWI	.04	3.03	<.001
Extroversion → Optimism → PWI	.04	2.33	<.01
Extroversion → Perceived control → PWI	-.01	-.91	>.05

The values of the B-weights, z-scores, and significance levels of the mediation paths provided in Table 3.5 indicate that, of the three components of the buffer system, only self-esteem and optimism were significant mediators of the relationship between stability and PWI, and extroversion and PWI. For the relationship between stability and PWI, the mediation effect was only partial, as the direct effect of stability on PWI remained significant in the presence of the mediators (β=.27, B=.24, p<.01). In contrast, self-esteem and optimism fully mediated the relationship between extroversion and PWI, as the direct path between extroversion and PWI was not significant in the presence of the mediators (β=.04, B=.02, p>.05). A comparison of the significant mediation path B-weights for both stability and extroversion reveals that the mediation between stability and PWI was much stronger (B=.13 and B=.12) than the mediation between extroversion and PWI (B=.04). Overall, the hypothesis that the homeostatic model provided an adequate fit to the data was not supported.

Multiple Discrepancies Theory

MDT asserts that a set of seven perceived discrepancies covering various aspects of an individual's life (for instance, the discrepancy between what one has and what one wants), predicts their SWB. Specifically an individual who reports lower perceived discrepancies is proposed to experience greater SWB than an individual who reports higher perceived discrepancies. A SEM was specified according to MDT to test whether this theory provides an adequate explanation of the data. It was hypothesised that the MDT model would not provide a better fit to the data than the homeostatic model. The MDT model of SWB is given in Figure 3.7. In this figure, the standardised regression paths are provided in addition to SMCs (in italics). The unstandardised values (and standard errors) for the MDT model are provided in Figure 3.8.

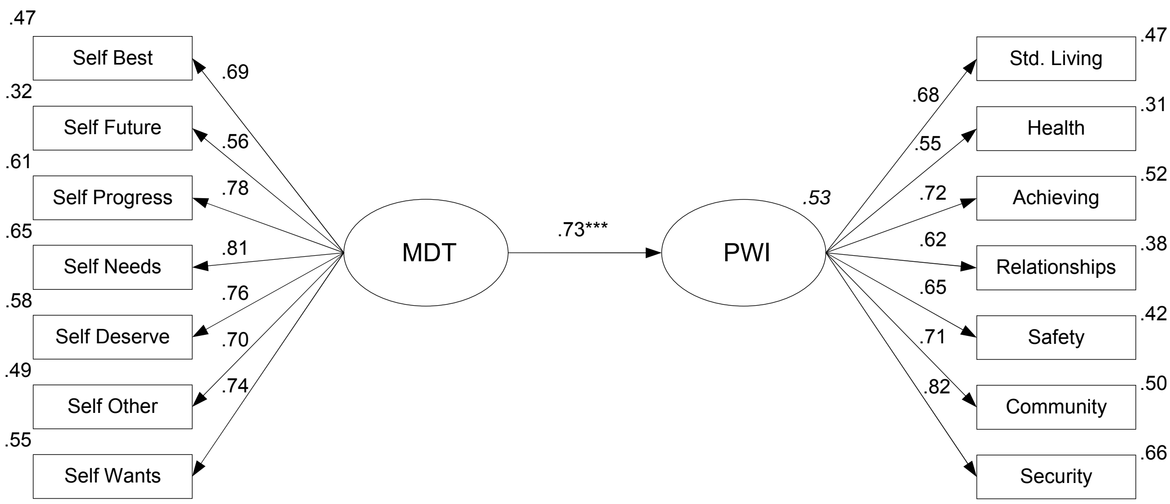
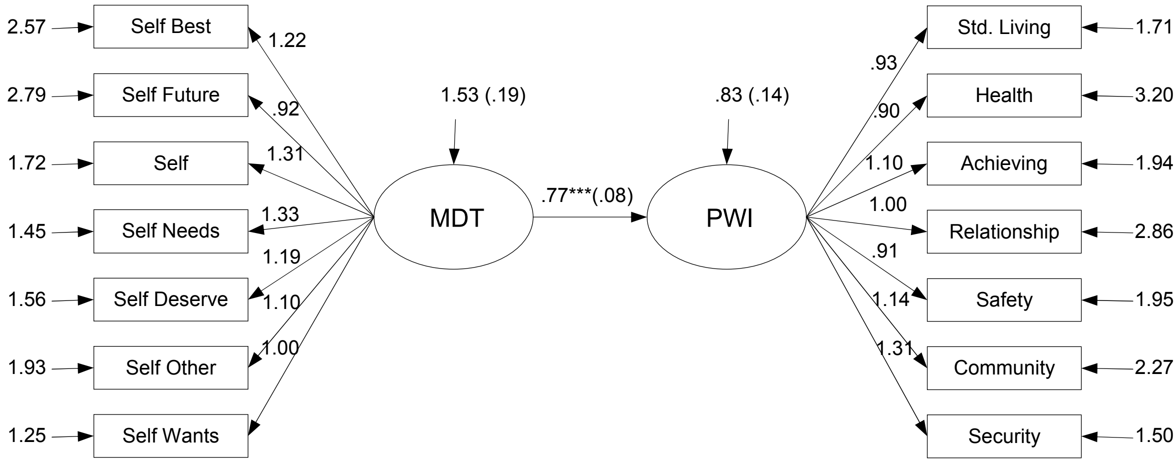


Figure 3.7: SEM of MDT (Standardised, N=387).



*** = *p*<.001

Figure 3.8: SEM of MDT (Unstandardised).

The absolute and relative fit indices of the homeostatic model of SWB are provided in Table 3.6.

Table 3.6: Absolute and relative fit indices of MDT model.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	406.51	348.51	76	<.001	4.59	.87	.90	.10	.53
Saturated	210.0	.000	0	-	-	1.0	1.0	-	-
Independence	2,746.34	2,718.34	91	<.001	29.87	.00	.00	.27	.00

The fit indices provided in Table 3.6 indicate that the MDT model does not provide an absolute fit, or an adequate relative fit to the data. The unstandardised regression paths provided in Figure 3.8, in addition to the standardised regression paths and SMCs provided in Figure 3.7, indicate that MDT strongly influences PWI (β=.73, B=.77, *p*<.001). A one unit increase in the latent variable MDT (higher values indicate lower discrepancies) results in a .77 point increase in PWI. This indicates that lower discrepancies are associated with higher levels of PWI. Together the set of perceived discrepancies accounts for 53% of the variance in PWI.

As both the homeostatic model and the MDT model do not provide an adequate fit to the data and are not nested, it is only possible to make comparisons of the variance accounted for and model parsimony. When a comparison is made of the variance accounted for by both models, it is evident that the MDT model explains 12% more variance in PWI.

A comparison of the parsimony of two independent SEMs is conducted by calculating the difference in AIC. This calculation takes into account both the error in the model and the number of parameters in the model, which allows a test of models with differing degrees of freedom (422 for homeostatic model vs. 76 for MDT model). This value is then assessed against a chi-square distribution with one degree of freedom. Application of this formula comparing the homeostatic and MDT models yields χ^2=4,276.46, df=1, p<.001. Thus, in contrast with the homeostatic model of SWB, the MDT model provides a more parsimonious explanation of the data. Although the results do not support the hypothesis that the MDT model provides an adequate fit to the data, the MDT model is a more parsimonious explanation of the data, and explains more variance in PWI, than the homeostatic model.

To comprehensively test the efficacy of MDT, a further SEM was specified and tested according to the sub-hypotheses given by Michalos (1985). Specifically, in addition to the hypothesis that SWB is the result of seven perceived discrepancies described above, Michalos posits that the discrepancy between what one has and wants is a mediating variable between all other perceived discrepancies and SWB. A SEM was specified to test this hypothesis. This model is given in Figure 3.9. In this figure, the standardised regression paths are provided in addition to SMCs (in italics). The unstandardised values for this model are provided in Figure 3.10.

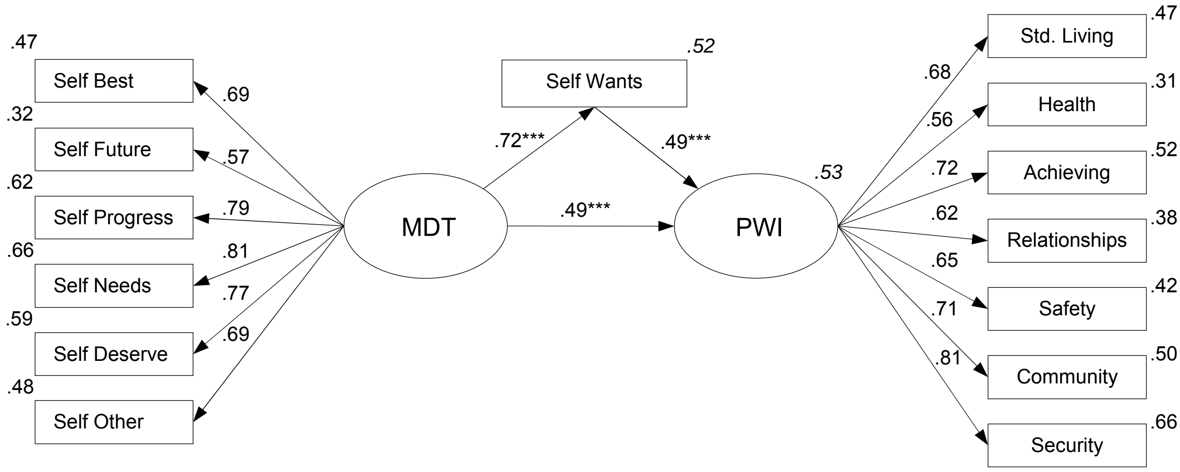


Figure 3.9: MDT self-wants mediation model predicting PWI (Standardised, N=387).

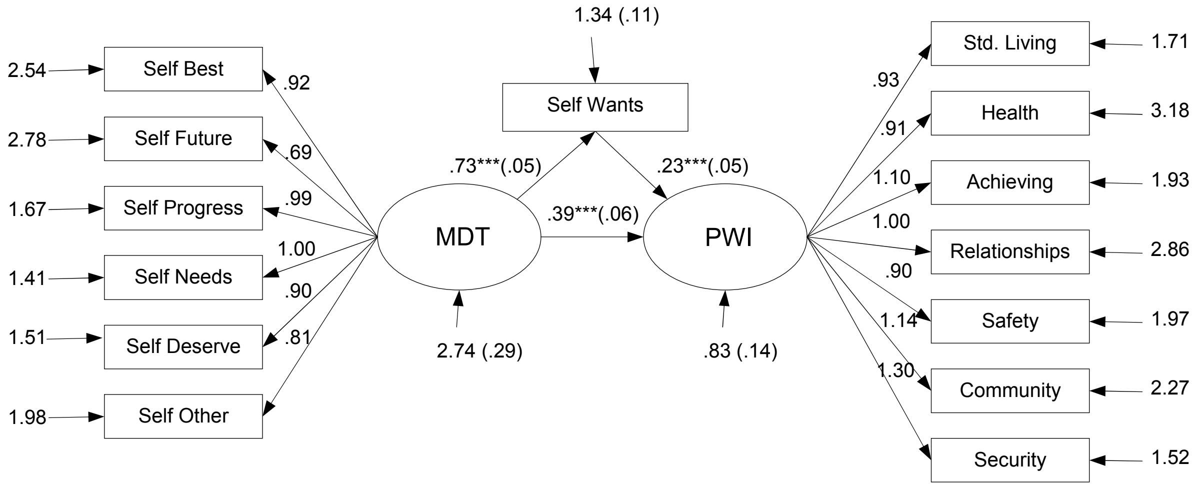


Figure 3.10: MDT self-wants mediation model predicting PWI (Unstandardised).

Absolute and relative fit indices for the MDT self-wants mediation model are provided in Table 3.7.

Table 3.7: Absolute and relative fit indices of MDT self-wants mediation model.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	389.59	329.59	75	<.001	4.40	.88	.90	.09	.53
Saturated	210.0	.000	0	-	-	1.0	1.0	-	-
Independence	2,746.34	2,718.34	91	<.001	29.87	.00	.00	.27	.00

The fit statistics given in Table 3.7 indicate that the MDT self-wants mediation model does not provide an absolute fit, or an adequate relative fit to the data. The standardised and unstandardised regression paths and SMCs provided in Figure 3.9 and Figure 3.10 indicate that MDT was strongly related with the self-wants discrepancy (β=.72, B=.73, p<.001), accounting for 52% of variance. Thus, lower discrepancies for the self-best, self-future, self-progress, self-deserves, self-needs, and self-other items are associated with lower self-wants discrepancies. In turn, lower self-wants discrepancies are associated with higher PWI (β=.49, B=.23, p<.001), as are lower discrepancies on the remaining six items (β=.49, B=.39, p<.001). Together, these discrepancies account for 53% of the variance in PWI.

A mediation analysis was conducted to determine whether the self-wants discrepancy mediated the effect of MDT on PWI. The B-weights and standard errors for each mediation analysis path are presented in Table 3.8 in addition to the z-score and significance level of the mediation path.

Table 3.8: B-weights, standard errors, and z-score for each path of MDT self-wants mediation model.

Pathway	*B*	*SE B*	*P*
MDT→ PWI	.39	.06	<.001
MDT→ Self-wants	.73	.05	<.001
Self-wants → PWI	.23	.05	<.001
MDT → Self-wants → PWI	.17		<.001 (z = 4.4)

The values contained in Table 3.8 indicate that the self-wants discrepancy significantly mediated the relationship between MDT and PWI (z=4.4, $p<.001$). As the direct path between MDT and PWI retained significance in the presence of the mediator (MDT to PWI, B=.39, $p<.001$), self-wants only partially mediated the relationship between MDT and PWI.

To test the hypothesis given by Michalos (1985) that the self-wants discrepancy is the strongest determinant of SWB, a comparison of the unstandardised regression coefficients was made for the paths MDT→PWI and self-wants→PWI. This comparison was made by converting these coefficients to z-scores using the formula given in Equation 3.2.

$$Z = \frac{Bweight}{SE\ Bweight} \qquad \text{(Eqn 3.2)}$$

This conversion yields values of 6.5 for MDT→PWI, and 4.6 for self-wants→PWI. The difference between these z-scores is equal to 1.90, $p>.05$. Thus the self-wants discrepancy was not a significantly greater predictor of PWI in this sample.

A comparison of the MDT self-wants mediation model (Figure 3.9) to the MDT model given in Figure 3.7 using the AIC difference test yields χ^2=16.92, $p<.001$. Thus, the MDT self-wants mediation model provides a more parsimonious explanation of the data than the MDT model given in Figure 3.7 whilst explaining the same amount of variance. However the MDT self-wants mediation model does not give an acceptable fit to the data.

In the development of MDT by Michalos (1985), a global measure of LS was used as the dependent variable. Given that the PWI is a domain-based measure of SWB, the above analyses were repeated with a global measure of SWB (satisfaction with life as a whole; LS) in place of the PWI. The MDT self-wants mediation model predicting LS is given in Figure 3.11. In this figure, standardised regression paths and SMCs (in italics) are provided. The unstandardised values (and standard errors) for this model are provided in Figure 3.12.

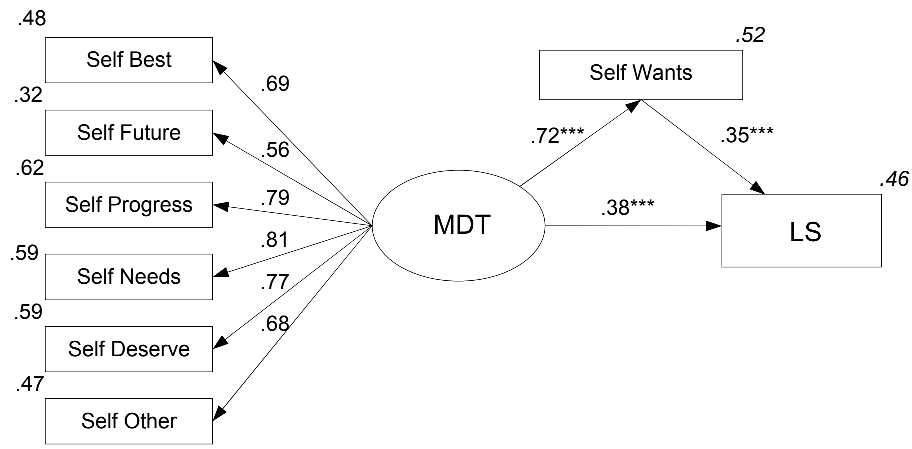


Figure 3.11: MDT self-wants mediation model predicting LS (Standardised, N=387).

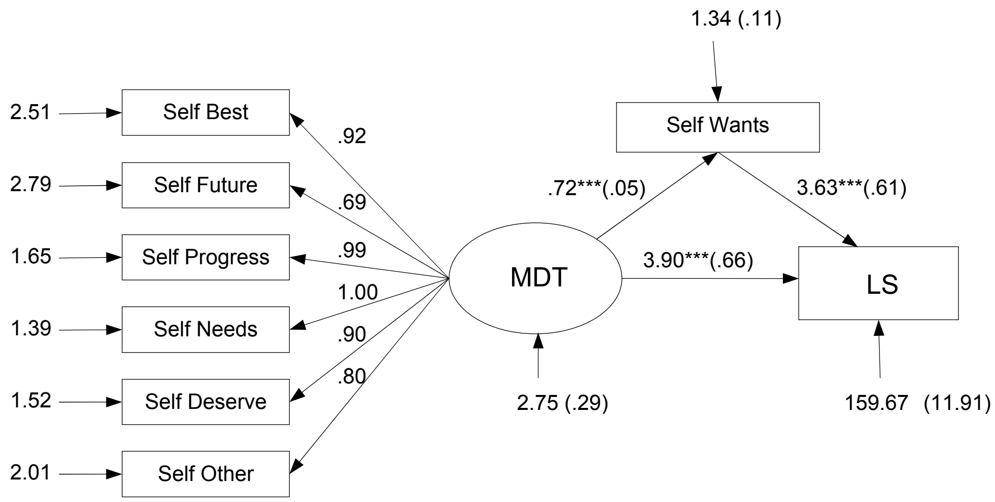


Figure 3.12: MDT self-wants mediation model predicting LS (Unstandardised).

Absolute and relative fit indices for the MDT self-wants mediation model predicting LS are provided in Table 3.9.

Table 3.9: Absolute and relative fit indices of MDT self-wants LS mediation model.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	171.56	137.56	19	<.001	7.24	.91	.92	.13	.46
Saturated	72.0	.000	0	-	-	1.0	1.0	-	-
Independence	1,583.53	1,567.53	28	<.001	55.98	.00	.00	.38	.00

The absolute and relative fit indices presented in Table 3.9 indicate a poor fit of the MDT self-wants LS model to the data. As in the MDT self-wants model predicting PWI (Figure 3.9), the standardised and unstandardised regression weights and SMCs given in Figure 3.11 and Figure 3.12 indicate that MDT was strongly related to the self-wants discrepancy (β=.72, B=.72, p<.001), accounting for 52% of the variance. In addition, self-wants and MDT were both strongly related to LS (β=.35, B=3.63, p<.001 and β=.38, B=3.90, p<.001 respectively). Thus, lower perceived discrepancies are associated with higher ratings of global LS. Together, the set of perceived discrepancies account for 46% of the variance in LS.

A mediation analysis was conducted to determine whether the self-wants discrepancy significantly mediated the relationship between MDT and LS. The B-weights, standard errors, z-score, and significance levels for all mediation analysis paths are presented in Table 3.10.

Table 3.10: B-weights, standard errors, and z-score for each path of MDT self-wants LS mediation model.

Pathway	***B***	***SE B***	***P***
MDT→ LS	3.90	.66	<.001
MDT→ Self-wants	.72	.05	<.001
Self-wants→ LS	3.63	.61	<.001
MDT → Self-wants → LS	2.61		<.001 (z = 5.5)

The data contained in Table 3.10 indicate that the self-wants discrepancy was a significant mediator between MDT and LS (z=5.5, $p<.001$). This mediation effect was partial, as the direct effect of MDT to LS remained significant in the presence of the mediator (B=3.90, $p<.001$).

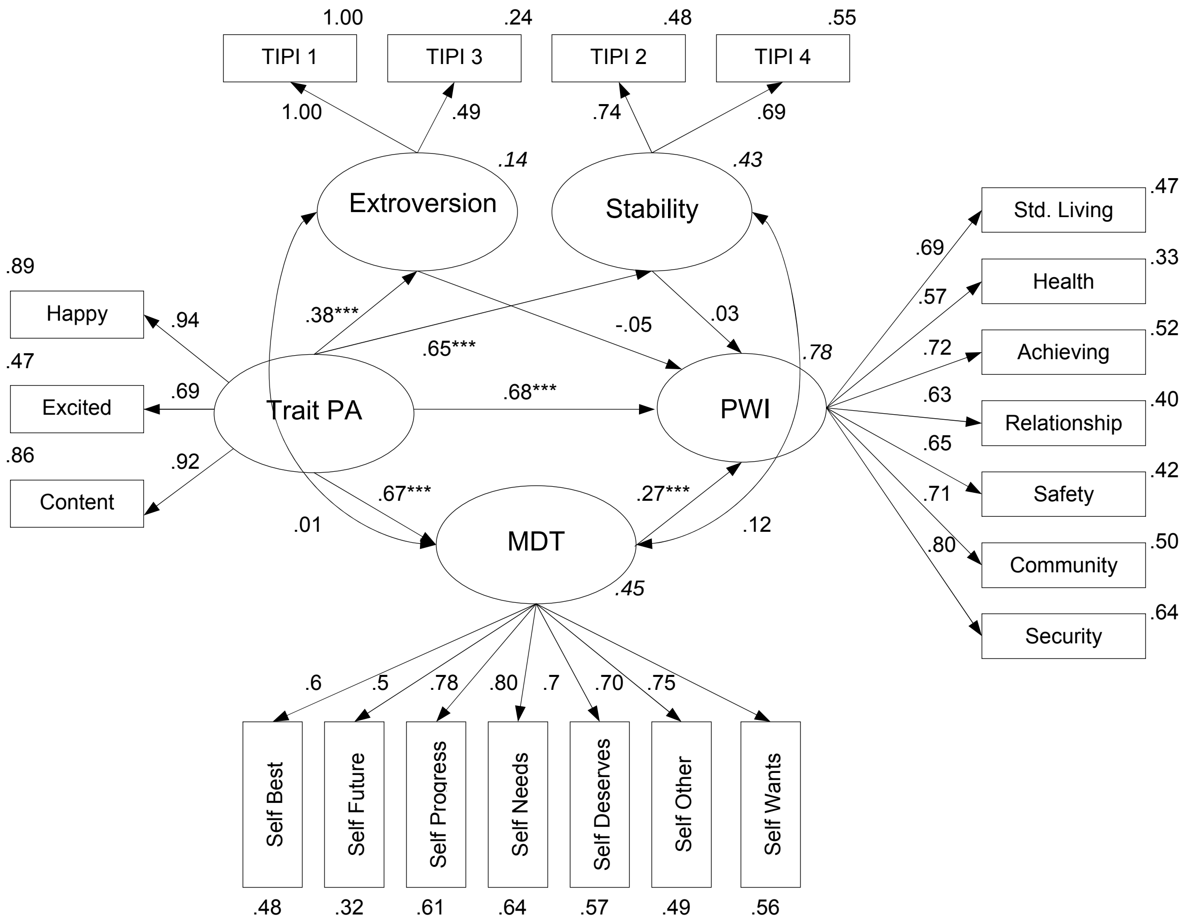
To determine the relative strength of self-wants and MDT on LS, a comparison of the unstandardised regression coefficients was made. The conversion of the B-weights to z-scores yielded values of 5.91 for MDT→LS and 5.95 for self-wants→LS, $Z_{difference}=-.04$, $p>.05$. Thus, the direct effect of self-wants on LS is not significantly different from the direct effect of the six perceived discrepancies on LS. This result does not support the hypothesis that the self-wants discrepancy is the strongest determinant of LS.

The AIC difference test was used to compare the parsimony of the MDT self-wants LS model (Figure 3.11) to the MDT self-wants PWI model (Figure 3.9). This yielded $\chi^2=218.03$, $p<.001$. The MDT self-wants model with LS as the dependent variable provided a more parsimonious explanation of the data than the MDT self-wants model with PWI as the dependent variable. However, a comparison of the relative fit indices for both models reveals the MDT self-wants PWI model (Table 3.7) to provide a better relative fit to the data than the MDT self-wants LS model (Table 3.9; difference in

χ^2/df=-2.84, RMSEA=-.04, NFI=-.03, CFI=-.02). In addition, the MDT self-wants PWI model explained 7% more variance in the DV than the MDT self-wants LS model. Replacing the PWI with LS as the measure of SWB in the MDT self-wants model did not result in an adequate fit of the MDT self-wants model to the data. Importantly, neither MDT self-wants model provided an absolute fit, or an adequate fit to the data.

Affective-Cognitive Model

The affective-cognitive model asserts that five trait affects (happy, excited, content, satisfied, discontent; Davern, 2004) which combine to form a latent factor, directly influence SWB, MDT, and the five factors of personality. MDT and personality are also hypothesised to directly influence SWB. A test of this model by Davern (2004) supported these predictions, however the model did not provide an absolute fit to the data (χ^2=466.91, *df*=215, *p*<.001, χ^2/df=2.2, RMSEA=.04, AIC=636.91, SMC=.88). In a subsequent revision of the affective-cognitive model by Davern, Cummins, and Stokes (2007), the trait affect items of discontent and satisfied were removed, leaving three positive trait affect items (happy, content, and excited) forming a latent construct called trait PA. In addition, the five factors of personality were not combined to form a latent construct as they were in Davern (2004). Despite these changes, the model provided an adequate relative fit to the data (χ^2=5,114.61, *df*=1,961, *p*<.001, χ^2/df=2.6, RMSEA=.04, AIC=5,482.61, SMC=.91) and explained 3% more variance than the original affective-cognitive model. Thus, an affective-cognitive model was tested according to the revised model given in Davern et al. Nevertheless, as data for 10 affect items (representative of the circumplex model of emotion), was collected, an analysis will later be conducted to verify that the items used by Davern et al. are the strongest predictors of PWI. In addition, only the dimensions of extroversion and stability were included in the model as previous research has demonstrated that, of the five factors, these two dimensions are most strongly related to SWB (Davern, 2004; DeNeve & Cooper, 1998). In this revised affective-cognitive model, extroversion, stability, and MDT are hypothesised to mediate the relationship between trait PA and PWI. This model is given in Figure 3.13 along with standardised regression paths, SMCs (in italics), and correlations. The unstandardised values (and standard errors) for this model are presented in Figure 3.14.



* = $p < .05$
** = $p < .01$
*** = $p < .001$

Figure 3.13: Affective-Cognitive model of SWB incorporating extroversion, stability, and MDT (Standardised, N=387).

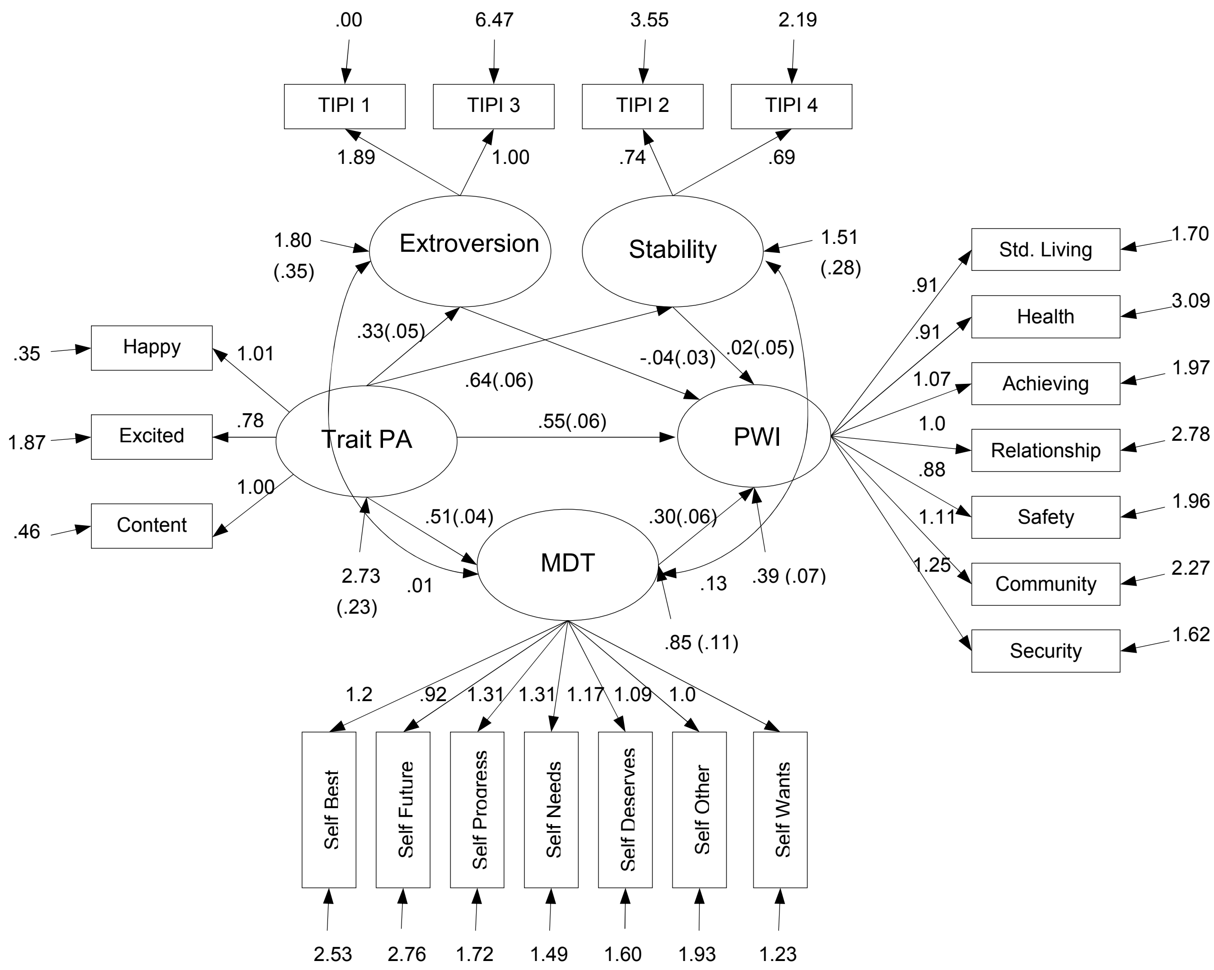


Figure 3.14: Affective-Cognitive model of SWB incorporating extroversion, stability and MDT (Unstandardised).

Absolute and relative fit indices for the affective-cognitive model are provided in Table 3.11.

Table 3.11: Absolute and relative fit indices for affective-cognitive model incorporating extroversion, stability, and MDT.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	677.99	577.99	181	<.001	3.19	.87	.91	.08	.78
Saturated	462.0	.000	0	-	-	1.0	1.0	-	-
Independence	4,551.15	4,509.15	210	<.001	21.47	.00	.00	.38	.00

The absolute and relative fit indices presented in Table 3.11 indicate that the affective-cognitive model does not provide an absolute fit, or an acceptable relative fit to the data. The standardised and unstandardised regression weights and SMCs provided in Figure 3.13 and Figure 3.14 indicate that trait PA strongly predicts MDT (β=.67, B=.51, p<.001), accounting for 45% of the variance. Trait PA is also moderately related to extroversion (β=.38, B=.33, p<.001) and strongly related to stability (β=.65, B=.64, p<.001), accounting for 14% and 43% of variance respectively. Extroversion and stability do not significantly predict PWI, whereas trait PA strongly predicts PWI (β=.68, B=.55). MDT is also significantly predictive of PWI (β=.27, B=.29), however this effect is not as strong in comparison to trait PA. Together these variables account for 78% of variance in PWI.

A mediation analysis was conducted to determine whether MDT, extroversion, or stability mediated the effect of trait PA on PWI. The B-weights, standard errors, z-scores, and significance levels of each mediation path are presented in Table 3.12.

Table 3.12: B-weights, z-scores, and significance levels for mediation analysis paths in the affective-cognitive model of SWB.

Mediation Path	***B***	***z-score***	***P***
Trait PA → Stability → PWI	.01	.40	>.05
Trait PA → Extroversion → PWI	-.01	-1.29	>.05
Trait PA → MDT→ PWI	.15	4.64	<.001

The data presented in Table 3.12 indicate that whilst extroversion and stability did not significantly mediate the relationship between trait PA and PWI, MDT was a significant mediator. This mediation effect was only partial as the direct path between trait PA and PWI remained significant (β=.67, B=.55, p <.001) in the presence of MDT.

The AIC difference test was used to compare the parsimony of the affective-cognitive model (Figure 3.13) to the parsimony of the MDT (Figure 3.7), MDT self-wants (Figure 3.9), and homeostatic (Figure 3.5) models. This test yielded χ^2=-273.0, p<.001 for comparison to the MDT model; χ^2=-289.92, p<.001 for comparison to the MDT self-wants model; and χ^2=4,005.4, p<.001 for comparison to the homeostatic model. Thus the affective-cognitive model provides a significantly less parsimonious explanation of the data compared to the MDT models. However, when comparison is made of the relative fit indices for the MDT models (Table 3.6 and Table 3.7), the affective-cognitive model (Table 3.11) provides a slightly better fit to the data and explains up to 34% more variance in PWI. The affective-cognitive model also provided a more parsimonious explanation of the data than the homeostatic model and explained 37% more variance in PWI.

Alternative Nested Affective-Cognitive Model

The fit indices presented in Table 3.11 for the affective-cognitive model indicate that the model did not provide an absolute, or a relative fit to the data. In addition, extroversion and stability were found to be weakly related to PWI. As such, testing proceeded by examining whether the removal of extroversion and stability would improve model fit. In this nested alternative model, MDT is hypothesised to mediate the relationship between trait PA and SWB. This MDT-affective model is provided in Figure 3.15 along with standardised regression paths and SMCs (in italics). Unstandardised values (and standard errors) for this model are provided in Figure 3.16.

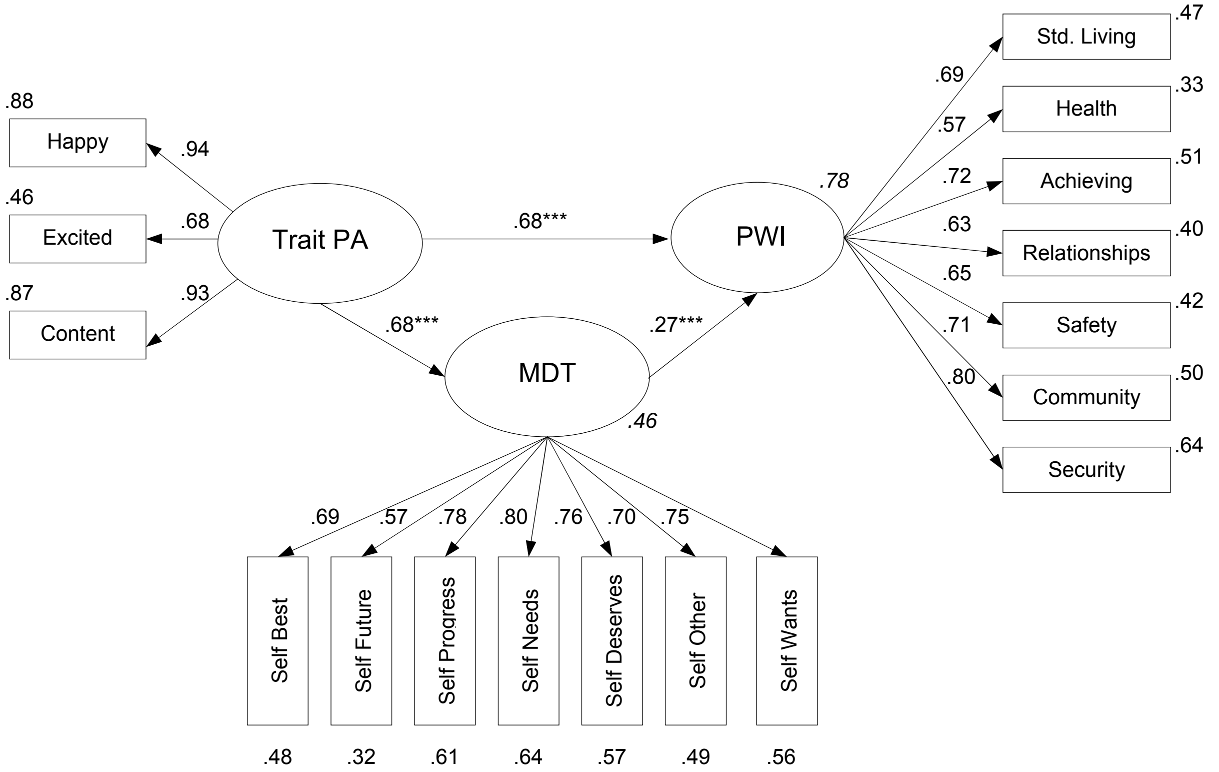


Figure 3.15: MDT-Affective model of SWB (Standardised, N=387).

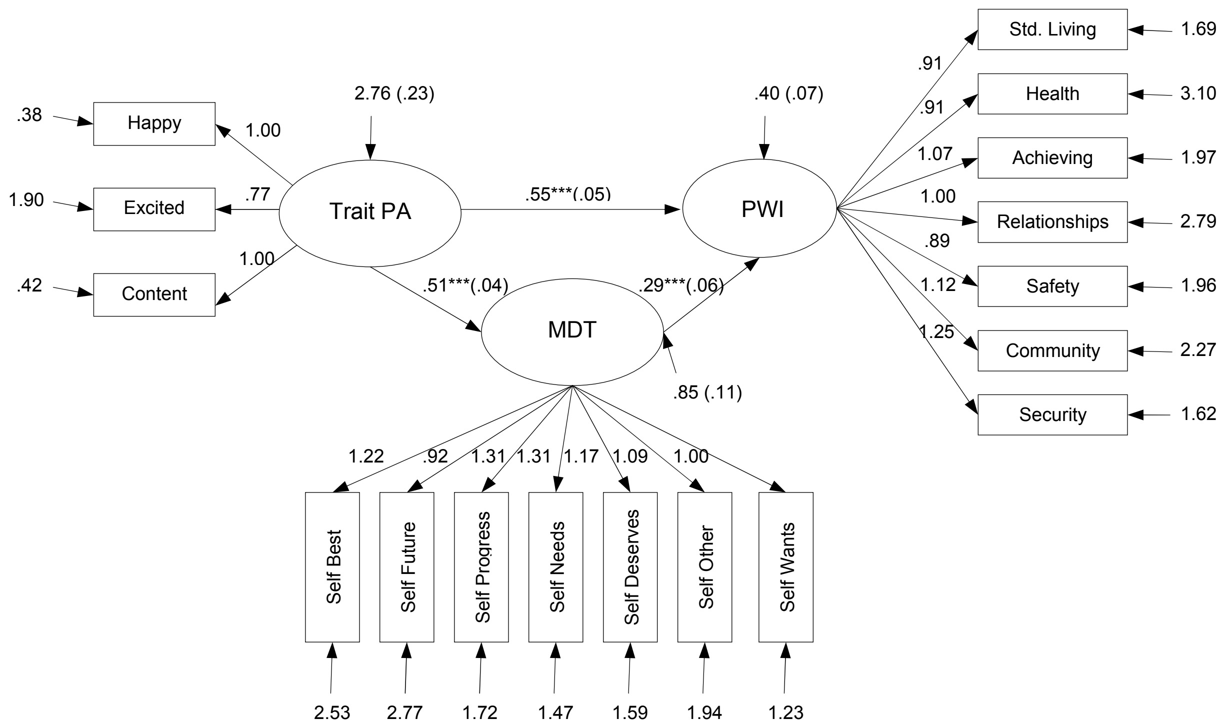


Figure 3.16: MDT-Affective model of SWB (Unstandardised).

Absolute and relative fit indices for the MDT-affective model of SWB are provided in Table 3.13.

Table 3.13: Absolute and relative fit indices for MDT-affective model.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	519.34	445.34	116	<.001	3.8	.89	.91	.09	.78
Saturated	306.0	.000	0	-	-	1.0	1.0	-	-
Independence	4,001.14	3,967.14	136	<.001	29.17	.00	.00	.27	.00

Despite explaining 78% of the variance in PWI, the fit indices presented in Table 3.13 indicate that the MDT-affective model does not provide an absolute fit, or an acceptable relative fit to the data. The standardised and unstandardised regression weights and SMCs provided in Figure 3.15 and Figure 3.16 indicate that trait PA is a powerful predictor of PWI (β=.68, B=.55, p<.001) and MDT (β=.68, B=.51, p<.001). In addition, trait PA accounted for 46% of the variance in MDT. The direct effect of MDT on PWI (β=.27, B=.29, p<.001) is weak in comparison to the direct effect of trait PA on PWI. Together, trait PA and MDT explain 78% of variance in PWI.

A mediation analysis was conducted to determine whether the effect of trait PA on PWI was mediated by MDT. The B-weights, standard errors, and z-score of the mediation analysis paths are presented in Table 3.14.

Table 3.14: B-weights, standard errors, and z-score for mediation analysis paths in MDT-affective model of SWB.

Mediation Path	*B*	*SE B*	*P*
Trait PA → MDT	.51	.04	<.001
MDT → PWI	.29	.06	<.001
Trait PA → MDT → PWI	.15		<.001 (z = 4.6)

The data presented in Table 3.14 indicate that MDT significantly mediated the effect of trait PA on PWI. This effect was only partial, as the direct effect of trait PA on PWI remained significant in the presence of MDT (β=.68, B=.55, p<.001). Further interrogation of the MDT-affective model presented in Figure 3.15 indicates that the relationship between MDT and PWI decreased dramatically from β=.73 (B=.77, see Figure 3.16) to β=.27 (B=.29, see Figure 3.16) in the presence of trait PA.

As the MDT-affective model is a nested model of the affective-cognitive model (Figure 3.13), a χ^2 difference test can be used to compare the fit of the two models. This statistic is calculated by subtracting the chi-square value of the nested model from the chi-square value of the original model. This value is then assessed against the chi-square distribution with degrees freedom equal to *df* of the nested model, subtracted from *df* of the original model. Applying this calculation yields χ^2=132.21, *df*=64, p<.001. Thus the nested MDT-affective model (Figure 3.15) provides a significantly better fit than the original affective-cognitive model. To compare the parsimony of the MDT-affective model to the parsimony of the affective-cognitive model, and the MDT self-wants model (Figure 3.9), the AIC difference test was used. This calculation yields χ^2=158.65, *df*=1, p<.001 for the affective-cognitive model, and χ^2=-129.75, *df*=1, p<.001 for the MDT self-wants model. Thus the MDT-affective model provided a more parsimonious explanation of the data than the affective-cognitive model, and a less parsimonious explanation of the data than the MDT self-wants model. However the MDT-affective model explains 25% more variance in PWI than the MDT self-wants model.

Overall, removing the personality dimensions of extroversion and stability from the affective-cognitive model resulted in a significantly better fit to the data. This nested alternative model also provides a more parsimonious explanation of the data whilst explaining the same amount of variance in PWI as the affective-cognitive model. Nevertheless, the nested MDT-affective model did not provide an absolute fit, or an acceptable relative fit to the data.

Trait PA and Subjective Wellbeing

Testing then proceeded by examining whether the trait affect items used by Davern (2004) and Davern et al. (2007) in the affective-cognitive model were the strongest predictors of PWI in the current sample. In this test, nine of the 10 affect items originally used by Davern (2004) were entered together as independent variables and regressed onto LS and PWI separately to determine the relative contribution of each item in predicting SWB. The adjective “satisfied” was excluded from the analysis, as it is similar to questions used in measuring the dependent variable (i.e., “How satisfied are you with your life as a whole?”) and thus may have introduced a confound. The unstandardised B-weights, standardised regression coefficients (β), the semipartial correlations (sr^2), R^2 and adjusted R^2 are presented in Table 3.15 for LS and Table 3.16 for PWI.

Table 3.15: Standard multiple regression predicting LS by nine affective adjectives (*N*=387).

Variable	*B*	*SE B*	*β*	*sr*^{2}
Happy	2.5***	.68	.26	.01
Content	5.0***	.62	.52	.06
Unhappy	-.50	.46	-.06	.00
Discontent	.21	.46	.03	.00
Active	.19	.35	.02	.00
Alert	.02	.43	.00	.00
Excited	.29	.39	.03	.00
Sleepy	.02	.24	.00	.00
Quiet	-.12	.28	-.01	.00
* *p* <.05; ** *p* <.01; *** *p* <.001				R^2 = .65
				Adjusted R^2 = .65

Table 3.16: Standard multiple regression predicting PWI by nine affective adjectives (*N*=387).

Variable	*B*	*SE B*	*β*	*sr*^{2}
Happy	1.60**	.61	.19	.01
Content	3.91***	.56	.47	.05
Unhappy	-.50	.42	-.07	.00
Discontent	-.06	.41	-.01	.00
Active	.80*	.31	.11	.01
Alert	.47	.39	.05	.00
Excited	.24	.36	.03	.00
Sleepy	-.15	.22	-.02	.00
Quiet	.08	.25	.01	.00
* *p* <.05; ** *p* <.01; *** *p* <.001				R^2 = .63
				Adjusted R^2 = .62

The R^2 for both regressions were significantly different from zero, $F(9,377)=79.19$, $p<.001$ (LS), and $F(9,377)=70.55$, $p<.001$ (PWI). Semi-partial r^2 revealed two of the nine affect items contributed significant unique variance to the prediction of LS: happy (sr^2=.01) and content (sr^2=.06). For the PWI, three affect items contributed significant unique variance: happy (sr^2=.01), content (sr^2=.05), and active (sr^2=.01). Altogether, 65% of the variability in satisfaction with life as a whole, and 63% of variability in PWI was predicted by knowing scores on these nine affect adjectives.

The regression predicting PWI (Table 3.16) indicated that the three adjectives of happy, content, and active were the strongest predictors of PWI. These three variables were then entered into a standard multiple regression predicting PWI. The regression was significantly different from zero, R^2=.62, $F(3,383)=208.43$, $p<.001$. Thus, scores on only these three variables explained 62% of variance in PWI. The addition of the other six affect items increased the variance explained by only 1%.

A standard regression was then conducted to determine the predictive power of affect on individuals who experience compromised SWB (defined as a score on the PWI less than 60, n=69, M=47.23). The regression was significantly different from zero, $F(3,65)=20.63$, $p<.001$. For these individuals, 49% of the variability in PWI was accounted for by knowing scores on only the three affect adjectives of happy (β=.35, $p<.05$), content (β=.39, $p<.01$), and active (β=.02, $p>.05$). The remaining six affect items increased the variance explained by only 6% ($p>.05$).

Affective Model of Subjective Wellbeing

The results of the regressions testing the relative predictive power of nine trait affect items for PWI indicated that the three affect adjectives of happy, content, and active were most strongly related to PWI, accounting for between 49% and 62% of variance. As the MDT models, the homeostatic model, the affective-cognitive model, and the MDT-affective model provided inadequate fits to the data, an alternative, simpler model of SWB incorporating these three trait affects was specified and tested. In this model, trait happiness, contentment, and activity are hypothesised to form a latent construct called 'trait positive affect' (trait PA), which directly predicts PWI. This model is presented in Figure 3.17 along with standardised regression paths, SMCs (in italics) and correlations. The unstandardised values (and standard errors) for this model are presented in Figure 3.18.

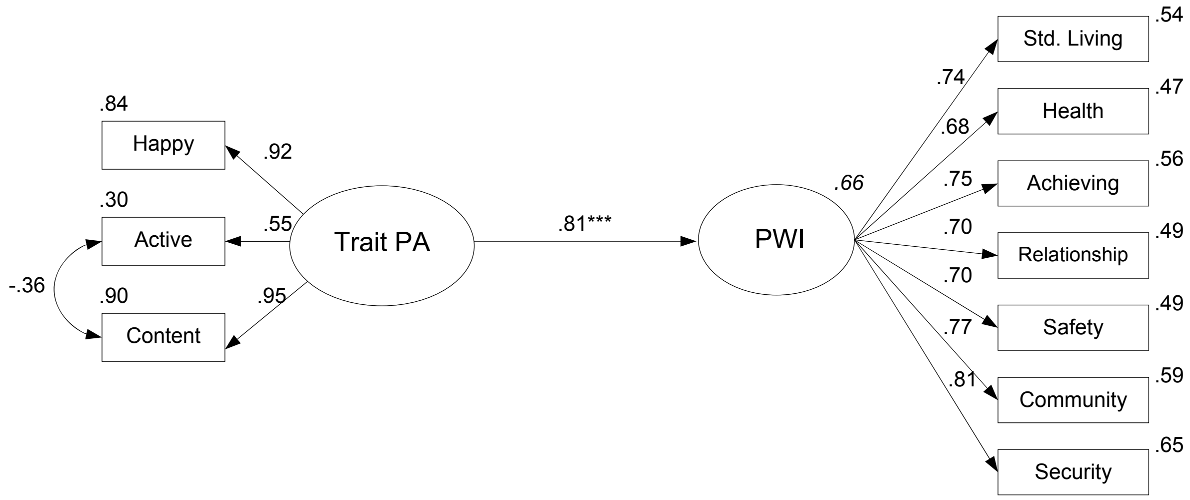


Figure 3.17: Trait PA Affective model of SWB (Standardised, N=387).

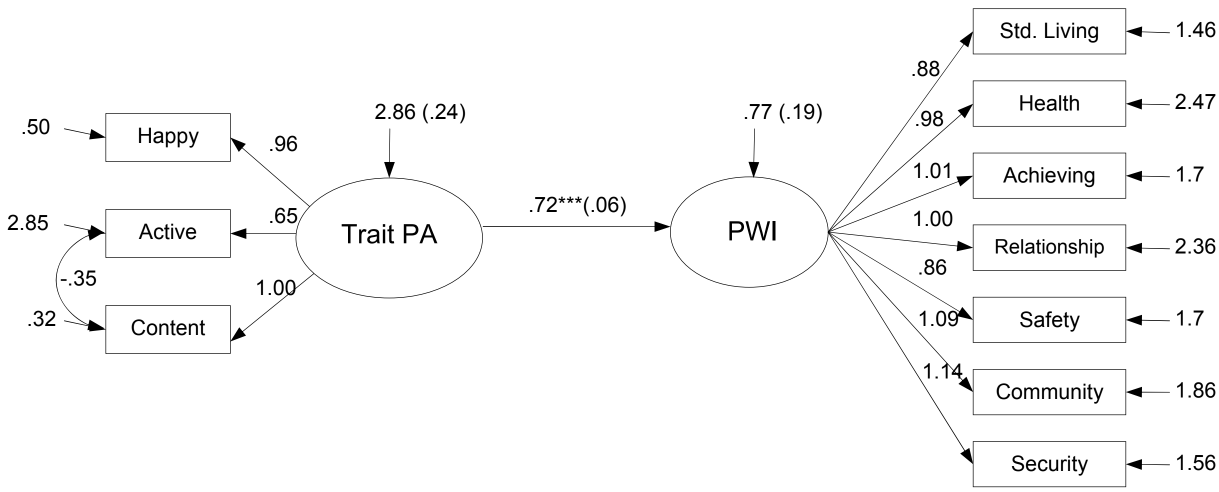


Figure 3.18: Trait PA Affective model of SWB (Unstandardised).

The absolute and relative fit indices for the trait PA affective model of SWB are provided in Table 3.17.

Table 3.17: Absolute and relative fit indices for trait PA affective model of SWB (N=387).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	103.68	19.68	13	>.05	1.5	.99	1.0	.04	.66
Saturated	110.00	.000	0	-	-	1.0	1.0	-	-
Independence	2,166.67	2,146.67	45	<.001	47.7	.00	.00	.35	.00

The indices presented in Table 3.17 indicate an excellent and absolute fit to the data for the trait PA affective model. The standardised and unstandardised regression weight and SMC provided in Figure 3.17 and Figure 3.18 indicates that trait PA is strongly related to PWI (β=.81, B=.72, p<.001), accounting for 66% of the variance.

When comparison is made between the absolute and relative fit of the trait PA affective model and the other models tested (homeostatic model, MDT models, affective-cognitive model, MDT-affective model), it is clear that the best fit to the data is given by the trait PA affective model as it is the only model to provide an absolute fit and an acceptable relative fit.

To compare the parsimony of the trait PA model to the parsimony of the other models tested, the AIC difference test was used. This test yielded χ^2=4,581.21, p<.001 for comparison to the homeostatic model; 302.83, p<.001 for comparison to the MDT model; 285.91, p<.001 for comparison to the MDT self-wants model; 67.88, p<.001 for comparison to the MDT self-wants LS model; 575.83, p<.001 for comparison to the affective-cognitive model; and 341.62, p<.001 for comparison to the MDT-affective model. Thus the trait PA affective model provides a more parsimonious explanation of the data than all of the other models tested. A comparison of the relative and absolute fit indices for each model tested is presented in Table 3.18.

Table 3.18: Absolute and relative fit indices for the homeostatic model, MDT model, MDT self-wants mediation model, affective-cognitive model, MDT-affective model, and trait PA affective model.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Homeostasis	4,682.97	4,536.97	423	<.001	10.73	.50	.52	.16	.41
MDT	406.51	348.51	76	<.001	4.59	.87	.90	.10	.53
MDT self-wants	389.59	329.59	75	<.001	4.40	.88	.90	.09	.53
MDT self-wants LS	171.56	137.56	19	<.001	7.24	.91	.92	.13	.46
Affective-cognitive	677.99	577.99	181	<.001	3.19	.87	.91	.08	.78
MDT-affective	519.34	445.34	116	<.001	3.8	.89	.91	.09	.78
Trait PA affective	103.68	19.68	13	>.05	1.5	.99	1.00	.04	.66

The absolute and relative fit indices presented in Table 3.18 indicate that the affective-cognitive and MDT-affective models predict the largest amount of variance in PWI, however these models do not fit the data. The only model to provide an absolute fit to the data is the trait PA affective model. In addition, this model provides the best relative fit of the models tested, accounts for a substantial amount of variance in PWI, and is the most parsimonious model tested.

As trait PA was found to be the most powerful determinant of SWB, a series of partial correlations controlling for trait PA were conducted between the PWI, LS, and the variables that have been proposed by homeostatic theory, MDT, and a number of other researchers (Cha, 2003; Diener & Lucas, 1999; Hills & Argyle, 2001; Lucas et al., 1996; Vitterso, 2001) to influence SWB. The results of the partial correlation analyses for PWI are presented in Table 3.19, and for LS are presented in Table 3.20.

Table 3.19: Pearsons and partial correlations between PWI, personality, cognitive buffers, and MDT.

Variable	Pearson *r* with PWI	*sr*^{2} (controlling for trait PA)	Magnitude of reduction in Pearson *r*
Extroversion	.23***	-.01	.24
Stability	.46***	.10*	.36
Self-esteem	.55***	.11*	.44
Optimism	.48***	.12*	.36
Perceived control	.32***	-.01	.33
Self-wants	.60***	.27***	.33
Self-other	.56***	.34***	.22
Self-deserves	.46***	.23***	.23
Self-needs	.50***	.24***	.26
Self-progress	.49***	.21***	.28
Self-future	.41***	.15**	.26
Self-best	.46***	.12*	.34

* *p* <.05; ** *p* <.01; *** *p* <.001.

Table 3.20: Pearsons and partial correlations between LS, personality, cognitive buffers, and MDT.

Variable	Pearson *r* with LS	*sr*^{2} (controlling for trait PA)	Magnitude of reduction in Pearson *r*
Extroversion	.26***	.09	.17
Stability	.46***	.14**	.32
Self-esteem	.57***	.20***	.37
Optimism	.43***	.06	.37
Perceived control	.32***	.01	.31
Self-wants	.62***	.39***	.23
Self-other	.52***	.31***	.21
Self-deserves	.43***	.25***	.18
Self-needs	.50***	.31***	.19
Self-progress	.48***	.26***	.22
Self-future	.36***	.12*	.24
Self-best	.48***	.22**	.26

* *p* <.05; ** *p* <.01; *** *p* <.001.

The partial correlations presented in Tables 3.19 and 3.20 reveal that once the shared variance between the PWI or LS, and trait PA is controlled for, the relationship of personality, the buffers, and MDT to PWI or LS is strongly reduced. The magnitude of the reduction in zero-order correlations ranged from .22 to .44 for PWI (*M*=.30), and .17 to .37 for LS (*M*=.26). Although the correlations between each perceived discrepancy and PWI were strongly reduced, all of the perceived discrepancies were still significantly related to PWI once the shared variance due to trait PA was controlled. Notably, the relationship between extroversion, stability, and PWI and LS was substantially reduced when controlling for trait PA. In the case of extroversion, the relationship became non-significant. A hierarchical regression was conducted to test the relative predictive power of each of these variables to PWI and LS with trait PA controlled. The results of these regressions are presented in Table 3.21 for PWI as the DV, and Table 3.22 for LS as the DV.

Table 3.21: Hierarchical regression predicting PWI by trait PA, self-esteem, perceived control, optimism, personality and MDT (*N*=387).

Variable	*B*	*SE B*	*β*	*sr*^{2}	ΔR^2
Step 1					
1. Happy	2.04***	.57	.24	.01	.62***
2. Content	4.14***	.54	.50	.06	
3. Active	1.0***	.27	.14	.01	
total unique variance = .08					
total shared variance = .54					
Step 2					.01
1. Happy	1.62**	.58	.19	.01	
2. Content	3.94***	.54	.47	.05	
3. Active	.97***	.27	.13	.01	
4. Self-esteem	.05	.04	.06	.00	
5. Perceived control	-.09	.07	-.05	.00	
6. Optimism	.22	.13	.08	.00	
7. Extroversion	-.01	.11	.00	.00	
8. Stability	.14	.14	.04	.00	
additional unique variance = .00					
additional shared variance = .01					
Step 3					.03***
1. Happy	1.58**	.56	.19	.01	
2. Content	2.97***	.54	.36	.03	
3. Active	1.04***	.26	.14	.01	
4. Self-esteem	.03	.04	.03	.00	
5. Perceived control	-.09	.07	-.05	.00	
6. Optimism	.12	.12	.04	.00	
7. Extroversion	-.03	.10	-.01	.00	
8. Stability	.09	.14	.03	.00	
9. MDT	.34***	.06	.24	.03	
additional unique variance = .03					
additional shared variance = .00					

* *p* <.05; ** *p* <.01; *** *p* <.001 — R^2 = .66, Adjusted R^2 = .66

The data presented in Table 3.21 indicate that none of the variables that comprise homeostatic theory significantly predicted PWI after controlling for trait PA. MDT was significantly predictive of PWI but only increased the variance explained by 3%. In comparison, trait PA explained 62% of variance in PWI. The hierarchical regression was repeated with LS as the DV. The results of this regression are presented in Table 3.22.

Table 3.22: Hierarchical regression predicting LS by trait PA, self-esteem, perceived control, optimism, personality and MDT (*N*=387).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					
1. Happy	2.81***	.62	.29	.02	.65***
2. Content	5.09***	.59	.53	.07	
3. Active	.24	.30	.03	.00	
total unique variance = .09					
total shared variance = .56					
Step 2					.01
1. Happy	2.41***	.64	.25	.01	
2. Content	4.91***	.60	.51	.06	
3. Active	.23	.30	.03	.00	
4. Self-esteem	.10*	.05	.10	.00	
5. Perceived control	-.06	.08	-.03	.00	
6. Optimism	-.15	.14	-.05	.00	
7. Extroversion	.11	.12	.03	.00	
8. Stability	.21	.16	.05	.00	
additional unique variance = .00					
additional shared variance = .01					
Step 3					.02***
1. Happy	2.38***	.62	.24	.01	
2. Content	4.01***	.61	.42	.04	
3. Active	.30	.29	.04	.00	
4. Self-esteem	.08	.04	.08	.00	
5. Perceived control	-.06	.07	-.03	.00	
6. Optimism	-.24	.14	-.08	.00	
7. Extroversion	.10	.11	.03	.00	
8. Stability	.16	.15	.04	.00	
9. MDT	.32***	.06	.20	.02	
additional unique variance = .02					
additional shared variance = .00					

* *p* <.05; ** *p* <.01; *** *p* <.001 R^2 = .68
Adjusted R^2 = .68

The results of the hierarchical regression with LS as the DV are similar to results obtained with PWI as the DV. Specifically, trait PA predicted a substantial amount of variance in LS (65%) whilst the addition of the homeostatic variables only predicted a further 1% variance. Similarly, MDT, although significant, only predicted a further 3% variance in LS. However, as MDT was a significant predictor of PWI and LS, two additional hierarchical regressions were conducted to determine which of the MDT items significantly predicted PWI and LS. The results of this regression with PWI as the DV are presented in Table 3.23, whilst the results with LS as the DV are presented in Table 3.24.

Table 3.23: Hierarchical regression predicting PWI by trait PA and MDT discrepancy items.

Variable	***B***	***SE B***	***β***	***sr²***	**Δ*R²***
Step 1					
1. Happy	2.04***	.57	.24	.01	.62***
2. Content	4.14***	.54	.50	.06	
3. Active	1.0***	.27	.14	.01	
total unique variance = .08					
total shared variance = .54					
Step 2					.06***
1. Happy	1.94***	.53	.23	.01	
2. Content	2.69***	.54	.32	.02	
3. Active	1.03***	.25	.14	.01	
4. Self-wants	.85*	.04	.10	.00	
5. Self-other	1.27***	.39	.17	.01	
6. Self-deserve	.21	.31	.03	.00	
7. Self-needs	.22	.35	.03	.00	
8. Self-progress	.30	.36	.04	.00	
9. Self-future	.26	.33	.04	.00	
10. Self-best	-.24	.28	-.04	.00	
additional unique variance = .01					
additional shared variance = .05					
* *p*<.05; ** *p*<.01; *** *p*<.001					R^2 = .68
					Adjusted R^2 = .67

The hierarchical regression presented in Table 3.23 indicates that the discrepancy between what one has and what relevant others have (self-other) is the third strongest predictor of PWI, behind the trait PA items of happy and content. The self-wants discrepancy was the only other MDT item to significantly predict PWI. This self-wants discrepancy is proposed by Michalos to be the strongest determinant of SWB of the seven perceived discrepancies; however the results given in Table 3.23 do not support this hypothesis. The regression presented in Table 3.23 was repeated with LS as the DV. The results of this regression are presented in Table 3.24.

Table 3.24: Hierarchical regression predicting LS by trait PA and MDT discrepancy items.

Variable	*B*	*SE B*	*β*	*sr*^{2}	ΔR^2
Step 1					
1. Happy	2.81***	.62	.29	.02	.65***
2. Content	5.09***	.59	.53	.07	
3. Active	.24	.30	.03	.00	
total unique variance = .08					
total shared variance = .54					
Step 2					.04***
1. Happy	2.57***	.60	.26	.02	
2. Content	3.76***	.61	.39	.03	
3. Active	.25***	.28	.03	.00	
4. Self-wants	1.52**	.44	.15	.01	
5. Self-other	.76*	.34	.09	.00	
6. Self-deserve	-.23	.39	-.03	.00	
7. Self-needs	.43	.40	.05	.00	
8. Self-progress	.36	.37	.04	.00	
9. Self-future	-.35	.31	-.04	.00	
10. Self-best	.17	.32	.02	.00	
additional unique variance = .01					
additional shared variance = .03					
* *p*<.05; ** *p*<.01; *** *p*<.001					R^2 = .69
					Adjusted R^2 = .68

The result of the hierarchical regression in Table 3.24 with LS as the DV are similar to results obtained with PWI as the DV. Specifically, trait PA predicted a substantial amount of variance in LS, whilst the addition of MDT, although significant, only predicted a further 4% variance in LS. When LS is used as the DV, the self-wants discrepancy is a slightly stronger predictor than the self-other discrepancy. Although the results of the hierarchical regressions presented in Tables 3.21 and 3.22 indicate MDT is significantly predictive of LS and PWI, the amount of additional variance predicted is small in comparison with the amount of variance trait PA predicted in PWI and LS. In addition, the MDT-affective model of SWB (Figure 3.15) did not provide an acceptable fit to the data, whereas the trait PA affective model provided an absolute fit.

Summary of Results

In summary, testing of three alternative theoretical models of SWB revealed none provided an adequate fit to the data. Additional testing indicated the strongest predictor of SWB to be trait PA, comprised of the affects happy, content, and active. A SEM in which trait PA was the sole predictor of PWI was the only model tested that provided an absolute fit to the data. Furthermore, this model predicted a substantial amount of variance in PWI (66%) whilst also demonstrating a high degree of parsimony. Further analyses revealed that the relationships between PWI and LS, and personality (extroversion and stability), MDT, self-esteem, perceived control, and optimism, were substantially reduced once the shared variance due to trait PA is accounted for. Together these results suggest that the trait PA affective model of SWB provided the best explanation of the data.

Section 3.3: DISCUSSION

The aim of the current study was to determine the relative efficacy of three different theoretical models of SWB; homeostatic theory, MDT, and affective-cognitive theory. It was hypothesised that homeostatic theory would better predict SWB compared with MDT. The specification and testing of SEMs according to both theories did not support this hypothesis. The MDT model explained up to 12% more variance in SWB than the homeostatic model and provided a better fit to the data (see Table 3.18). Contrary to what was hypothesised, the homeostatic model did not provide a better fit to the data than the affective-cognitive model, whilst the affective-cognitive model provided a better fit to the data than the MDT models. However, none of the three theoretical models tested provided an adequate fit to the data (see Table 3.18). Further testing indicated trait PA to be a powerful determinant of SWB. As such, a SEM was specified and tested in which trait PA was the sole predictor of SWB. This model was the only model tested that provided an absolute fit to the data and an acceptable relative fit. In addition this model accounted for a substantial amount of variance in SWB (66%) and was highly parsimonious.

Homeostatic Theory of Subjective Wellbeing

Some of the central hypotheses of homeostatic theory were supported by the results. Firstly, testing indicated that as SWB fell below normal levels, depressive symptomatology increased. This negative relationship between SWB and depression was much stronger for individuals with below normal SWB than for individuals with normal SWB. This result is supportive of the hypothesis that once homeostatic defeat occurs, SWB decreases and depression increases.

Secondly, the prediction that extroversion and stability directly influence SWB was only partially supported. Increased stability related to increased SWB; however extroversion did not significantly predict SWB (see Figure 3.5). Partial support was also found for the hypotheses that extroversion and stability influence SWB indirectly, through the buffer system, and that the buffer system influences SWB directly. Extroversion and stability significantly influenced all three components of the buffer system, with increases in extroversion and stability relating to increased self-esteem, optimism, and perceived control. Two of the three components of the buffer system also significantly influenced SWB, with higher self-esteem and optimism relating to higher SWB.

However a hierarchical regression revealed that after controlling for trait PA, extroversion and stability, and the buffer system, did not significantly predict SWB (see Table 3.21). This finding, taken together with the findings that extroversion did not significantly influence SWB directly, and that stability was only moderately related to SWB, is important as considerable research has suggested that personality is strongly related to SWB (c.f. Brebner, Donaldson, Kirby & Ward, 1995; Diener et al., 2003; Diener & Lucas, 1999; Hills & Argyle, 2001; Vitterso, 2001). In particular, it is commonly believed that high SWB is characteristic of extroverts whilst low SWB is characteristic of introverts (Myers & Diener, 1995). These conclusions have been reached on the basis of moderate zero-order correlations between SWB and personality, which were replicated in the current study. However, once the shared variability due to trait PA is removed, these correlations shrink substantially (from .23 to -.01 for extroversion and from .46 to .10 for stability; see Table 3.19). This finding is consistent with Davern (2004) who also found that once removing shared variance with trait PA, personality (as measured by the NEO-FFI) exerted no influence on SWB. This pattern of reduced correlations after accounting for trait PA was also found in the relationships between the components of the buffer system and SWB. Specifically, the zero-order correlations between self-esteem, optimism, and perceived control reduced by .44, .36, and .33 respectively (see Table 3.19). Thus, in contrast with previous research, it seems that the personality dimensions of extroversion and neuroticism, and optimism, self-esteem, and perceived control are not strongly related to SWB once the effect of trait PA has been accounted for. These findings not only illustrate the central importance of trait PA to SWB judgements, but also highlight the need for future SWB research to remove the shared variability due to trait PA prior to testing relations between SWB and other constructs.

Of the theoretical models tested, the SEM specified according to homeostatic theory predicted the least amount of variance and provided the worst fit to the data (see Table 3.18). The results indicated the trait PA affective model provided the best and simplest explanation of the data. Therefore trait levels of happiness, contentment, and activity explain much of the variance in SWB.

Multiple Discrepancies Theory

As hypothesised, MDT accounted for some variance in SWB. The effect was in the proposed direction; individuals who reported small perceived gaps between multiple standards of comparison reported experiencing higher levels of SWB (see Figure 3.7). However, as mentioned previously, the MDT models provided a significantly worse fit to the data than the trait PA affective model and explained up to 22% less variance in SWB. Furthermore, two of the central predictions of MDT were not supported by the results. The self-wants discrepancy was not the strongest determinant of SWB and did not fully mediate the relationship between the set of perceived discrepancies and SWB (see Figure 3.9 and Table 3.8). The only other perceived discrepancy to significantly predict SWB was the self-other discrepancy (see Tables 3.23). This discrepancy was 1.7 times more powerful in predicting SWB compared to the self-wants discrepancy, and the third strongest predictor of SWB overall (behind *happy* and *content*). This suggests that favourable comparisons between oneself and relevant others exerts a moderately positive influence on SWB. For every unit decrease in this perceived discrepancy, SWB increased by 1.27 points in this sample. In comparison, every unit increase in trait contentment increased SWB by 2.69 points. A comparison of the beta-weights for these two variables indicates that trait contentment is 1.9 times more powerful than social comparison in predicting SWB. In addition, although testing of the MDT-affective model indicated that MDT partially mediated the relationship between trait PA and SWB, MDT only added 6% unique variance to the prediction of PWI (see Table 3.23), and 4% to the prediction of LS (see Table 3.24). Furthermore, the strength of the relationship between MDT and SWB decreased by almost two-thirds in the presence of trait PA (β decreased from .73 (see Figure 3.7) to .27 (see Figure 3.15). Finally, trait PA accounted for 46% of the variance in MDT (see Figure 3.15). These results suggest a significant affective process operating in what are hypothesised by MDT as cognitive evaluations of perceived gaps in an individual's life.

Affective-Cognitive Model of Subjective Wellbeing

Partial support was found for the utility of an affective-cognitive model of SWB. Some of the central hypotheses of this model were supported by the results. Specifically, trait PA was found to strongly predict extroversion, stability, MDT, and SWB (see Figure 3.13). MDT also partially mediated the relationship between trait PA and SWB. However, this mediation effect was weak in comparison with the direct effect of trait PA on SWB. In addition, the affective-cognitive model did not provide an adequate fit to the data (see Table 3.18).

Trait PA Affective Model of Subjective Wellbeing

After finding that the affective-cognitive model did not provide an adequate fit to the data, further testing was conducted to determine the relative predictive power of affect for SWB. This testing indicated that trait PA (comprising happiness, contentment, and activity) was a powerful determinant of SWB (see Table 3.16). As such, a SEM was developed in which trait PA was the sole predictor of SWB. Testing of this model indicated an absolute fit to the data. In addition, the trait PA affective model was the most parsimonious model tested and explained a substantial amount of variance in SWB (see Table 3.18). Thus, high levels of trait happiness, contentment, and activity were related with high levels of SWB. The results of hierarchical regressions also indicated that trait PA was the most powerful predictor of SWB in this sample (see Table 3.21 and Table 3.22). Together, these results strongly suggest that trait PA is a powerful determinant of an individual's judgements of subjective satisfaction, with both life as a whole, and across various domains. These results also provide strong support for the argument that SWB is affective, rather than cognitive, in nature.

Although MDT only represents one way in which to measure the cognitive component of SWB, it has been heralded as the most thorough and articulate of the gap theories of SWB (Andrews & Robinson, 1991). As results of SEM indicated that theoretical models incorporating MDT and personality provided poor explanations of the data, whilst a purely affective model provided the best explanation of the data, evidence is mounting that SWB judgements are primarily influenced by an individual's trait affect. Further evidence that SWB is affective in nature is provided by studies in which life satisfaction, hypothesised as the cognitive component of SWB, was found to correlate strongly with affect (Lucas et al., 1996; Pavot et al., 1991). Specifically Lucas et al. found, across two separate samples using both self-reports and informant reports, that LS and positive affect correlated between .43 and .56, with an average correlation of .50. The correlations between LS and negative affect ranged from -.30 to -.51 (M=-.41). Furthermore, using two different measures of LS and affect in a third sample yielded similar strong correlations. Life satisfaction and positive affect correlated between .42 and .65 (M=.53), whilst LS and negative affect correlated between -.36 and -.58 (M=-.48). Strong correlations between LS and affect were also found in two studies conducted by Pavot et al. In study 1, 39 participants completed three measures of LS and five daily measures of positive and negative affect. The correlations between LS and affect balance (operationalised as PA - NA) ranged from .61 to .77 (M=.71). In study 2, a larger number of participants (n=130) completed daily reports of affect for 42 days. Life satisfaction and PA were strongly correlated (r=.62) as were LS and affect balance (r=.58). Interestingly, peer rated PA also correlated strongly with self-rated LS (*r*=.64). Thus, it seems that LS is not a purely cognitive measure of SWB as it is strongly influenced by affect.

This evidence is at odds with the prevailing view of notable SWB researchers such as Diener (1984, 1996), and Diener et al. (1999) who argue that SWB is formed by a blend of cognition and affect. Diener (1984, 1996) conceptualises SWB as comprising two separate components that come together to form a higher order construct of SWB. An individual's life satisfaction judgements make up the cognitive component, whilst hedonic balance comprises the affective component.

Hedonic balance is conceptualised by Diener (1996) to be the balance of pleasant and unpleasant experiences. These experiences consist of a person's reaction to activities in which they are involved and to life events. This definition of affect is problematic as it implies a cognitive structure; the affect is experienced *relative to* an object (i.e., Fred is afraid *of the shark*). This conceptualisation of affect ignores the type of affect not felt in relation to an object, and thus is reflective of only part of an individual's total affective life. This objection is supported by Russell and Feldman Barrett (1999), who regard affect as consisting not only of "prototypical emotional episodes" (which is synonymous with Diener's Hedonic Balance) but also, "Core Affect", affect that is not experienced in relation to an object. Core affect represents the most elementary consciously accessible affective feelings and thus can be experienced without the presence of a known stimulus (i.e., it is free-floating; Russell, 2003). It is a blend of hedonic (pleasant-unpleasant) and arousal (activation-deactivation) values, and is regarded by Russell to be primitive, universal and ubiquitous (Russell, 2003). Russell (2003) has likened core affect to felt body temperature in that it is always there, consciously accessible, very salient at extremes, existed prior to words used to describe it, and prior to any attribution about what is making you hot or cold. Thus, Diener's (1984, 1996) conceptualisation of SWB is inadequate, as it excludes a large part of an individual's affective life that the present study has demonstrated to be important. In addition, what is hypothesised by Diener as the cognitive component of SWB has been found in this study, and in previous research (Lucas et al., 1996; Pavot et al., 1991) to be largely driven by affect.

Accordingly, this study suggests a different structure of SWB. Whereas Diener (1996) argues that affect and cognition are blended to create a higher order construct called SWB, this study suggests that affect is not a component of SWB but rather a distinct process that strongly influences evaluations of life satisfaction. It is these evaluations of life satisfaction, both global and across various domains, that form SWB. In support of this alternative conceptualisation of SWB, Russell and Feldman Barrett (1999) argue that core affect and evaluation are separate processes. Evaluations are necessarily about something, whereas core affect is an elementary affective tonicity that can exist without being attributed to an object. Applied to this study, asking how one felt over a given period (i.e., how happy you feel in general; trait PA) can be conceptualised as core affect, whereas asking how one feels in relation to an object (i.e., how satisfied you are with life) is an evaluation.

The distinction between core affect and evaluation can be likened to the distinction between affect and cognition (here defined as cognitive appraisal processes). Researchers have long debated the relative independence of emotion and cognition. In 1980, Zajonc (1980, 1984, 1998) proposed the affective primacy hypothesis, in which gross emotional reactions were thought to precede cognitions. Since this time, a number of studies have demonstrated effects that support the affective primacy hypothesis (Dimberg, Thunberg, & Elmehed, 2000; Murphy, Monahan, & Zajonc, 1995; Murphy & Zajonc, 1993; Ohman & Soares, 1994; Whalen, Rauch, Etcoff, McInerney, Lee & Jenike, 1998). In the study conducted by Whalen et al., participants' amygdala activation was measured following the suboptimal presentation (presentation of a stimulus under conditions below conscious awareness) of happy and fearful faces. Using functional Magnetic Resonance Imaging (fMRI), Whalen et al. found significantly increased amygdala activation when participants viewed the fearful faces, and significantly decreased activation when viewing the happy faces. Thus, despite participants having no explicit knowledge of the emotional stimuli presented, the emotional stimuli differentially activated the amygdala in concordance with the valence of stimuli presented. In a similar study conducted by Murphy and Zajonc (1993), the suboptimal presentation of happy and scowling faces temporarily shifted participants core affect in the direction of the affective tone of the stimulus (happy or angry). This shift in core affect rendered subsequent ratings of novel stimuli more positive or negative according to the tone of the suboptimal stimulus (happy faces were associated with significantly more positive ratings of the novel stimuli whilst scowling faces were associated with significantly more negative ratings of the novel stimuli). These findings strongly suggest the existence of an elementary affective tonicity that is independent of cognition, and that is used to inform cognition and behaviour. This affective tonicity is taken to be core affect. Temporary changes in core affect, as demonstrated in Whalen et al. and Murphy and Zajonc, led directly to measurable changes in brain activation and subjective ratings of novel stimuli that were consistent with the direction of change in core affect. This evidence provides strong support for the hypothesis that affect is independent of cognition. Thus core affect is an elementary affective process that does not require the presence of an object for its existence. This distinction between core affect and cognition provides further support for the proposal that core affect and cognitive evaluations of life satisfaction are separate processes, with one (core affect) heavily influencing the other (SWB).

It is imperative to note that invoking an individual's core affect as an explanation of their SWB without qualifying the affective tonicity of that core affect is confusing and of little practical or scientific utility. This is because core affect is the underlying affective process operating below conscious awareness. Individuals cannot have high or low core affect; they can however, have any combination of pleasant or unpleasant and activated or deactivated core affect (for example, an individual scoring high on the pleasantness dimension and high on the activation dimension would have pleasant-activated core affect; see Figure 3.19). Thus it is proposed that the use of core affect always be qualified by the tonicity of that affect using the combinations of the dimensions of Russell's (2003) circumplex model of affect; pleasantness-unpleasantness and activation-deactivation. These combinations are proposed to be: pleasant core affect, unpleasant core affect, activated core affect, deactivated core affect, pleasant-activated core affect, unpleasant-activated core affect, pleasant-deactivated core affect, and unpleasant-deactivated core affect. These eight combinations are illustrated schematically in Figure 3.19.

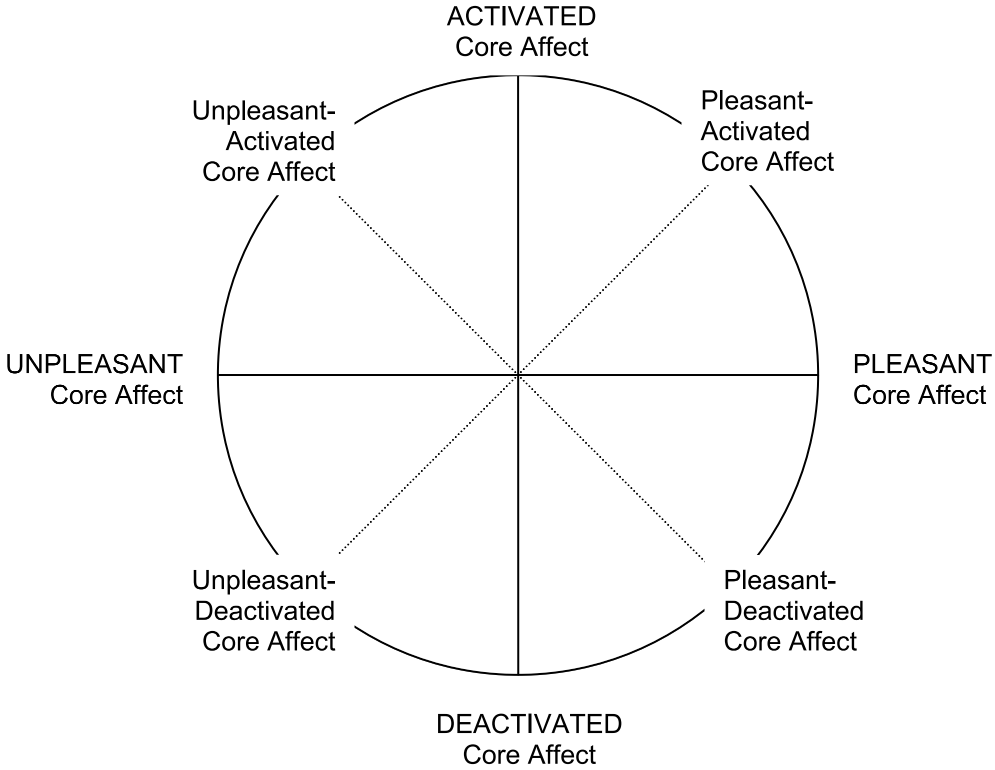


Figure 3.19: Circumplex model of core affect tonicity according to the pleasantness-unpleasantness and activation-deactivation dimensions of Russell's (2003) circumplex model of affect. The location of an individual on this circumplex is determined by scores on items measuring pleasantness-unpleasantness and activation-deactivation. For example, deactivated core affect is characterised by low scores on the pleasantness-unpleasantness dimension and high scores on the deactivated dimension, whereas pleasant core affect is characterised by low scores on the activated-deactivated dimension and high scores on the pleasantness dimension.

It is proposed that individuals have their own baseline level of core affect. This baseline level is likely to be determined by genetic factors in combination with environmental influences. An individual's baseline core affect is given by a combination of values on the pleasantness-unpleasantness and activation-deactivation dimensions (this thesis does not attempt to establish whether core affect is unipolar or bipolar in nature, however this is a topic that future research must consider). Thus, every individual can be located at a point on the circumplex model of core affect tonicity given in Figure 3.19. For example, an individual who reports relatively high levels of trait unhappiness and quietness would be considered to have unpleasant-deactivated core affect, and as a consequence, low SWB. In contrast, an individual who reports relatively high levels of trait happiness, contentment, and activity would be considered to have pleasant-activated core affect (henceforth PACA), and thus, high SWB. The results of this study have demonstrated this effect, with individuals who have PACA reporting high SWB (the SEMs based on PACA consistently accounted for a large majority of variance in SWB and were the only models tested that provided an absolute and parsimonious fit to the data). It is also highly likely that the dimensions of pleasantness-unpleasantness and activation-deactivation reflect specific brain states, as there is strong evidence that affect is intimately linked to brain activation (Damasio, 1994; LeDoux, 1995a, 1995b, 1996).

Temporary shifts away from an individual's baseline level of core affect (any event, external or internal, that temporarily alters baseline core affect), like those observed in Whalen et al. (1998) and Murphy and Zajonc (1993), may result in reports of SWB that are artificially skewed towards the tonicity of the agent of influence. For example, an individual with a baseline level of unpleasant-deactivated core affect who has just won $100 in the lotto is likely to report high SWB due to the temporary shift in core affect towards pleasantness. However this report of SWB would be an inaccurate measure of that individuals true SWB. Evidence that temporarily altering core affect leads to differential reports of SWB was found by Forgas and Moylan (1987) after interviewing 980 individuals who had just viewed happy, sad, or aggressive films. Individuals who viewed a happy film rated their life satisfaction significantly higher than those who viewed sad or aggressive films, and significantly higher than a control group. In this study, a temporary shift towards pleasantness in one's baseline level of core affect led to reports of increased life satisfaction.

The research conducted by Whalen et al. (1998), Murphy and Zajonc (1993), and Forgas and Moylan (1987) demonstrates that temporarily altering an individual's baseline level of core affect leads to subsequent judgments that are congruent in affective tone with the agent of change (i.e., happy films led to higher judgments of life satisfaction than sad and angry films). This raises two important issues. Firstly, it is fundamentally important that an individual's *baseline* core affect is measured and not core affect that has been temporarily altered due to external or internal influences. To achieve this, core affect must be measured repeatedly over time and averaged to correct for such fluctuations. This issue is addressed in Study 4 (Chapter 6). Secondly, the research of Forgas and Moylan raises a possible alternative explanation of the current results. That is, individuals might have used PACA as a heuristic to answer questions of life satisfaction. If this hypothesis were correct, then state PACA should be more strongly related to SWB than trait PACA. As state affect was not measured in the current study, this alternative explanation of the results cannot be falsified; however this issue is addressed in Study 3 (Chapter 5).

Another possible alternative explanation for the results of the current study would argue that PACA and SWB are so similar as to be practically the same, thereby accounting for the large amount of variance that PACA predicts in SWB. To address this alternative explanation, it is necessary to return to the results of the present study. Although PACA was able to predict 66% of the variance in SWB, 34% of variance remained unaccounted for, which necessitates the two concepts are different. Secondly, the prediction of SWB by PACA is not tautological; it is an explanation in terms of another concept. The combustion of paper serves as a good example. As paper burns, it becomes heavier. Oxygen is added to carbon, fully explaining the growth in weight of the burning paper. This does not mean that adding oxygen is tautological with paper burning. Similarly, in this study, we are reducing the explanation of SWB to PACA. Using PACA, we are able to predict, with a high degree of certainty, a person's satisfaction with life.

In conclusion, the findings of the current study strongly suggest that SWB can no longer be conceptualised as an equal blend of cognitive and affective components coming together to form a higher order construct of SWB. This study did not find support for an affective-cognitive model of SWB, or for a model of SWB based on MDT or homeostatic theory. It did however, support a model of SWB that proposes trait PACA as the major determinant of SWB. It appears that one's trait PACA strongly determines one's SWB.

As the findings of the current study run counter to a large body of previous research, replication is essential to increase confidence in the PACA model of SWB. It is mainly thorough replication of findings in independent samples that confidence in scientific theories is increased. This is because replication serves as an important safeguard against Type 1 errors. A result of $p<.05$ could easily have occurred by chance. However if the effect was really due to chance, the likelihood of repeatedly obtaining significance at this level is greatly diminished (Nickerson, 2000). In addition, Tukey (1969) notes that solid evidence of an effect is not established by a single demonstration of significance at the .05 level; rather, solid evidence is demonstrated by the ability to obtain results at the .05 level repeatedly. Thompson (1996) also states that, ideally, such replication studies should be conducted with new samples. Accordingly, the following study aimed to replicate the findings of the current study in three independent samples.

CHAPTER 4: STUDY 2

Section 4.1: INTRODUCTION AND METHODOLOGY

Introduction

Study 1 compared the efficacy of three theoretical models of SWB; the homeostatic model, MDT, and the affective-cognitive model. Results indicated the poorest fit to the data, and the least powerful predictor of SWB, was the homeostatic model. In comparison, MDT provided a slightly better fit to the data and predicted up to 12% more variance in SWB. However the MDT model did not provide an absolute, or even an adequate fit to the data. Testing of the third theoretical model, the affective-cognitive model, also indicated an inadequate fit to the data. Further testing revealed the greatest support for a model of SWB based solely on pleasant-activated core affect (PACA). Specifically this model (in which trait PACA is the sole predictor of SWB), was the only model that provided an absolute fit to the data. In addition, the PACA model was the most parsimonious model tested, and accounted for a substantial amount of variance in SWB (66%). Furthermore, after controlling for trait PACA, MDT increased the explained variance in SWB by only 6%, whilst the variables that comprise the homeostatic theory of SWB (self-esteem, optimism, perceived control, extroversion, and stability) increased the variance explained by a non-significant 1%. In comparison, trait PACA predicted 62% of variance in SWB. Thus it seems that PACA, and not cognition, is the most important predictor of SWB. However as Sohn (1998) notes, progress in Science is not measured by assessing the truth of findings in isolation. Replication of findings is vitally important as it is by replication that confidence in such findings is increased (Nelson, Rosenthal, & Rosnow, 1986). As such, Study 2 was conducted to replicate the results of Study 1 in three independent samples. It was hypothesised that the trait PACA model of SWB would provide a better explanation of the data than the homeostatic model, affective-cognitive model, MDT-affective model, and MDT self-wants model.

Participants

Sample 1

This sample comprised individuals that responded to the sixth longitudinal survey of the Australian Unity Wellbeing Index (June, 2005; henceforth L-AUWBI 6, the index is described in section 3.1 of Chapter 3). In total, 1,732 surveys were mailed to participants, and 682 were returned, yielding a 39% response rate. Of the 682 participants, 39% were male and 61% female. Participants ranged in age from 18 to 92 years old, with a mean of 54.3 (*SD*=15.4).

Sample 2

Sample 2 comprised of individuals that responded to the seventh longitudinal survey of the Australian Unity Wellbeing Index (henceforth L-AUWBI 7, August, 2005). In total, 675 surveys were mailed to participants and 198 were returned, yielding a 29% response rate. Males comprised 46% of the sample whilst females comprised 54%. Participants ranged in age from 24 to 88 years old, with a mean of 59.5 (*SD*=14.2).

Sample 3

This sample comprised individuals that responded to the eighth survey of the Australian Unity Wellbeing Index (henceforth AUWBI 8, August, 2003). In total, 1,980 questionnaires were mailed to participants and 854 were returned, yielding a 43% response rate. Males comprised 46% of the sample whilst females comprised 54%. Participants ranged in age from 18 to 86 years, with a mean age of 52 years (*SD*=15.37).

Materials

L-AUWBI 6 and L-AUWBI 7

The materials and procedure for L-AUWBI 6 and L-AUWBI 7 were identical to those used in Study 1 with minor exceptions. Constraints imposed on the length of the questionnaire prevented an inclusion of the MDT items and restricted the number of affect items to five. The affect items were chosen based on Study 1 results and previous research (Davern, 2004). Active was replaced by excited as the item chosen to represent the activation quadrant due to the use of this data for another unassociated project. However, this is not problematic as previous research has suggested that excited is a good marker for the activation quadrant of the circumplex model (Davern, 2004). The five items chosen to measure affect were happy, satisfied, content (to measure the pleasant axis of circumplex model of emotion), depressed (unpleasant axis), and excited (activated axis). The adjective satisfied is omitted from all analyses due to similarity with the question used in measuring the dependent variable (i.e., “How satisfied are you with…?”). It was included in the survey as this data forms part of a larger longitudinal project run by the Psychology Department at Deakin University, Australia (the

Australian Unity Wellbeing Index, for a detailed description see Chapter 3, Section 3.1, and Cummins et al., 2005).

The questionnaires used to measure SWB and the variables that comprise the homeostatic theory of SWB were all identical to those used in Study 1 (see Chapter 3, Section 3.1 for descriptions). As in Study 1, the relinquished control subscale of the perceived control scale was excluded from all analyses due to low scale reliability (alpha=.30, L-AUWBI 6; alpha=.18, L-AUWBI 7). Cronbach's alpha's for each scale are provided in Table 4.1.

Table 4.1: Cronbach's alpha coefficients for scales used in L-AUWBI 6 and L-AUWBI 7.

Scale	Alpha Coefficient (L-AUWBI 6)	Alpha Coefficient (L-AUWBI 7)
PWI	.86	.86
Self-esteem	.89	.87
Primary control	.64	.68
Secondary control	.79	.84
Relinquished control	.30	.18
Optimism	.84	.86
Extroversion	.64	.69
Stability	.68	.56

AUWBI 8

The questionnaire used in AUWBI 8 included the PWI to measure SWB, the affect items measuring trait PACA (happy, content, and excited), and the original 7-items of MDT taken from Michalos (1985). Cronbach's alpha for the PWI in this sample was .84, and for MDT was .89.

Procedure

The procedure for the distribution and return of questionnaires was identical with the procedure of Study 1. That is, after approval from the Deakin University Human Research Ethics Committee (DUHREC) a questionnaire packet was mailed to participants. This packet contained the questionnaire, a plain language statement describing the research, and a reply-paid envelope for the return of the questionnaire. As in Study 1, responses to the questionnaires were confidential. The instructions for each scale of the questionnaire in L-AUWBI 6, L-AUWBI 7, and AUWBI 8 were identical to the instructions given in Study 1 with the exception of the MDT items in AUWBI 8, which were the original items as provided by Michalos (1985). As in Study 1, the order of the scales remained constant for each participant. Once the questionnaires were returned, the responses were entered directly into SPSS for Windows (12.0; SPSS, Inc., Chicago, Il).

Section 4.2: RESULTS

Data Preparation

Data were analysed using SPSS for Windows (12.0; SPSS, Inc., Chicago, Il) and AMOS (5.0; Smallwaters Corp, Chicago, Il). Prior to analysis data were screened for multivariate outliers. The application of Mahalanobis distance indicated 12 cases as outliers for L-AUWBI 6, $p<.001$, 5 cases for L-AUWBI 7, $p<.001$, and 8 cases for AUWBI 8, $p<.001$. Upon examination, these outliers were considered to constitute normal and expected responses. Furthermore, an examination of residuals indicated no difference with outliers deleted, thus we decided to retain the cases. Accordingly, interpretation will proceed cautiously. Univariate outliers were assessed through the computation of z-scores for each variable. Scores were considered univariate outliers if $z > 4$, $p<.001$ (Tabachnick & Fiddell, 2001). Application of this analysis indicated z-scores exceeding four on 4-items for L-AUWBI 6 (happy; items 3 and 4 of RSE; and PWI), two items for L-AUWBI 7 (life satisfaction and item 3 of RSE), and three items for AUWBI 8 (PWI; PWI domain of standard of living; and PWI domain of safety). However in each sample, less than five cases recorded z-scores in excess of four. Upon inspection of the data, scores were considered to constitute normal and expected responses. For these reasons, it was decided to retain the cases.

A missing values analysis for L-AUWBI 6 indicated the maximum percentage of missing data on any variable to be 1.7% of cases (for item 6, RSE scale*)*. In addition, only three other variables had missing data of more than 1.5% of cases. The maximum percentage of missing data on any variable for L-AUWBI 7 was 4% (perceived control item 5). For AUWBI 8 the maximum percentage of missing data was 4.1%. As the maximum percentage of missing data in each sample was less than 5%, the missing data was considered to be suitable for regression replacement (Tabachnick & Fiddell, 2001).

The assumption of normality was assessed for each sample. For L-AUWBI 6, an inspection of expected normal probability plots of standardised residuals indicated no violations of normality. Normality was further assessed by examining raw scores of skew and kurtosis for each variable. This examination revealed positive skew to have exceeded a raw score of 2.0 on four items. The items were all contained in the DASS and were *trembling in hands* (skewness=2.37, *SE*=.09)*, close to panic* (skewness=2.27, *SE*=.09)*, life felt meaningless* (skewness=2.26, *SE*=.09)*,* and *scared for no good reason* (skewness=2.47, *SE*=.09). These same four items were also the only items in Study 1 (L-AUWBI 5) that exhibited positive skew exceeding a raw score of 2.0. As such, scores on these items are not unexpected and are considered to be normal. Furthermore, inspection of histograms revealed a similar distribution of scores on each item. This similar distribution mitigates the potential distorting effect of mild skew (Bradley, 1980). In addition, the skewness values for each scale summary score on the DASS equalled 1.65 for anxiety, .95 for stress, and 1.45 for depression. No excessive kurtosis was found in any variable as evidenced by a maximum kurtosis value of 6.03 (*scared for no good reason).* Thus it was concluded that the data for L-AUWBI 6 did not violate the assumption of normality.

An inspection of expected normal probability plots of standardised residuals for L-AUWBI 7 indicated no violations of normality. Normality was further assessed by examining raw scores of skew and kurtosis for each variable. Five items exhibited positive skewness exceeding a raw score of 2.0. The items were all contained in the DASS and were *breathing difficulty* (skewness=2.18, *SE*=.18), *trembling in hands* (skewness=2.33, *SE*=.18)*, close to panic* (skewness=2.55, *SE*=.18)*, life felt meaningless* (skewness=2.49, *SE*=.18)*,* and *scared for no good reason* (skewness=2.76, *SE*=.18). Only one variable in L-AUWBI 7 exceeded a raw score of 7.0 for kurtosis. This variable was also contained in the DASS, and was *scared for no good reason* (kurtosis=8.47, *SE*=.35). Four of the five items that exhibited positive skew were also found to have exceeded a skewness score of 2.0 in L-AUWBI 5 and L-AUWBI 6. Thus these responses were considered normal and expected. In addition, the skewness and kurtosis scale scores for depression (skewness=1.53, *SE*=.18; kurtosis=1.80, *SE*=.35), anxiety (skewness=1.37, *SE*=.18; kurtosis=.94, *SE*=.35), and stress (skewness=1.14, *SE*=.18; kurtosis=1.17, *SE*=.35) did not exceed 2.0.

The assumption of normality for AUWBI 8 was not violated according to inspection of expected normal probability plots of standardised residuals. An examination of raw skewness and kurtosis scores indicated two items exceeded a raw skewness score of 2.0. These items were contained in the DASS, and were *not worth much as a person* (skewness=2.20, *SE*=.08), and *life felt meaningless* (skewness=2.78, *SE*=.08). The kurtosis score exceeded 7.0 on only one item, *life felt meaningless* (kurtosis=7.78, *SE*=.08). Inspection of the histogram for this item revealed a large number of cases had recorded values of zero, thus causing the leptokurtic distribution. The raw kurtosis score for the depression scale score was 3.19 (*SE*=.17). Although this value exceeds 2.0, an inspection of the histogram revealed a large clustering of cases recording very low depression scale scores. This distribution pattern is expected in a sample of the general population. In addition, the raw skewness score for the depression scale was below 2.0 (skewness=1.64, *SE*=.08). Accordingly, the assumption of normality was not considered to have been violated.

In each sample (L-AUWBI 6, L-AUWBI 7, and AUWBI 8), departures from strict normality were not in variables central to any of the hypotheses to be explored. As such, transformations would be of little value.

Means, Standard Deviations, and Correlations between Variables

As in Study 1, testing firstly proceeded by examining the means, standard deviations, and correlations between all measured variables for L-AUWBI 6 and L-AUWBI 7. Given that the variables measured in AUWBI 8 differ, this analysis for AUWBI 8 is presented separately following the results for L-AUWBI 6 and L-AUWBI 7. The means, standard deviations, and correlations for L-AUWBI 6 and L-AUWBI 7 are given in Table 4.2 and Table 4.3 respectively.

Table 4.2: Means, standard deviations, and correlations between variables for L-AUWBI 6 (N=682).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. PWI																					
2. Std. Living	.73																				
3. Health	.67	.44																			
4. Achieving	.79	.55	.49																		
5.Relationships	.75	.48	.40	.58																	
6. Safety	.69	.39	.39	.39	.39																
7. Community	.73	.45	.37	.53	.48	.47															
8. Security	.81	.56	.42	.57	.49	.62	.55														
9. Life Sat.	.71	.69	.48	.73	.65	.38	.50	.58													
10. Happy	.70	.56	.49	.65	.64	.43	.52	.57	.78												
11. Content	.72	.60	.48	.69	.66	.41	.55	.60	.78	.89											
12. Excited	.48	.34	.33	.47	.44	.28	.40	.34	.50	.61	.55										
13. Depressed	-.43	-.26	-.31	-.38	-.34	-.24	-.27	-.33	-.40	-.46	-.43	-.16									
14.Self-esteem	.58	.42	.43	.57	.40	.38	.43	.47	.55	.61	.59	.36	-.53								
15. Perc. control	.38	.31	.26	.34	.29	.26	.30	.29	.35	.44	.44	.40	-.26	.47							
16. Optimism	.49	.38	.36	.45	.35	.39	.39	.43	.46	.56	.53	.38	-.39	.62	.53						
17.Extroversion	.24	.16	.11	.27	.22	.21	.29	.17	.25	.31	.27	.29	-.18	.36	.22	.30					
18. Stability	.44	.26	.37	.41	.28	.28	.33	.34	.42	.47	.46	.24	-.47	.63	.28	.49	.18				
19. DASS Ax.	-.45	-.29	-.48	-.40	-.31	-.30	-.30	-.34	-.37	-.43	-.40	-.21	.44	-.56	-.25	-.37	-.14	-.52			
20. DASS. St.	-.50	-.30	-.43	-.43	-.37	-.30	-.35	-.41	-.44	-.54	-.52	-.25	.50	-.56	-.24	-.44	-.15	-.61	.75		
21. DASS Dep.	-.62	-.44	-.48	-.63	-.49	-.37	-.43	-.51	-.58	-.65	-.65	-.40	.52	-.70	-.37	-.52	-.26	-.57	.71	.75	
M	72.22	75.76	71.27	68.08	74.65	77.55	68.22	70.02	76.41	7.43	7.32	6.02	2.99	74.72	42.29	20.34	10.76	13.77	5.62	10.42	8.00
SD	15.86	15.04	15.41	16.53	18.42	16.79	14.43	14.37	18.36	1.82	1.93	2.03	2.46	17.52	9.34	5.66	4.96	4.44	7.22	9.09	8.99

Note: Correlations of .14 and above are statistically significant at p <.001.

Table 4.3: Means, standard deviations, and correlations between variables for L-AUWBI 7 (*N*=198).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. PWI																					
2. Std. Living	.74																				
3. Health	.65	.40																			
4. Achieving	.81	.51	.62																		
5.Relationships	.68	.43	.35	.53																	
6. Safety	.65	.42	.26	.33	.34																
7. Community	.82	.53	.36	.57	.46	.53															
8. Security	.80	.53	.31	.55	.39	.54	.72														
9. Life Sat.	.76	.63	.59	.71	.66	.38	.55	.47													
10. Happy	.70	.47	.52	.70	.51	.34	.55	.53	.71												
11. Content	.65	.47	.50	.65	.47	.35	.51	.45	.65	.85											
12. Excited	.41	.26	.36	.50	.35	.11	.26	.25	.43	.58	.50										
13. Depressed	-.50	-.28	-.32	-.47	-.44	-.33	-.37	-.39	-.53	-.57	-.52	-.43									
14.Self-esteem	.46	.30	.29	.51	.44	.23	.38	.30	.51	.55	.52	.36	-.51								
15. Perc. control	.42	.34	.32	.40	.34	.17	.36	.24	.43	.41	.31	.25	-.24	.46							
16. Optimism	.53	.40	.33	.47	.44	.34	.44	.40	.49	.65	.61	.43	-.44	.60	.58						
17.Extroversion	.31	.17	.18	.37	.27	.08	.25	.24	.24	.29	.28	.31	-.21	.30	.24	.28					
18. Stability	.28	.16	.14	.26	.22	.18	.22	.25	.30	.40	.41	.21	-.39	.51	.31	.52	.14				
19. DASS Ax.	-.33	-.25	-.34	-.29	-.27	-.23	-.18	-.15	-.35	-.36	-.39	-.22	.51	-.44	-.17	-.39	-.14	-.39			
20. DASS. St.	-.35	-.20	-.24	-.35	-.21	-.25	-.25	-.25	-.35	-.41	-.45	-.16	.48	-.48	-.15	-.40	-.10	-.53	.66		
21. DASS Dep.	-.52	-.34	-.45	-.58	-.45	-.27	-.40	-.35	-.52	-.59	-.61	-.35	.64	-.67	-.18	-.52	-.27	-.45	.68	.71	
M	72.45	76.65	68.61	69.64	77.16	76.24	69.31	69.58	77.84	7.36	7.38	5.55	2.75	75.95	42.92	20.97	10.59	14.18	4.91	9.76	7.42
SD	14.79	14.07	14.38	14.19	15.71	16.07	14.20	14.87	16.91	1.83	1.87	2.12	2.41	16.96	8.68	5.57	4.91	3.95	6.12	8.90	8.62

Note: Correlations of .25 and above are statistically significant at p <.001.

An examination of the correlations between variables presented in Tables 4.2 and 4.3 indicates that, across both samples, the correlations between the PWI, LS, and trait happiness and contentment were consistently among the strongest correlations observed. Across both samples, the mean overall PWI score differed by less than 1 point. In addition, the mean PWI score for Study 1 (L-AUWBI 5) was identical to the mean PWI score for L-AUWBI 7, although the distribution of scores differed slightly (L-AUWBI 5 *SD*=17.19, L-AUWBI 7 *SD*=14.79). The highest satisfaction scores among the domains for both samples were *standard of living*, *personal relationships,* and *safety.* Participants in Study 1 also recorded the highest satisfaction scores in these three domains. These results are consistent with Davern (2004) who found the highest satisfaction ratings for these three domains.

As in Study 1, all three variables comprising the buffer system (self-esteem, perceived control, and optimism) were moderately positively related with PWI and LS in L-AUWBI 6 and L-AUWBI 7. Extroversion and stability were also positively related with PWI and LS across both samples. As expected, depression, stress, and anxiety were moderately negatively related with PWI and LS in both samples.

The variables comprising PACA (happiness, contentment, and excited), in addition to strongly relating with PWI and LS, were moderately positively related with self-esteem, perceived control, optimism, extroversion, and stability in both L-AUWBI 6 and L-AUWBI 7. These results are consistent with the pattern of correlations observed in Study 1.

Depression and Subjective Wellbeing

The results of Study 1 identified a negative relationship between depression and SWB. This result is important as it supports one of the central predictions of homeostatic theory; that loss of SWB results in increased depressive symptomatology. As such, the current study attempted to replicate this result in L-AUWBI 6 and L-AUWBI 7. PWI mean scores according to depression category are presented in Table 4.4 for L-AUWBI 6 and L-AUWBI 7.

Table 4.4: PWI mean scores according to depression category for L-AUWBI 6 (N=683) and L-AUWBI 7 (N=198).

Depression Scores	Depression Category	% of Total *N*	PWI *M*	PWI *SD*	*N*
L-AUWBI 6					
1-9	Normal	68.9	77.73	11.92	470
10-13	Mild	8.9	70.47	14.62	61
14-20	Moderate	10.0	59.92	12.54	68
21-27	Severe	7.2	55.02	16.30	49
28+	Extremely Severe	5.0	48.61	17.70	34
L-AUWBI 7					
0-9	Normal	72.2	77.00	11.68	143
10-13	Mild	6.6	62.79	13.65	13
14-20	Moderate	10.6	63.81	15.36	21
21-27	Severe	7.1	58.06	17.44	14
28+	Extremely Severe	3.5	53.27	19.13	7

The data displayed in Table 4.4 indicate that, as in Study 1, the majority of participants across both samples reported normal depression scores. In addition, as depression increases above ‘mild’, PWI scores fall dramatically. This pattern is consistent with results observed in Study 1. A one-way between-groups analysis of variance was conducted to determine whether PWI differed significantly across depression categories (the analysis was only conducted for L-AUWBI 6 due to the small cell sample sizes in L-AUWBI 7). This analysis indicated a statistically significant difference in PWI scores across the six depression groups (Welch=(4, 677)=66.63, R^2=.28, p<.001). Post-hoc comparisons using the Dunnett T3 indicated that participants who reported an extremely severe depression score significantly differed from all other depression categories with the exception of the severe category (p>.05). In addition, participants who reported depression scores ranging from 0 to 9 (normal) significantly differed from all depression categories. Participants with PWI scores in the moderate and severe depression categories did not significantly differ from each other. The negative relationship between depression and PWI is evident in xy-plots presented in Figure 4.1 for L-AUWBI 6 and Figure 4.2 for L-AUWBI 7.

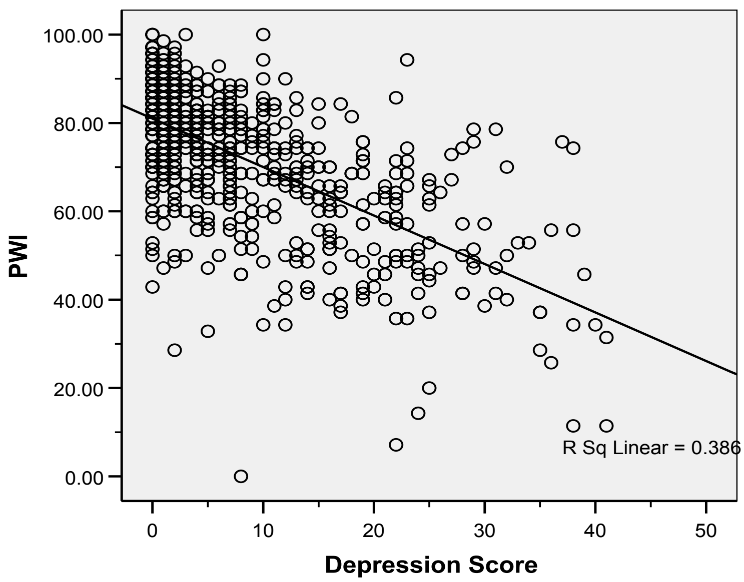


Figure 4.1: XY-plot of individual PWI and depression scores for L-AUWBI 6 (N=682). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

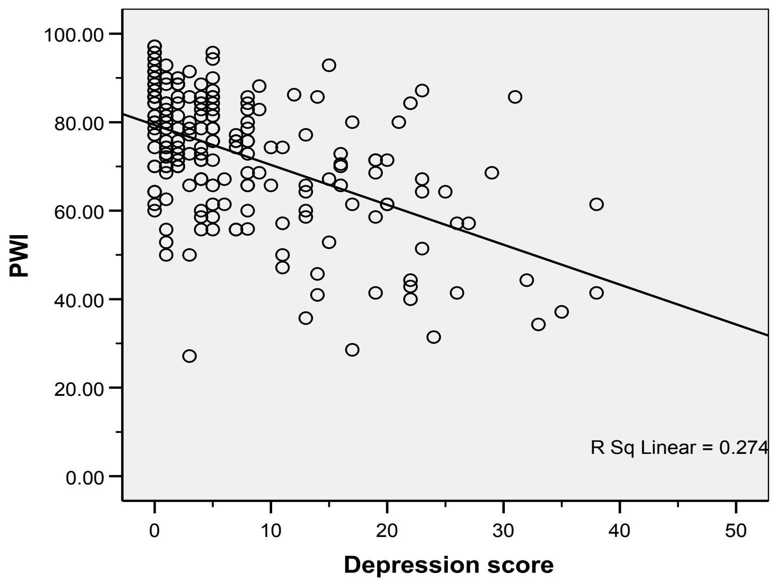


Figure 4.2: XY-plot of individual PWI and depression scores for L-AUWBI 7 (N=198). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

The R^2 statistic presented in both figures shows that, for L-AUWBI 6, 39% of the variance in PWI was accounted for by depression scores, whilst for L-AUWBI 7 this number fell to 27%. The Pearson correlation between depression and PWI for L-AUWBI 6 was -.62, and for L-AUWBI 7 was -.52.

To further test the relationship between depression and SWB, Study 1 created and contrasted xy-plots of depression and SWB for two groups; individual's with below normal levels of SWB (PWI<65) and individuals with normal levels of SWB (PWI >65). The result supported the hypothesis of homeostatic theory that the relationship between depression and SWB for the below normal SWB group would be more strongly negative than for the normal SWB group. This analysis is repeated here on L-AUWBI 6 only as the sample size of the below normal SWB group in L-AUWBI 7 (*n*=52) is too small to yield reliable data. The xy-plots of PWI and depression for the PWI<65 group and PWI >65 group are presented in Figure 4.3 and Figure 4.4 respectively.

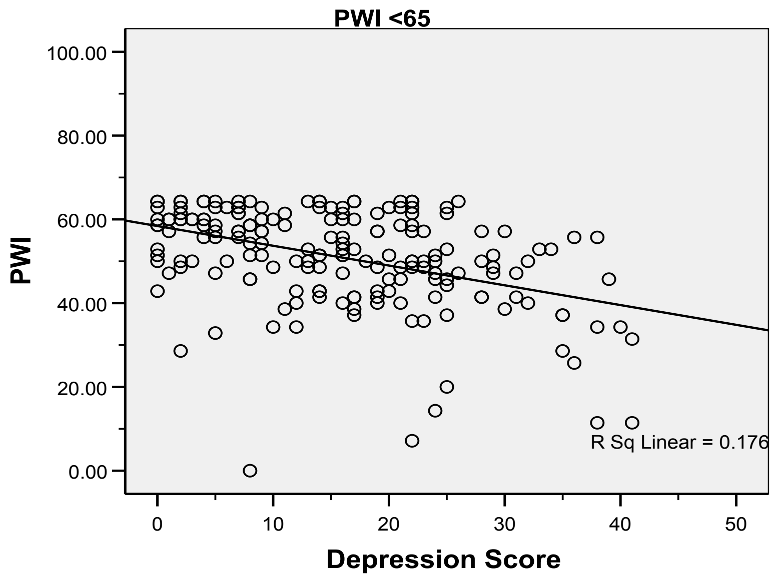


Figure 4.3: XY-plot of individual PWI and depression scores for individuals with below normal SWB (PWI<65; n=183). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

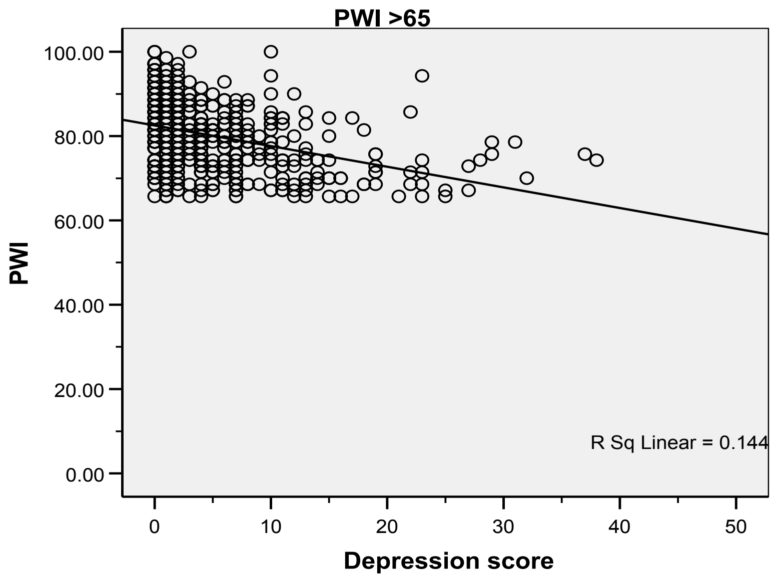


Figure 4.4: XY-plot of individual PWI and depression scores for individuals with normal SWB (PWI>65; n=499). The ordinate reveals PWI scores ranging from 0 to 100 and the abscissa represents depression scores ranging from 0 (normal) to 50 (extremely severe).

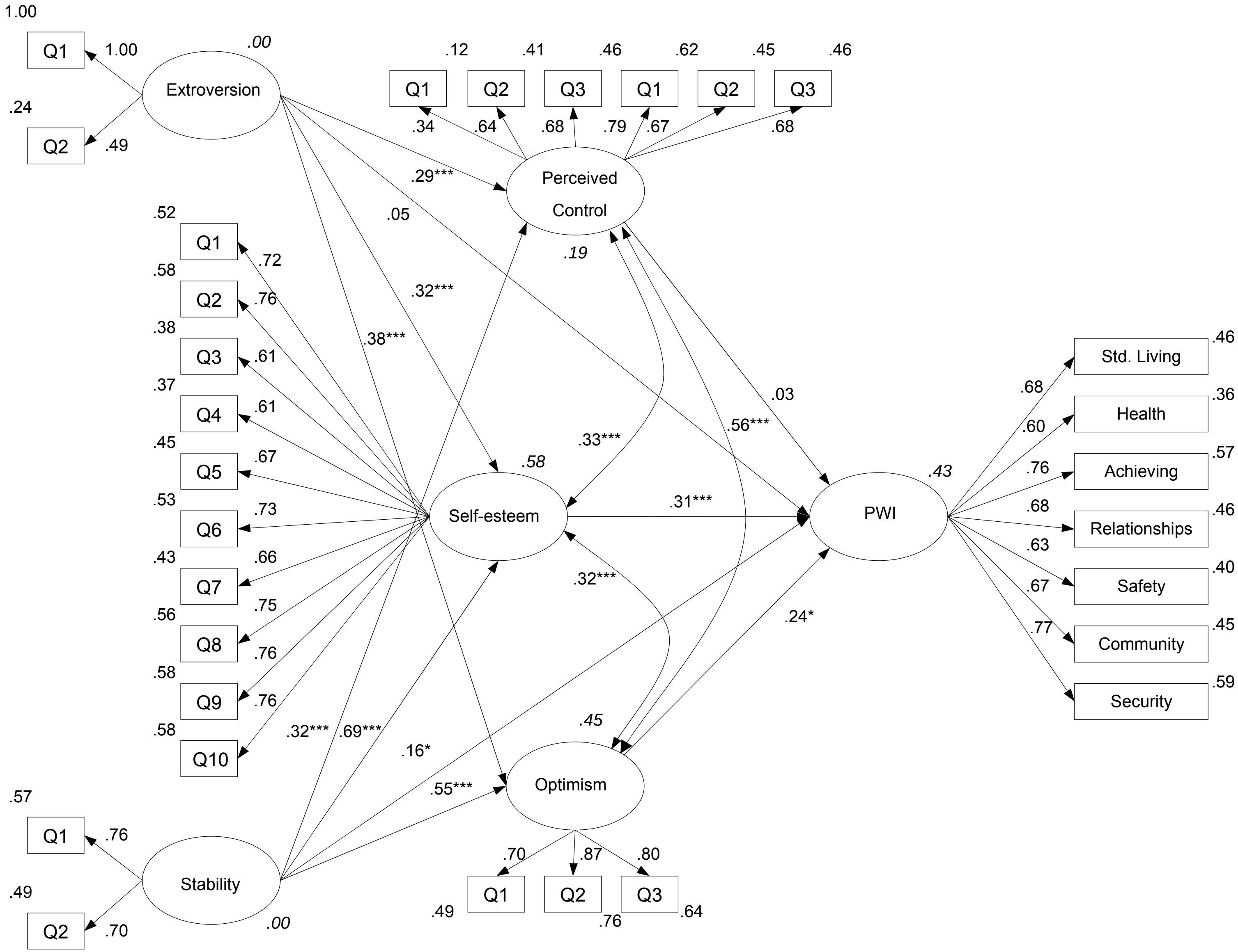
Inspection of the x-y plots presented in Figures 4.3 and 4.4 reveals the amount of variance accounted for by depression to be similar across both groups (18% vs. 14%). The Pearson correlations for the below normal SWB group and depression was -.42, and for the normal SWB group was -.38. These correlations were not significantly different ($z=-.55$, $p>.05$). However, the trend of a reduced relationship between depression and SWB for PWI >65 was in the direction hypothesised by homeostatic theory. This result is similar in direction to the result obtained in Study 1, although the effect was less pronounced in this sample.

Comparison of Homeostatic Model and PACA Model of Subjective Wellbeing (L-AUWBI 6 and L-AUWBI 7)

The fit of the structural equation models (SEM) was assessed according to the same criteria detailed in section 3.2 of Study 1. These criteria consist of χ^2, χ^2/df, AIC, RMSEA, NFI, CFI, and SMC. Using maximum likelihood estimation, SEMs were specified according to each theoretical model under investigation, the homeostatic model and the trait PACA model. These SEMs are identical to those tested in Study 1. Measurement models for both theories were constructed and assessed. Inspection of these models revealed all assumptions had been met, as evidenced by absence of negative variances, and absence of multi-collinearity.

Homeostatic Model of Subjective Wellbeing

Testing proceeded by firstly constructing and assessing SEMs specified according to homeostatic theory for L-AUWBI 6 and L-AUWBI 7. These SEMs are identical to the model tested in Study 1. The homeostatic model for L-AUWBI 6 is presented in Figure 4.5. The standardised regression paths, SMCs (in italics), and correlations are presented in this figure. The unstandardised values and standard errors (in parentheses) are presented in Figure 4.6.



* = $p < .05$
** = $p < .01$
*** = $p < .001$

Figure 4.5: Homeostatic model of Subjective Wellbeing for L-AUWBI 6 (Standardised; N=682).

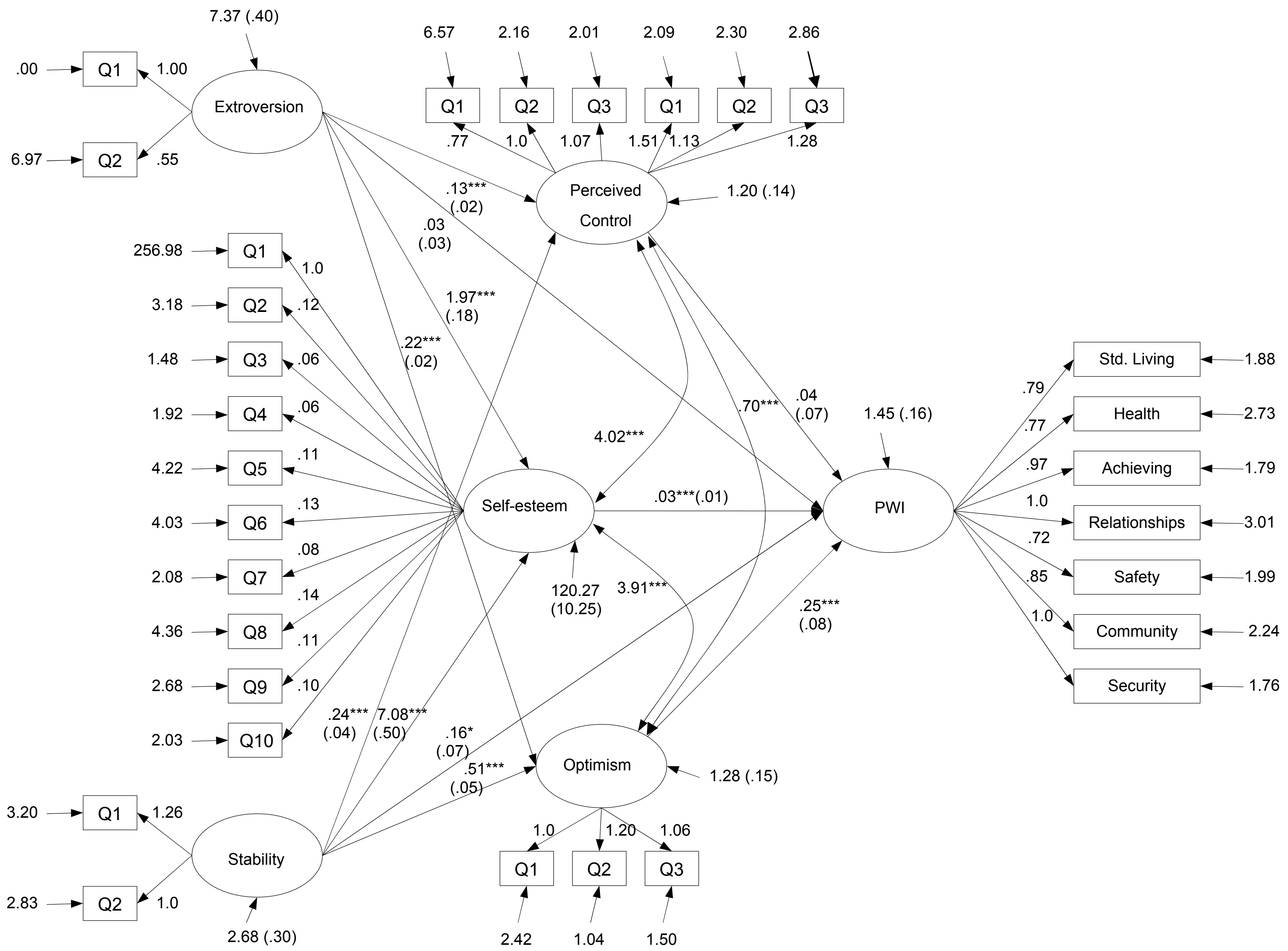


Figure 4.6: Homeostatic model of Subjective Wellbeing for L-AUWBI 6 (Unstandardised).

* = $p < .05$
** = $p < .01$
*** = $p < .001$

Absolute and relative fit indices for the homeostatic model of SWB in L-AUWBI 6 are presented in Table 4.5.

Table 4.5: Absolute and relative fit indices for homeostatic model in L-AUWBI 6 (N=682).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	7,956.48	7,810.48	423	<.001	18.46	.50	.51	.16	.43
Saturated	992.0	.000	0	-	-	1.0	1.0	-	-
Independence	15,520.40	15,458.40	465	<.001	33.24	.00	.00	.22	.00

The fit indices presented in Table 4.5 indicate that the homeostatic model does not provide an absolute fit, or a relative fit to the data. This result is consistent with the non-fit of the homeostatic model in Study 1. In addition, the relationships between the variables comprising homeostatic theory follow a similar pattern of relationships found in Study 1. Specifically, the standardised and unstandardised regression paths and SMCs provided in Figure 4.5 and Figure 4.6 indicate that extroversion did not significantly predict PWI (β=.05, B=.03, p>.05), and stability, although significant, was not strongly predictive of PWI (β=.16, B=.16, p<.05). Extroversion and stability exerted a moderate influence on all three components of the buffer system (β range from .29 to .69), accounting for between 19 and 58% of variance. As in Study 1, perceived control was the only component of the buffer system not to significantly predict PWI. Optimism and self-esteem exerted moderate direct effects on PWI (β=.24 and β=.31 respectively). Overall the combination of extroversion, stability, and the cognitive buffers predicted 43% of the variance in PWI.

A mediation analysis was conducted to determine whether any component of the buffer system mediated the relationship between extroversion or stability and PWI. The

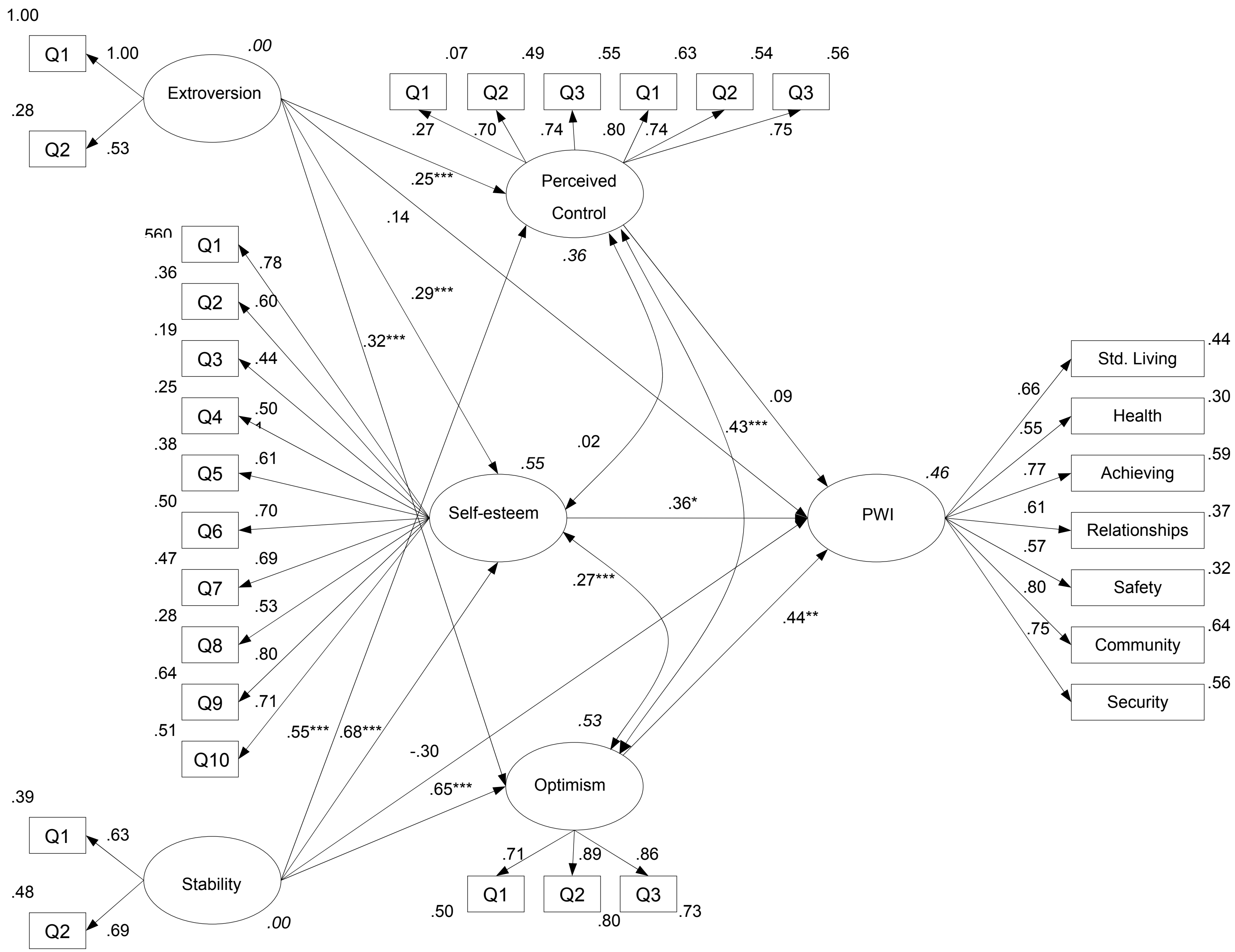
B-weights, z-scores, and significant levels of each mediation path are provided in Table 4.6.

Table 4.6: B-weights, z-scores, and significance levels of each mediation path for the homeostatic model of SWB in L-AUWBI 6.

Mediation Path	***B***	***z-score***	***P***
Stability → Self-esteem → PWI	.22	4.71	<.001
Stability → Optimism → PWI	.13	3.42	<.001
Stability → Perceived control → PWI	.01	.47	>.05
Extroversion → Self-esteem → PWI	.05	3.49	<.001
Extroversion → Optimism → PWI	.04	2.75	<.01
Extroversion → Perceived control → PWI	.01	.56	>.05

The data contained in Table 4.6 indicate that the only component of the buffer system not to significantly mediate the relationship between stability, extroversion, and PWI was perceived control. This result is consistent with results obtained in Study 1. As the direct effect of stability on PWI retained significance in the presence of the mediators (stability to PWI, B=.16, p<.05), self-esteem and optimism only partially mediated the relationship between stability and PWI. For extroversion, the mediation effect was full as the direct relationship between extroversion and PWI was not significant in the presence of the mediators (B=.03, p>.05). These results indicate that high levels of stability and extroversion are associated with high levels of self-esteem and optimism, which in turn, are associated with higher PWI scores.

Overall, the results testing the homeostatic model in L-AUWBI 6 confirm the results obtained in Study 1. The hypothesis that the homeostatic model provides an adequate fit to the data is not supported. Testing then proceeded by examining the homeostatic model of SWB in another independent sample; L-AUWBI 7. The model tested is identical to the model specified in Figure 4.5. This model, along with standardised regression paths, SMCs (in italics), and correlations, is presented in Figure 4.7. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 4.8.



* $= p < .05$
** $= p < .01$
*** $= p < .001$

Figure 4.7: Homeostatic model of Subjective Wellbeing for L-AUWBI 7 (Standardised; N=198).

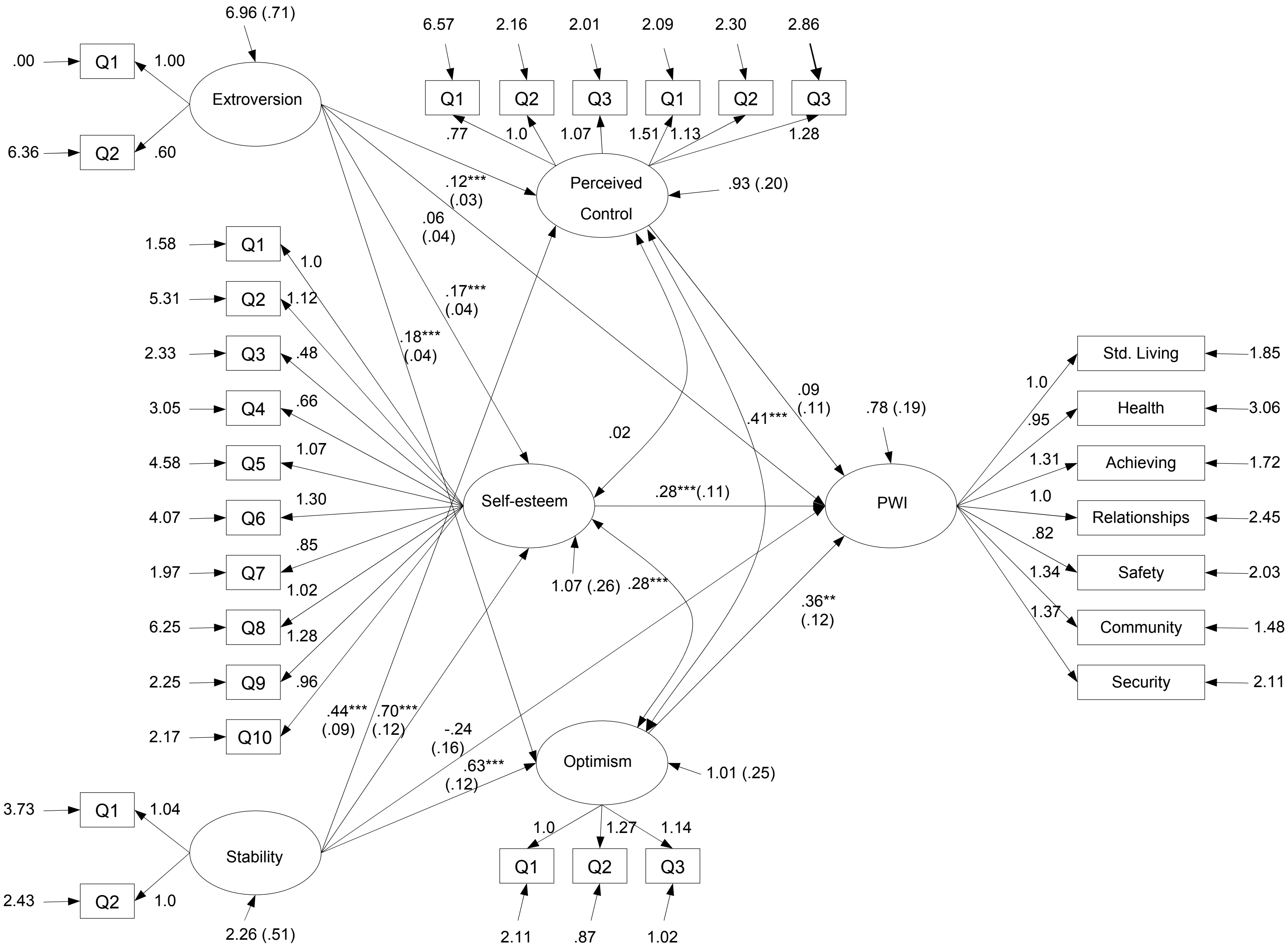


Figure 4.8: Homeostatic model of Subjective Wellbeing for L-AUWBI 7 (Unstandardised).

* = $p < .05$
** = $p < .01$
*** = $p < .001$

Absolute and relative fit indices for the homeostatic model in L-AUWBI 7 are presented in Table 4.7.

Table 4.7: Absolute and relative fit indices for homeostatic model in L-AUWBI 7 (*N*=198).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	1,073.56	867.56	392	<.001	2.21	.74	.83	.08	.46
Saturated	990.0	.000	0	-	-	1.0	1.0	-	-
Independence	3,370.44	3,310.44	465	<.001	7.12	.00	.00	.18	.00

The fit indices presented in Table 4.7 indicate that the homeostatic model does not provide an absolute fit, or an adequate relative fit to the data. The inadequate fit of the homeostatic model in L-AUWBI 7 is consistent with results obtained in L-AUWBI 6 and Study 1.

The relationships between the variables comprising the homeostatic model in L-AUWBI 7 follow a similar pattern of relationships observed in L-AUWBI 6 and Study 1, with the exception that stability is not significantly predictive of PWI (β=-.30, B=-.24, p>.05). Extroversion was also not significantly predictive of PWI (β=.14, B=.06, p>.05); however both extroversion and stability were significantly and moderately predictive of all three components of the buffer system (β range from .25 to .68), accounting for between 36 and 55% of variance in these components. Of the variables comprising the buffer system, only perceived control did not significantly predict PWI. In this sample, optimism (β=.44), and not self-esteem (β=.36), was the strongest predictor of PWI. Together these variables accounted for 46% of the variance in PWI.

As in L-AUWBI 6, mediation analyses were conducted to determine whether any component of the buffer system mediated the relationship between extroversion or stability and PWI in L-AUWBI 7. The B-weights, z-scores, and significance levels for each mediation path are presented in Table 4.8.

Table 4.8: B-weights, z-scores, and significance levels of each mediation path for homeostatic model of SWB in L-AUWBI 7.

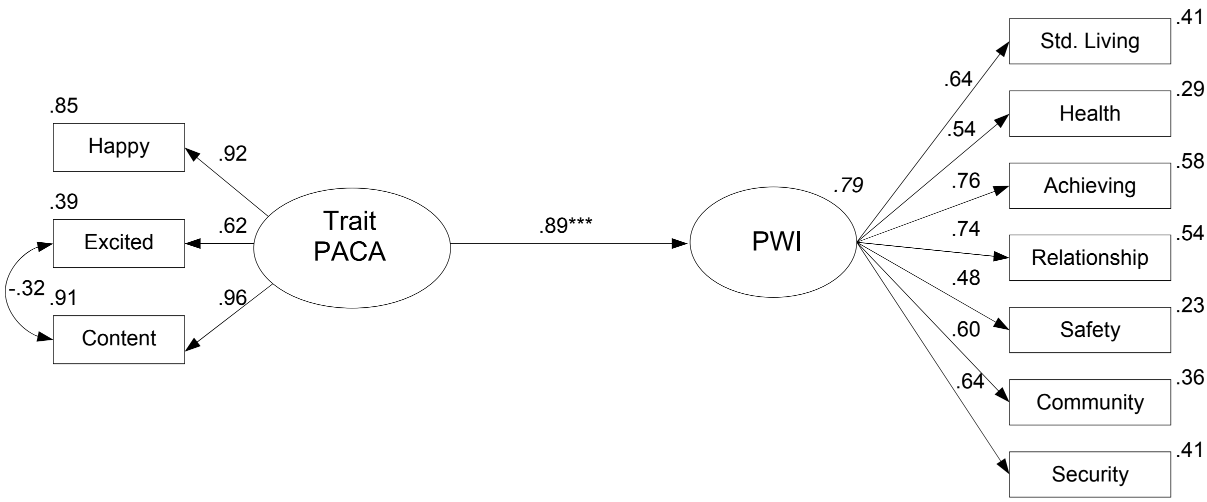
Mediation Path	***B***	***z-score***	***P***
Stability → Self-esteem → PWI	.20	2.30	<.05
Stability → Optimism → PWI	.23	2.58	<.01
Stability → Perceived control → PWI	.04	.79	>.05
Extroversion → Self-esteem → PWI	.05	2.14	<.05
Extroversion → Optimism → PWI	.07	2.45	<.01
Extroversion → Perceived control → PWI	.01	.78	>.05

The data in Table 4.8 are similar to the results obtained for the mediation analyses conducted in L-AUWBI 6 and Study 1. Specifically, perceived control was the only component of the buffer system that did not significantly mediate the relationship between extroversion, stability, and PWI. As the direct path between stability and PWI (B=-.24, p>.05), and extroversion and PWI (B=.06, p>.05), was not significant in the presence of the mediators, self-esteem and optimism fully mediated the relationship between stability and PWI, and extroversion and PWI. Thus, higher levels of extroversion and stability were associated with higher levels of self-esteem and optimism, which in turn, were associated with higher levels of PWI.

The results obtained for testing of the homeostatic model in L-AUWBI 7 provide further confirmation of results obtained in L-AUWBI 6 and Study 1. That is, in contrast with the hypothesis, the homeostatic model did not provide an adequate fit to the data.

Trait PACA Model of Subjective Wellbeing

In Study 1, the testing of three alternative theoretical models of SWB (the homeostatic model, MDT, and the affective-cognitive model) revealed that none of these models provided an absolute fit, or an adequate relative fit to the data. This led to the proposal and testing of an alternative, simpler model of SWB in which trait PACA was the sole predictor of PWI. This PACA model of SWB was found to provide an absolute fit to the data whilst also demonstrating a high degree of parsimony and explaining a large amount of variance in SWB (66%). In an attempt to replicate this result, the trait PACA model is tested in L-AUWBI 6 and L-AUWBI 7. These models are identical to the model tested in Study 1 with the exception that *active* has been replaced by *excited*. The PACA model for L-AUWBI 6 is presented in Figure 4.9. Standardised regression paths, SMC (in italics), and correlations are presented in this Figure. The unstandardised values, including standard errors (in parentheses) are presented in Figure 4.10.



*** = p <.001

Figure 4.9: Trait PACA model of SWB for L-AUWBI 6 (Standardised; N=682).

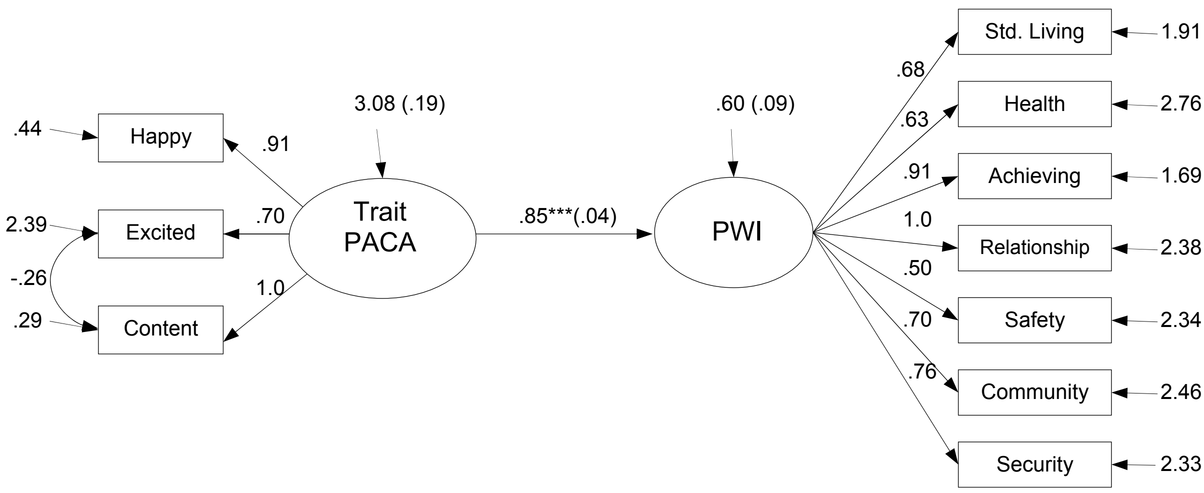


Figure 4.10: Trait PACA model of SWB for L-AUWBI 6 (Unstandardised).

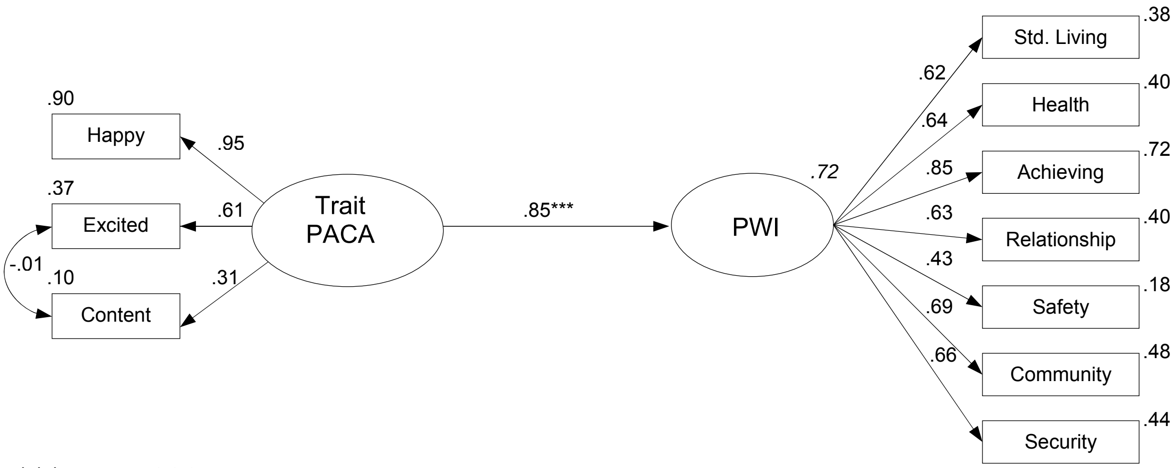
Absolute and relative fit indices for the trait PACA model in L-AUWBI 6 are presented in Table 4.9.

Table 4.9: Absolute and relative fit indices for trait PACA model in L-AUWBI 6.

Model	**AIC**	**χ^2**	***df***	***P***	**χ^2/df**	**NFI**	**CFI**	**RMSEA**	**SMC**
Specified	111.43	49.43	24	<.01	2.06	.99	.99	.04	.79
Saturated	110.0	.000	0	-	-	1.0	1.0	-	-
Independence	3,669.38	3,649.38	45	<.001	81.10	.00	.00	.18	.00

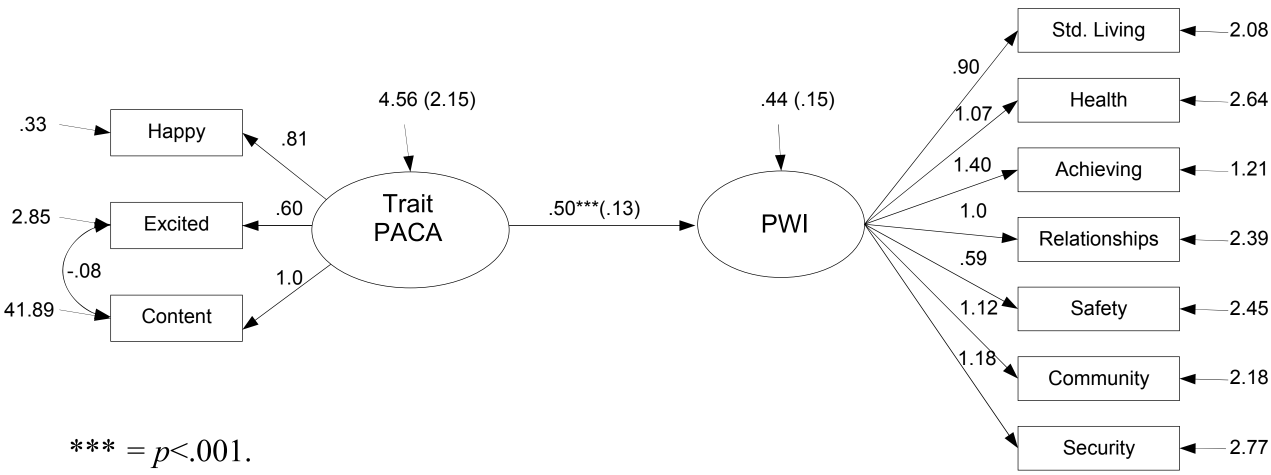
The absolute and relative fit indices presented in Table 4.9 indicate a good relative fit of the trait PACA model to the data. The standardised and unstandardised regression paths and SMCs provided in Figure 4.9 and Figure 4.10 indicate that trait PACA is a powerful predictor of PWI (β=.89, B=.85, p<.001). In this sample, the trait PACA model accounts for 79% of variance in PWI.

The trait PACA model of SWB for L-AUWBI 7 is presented in Figure 4.11 along with standardised regression paths, SMC (in italics), and correlations. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 4.12.



*** = p <.001

Figure 4.11: Trait PACA model of SWB for L-AUWBI 7 (Standardised, N=198).



*** = p<.001.

Figure 4.12: Trait PACA model of SWB for L-AUWBI 7 (Unstandardised).

Absolute and relative fit indices for the trait PACA model in L-AUWBI 7 are presented in Table 4.10.

Table 4.10: Absolute and relative fit indices for trait PACA model of SWB in L-AUWBI 7 (N=198).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	116.33	22.33	18	>.05	1.24	1.0	1.0	.04	.72
Saturated	130.0	.000	0	-	-	1.0	1.0	-	-
Independence	864.32	844.32	55	<.001	15.35	.00	.00	.18	.00

The fit indices given in Table 4.10 indicate an absolute fit to the data. This result is in agreement with the absolute fit obtained for this model in Study 1. The standardised and unstandardised regression paths and SMC provided in Figure 4.11 and Figure 4.12 indicate that trait PACA strongly predicts PWI (β=.50, B=.85, p<.001). In addition, the trait PACA model is a more parsimonious explanation of the data than the saturated model whilst accounting for 72% of the variance in PWI.

The results for both trait PACA models confirm results obtained in Study 1. Across three independent samples, the trait PACA affective model of SWB is highly parsimonious, predicts considerable variance in SWB, and is the only theoretical model tested to provide an absolute fit to the data in two of the three samples. A comparison of the absolute and relative fit indices for the homeostatic models and trait PACA models in L-AUWBI 6 and L-AUWBI 7 is given in Table 4.11.

Table 4.11: Absolute and relative fit indices for homeostatic and trait PACA models of SWB in L-AUWBI 6 and L-AUWBI 7.

Model	**AIC**	χ^2	***df***	χ^2/df	***P***	**NFI**	**CFI**	**RMSEA**	**SMC**
Homeostasis $_a$	7,956.48	7,810.48	423	18.46	<.001	.50	.51	.16	.43
Trait PACA $_a$	111.43	49.43	24	2.06	<.01	.99	.99	.04	.79
Homeostasis $_b$	1,073.56	867.56	392	2.21	<.001	.74	.83	.08	.46
Trait PACA $_b$	116.33	22.33	18	1.24	>.05	1.00	1.00	.04	.72

Note: a = L-AUWBI 6; b = L-AUWBI 7.

The fit indices presented in Table 4.11 indicate the homeostatic model in both samples provides a poor fit to the data and lacks parsimony. In comparison, for both samples, the trait PACA model yields a better fit to the data, is more parsimonious and explains more variance in PWI. Thus, it can be concluded that in two independent samples, the trait PACA model of SWB is superior to the homeostatic model. In addition, results follow the same pattern as those obtained in Study 1, providing further support for the proposition that trait PACA is a powerful determinant, and parsimonious explanation of SWB.

Partial Correlations Controlling for Trait PACA

As in Study 1, partial correlations controlling for trait PACA were conducted between the variables proposed by homeostatic theory (and a number of other researchers, Cha, 2003; Compton, 2000; Diener & Lucas, 1999; Lucas et al., 1996; Vitterso, 2001) to be predictive of SWB. The partial correlations for both L-AUWBI 6 and L-AUWBI 7 are given in Table 4.12.

Table 4.12: Pearsons and partial correlations between PWI, personality, and cognitive buffers in L-AUWBI 6 (*N*=682) and L-AUWBI 7 (*N*=198).

Variable	**Pearson *r* with PWI**	**sr^2 (controlling for trait PACA)**	**Magnitude of reduction in Pearson *r***
L-AUWBI 6			
Extroversion	.24***	.01	.23
Stability	.44***	.21***	.23
Self-esteem	.58***	.28***	.30
Optimism	.49***	.17***	.32
Perceived control	.38***	.07	.31
L-AUWBI 7			
Extroversion	.30***	.24**	.06
Stability	.28***	.21**	.07
Self-esteem	.46***	.37***	.09
Optimism	.54***	.42***	.12
Perceived control	.40***	.25**	.15

* *p* <.05; ** *p* <.01; *** *p* <.001.

The data contained in Table 4.12 indicate a dramatic reduction in the correlations between personality, the cognitive buffer system, and PWI for L-AUWBI 6. The most striking result is the near zero correlation between extroversion and PWI once the shared variance due to trait PACA is controlled. This result is almost identical to the partial correlation of -.01 between extroversion and PWI obtained in Study 1. The range of the reductions in the zero-order correlations is similar to the range obtained in Study 1 (.23 to .32 vs .20 to .44 for Study 1). However, this pattern of results was not observed in L-AUWBI 7. The magnitude of reductions did not exceed .15 and all correlations remained significant. This unexpected pattern of results may have been caused by some disattenuation in the data due to the relatively small sample size in L-AUWBI 7.

Hierarchical Regressions Controlling for Trait PACA

In Study 1 a hierarchical regression was conducted to test the relative predictive power of each variable that comprises the homeostatic theory of SWB. The results indicated that none of the variables tested were significantly predictive of PWI after controlling for trait PACA. The current study attempted to replicate this result in two independent samples. The hierarchical regressions are identical to those conducted in Study 1, and are presented in Table 4.13 for L-AUWBI 6 and Table 4.14 for L-AUWBI 7.

Table 4.13: Hierarchical regression predicting PWI by trait PACA, self-esteem, perceived control, optimism, and personality in L-AUWBI 6 (N=682).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.54***
1. Happy	2.39***	.53	.27	.01	
2. Content	3.53***	.48	.43	.04	
3. Excited	.61*	.26	.08	.00	
total unique variance = .05					
total shared variance = .49					
Step 2					.03***
1. Happy	1.61**	.53	.19	.01	
2. Content	3.05***	.47	.37	.03	
3. Excited	.67*	.26	.09	.00	
4. Self-esteem	.16***	.04	.18	.01	
5. Perceived control	-.01	.05	.00	.00	
6. Optimism	.10	.10	.03	.00	
7. Extroversion	-.07	.09	-.02	.00	
8. Stability	.15	.12	.04	.00	
additional unique variance = .01					
additional shared variance = .02					
* *p* <.05; ** *p* <.01; *** *p* <.001					R^2 = .57
					Adjusted R^2 = .56

The results presented in Table 4.13 indicate that, in contrast with results of Study 1, self-esteem significantly predicted PWI after controlling for trait PACA. However, the addition of the homeostatic theory variables in step 2 yielded an increase in prediction of only 3%. In comparison, trait PACA predicted 54% of variance in PWI. The hierarchical regression presented in Table 4.13 is repeated for L-AUWBI 7. The results of this regression are presented in Table 4.14.

Table 4.14: Hierarchical regression predicting PWI by trait PACA, self-esteem, perceived control, optimism, and personality in L-AUWBI 7 (N=198).

Variable	B	$SE\ B$	β	sr^2	ΔR^2
Step 1					.49***
1. Happy	5.56***	.52	.69	.30	
2. Content	.08	.12	.04	.00	
3. Excited	.02	.44	.00	.00	
total unique variance = .30					
total shared variance = .19					
Step 2					.05**
1. Happy	4.46***	.62	.55	.13	
2. Content	.07	.11	.03	.00	
3. Excited	-.24	.43	-.04	.00	
4. Self-esteem	.07	.06	.09	.00	
5. Perceived control	.28**	.09	.16	.02	
6. Optimism	.09	.06	.12	.01	
7. Extroversion	.27	.16	.09	.01	
8. Stability	-.37	.23	-.10	.01	
additional unique variance = .05					
additional shared variance = .00					
* p <.05; ** p <.01; *** p <.001					R^2 = .54
					Adjusted R^2 = .52

The results contained in Table 4.14 for L-AUWBI 7 are similar to the results of the regression for L-AUWBI 6 presented in Table 4.13. Trait PACA explained 49% variance in PWI, whilst the addition of the homeostatic variables only predicted an extra 5% variance. Of the homeostatic variables, only perceived control significantly predicted PWI after controlling for trait PACA.

Comparison of an Affective-Cognitive Model of SWB, PACA Model of SWB, and MDT (AUWBI 8)

As in Study 1, testing began by examining the correlations between all measured variables. These correlations, in addition to means and standard deviations, are presented in Table 4.15.

Table 4.15: Means, standard deviations and correlations between variables for AUWBI 8 (N=854).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.
1. PWI																					
2. Std. Living	.70																				
3. Health	.64	.33																			
4. Achieving	.75	.54	.42																		
5. Relationships	.70	.44	.28	.56																	
6. Safety	.67	.32	.35	.31	.33																
7. Community	.73	.38	.37	.47	.42	.46															
8. Security	.79	.51	.43	.46	.39	.61	.52														
9. Life satisfaction	.74	.63	.42	.68	.62	.33	.48	.50													
10. Happy	.71	.47	.43	.63	.66	.35	.47	.50	.74												
11. Content	.72	.58	.39	.65	.64	.36	.46	.50	.76	.76											
12. Excited	.58	.40	.37	.50	.46	.32	.41	.45	.57	.66	.56										
13. Extroversion	.39	.24	.27	.36	.27	.17	.34	.28	.36	.43	.39	.42									
14. Neuroticism	-.49	-.32	-.28	-.46	-.38	-.28	-.30	-.39	-.47	-.52	.53	-.35	-.40								
15. Self-wants	.69	-.60	-.38	-.67	-.55	-.33	-.42	-.50	.71	.68	.71	.54	.38	-.50							
16. Self-other	.55	-.48	-.27	-.50	-.40	-.28	-.38	-.41	.52	.49	.54	.45	.33	-.40	.65						
17. Self-deserves	.53	-.52	-.31	-.46	-.40	-.23	-.34	-.37	.54	.47	.52	.40	.27	-.35	.59	.50					
18. Self-needs	.53	-.50	-.29	-.44	-.41	-.25	-.35	-.39	.49	.46	.51	.39	.25	-.35	.55	.50	.76				
19. Self-progress	.56	-.55	-.32	-.48	-.42	-.26	-.35	-.41	.57	.51	.54	.42	.29	-.40	.63	.56	.67	.67			
20. Self-future	.38	-.33	-.24	-.31	-.29	-.23	-.22	-.28	.37	.39	.37	.43	.32	-.23	.40	.30	.39	.36	.46		
21. Self-best	.52	-.43	-.31	-.47	-.44	-.26	-.32	-.35	.55	.55	.54	.46	.32	-.33	.57	.43	.55	.55	.60	.50	
M	73.05	75.94	69.55	73.07	76.67	76.03	71.29	69.05	73.26	7.24	7.16	5.75	26.97	18.29	70.3	67.9	60.2	58.2	60.6	58.4	57.6
SD	14.04	18.11	20.66	18.51	21.86	18.32	19.86	20.78	18.54	1.98	2.10	2.40	6.24	8.28	18.5	20.3	21.9	22.3	22.6	19.6	22.7

Note: Correlations of .29 and above are statistically significant at p <.001.

The data presented in Table 4.15 reveals the strongest correlations were observed between PWI, LS, and trait happiness and contentment. This result is consistent with results for L-AUWBI 6 and L-AUWBI 7. Extroversion and neuroticism are also moderately related with PWI and LS whilst the variables comprising trait PACA are moderately related with extroversion and neuroticism.

The means and standard deviations for each domain of the PWI indicate that, as in Study 1, the highest satisfaction ratings were for the domains of *standard of living*, *personal relationships*, and *safety.* The mean PWI score of 73.05 is very similar to the mean PWI scores of 72.45 in L-AUWBI 5 (Study 1), 72.22 in L-AUWBI 6, and 72.45 in L-AUWBI 7. The means of the MDT items given in Table 4.15 indicate the largest discrepancy rating for *what one has now vs. best in previous experience.* The mean discrepancy ratings for all items in the current sample were very similar to mean ratings in Study 1. The overall mean discrepancy score of 61.9 indicates a relative lack of perceived discrepancies in this sample. Each perceived discrepancy was moderately positively related with PWI, LS, and the variables comprising trait PACA.

Affective-Cognitive Model of Subjective Wellbeing

As in Study 1, structural equation modelling was used to compare the utility of the theoretical models of SWB (affective-cognitive, MDT-affective, MDT, and the trait PACA model). Fit of the SEMs were assessed against the same criteria used in Study 1. Testing proceeded by examining the affective-cognitive model. This model is identical to the model specified in Study 1 with the exception that extroversion and stability were measured using the NEO-FFI (Costa & McCrae, 1992). Thus, for this model only, stability is renamed neuroticism. The affective-cognitive model is presented in Figure 4.13 along with standardised regression paths, SMCs (in italics) and correlations. The unstandardised values, including standard errors (in parentheses) are given in Figure 4.14.

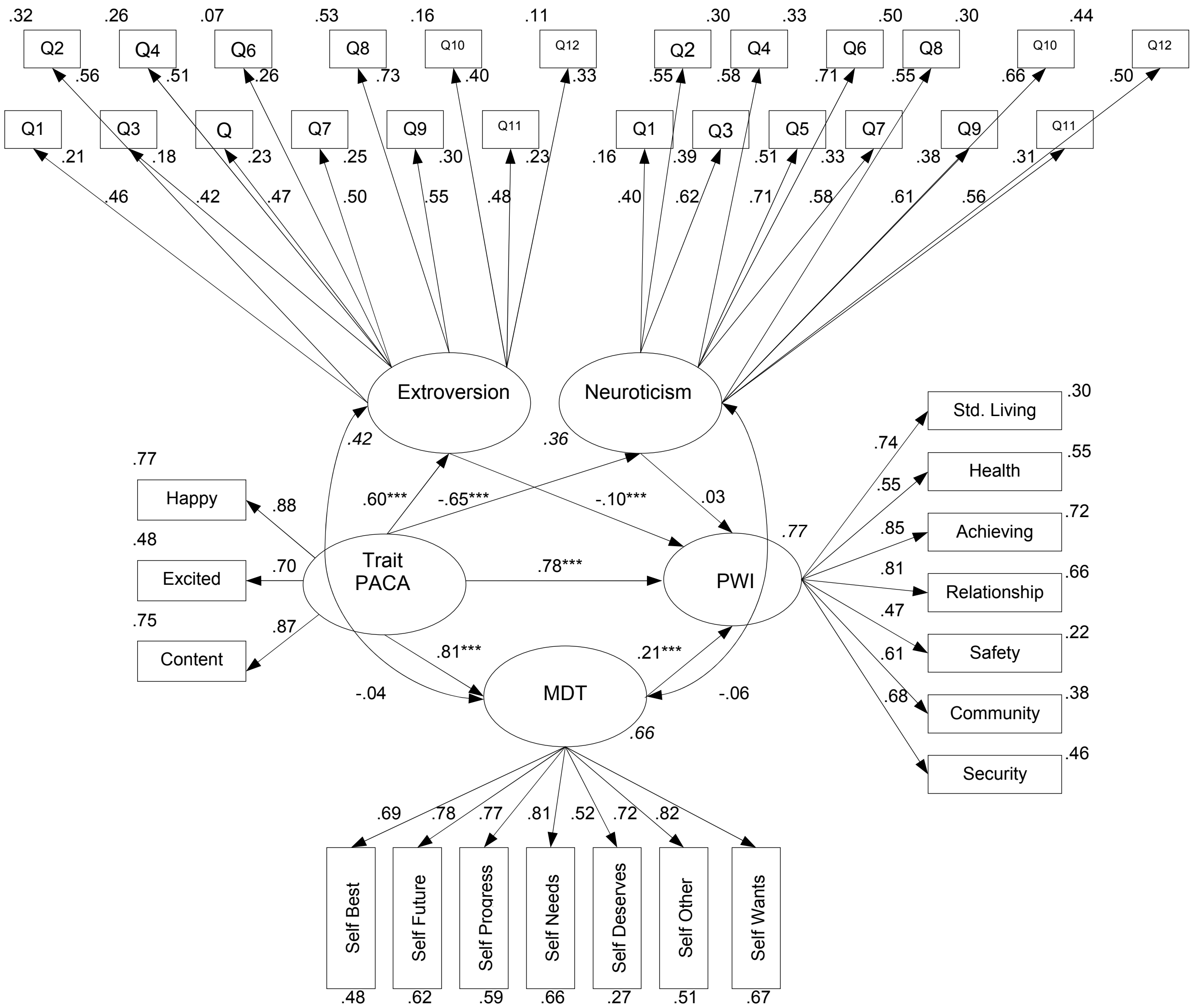


Figure 4.13: Affective-Cognitive model of SWB (Standardised; N=854).

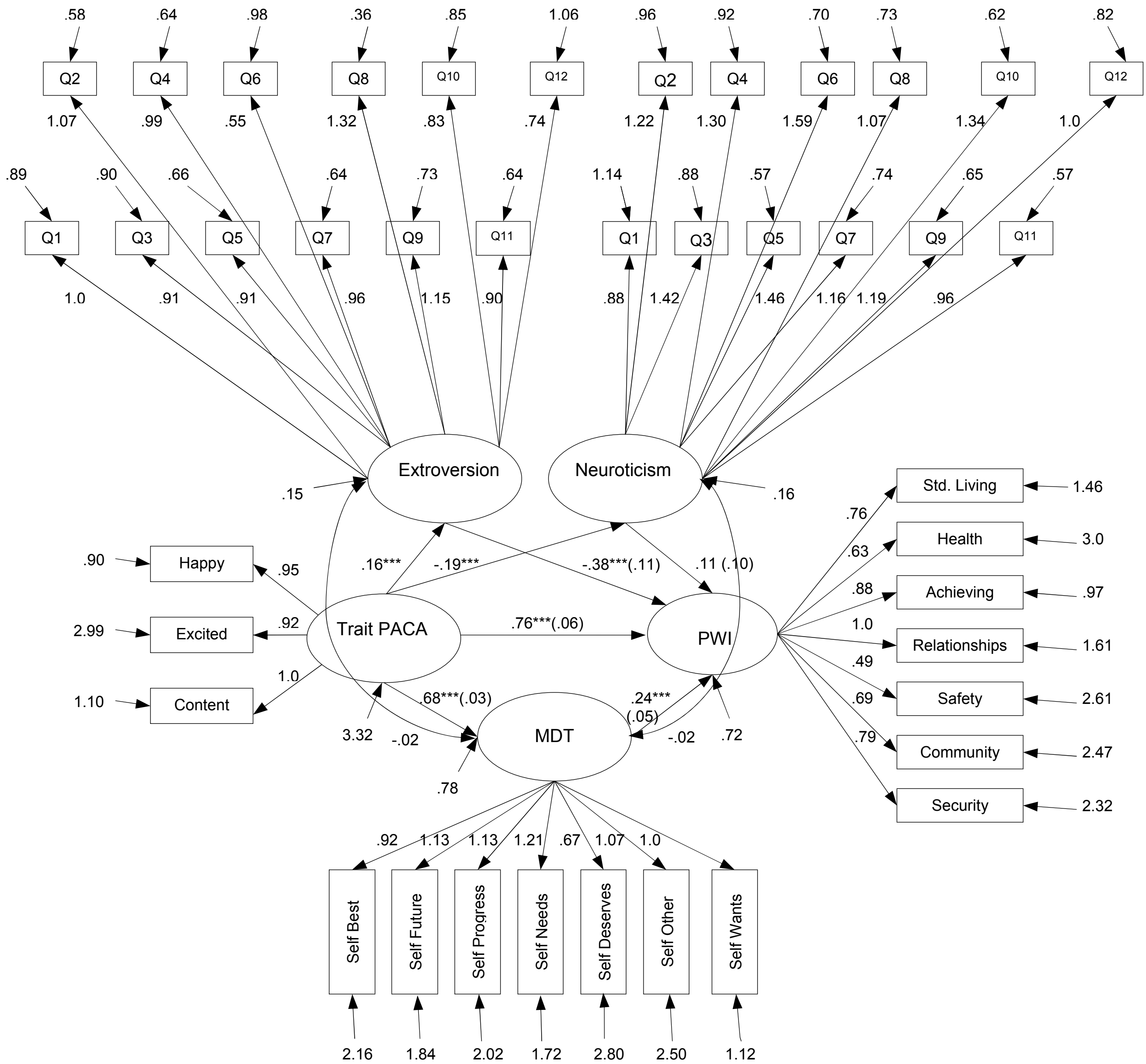


Figure 4.14: Affective-Cognitive model of SWB (Unstandardised).

Absolute and relative fit indices for the affective-cognitive model are provided in Table 4.16.

Table 4.16: Absolute and relative fit indices for affective-cognitive model incorporating extroversion, stability, and MDT in AUWBI 8 (*N*=854).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	2,918.54	2,614.54	750	<.001	3.5	.83	.87	.05	.77
Saturated	1,804.0	.000	0	-	-	1.0	1.0	-	-
Independence	15,259.44	15,177.44	861	<.001	17.63	.00	.00	.14	.00

The fit indices provided in Table 4.16 indicate that the affective-cognitive model does not provide an absolute fit, or a relative fit to the data. This result confirms the inadequate fit obtained for this model in Study 1. The standardised and unstandardised regression weights and SMCs provided in Figure 4.13 and Figure 4.14 reveal that the relationships between the variables comprising the affective-cognitive model for AUWBI 8 are very similar to results obtained in Study 1. Specifically, trait PACA is strongly related with extroversion (β=.60, B=.16, p<.001), neuroticism (β=-.65, B=-.19, p<.001), and MDT (β=.81, B=.68, p<.001), accounting for 42%, 36%, and 66% of variance respectively. However, extroversion, neuroticism, and MDT are not strongly related with PWI (extroversion→PWI, β=-.10, B=-.38, p<.001; neuroticism→PWI β=.03, B=.11, p>.05; MDT→PWI, β=.21, B=.24, p<.001). In contrast, trait PA is the strongest predictor of PWI (β=.78, B=.76, p<.001). Together these variables account for 77% of variance in PWI.

A mediation analysis was then conducted to determine whether MDT, extroversion, or neuroticism mediated the effect of trait PACA on PWI. The B-weights, standard errors, and z-scores for each mediation path are presented in Table 4.17.

Table 4.17: B-weights, z-scores, and significance levels of each mediation analysis path for affective-cognitive model of SWB in AUWBI 8.

Mediation Path	***B***	***z*-score**	***P***
Trait PA → Neuroticism → PWI	-.02	-1.1	>.05
Trait PA → Extroversion → PWI	-.22	-3.2	<.001
Trait PA → MDT → PWI	.16	4.7	<.001

The data contained in Table 4.17 indicate that only extroversion and MDT significantly mediated the relationship between trait PA and PWI. This mediation effect was partial, as the path between trait PA and PWI remained significant in the presence of the mediators (β=.78, B=.76, p<.001). Thus, higher levels of trait PACA were associated with lower perceived discrepancies, which in turn, were associated with higher PWI. In addition, high levels of trait PACA were associated with higher extroversion, but as the relation between extroversion and PWI was negative, this is associated with lower scores on PWI.

Overall the results testing the affective-cognitive model in AUWBI 8 confirm results obtained in Study 1. The relationships between the variables that comprise this model were almost identical with relationships observed in Study 1. In addition, in two independent samples, the affective-cognitive model did not provide an acceptable fit to the data.

MDT-Affective Model of Subjective Wellbeing

In Study 1, as the affective-cognitive model did not provide an adequate fit to the data, a nested alternative model, in which personality was omitted, was specified and tested. This MDT-affective model, although not providing an absolute or an acceptable relative fit in Study 1, provided a more parsimonious explanation of the data. Thus, the current study will attempt to replicate these findings by specifying and testing a nested MDT-affective model that is identical to the model tested in Study 1. This model is given in Figure 4.15 along with standardised regression paths and SMCs (in italics). The unstandardised values, including standard errors (in parentheses) are given in Figure 4.16.

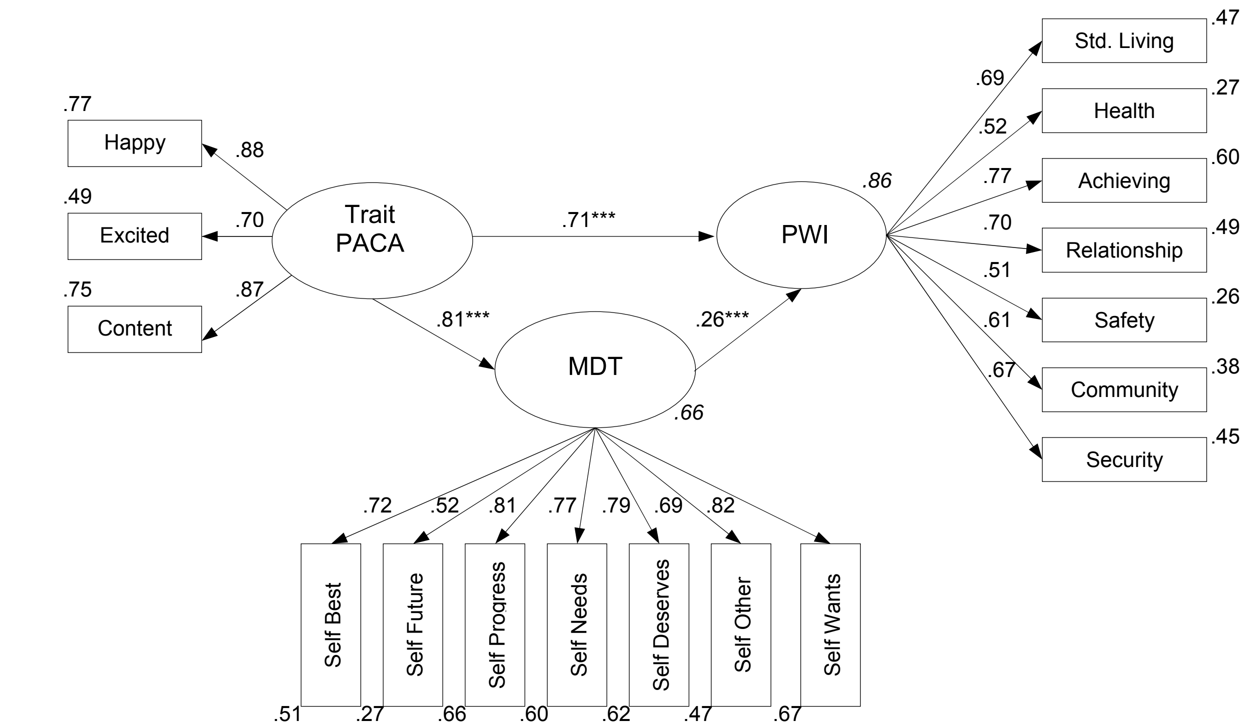


Figure 4.15: MDT-Affective model of SWB (Standardised; N=854).

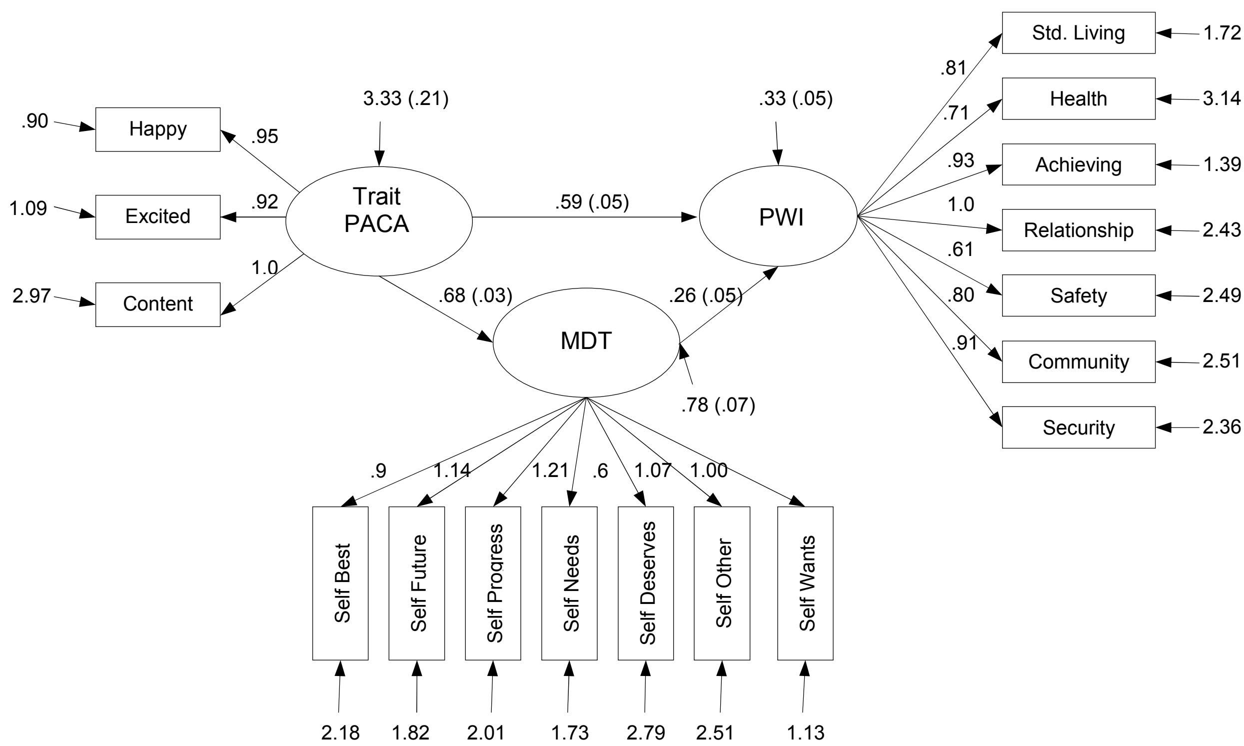


Figure 4.16: MDT-Affective model of SWB (Unstandardised).

Absolute and relative fit indices for the MDT-affective model are provided in Table 4.18.

Table 4.18: Absolute and relative fit indices for MDT-affective model in AUWBI 8 (N=854).

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	1,231.80	1,157.80	116	<.001	9.98	.87	.88	.10	.86
Saturated	306.0	.000	0	-	-	1.0	1.0	-	-
Independence	8,622.55	8,588.55	136	<.001	63.15	.00	.00	.27	.00

The fit indices presented in Table 4.18 indicate that the MDT-affective model provides an inadequate fit to the data. If MDT (in Figure 4.15) is replaced by the MDT self-wants mediation model (see Chapter 3, Figure 3.9), model fit is slightly improved (χ^2/df=9.89), but is still inadequate. As this is a nested model of the original affective-cognitive model, the chi-square difference test was used to determine the increase or decrease in fit. Application of this test yielded χ^2=1,456.7, df=634, p<.001. Thus the MDT-affective nested model provides a significantly better fit than the original affective-cognitive model given in Figure 4.13.

The standardised and unstandardised regression paths and SMCs given in Figure 4.15 and Figure 4.16 indicate that trait PACA is a powerful determinant of PWI (β=.71, B=.59, p<.001) and MDT (β=.81, B=.68, p<.001). In comparison, MDT is only moderately related to PWI when the effect of trait PACA is accounted for (β=.26, B=.26, p<.001). Trait PACA also accounts for 66% of the variance in MDT. Together, trait PACA and MDT explain 86% of the variance in PWI. These results are very similar with results obtained in Study 1 (see Chapter 3, Figures 3.15 and 3.16).

As in Study 1, a mediation analysis was conducted to determine whether the effect of trait PA on PWI was mediated by MDT. The B-weights, standard errors, and z-score of the mediation analysis paths are presented in Table 4.19.

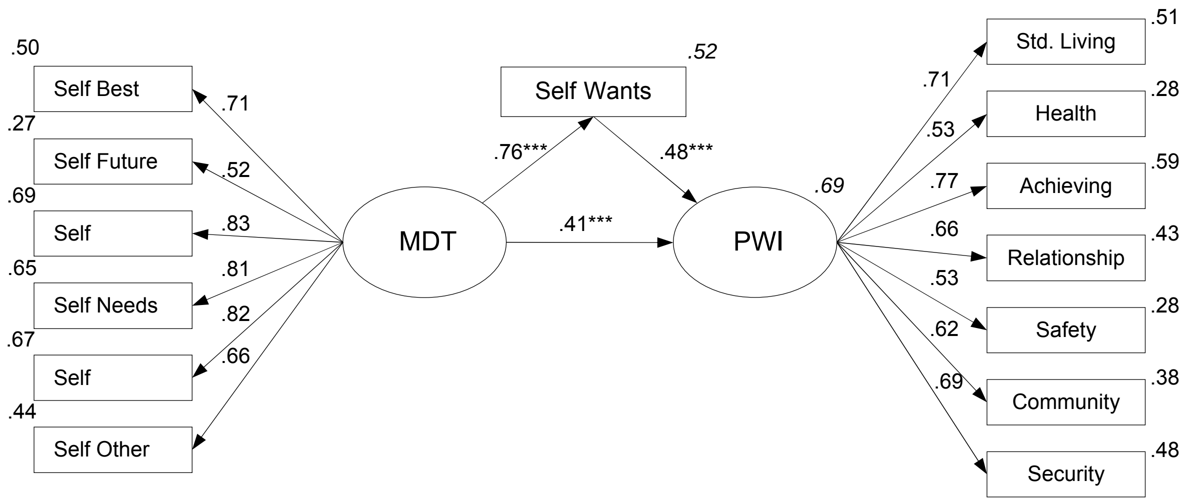
Table 4.19: B-weights, standard errors, and z-score of each mediation analysis path for the MDT-affective model of SWB (AUWBI 8).

Mediation Path	***B***	***SE B***	***P***
Trait PACA → MDT	.68	.03	<.001
MDT → PWI	.26	.05	<.001
Trait PACA → MDT → PWI	.18		<.001 (z = 5.1)

The mediation analysis indicates that MDT did significantly mediate the relation between trait PACA and PWI, however this effect was only partial as the direct effect of trait PACA on PWI remained significant (β=.71, B=.59, p<.001) in the presence of MDT. In addition, an examination of the beta weights given in Figure 4.15 indicates the effect of MDT on PWI was weak (β=.26, B=.26, p<.001) relative to the direct effect of trait PACA on PWI (β=.71, B=.59, p<.001).

Overall the results testing the MDT-affective model confirm the results obtained in Study 1. That is, the mediation effect of MDT on PWI, although significant, was weak in comparison to the direct effect of trait PACA on PWI. Trait PACA also accounts for a large amount of variance in MDT (66% in AUWBI 8, 46% in L-AUWBI 5, Study 1). Whilst the MDT-affective model provides a significantly better fit than the affective-cognitive model, it does not provide an absolute fit, or an acceptable relative fit to the data.

The MDT model of SWB proposes that SWB is directly influenced by a set of perceived discrepancies covering various aspects of an individual's life and circumstances. For example, one of the discrepancies measures the difference between what an individual has and what they want. It is hypothesised that lower perceived discrepancies lead to higher SWB, with results in Study 1 supporting this hypothesis. However structural equation modelling indicated that the MDT models tested did not provide an absolute fit, or an acceptable relative fit to the data. In Study 1, of the MDT models tested, the MDT self-wants mediation model provided the closest fit to the data. In an attempt to replicate this result, the MDT self-wants mediation model is tested in the current sample. The model is identical to the model tested in Study 1. This model is presented in Figure 4.17 with standardised regression paths and SMCs (in italics). The unstandardised values and standard errors (in parentheses) are given in Figure 4.18.



*** = *p* <.001.

Figure 4.17: MDT self-wants mediation model for AUWBI 8 (Standardised, N=854).

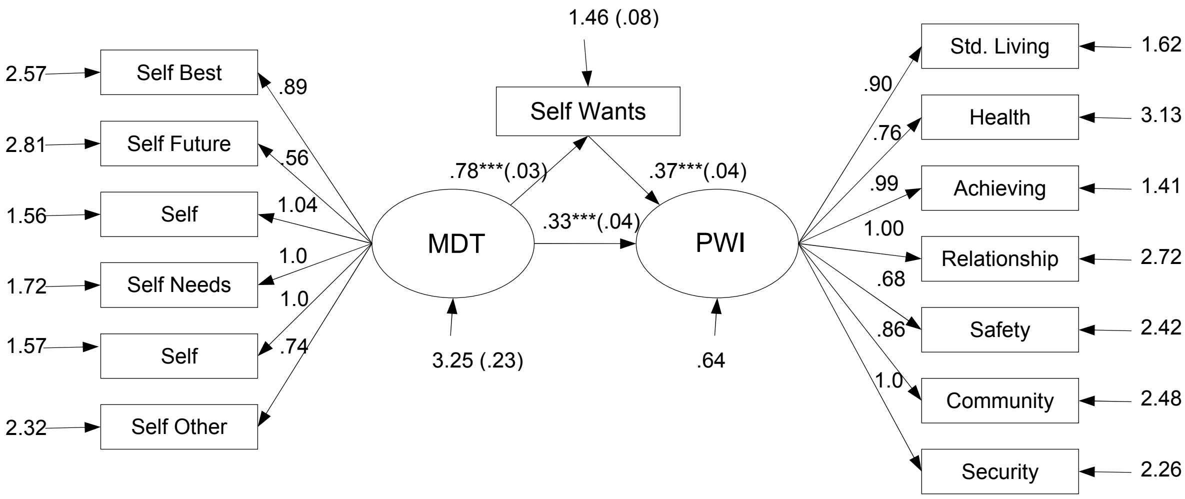


Figure 4.18: MDT self-wants mediation model for AUWBI 8 (Unstandardised).

Absolute and relative fit indices for the MDT self-wants mediation model are presented in Table 4.20.

Table 4.20: Absolute and relative fit indices for MDT self-wants mediation model in AUWBI 8.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	773.96	713.96	75	<.001	9.52	.88	.89	.10	.69
Saturated	210.0	.000	0	-	-	1.0	1.0	-	-
Independence	6,148.70	6,130.70	91	<.001	67.26	.00	.00	.28	.00

The fit indices presented in Table 4.20 indicate that the MDT self-wants mediation model provides a poor fit to the data. This result is consistent with the result obtained in Study 1. The standardised and unstandardised regression weights and SMCs provided in Figure 4.17 and Figure 4.18 indicate that the set of perceived discrepancies strongly predicted the self-wants discrepancy (β=.76, B=.78, p<.001), accounting for 52% of the variance. The direct path between the set of perceived discrepancies and PWI remained significant after controlling for the effect of the self-wants discrepancy (β=.41, B=.33, p<.001), whilst the self-wants discrepancy also significantly predicted PWI (β=.48, B=.37, p<.001). The SMC indicates that 69% of the variance in PWI was accounted for by the perceived discrepancies.

A mediation analysis indicated the effect of MDT on PWI was partially mediated by the self-wants discrepancy. This mediation effect was significant, z=8.7, *p*<.001. The B-weights, standard errors, and z-score of the mediation analysis paths are presented in Table 4.21.

Table 4.21: B-weights, standard errors, and z-score for mediation analysis paths in the MDT self-wants mediation model (AUWBI 8).

Mediation Path	***B***	***SE B***	***P***
MDT→PWI	.33	.04	<.001
MDT→Self-wants	.78	.03	<.001
Self-wants→PWI	.37	.04	<.001
MDT→Self-wants→PWI	.29		<.001 (z = 8.7)

The result of the mediation analysis indicates that the direct path between MDT and PWI remained significant in the presence of self-wants mediator. This result is inconsistent with Michalos' (1985) hypothesis that the self-wants discrepancy fully mediates the relationship between the set of perceived discrepancies and SWB. However this result replicates the results of Study 1 (see Chapter 3, Table 3.8).

The results testing the MDT self-wants mediation model supports the hypothesis that lower perceived discrepancies are associated with higher levels of PWI, however, as in Study 1, the MDT self-wants mediation model does not provide an acceptable fit to the data.

Trait PACA Model of Subjective Wellbeing

In Study 1 the testing of alternative theoretical models of SWB led to the development of the trait PACA model. This model was found to provide the best explanation of the data as it was the only model that gave an absolute fit. The trait PACA model also accounted for a considerable amount of variance in PWI (66%) whilst demonstrating a high degree of parsimony. This model was specified and tested in the current sample in an attempt to replicate the results of Study 1. The trait PACA model in AUWBI 8 is given in Figure 4.19 along with standardised regression paths, SMCs (in italics), and correlations. The unstandardised values and standard errors (in parentheses) are presented in Figure 4.20. The trait PACA model given in these figures is identical to the model tested in Study 1 with the exception that *active* has been replaced with *excited* as active was not measured in AUWBI 8.

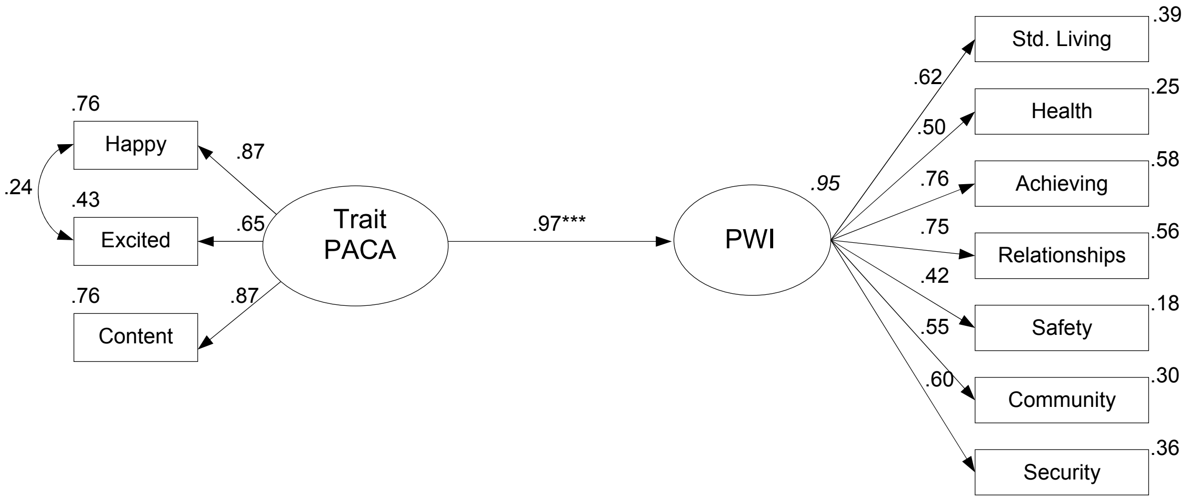


Figure 4.19: Trait PACA model of SWB in AUWBI 8 (Standardised; N=854).

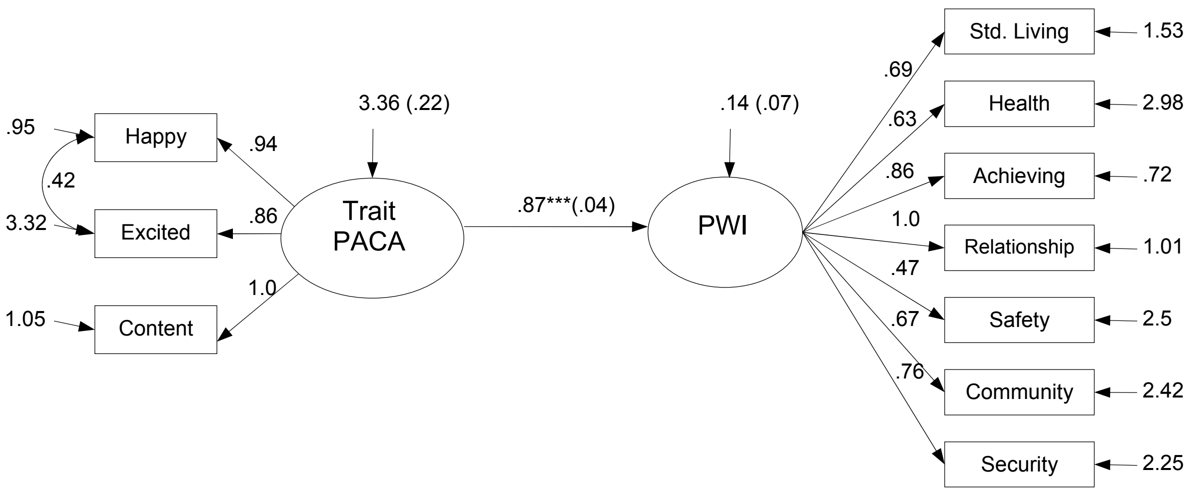


Figure 4.20: Trait PACA model of SWB in AUWBI 8 (Unstandardised).

Absolute and relative fit indices for the trait PACA model of SWB are provided in Table 4.22.

Table 4.22: Absolute and relative fit indices for trait PACA model of SWB in AUWBI 8 (N=854).

Model	**AIC**	χ^2	***df***	***P***	χ^2/df	**NFI**	**CFI**	**RMSEA**	**SMC**
Specified	143.14	77.14	22	<.001	3.5	.98	.99	.05	.95
Saturated	110.0	.000	0	-	-	1.0	1.0	-	-
Independence	4,298.03	4,278.03	45	<.001	95.08	.00	.00	.33	.00

The fit indices given in Table 4.22 indicate that the trait PACA model does not provide an absolute fit, but does provide an acceptable relative fit to the data. In addition, this model is highly parsimonious and explains 95% of variance in PWI. The standardised and unstandardised regression paths and SMCs provided in Figure 4.19 and Figure 4.20 indicate trait PACA to strongly predict PWI (β=.97, B=.87, p<.001). This result is consistent with results obtained in L-AUWBI 6, L-AUWBI 7, and Study 1.

AIC difference tests were used to compare the parsimony of the trait PACA model to the other models tested (affective-cognitive, MDT self-wants, MDT-affective). These analyses yielded values of 2,773.4, p<.001 for the affective-cognitive model; 628.88, p<.001 for the MDT self-wants model; and 1,086.73, p<.001 for the MDT-affective model. Thus, as in Study 1, the trait PACA model provided a more parsimonious explanation of the data than all of the other models tested. A comparison of absolute and relative fit indices for all models tested across the three samples (L-AUWBI 6, L-AUWBI 7, AUWBI 8) is given in Table 4.23.

Table 4.23: Summary of absolute and relative fit indices for six alternative theoretical models of SWB across three samples.

Model	**AIC**	χ^2	***df***	***P***	χ^2/df	**NFI**	**CFI**	**RMSEA**	**SMC**
Homeostasis $_a$	7,956.48	7,810.48	423	<.001	18.46	.50	.51	.16	.43
Homeostasis $_b$	1,073.56	867.56	392	<.001	2.21	.74	.83	.08	.46
Trait PACA $_a$	111.43	49.43	24	<.01	2.06	.99	.99	.04	.79
Trait PACA $_b$	116.33	22.33	18	>.05	1.24	1.00	1.00	.04	.72
Affective-Cognitive $_c$	2,918.54	2,614.54	750	<.001	3.50	.83	.87	.05	.77
MDT-Self Wants $_c$	773.96	713.96	75	<.001	9.52	.88	.89	.10	.69
MDT-Affective $_c$	1,231.8	1,157.8	116	<.001	9.98	.87	.88	.10	.86
Trait PACA $_c$	143.14	77.14	22	<.001	3.50	.98	.99	.05	.95

Note: a = L-AUWBI 6; b = L-AUWBI 7; c = AUWBI 8

The data contained in Table 4.23 indicate that, consistent with the hypotheses, the trait PACA model provided the best fit to the data, predicted a substantial amount of variance in SWB, and was the most parsimonious model tested.

Section 4.3: DISCUSSION

The aim of Study 2 was to provide further evidence that SWB is determined by trait PACA by replicating the findings of Study 1. In three independent samples, SEMs specified according to the trait PACA model yielded superior fits to the data than SEMs specified according to either homeostatic theory, MDT, or affective-cognitive theory (see Table 4.23). In addition, the trait PACA models consistently demonstrated far greater parsimony and predicted up to 36% more variance in SWB than the homeostatic models, and up to 26% more variance than the MDT models (see Table 4.23). This supports the conclusion of Study 1 that SWB is strongly determined by trait PACA.

Comparison of Homeostatic Theory and the Trait PACA Model of Subjective Wellbeing (L-AUWBI 6and L-AUWBI 7)

One of the core premises of homeostatic theory is that the failure of SWB homeostasis results in increased depressive symptomatology. Consistent with Study 1, a strong negative relationship was found between individuals experiencing moderate to extremely severe depression and SWB (see Table 4.4 and Figures 4.1 and 4.2). Partial support was also found for the central hypotheses of homeostatic theory. Specifically, testing of the homeostatic model using SEM indicated that two of the three components of the buffer system, self-esteem and optimism, significantly predicted SWB (see Figures 4.5 and 4.7). In addition, extroversion and stability significantly and positively influenced all three components of the buffer system. However, contrary to the predictions of homeostatic theory, extroversion exerted a non-significant effect on SWB in both L-AUWBI 6 and L-AUWBI 7, whilst stability exerted a significant, but weak influence on SWB in L-AUWBI 6 only. The effects of extroversion and stability on PWI were also mediated by self-esteem and optimism (see Tables 4.6 and 4.8). High scores on extroversion and stability were associated with higher self-esteem, optimism, and perceived control, which in turn, related with higher SWB. These results support the homeostatic theory hypothesis that extroversion and stability indirectly influence SWB through the system of cognitive buffers. However in both samples, once the effect of trait PACA on SWB was accounted for, none of the components of the buffer system predicted more than 2% unique variance in SWB (see Tables 4.13 and 4.14). In addition, partial correlations controlling for trait PACA revealed that once shared variance due to trait PACA is removed, the relationship between personality, the buffer system, and SWB is considerably reduced (see Table 4.12). These results are consistent with the results of Study 1, further substantiating the conclusions of Study 1 that the variables comprising homeostatic theory are only weakly related to SWB once the effect of trait PACA is removed. The SEMs specified according to homeostatic theory also provided a poor fit to the data and lacked parsimony (see Table 4.23). This result replicates the findings of Study 1, and when considered together with the above findings, suggests that homeostatic theory is an inadequate explanation of SWB.

In comparison with the homeostatic models, the trait PACA models provided an excellent fit to the data in both L-AUWBI 6 and L-AUWBI 7 (see Table 4.23). In addition, trait PACA was a strong predictor of SWB (β-weights ranged from .85 to .97, B-weights ranged from .50 to .87), and consistently accounted for a majority of the variance in SWB (SMC ranged from .72 to .95) in both samples. These results are almost identical with results of Study 1, providing further support for the conclusion that a trait PACA model provides a better explanation of SWB than homeostatic theory.

MDT, Affective-Cognitive Model, and Trait PACA model of Subjective Wellbeing (AUWBI 8)

Overall, as in Study 1, a majority of the sample reported a relative lack of perceived discrepancies. Testing of a SEM specified according to MDT indicated that MDT accounted for 69% of variance in SWB. This effect was in the proposed direction, with smaller discrepancies resulting in higher SWB. As hypothesised by MDT, the self-wants discrepancy did mediate the relationship between the other perceived discrepancies and SWB (see Table 4.21). Smaller discrepancies on the other items led to a lower discrepancy between what one has and wants. This in turn, led to higher SWB scores. However self-wants only partially mediated the relationship between the set of perceived discrepancies and SWB, whereas MDT predicts self-wants to fully mediate the relationship and be the strongest predictor of SWB (Michalos, 1985). This hypothesis was not supported in the current study, nor was it supported in Study 1. In addition, as in Study 1, the MDT model provided a poor fit to the data and lacked parsimony (see Table 4.23). In comparison, the trait PACA model provided a significantly better fit to the data and was much more parsimonious. An MDT-affective model also did not yield an adequate fit to the data. Although this model accounted for an additional 17% of variance in SWB compared to the MDT-Self wants model, trait PACA was 2.7 times more powerful than MDT in predicting SWB (see Figure 4.15). In addition, trait PACA accounted for 66% of variance in MDT (see Figure 4.15), indicating that trait PACA strongly determines an individual's self-reported perceived discrepancy scores. These results are almost identical with the results of Study 1 (see Chapter 3, Figure 3.15) and provide strong support for the conclusion in Study 1 that the PACA model is a better explanation of SWB than MDT.

Conclusions and Future Directions

Overall, this set of results suggests that the old paradigm in SWB research, in which SWB is proposed to be driven by cognition and personality, is inadequate. The findings of Study 1 and Study 2 strongly suggest that SWB is predominantly determined by an individual's trait level of PACA. These findings have wide ranging implications for the SWB field, as they cast doubt on a number of previously commonly held beliefs that self-reported satisfaction judgements are strongly influenced by cognitions and personality (Brebner et al., 1995; Diener & Lucas, 1999; Hills & Argyle, 2001; Michalos, 1985; Vitterso, 2001). Rather, it seems that trait PACA, and not cognition or personality, strongly influences an individual's life satisfaction.

One alternative explanation for these results can be found in a discussion of the methods used to measure SWB by Schwarz and Strack (1999). These authors found that SWB was significantly influenced by a person's current mood. They argue that because the question used to assess SWB is so abstract and requires an inordinate amount of cognitive effort, people use heuristics to arrive at an answer. Schwarz and Strack propose current mood as one such heuristic. This raises the potential that individuals are using trait PACA as a heuristic for satisfaction judgements. As such, before strong conclusions can be drawn about the efficaciousness of a trait PACA model as an explanation of SWB, this alternative explanation must be ruled out. One promising framework with which to test this hypothesis is provided by reaction time studies. Reaction times are frequently interpreted as measures of processing speed (Smith, 1968). As such, individual differences in affective processing, and how such differences relate to SWB, could be investigated within this paradigm.

Research has demonstrated that individuals are faster at retrieving information that is consistent with their state and trait mood (Singer & Salovey, 1988). One method that has been used to assess the speed of affective information processing is valence identification tasks, a form of choice reaction time task. Typically in these tasks, an individual is presented with a word or picture, and required to correctly identify the valence of the target. Individual differences in the speed of correct valence identification of targets have been found to correlate with self-reported SWB (Robinson, Solberg, Vargas & Tamir, 2003), negative affect (Robinson, Meier & Vargas, 2005; Robinson et al., 2003; Tamir & Robinson, 2004), positive affect (Robinson et al., 2003), depression (Ruiz Caballero & Moreno, 1992), extroversion (Robinson et al., 2003; Tamir, Robinson & Clore, 2002), neuroticism (Tamir & Robinson, 2004) and self-reported somatic symptoms (Robinson, Vargas, Tamir & Solberg, 2004). In the study conducted by Robinson et al. (2004), the results indicated that individuals who were faster at making negative evaluations of words reported more negative affect, more somatic symptoms, and lower life satisfaction than individuals who were slower to make these evaluations. This result is consistent with the predictions of the associative network model of affect proposed by Bower (1981, 1987). In this model, information that is congruent with an individual's mood is more readily retrieved compared with information that is incongruent. This is due to the activation of perceptual categories and words related to the individual's particular mood (Singer & Salovey, 1988). Thus, the pre-existing affective state is maintained by production of mood-congruent responses (Forgas & Ciarrochi, 2002). Other research has supported this proposition. Siegle, Granholm, Ingram, and Matt (2001) measured the reaction time of depressed and non-depressed individuals in response to a valence identification task of neutral, positive, and negative words. The authors found that depressed individuals were slower to correctly identify positive words compared with non-depressed individuals.

A reaction time paradigm will allow an assessment of individual differences in affective information processing, and an assessment of whether such differences correspond or correlate with individual differences in SWB. If individuals are using trait PACA as a heuristic, then those high on trait PACA should be faster to correctly identify positive words, as compared to neutral and negative words, and be higher on SWB (because they are using affect-as-information to inform judgements, Tamir & Robinson, 2004). In addition, if the heuristic hypothesis is correct, then state PACA should be more strongly related to SWB than trait PACA due to the salience of state affect. These hypotheses are addressed within a self-report and reaction time paradigm in Study 3.

CHAPTER 5: STUDY 3

Section 5.1: INTRODUCTION

The findings of Studies 1 and 2 strongly suggest that subjective wellbeing is largely determined by a person's trait level of pleasant-activated core affect (PACA). This finding is incompatible with the structure of SWB proposed by Diener (1984, 1996). In this structure SWB is hypothesised to consist of two separate components; a cognitive component that is referred to as life satisfaction, and an affective component, referred to as hedonic balance (the balance of pleasant to unpleasant experiences). Together, according to Diener, these two components comprise the higher order construct of SWB. However this conceptualisation cannot account for the large influence trait PACA exerts on what is hypothesised as the cognitive component of SWB, life satisfaction. Other empirical research has also found that affect exerts a strong influence on life satisfaction (Lucas et al., 1996; Pavot et al., 1991; Schimmack, 2003).

The present study has been designed to falsify the trait PACA model of SWB by using a different paradigm than that which is normally employed in SWB research. Whereas Studies 1 and 2 relied on self-reports of affective traits, this study will use a behaviourally based measure of affective processing, thereby enabling an alternative test of the impact that individual differences in affective processing have on the prediction of SWB. Specifically, a Reaction Time (RT) paradigm will be used in which participants' response latencies to the categorisation of positive, neutral, and negative words are correlated with measures of SWB, PACA, and state and trait affect. In line with the principle of mood congruency (Bower, 1981, 1987), individual differences in affective processing will likely relate with differences in the speed of categorisation for positive and neutral, and negative and neutral words. Furthermore, in accordance with previous research examining the influence of affect on performance (Singer & Salovey, 1988), prior to this categorisation task participants will be induced to experience a positive or negative mood using the suboptimal presentation of emotional words.

It is necessary to examine, in more detail, the premises on which this study is founded. The first part of this introduction will focus on the principle, and evidence for, mood congruency. This will be followed by a discussion of the problems associated with mood induction. The next part of the introduction will then evaluate the empirical evidence for the effectiveness of one type of mood induction (suboptimal priming) in more detail, as this form of mood induction offers an effective solution to the problem of demand characteristics often associated with the induction of mood. Finally there will be a discussion on the advantages of using a reaction time paradigm, and a statement of hypotheses for the current study.

Mood Congruency

In the early 1980s theorists were engaged in a vigorous debate regarding the proper role of affect in information processing (Lazarus, 1982, 1984; Zajonc, 1980, 1984). On the one hand, Zajonc (1980, 1984) argued for a separate-systems view, whereby primitive affective reactions could precede, and were distinct from, cognitive processes. On the other hand, Lazarus (1982, 1984) argued that affective processes, by necessity, involved cognition. Somewhere in the middle of these two positions Bower (1981) proposed what is known as the associative network model of affect, in which affect and cognition are integrally linked within an associative network of cognitive representations (Forgas, 2000). In this model emotions are central units (nodes) in a semantic network, connected to related ideas, autonomic activity, muscular patterns and events (Bower, 1987). Once a node is stimulated, other nodes that are associated with the first node become activated. This activation in turn spreads to additional related nodes (Bower, 1987; Singer & Salovey, 1988). One of the principles that Bower derived based on this spreading activation concept is the principle of mood congruency. According to this principle, a particular mood activates an emotion node that in turn leads to a biased search of memory for related material. This leads to an increased availability of mood congruent memories (Bower, 1981, 1987; Singer & Salovey, 1988). Thus, retrieval of information that is congruent with an individual's mood is more likely. Empirical research has demonstrated this effect, with individuals in a particular mood state showing preferential recall (in speed or content) to information that is congruent with their mood (Forgas, 1995; Forgas & Bower, 1987; Joorman & Siemer, 2004; Ruiz Caballero & Moreno, 1992; Siegle et al., 2001; Singer & Salovey, 1988).

In one such study, Joorman and Siemer (2004) induced 119 dysphoric and non-dysphoric participants into both positive and negative moods and measured subsequent recall latencies to cued positive and negative autobiographical memories. Consistent with the mood congruency hypothesis, following positive mood induction, non-dysphoric participants recalled positive autobiographical memories significantly faster than negative autobiographical memories. However mood congruency effects were not found in dysphoric participants, or in non-dysphoric participants in the negative mood induction condition.

The mood congruency effect has also been found using choice reaction time tasks. For instance, Ruiz-Caballero and Moreno (1992) investigated the reaction times of 44 students to a Valence Identification Task (VIT). Half the students were split into two categories according to their depression score on the BDI: mildly depressed and non-depressed. The remaining 22 students were randomly assigned to receive either an elated mood induction, or a depressed mood induction. The induction involved the use of the Velten (1968) procedure whereby participants read a set of statements (such as "I feel unhappy") and were asked to identify with the statement as much as possible in order to feel the mood described. All participants then completed the VIT in which they were asked to classify a set of 24 words as either negative or positive. Participants who received the elation mood induction, and participants who were non-depressed, were faster to classify positive words compared to negative words. The effect sizes (calculated by converting the *F* score to R^2) for the non-depressed group, and the elation induced group were R^2=.16 and R^2=.26 respectively. This indicates that 16% and 26% of the variance in the VIT for non-depressed and elation induced participants was accounted for by word type (positive versus negative). However, participants who were classified as mildly depressed, and those who received the depression induction, were not faster to classify negative words compared with positive words.

Additionally, Forgas and Ciarrochi (2002) carried out a series of experiments in which negative, neutral, and positive moods were induced. Subsequent responses to a person-description task (experiment 1, *N*=60), a word-completion task (experiment 2, *N*=55), and a self-description task (experiment 3, *N*=48) were then measured. In each experiment, initial mood congruency effects were observed. Individuals receiving the positive mood induction generated more positive responses for each experimental task whereas individuals receiving negative mood induction generated more negative responses for each task.

The effect of mood congruency has also been assessed on judgments of subjective wellbeing. Schwarz and Clore (1983) conducted two experiments to investigate whether positive and negative mood would differentially affect wellbeing in the direction proposed by the mood congruency hypothesis. In the first experiment, 61 participants were asked to recall either a very positive, or a very negative life event. Following this, each participant rated their life satisfaction and general happiness. The results obtained were consistent with the mood congruency hypothesis. Participants who recalled a positive life event reported significantly higher life satisfaction (R^2=.69) and happiness (R^2=.67) than those participants who recalled a negative life event. In experiment 2, the authors investigated whether an individual's affective state would lead to differences in SWB by contacting 84 participants via telephone on sunny (positive mood) and rainy (negative mood) days. When the participant's attention was not drawn to the weather, results indicated the expected mood congruency effect. Participants called on sunny days reporting significantly higher SWB than participants called on rainy days (R^2=.04), however this effect was relatively weak.

Mood Induction and the Problem of Demand Characteristics

Many of the studies investigating the mood congruency hypothesis have used mood induction procedures to induce both positive and negative moods in the laboratory. In these studies, experimenters often induce a particular mood in one group of participants (i.e., positive), a different mood in another group of participants (i.e., negative), and then compare the two groups on a related task (i.e., memory recall task, Joorman & Siemer, 2004; or VIT, Ruiz-Caballero & Moreno, 1992). A variety of different methods have been used to induce mood, some more successful than others. The more popular mood induction techniques include self-statements (Velten, 1968), music, autobiographical recall, imagery, presentation of a film or story, and gifts (Martin, 1990; Westermann, Spies, Stahl & Hesse, 1996). Two separate reviews on the effectiveness and validity of different mood induction procedures have been conducted by Gerrards-Hesse, Spies, and Hesse (1994), and Westermann et al. (1996). Based on a review of over 250 studies, Gerrards-Hesse et al. concluded that the most effective mood induction procedures were film or story and gifts for an elated mood, and film or story, gifts, Velten self-statements, and imagery for depressed mood. Similarly, Westermann et al. concluded that for both elated and depressed moods, the film or story technique is best. However, both reviews included sections on possible demand effects. In particular, the reviews noted that the induced mood might be artifactual, as it is probable that using some induction techniques (i.e., Velten self-statements) will make the individual aware, either explicitly or implicitly, of the purpose of the study. Thus, the individual, wanting to be compliant, reports a change in mood in the desired direction regardless of whether the change in mood is real or artifactual. Indeed, the most effective mood induction techniques listed above have been noted by Westermann et al. to be particularly vulnerable to demand effects. Thus it stands to reason that the best forms of mood induction are ones in which the participant is unaware of the procedure used to induce mood.

Suboptimal Priming as a Mood Induction Procedure

One particular mood induction procedure offers an effective solution to the problems associated with demand effects. This procedure is termed *suboptimal priming,* and is defined as priming that occurs below conscious awareness. Specifically, suboptimal priming involves the presentation of a stimulus to a participant under viewing conditions that render conscious identification of the stimulus highly improbable (Murphy & Zajonc, 1993). The viewing condition is usually restricted to around 30 milliseconds for text, and under 30 milliseconds for pictures. The presentation of the prime is followed by the immediate masking of the prime by another, neutral stimulus for a longer duration than the prime. The masking of the stimulus is done to overwrite the representation of the prime in the visual iconic memory (Bargh & Chartrand, 2000). In addition, following the use of suboptimal priming, the experimenter conducts awareness checks to determine whether any individuals were consciously aware of the prime.

Suboptimal priming has been used in a wide variety of studies employing an array of methodologies. For instance, Friedman, McCarthy, Forster, and Denzler (2005) found that suboptimal priming of alcohol related words increased the attractiveness ratings of female photographs by men who expected alcohol to increase sexual desire. In another study, Ohman and Soares (1994) used pictures instead of words to suboptimally prime phobic responses in fearful individuals. In addition to a control group, the authors divided individuals into groups based on their phobia of either snakes or spiders. Skin conductance responses (SCR), one marker of an autonomic response to phobic stimuli, were significantly greater for individuals who were suboptimally primed with photographs of their specific phobia (spiders or snakes) compared with suboptimally primed photographs of flowers and mushrooms. In addition, the control group recorded no increase in SCR regardless of the stimuli presented. Ohman and Soares also supplemented the physiological data with self-report data that indicated phobic individuals experienced more arousal and more negativity in response to the phobic stimuli compared with the control stimuli and control groups. Based on these results, the authors concluded that suboptimal exposure to fear eliciting images in phobic individuals was able to stimulate an affective response. Ohman and Soares' research is important because it suggests that conscious awareness is not necessary to evoke an affective state. This supports Zajonc's (1980, 1998) argument that emotion is precognitive and thus does not require cognitive appraisal. Other studies have also found consistent and replicable changes in a dependent variable following suboptimal priming of a specific mood (Dimberg et al. 2000; Murphy et al., 1995). These studies add further weight to the argument that the experience of affect involves an element of automatic information processing that operates below conscious awareness, and is possibly precognitive (Murphy & Zajonc, 1993).

In a further demonstration of the effects of suboptimal priming, and of the primacy of affect, Murphy and Zajonc (1993) found that suboptimally primed positive and negative affect influenced subsequent ratings of previously novel Chinese ideographs. In particular, the authors found that when participants were presented with extremely brief (4ms) photographs of smiling and scowling faces, subsequent liking ratings and good/bad judgments of the target ideographs were rated in concordance with the primed affect. However, when the primes were presented optimally, no differences in ratings for the target ideographs were reported. Follow up studies conducted by the authors indicated that non-affective suboptimal priming (such as symmetrical objects) exerted no influence on judgments of an essentially cognitive nature (size, shape and symmetry of ideographs) whereas the same primes presented optimally did exert a significant influence. For example, optimal primes of symmetrical objects resulted in greater symmetry ratings of a target object (R^2=.32). The authors explained this effect in terms of the time at which processing occurs. For optimal priming, processing occurs later along a continuum, at which time the individual can access not only the affective significance of the stimulus, but also feature specific information such as the attractiveness of a face, or the shape of the object. For suboptimal priming of affective information, processing occurs much earlier, and by necessity, much more quickly, as only gross affective information is gathered. These affective reactions occurring below awareness are considered to be diffuse or free-floating, and as such, may 'spill-over' onto unrelated stimuli (such as the target ideographs), whereas affect accompanied by cognitive correlates and appraisals has a clearer origin and is less likely to be displaced or diffused (Murphy & Zajonc, 1993). The results of this study provide further support for the affective primacy hypothesis (Zajonc, 1980, 1998).

Together these findings provide evidence that information, especially of an affective nature, is processed by the brain despite a lack of conscious awareness. As such, suboptimal priming should be an effective mood induction technique, whilst also providing an excellent solution to the problems associated with demand effects.

The evidence reviewed above, suggesting that affective reactions can precede cognition, leads back to the debate between those theorists who believe cognition is a necessary component of emotion (Lazarus, 1991) and those theorists who believe affect and cognition can be conceptualised as separate-systems (LeDoux, 1996; Zajonc, 1980, 1998). According to LeDoux (1995b), the acceptance of one position over another depends on the definition of cognition. If cognition is defined to include sensory information processing (including automatic processes), then clearly emotion and cognition are not independent. However if cognition is defined as a process involving higher mental functions mediated by complex cortical processing (i.e., appraisal processes), then based on the evidence, it should be concluded that emotion does precede cognition (LeDoux). LeDoux argues that the former, broad definition of cognition is problematic, as the involvement of information procession for emotion does not equate emotion with cognition. LeDoux argues that cognitive processing is just one example of information processing (other examples include the immune system, a non-cognitive biological information processing system). This debate, and the research reviewed, is of particular importance to the understanding of trait PACA, the central component of the PACA model of SWB. Core affect is conceptualised by Russell as affect that does not require conscious awareness for its existence. The evidence reviewed provides clear support for the existence of affective processes, such as core affect, operating below the level of conscious awareness.

Advantages of Using a Reaction Time Paradigm

The trait measures of affect that were used in Studies 1 and 2, although important, should not be assumed to be able to capture information processing operations (Robinson et al., 2005). Robinson et al. argue that individuals have little awareness of how they perceive, categorise objects, retrieve information, and make judgments.

Indeed, such mental operations are reliant upon processes that are beyond the introspective access of the individual. As such, self-report should be supplemented by other measures to assess this information processing. An alternative to self-report, and one that has had a long history in psychology, is the use of reaction times to infer mental processing (Smith, 1968). Indeed, a reaction time paradigm is especially suited to the task of assessing the mood congruency hypothesis, which posits that the experience of a particular mood state primes into readiness information that is congruent with how one is feeling (Bower, 1987). Thus, reaction times for targets that are congruent with the particular mood state should be facilitated, and conversely, reaction times for information that is incongruent should be inhibited. Research has repeatedly found this effect (Joorman & Siemer, 2004; Ruiz Caballero & Moreno, 1992; Schwarz & Clore, 1983). Thus individual differences in RTs can be used to infer individual differences in information processing.

Summary

In summary, this study explicitly attempts to falsify the PACA model of SWB using a RT paradigm in conjunction with a self-report paradigm. The research reviewed found evidence of mood congruency effects. Specifically in this research, the priming of particular moods led to information (i.e., memories, Joorman & Siemer, 2004; positive words, Ruiz-Caballero & Moreno, 1992) that is congruent with these moods being recalled or responded to faster than information incongruent with the primed mood. This mood congruency effect was also demonstrated in reports of SWB, with participants who received positive mood priming subsequently rating life satisfaction and happiness significantly higher than individuals who received negative mood priming (Schwarz & Clore, 1983). However this review also found evidence that the mood induction procedures used in testing the mood congruency hypothesis are unreliable as they suffer from potential demand effects. That is, participants are often made aware that the experimenter is attempting to induce a particular mood, and as such, participants could report changes in mood based on this knowledge despite actual mood remaining unchanged. Suboptimal priming as a mood induction procedure was then proposed as an alternative method of priming that effectively solves the problem of demand effects. Research reviewed found suboptimal priming of particular stimuli resulted in participant's responses (and autonomic activity) that were consistent with the valence of the suboptimally presented material (Ohman & Soares, 1994). The research demonstrating the effectiveness of suboptimal priming also suggests that affective processes operate below conscious awareness. It is likely that core affect is one such process. This is in agreement with Russell's conceptualisation of core affect as a primitive and ubiquitous process that exists independently of objects and cognition.

Hypotheses

If the mood congruency theory is correct, following suboptimal priming of a positive mood, participants should record faster RTs for categorising positive versus neutral words. In addition, following the suboptimal priming of negative mood, participants should record faster times for categorising negative versus neutral words.

It is also expected that information congruent with an individual's trait mood (as measured by trait PACA and the PANAS) and SWB will be responded to faster in a reaction time task than incongruent information. Specifically, high levels of trait positive affect and SWB should lead to faster RTs for categorising positive versus neutral words, whilst high trait negative affect and low SWB should lead to faster RTs for negative versus neutral words.

Self-report Hypotheses

In accordance with the results of Studies 1 and 2, it is expected that trait PACA would be the strongest predictor of SWB, and that a SEM specified according to the PACA model of SWB would provide a parsimonious and absolute fit to the data. In addition, it was hypothesised that trait PACA would be a superior predictor of SWB compared with the positive and negative scales of the PANAS, as these scales only reflect the high activation positive and negative affects.

As trait PACA is assumed to be relative stable over time, and as SWB has been noted previously for demonstrating a high degree of stability (Cummins et al., 2005), it was hypothesised that trait PACA would be a better predictor of SWB compared with state PACA. The measurement of state PACA also allows a direct test of the heuristic hypothesis. Specifically, this hypothesis asserts that the strong relation between trait PACA and SWB is due to the use of PACA as a heuristic. According to the heuristic hypothesis, making life satisfaction judgments is an abstract and difficult task (Schwartz & Strack, 1999), increasing the likelihood that heuristics are used by individuals to come up with a response. If this heuristic hypothesis is correct, then state PACA, due to its salience, should be more strongly related to SWB than trait PACA. If trait PACA was found to be a stronger predictor of SWB, then the heuristic hypothesis would be an inadequate explanation of the data. Finally, in accordance with results of Studies 1 and 2, extroversion and stability were not expected to significantly predict additional variance in SWB after controlling for trait PACA.

Section 5.2: METHODOLOGY

Participants

Participants comprised a convenience sample of 60 individuals. Recruitment was conducted through advertisements placed around the Deakin University, Burwood campus, in addition to announcements made prior to undergraduate Psychology lectures and tutorials. Participants ranged in age from 18 to 53 years, with a mean age of 24.5 years (*SD* = 8.9). Of the 60 participants, 68% were females, and 32% were male.

Materials & Apparatus

Reaction times were measured using a Cedrus RB-530 (© Cedrus Corporation, USA) 5-button response pad connected to a desktop computer and a 17 inch LCD monitor. The experiment was set up and conducted using SuperLab Pro (version 2.0.4; © Cedrus Corporation, USA). Each participant completed a set of questionnaires prior to, and following the reaction time task. The questionnaires completed prior to the RT task consisted of the PWI, used as a measure of SWB (Cronbach's alpha = .80), and a measure of trait and state affect.

The measure of trait and state affect incorporated the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) which is a widely used measure of affect (Burger & Caldwell, 2000). However, research has shown that the PANAS only samples activated positive and negative affective states (Cropanzano et al., 2003). Thus, according to the circumplex model of emotion, the PANAS ignores a broad range of deactivated affective states. As such, the PANAS was supplemented with affect items to measure each quadrant of the circumplex model of emotion. These items were chosen on the basis of convergence with items used in Study 1 and Study 2, and previous research on the circumplex model of emotion (Davern, 2004; Yik et al., 1999). This resulted in 40 items to measure trait and state affect. The same items were used to measure trait and state affect, with only the instructions changing. For trait affect, individuals received the following instruction: “This scale consists of a number of words that describe different feelings and emotions. Read each word and then mark the appropriate number in the space next to that word. Indicate to what extent you feel this way in general.” For state affect, the instruction *in general* was replaced by *right now, that is, at this moment.* Responses were made using an 11-point end-defined unipolar scale (0-Not at all, 10-Extremely). Cronbach’s alpha’s for the trait and state affect scale were .83 and .86 respectively. The affect items that supplemented the PANAS were: happy, content, satisfied, and pleased for the pleasant octant of the circumplex; at ease, relaxed, serene, and calm for the pleasant deactivated octant; tired, fatigued, sleepy, and quiet for the deactivated octant; flat, bored, depressed, and gloomy for the unpleasant deactivated octant; and discontent, annoyed, sad, and unhappy for the unpleasant octant (affect items measuring pleasant-activated and unpleasant-activated octants are contained within the PANAS). As in Studies 1 and 2, PACA comprises the summation of the affects happy, content, and active. As these affects were measured using both the state and trait instructions, PACA is henceforth specified as state or trait (i.e., state PACA; trait PACA).

The TIPI was used as a brief measure of extroversion and neuroticism (reverse coded as stability). In the current sample, Cronbach's alpha for the extroversion scale was .81. Cronbach's alpha for the stability scale was .61. The words used in both the lexical decision task and the valence identification task were chosen based on the Affective Norms for English Words (ANEW; Bradley & Lang, 1999) word list. In addition, Siegle (1994) has written a program to be specifically used with the ANEW. The program is called the Balanced Affective Word List Creation (henceforth BAWLC) and generates an arbitrary length word list balanced for affective valence, word length, and word frequency. According to Siegle (1994), words were judged as positive if they had a valence rating of greater than seven; as negative if they had a valence rating of less than three; and as neutral if they had a valence rating of between four and six.

Procedure

Following ethics approval from Deakin University Human Research Ethics Committee (DU-HREC EC326-05) each participant read a Plain Language Statement (PLS) prior to giving their informed consent to participate. Participation was restricted to individual's aged 18 years or over. Information about the method used to induce a positive, negative, or neutral mood was not included in the PLS. This omission was necessary to avoid possible demand effects. That is, if an individual is made aware of the purpose of the study, or is aware that the experimenter is trying to induce a particular mood, then the individual may report an artifactual change in mood in order to please or frustrate the experimenter. Each participant was made aware of the suboptimal mood induction in a debriefing following participation. To ensure that no individual experienced lasting changes in negative mood following the negative mood induction, a debriefing statement was also provided that included the contact details of the Deakin University free counselling service as well as an independent counselling service. In addition, a gift of $10 was provided to the participant as a token of appreciation for their participation. Receipt of a token gift has been found to be effective in alleviating residual negativity (Westermann et al., 1996). Furthermore, the use of suboptimal priming as a mood induction technique is preferable to conscious priming mood induction techniques, as conscious priming, in which the individual is aware of the priming material, produces stronger and longer lasting effects (Bargh & Chartrand, 2000).

Each participant then completed the PWI questionnaire as well as the trait and state affect questionnaires. Following this, participants were randomly assigned to one of three priming conditions. Participants assigned to the first condition received positive priming (henceforth PP), participants assigned to the second condition received negative priming (henceforth NP), and participants assigned to the third condition received no priming (henceforth NoP). This third group served as a control group to compare the effects of positive and negative priming on RTs. For each RT task, participants were instructed to be as fast and as accurate as possible.

Practise Task (Animal vs. Non-animal Task)

The first task participants completed was a categorisation task that was unrelated to the experimental task. This task served two purposes. Firstly, the task provided practise for the participant. Secondly, the task enabled a measure of an individual's baseline speed of responding (baseline RT) to be obtained. This was subsequently used to control for individual differences in RT speed. In the practise task, participants were asked to correctly categorise words as either "animal" or "not animal". Once the participant was seated, a fixation point (+) was presented in the centre of the screen for 150ms. This fixation point signalled the start of the trials, and was followed by the first trial word. Each word was presented in the centre of the computer monitor. Participants were instructed to press the left button to categorise the word as *animal* and the right button to categorise as *not animal.* Each word was terminated by the participant's response. Participants completed two blocks, with five trials per block. Within each trial, 10 animal and 10 non-animal words were presented in a random order. The animal words were: dingo, kangaroo, bear, elephant, koala, possum, bat, wombat, ant, and monkey. As this was an Australian sample, the use of Australian animals was considered appropriate. The non-animal words were: chair, monitor, pencil, magazine, light poster, newspaper, diary, and window.

Lexical Decision Task for Suboptimal Priming

In this task participants were instructed to correctly categorise the presentation of a stimulus as either a word or a non-word. This task was used solely to unobtrusively present the suboptimal primes. Participants in the no-prime condition also completed this task without the presentation of the priming words. Priming words were chosen based on valence ratings given by the ANEW list (Bradley & Lang, 1999). The words were balanced for affective valence, word length, and word frequency using Siegle's (1994) BAWLC program. On the 8-point valence (1=completely unhappy, 9=completely happy) scale used by Bradley and Lang (1999), the positive words were judged more pleasant than the neutral words (M=8.26 and M=5.08 respectively; $t(19)=50.71$, $p<.001$). Similarly, the negative words were judged less pleasant than the neutral words (M=1.74 and M=5.08; $t(19)=-52.58$, $p<.001$). The positive and neutral words did not differ in character length (M=5.53 and M=5.79, $p>.05$) or frequency (M=50.0 and M=84.94, $p>.05$). The negative and neutral words also did not differ in character length (M=6.63 and M=5.79, $p>.05$) or frequency (M=62.19 and M=84.94, $p>.05$).

Priming words were paired with the non-words such that each priming word preceded the non-word. The non-word also served as a backward mask of the prime so that the prime was overwritten by the non-word in the visual iconic memory. The character length of the non-word was equal to or greater than the prime so that backward masking would be effective. Each prime was presented for 17ms. In pilot testing of this task with colleagues, 17ms was found to be the longest time at which the prime could not be consciously detected. Draine and Greenwald (1998) have also found that the physical and semantic properties of a prime presented for 17ms could not be consciously detected. As in the practise task, the presentation of the stimulus was preceded by a fixation point presented in the centre of the screen for 150ms. Non-words were random strings of letters, whilst words were chosen from the ANEW list based on valence ratings between four and six (indicating neutral words). Participants pressed the left button to classify the stimulus as a word, and the right button to classify the stimulus as a non-word. Participants completed two blocks, with three trials per block. Within each trial, 20 words, 20 non-words, and 20 (positive or negative) primes were presented in a random order. The words used for positive priming were: beach, orgasm, miracle, win, joke, comedy, cheer, music, laughter, rainbow, fun, success, hug, passionate, thrill, sweetheart, proud, love, cash, and affection. The words used for negative priming were: funeral, sick, cancer, gloom, drown, suffocate, ulcer, tragedy, misery, mutilate, hurt, morgue, torture, disaster, nightmare, betray, infection, rejected, failure, and slave. The neutral words were: radiator, stiff, office, knot, tool, paper, utensil, door, month, journal, scissors, cork, hydrant, column, icebox, street, jug, headlight, engine, and lawn.

Experimental Task: Valence Identification Task

The final RT task required participants to correctly categorise the valence of words as either positive or neutral (henceforth Positive versus Neutral; PvN), and negative or neutral (henceforth Negative versus Neutral; NvN). This allowed separable estimates of speed for the categorisation of positive or negative words for each participant. The positive, negative, and neutral words were chosen on the basis of valence ratings provided by Bradley and Lang (1999) in addition to Siegle's (1994) BAWLC program. Each word chosen for this task was unique and did not appear in any other part of this experiment. On the 8-point valence (1=completely unhappy, 9=completely happy) scale used by Bradley and Lang (1999), the positive words were judged more pleasant than the neutral words (M=7.52 and M=5.09 respectively; $t(14)=13.95$, $p<.001$). Similarly, the negative words were judged less pleasant than the neutral words (M=2.13 and M=5.16 respectively; $t(14)=-20.78$, $p<.001$). The positive and neutral words did not differ in character length (M=6.33 and M=6.93, $p>.05$) or frequency (M=11.0 and M=10.53, $p>.05$). The negative and neutral words also did not differ in character length (M=6.67 and M=5.67, $p>.05$) or frequency (M=10.07 and M=13.47, $p>.05$).

To avoid any practise effects for the neutral words, two unique groups of neutral words were used for the PvN and NvN task. In addition, the PvN and NvN tasks were counterbalanced to control for any effects associated with the order in which the tasks were completed. As in the animal/non-animal and word/non-word task, the beginning of the trial was preceded by the presentation of a fixation point for 150ms. Participants pressed the left button to classify the word as positive (for PvN) or negative (for NvN), and the right button to classify the word as neutral. Participants completed two blocks, with 10 trials per block. Within each trial 15 positive (negative for NvN) words and 15 neutral words were randomly presented. The positive words used in the PvN task were: bless, cake, caress, gentle, grateful, grin, heal, paradise, politeness, snuggle, soothe, sunrise, sunset, twilight, and warmth. The neutral words used in the PvN task were: curtains, elbow, golfer, indifferent, kettle, mantle, pamphlet, poster, statue, subdued, windmill, basket, bathroom, bench, and corridor. The negative words used in the NvN task were: anguished, burial, criminal, depressed, filth, grief, illness, lice, loneliness, lonely, maggot, massacre, poverty, stench, and tomb. The neutral words used in the NvN task were: banner, barrel, bus, cord, hairpin, ink, bread, taxi, tower, umbrella, vest, violin, cabinet, locker, and patent. Following the valence identification task, participants completed the state affect questionnaire and the PWI for a second time (hereafter called post priming).

Section 5.3: RESULTS

Type 1 Error Rate Adjustment

It is commonly accepted that in tests involving multiple comparisons, the probability of committing a Type 1 error increases as the number of tests in an entire set (family) of tests increases. To correct for this, researchers traditionally control the error rate (α) over the entire set of tests (Keselman, Cribbie, & Holland, 2002). However, when the number of tests is large, this form of familywise error (FWE) control often results in overly stringent α criterion levels. Thus, over multiple comparisons involving large numbers of tests, the power to detect effects can be substantially reduced using FWE procedures. In response to this, Benjamini and Hochberg (1995) developed an alternative procedure to control for Type 1 errors, the False Discovery Rate procedure (FDR). The FDR is defined as a ratio of the expected proportion of the number of false rejections to the total number of rejections. To calculate the FDR, firstly the experimenter decides on an acceptable α level (i.e., .05). Secondly, each test in the set (family) of tests is ordered by the experimenter and assigned a number based on its order (i.e., test 1=1). Following this, the threshold criterion (α) is calculated (see Equation 5.1).

$$FDR = \frac{k \times \alpha}{m} \qquad \text{(Eqn 5.1)}$$

where k=the order of tests (i.e., k=1…j) for j number of tests

α=criterion alpha level (i.e., .05)

m=the total number of tests in the entire set of tests

Each test in which the observed *p* value is less than the FDR threshold value is considered significant. A demonstration of the FDR in a hypothetical data set (six tests conducted at α=.05) illustrates its utility. The *k* values, criterion *α*, FDR adjusted criterion *α*, and observed *p* values for this hypothetical data are provided in Table 5.1.

Table 5.1: False Discovery Rate for six tests at *α*=.05 in a hypothetical data set.

k	**Criterion α**	**FDR adjusted criterion α**	**Observed *p* value**
1	.05	.008	.001
2	.05	.017	.004
3	.05	.025	.020
4	.05	.033	.040
5	.05	.042	.070
6	.05	.050	.080

The data presented in Table 5.1 indicates that only tests 1, 2, and 3 are significant. If the commonly used Bonferroni FWE procedure were applied to the data contained in Table 5.1 (.05/6 =.008), only tests 1 and 2 would be considered significant. The utility of the FDR procedure was explicitly compared to an FWE procedure by Keselman et al. (2002). These authors found that using the FDR procedure resulted in increased power to detect effects in comparison with the FWE procedure. On this basis, the authors strongly recommended the use of the FDR procedure to control for Type 1 errors when multiple comparisons are conducted. Accordingly, the FDR procedure was applied in the current study when multiple comparisons were performed.

Data Preparation

The analysis of results began with a missing values analysis to determine whether data were missing at random. This analysis indicated a maximum percentage of missing data on any one variable to be 1.7%. As Tabachnick and Fiddel (2001) suggest that missing data of less than 5% can be ignored, the data was judged to be suitable for regression replacement, which is a superior method of data replacement than mean substitution and a more objective method than using prior knowledge (Tabachnick & Fidell). Data were then screened for multivariate and univariate outliers. No multivariate outliers were detected as assessed by Mahalanobis distance. Univariate outliers, indicated by z-scores exceeding four, were detected in 7-items (state happiness, depression, guilt, upset, ashamed (time 1 and time 2), hostile, sadness (time 1 and time 2)). However for each item, only one case exceeded a z-score of four. Furthermore, inspection of the data indicated raw scores constituted normal and expected responses. For these reasons, cases were retained.

The assumption of normality was assessed through an examination of raw skewness and kurtosis scores for each variable. This analysis revealed 10 items exceeded a raw skewness score of 2.0 (age skewness=2.01; upset state t1=2.76; guilty, state t1=2.65, state t2=2.03; scared state t1=2.15; hostile, state t1=3.54, state t2=2.51; ashamed, state t1=3.03, state t2=2.45; depressed state t1=2.15; sad state t2=2.14; all *SD*'s=.31). An examination of histograms for each of these items indicated positive skew. Thus, a number of individuals scored at very low levels on these items. This pattern of responses to items assessing negative affect is to be expected in a sample of the general population. In addition, the similar shape of distribution on each item mitigates the potential distorting effect of mild skew (Bradley, 1980). An analysis of raw kurtosis scores indicated four items exceeded a raw score of 7.0 (upset state t1=10.09; hostile state t1=15.15; guilty state t1=7.03; ashamed state t1=11.17; all *SD*'s=.61). An examination of histograms indicated a leptokurtic distribution for each of these items.

Thus responses to these items clustered around very low values. This pattern of responses to items assessing negative affect is not unexpected in a sample of the general population. It was concluded from the analysis of raw skewness and kurtosis scores, and from an inspection of histograms, that the assumption of normality was not strongly violated.

For the computation of the RT means, error trials were excluded in addition to extremely long (over 3.0s) and extremely short (under 0.1s) times. Extremely long times likely reflect a lack of attention and extremely short times likely reflect the anticipation of a particular stimulus. The omission of such responses is also advised by Bargh and Chartrand (2000) on the basis of the large impact outliers can exert on results. In the same vein, Ratcliff (1993) notes that outliers can have a significant impact on the distribution of RTs. Specifically, as RTs are normally positively skewed, extremely long RTs can increase the mean, inflate the standard deviation and increase skewness. Log transformations for RT data have been found by Ratcliff to return a normal distribution. As such each RT was log transformed (log Base 10) to normalize the distribution.

Mean RTs were calculated for each block of the animal/non-animal task, and for each block of the valence identification task (PvN and NvN). The average was then taken across both blocks for each task to provide a stable measure of RT. Residualised PvN and NvN categorisation scores (henceforth ResPvN and ResNvN) were created by subtracting the target block mean RT (PvN or NvN) from the control block (animal/non-animal) mean RT. This was done to control for individual differences in speed of responding. A negative score on this variable would indicate that a person was faster to distinguish between positive and neutral (or negative and neutral) words than would be expected based on his or her animal/non-animal performance; a positive score indicates the opposite. Mean RTs for each experimental task are presented in Table 5.2.

Table 5.2: Mean RTs for PvN, NvN, and animal/non-animal experimental tasks, and residualised mean RTs for PvN and NvN.

RT Task	**Mean RT**	***SD***	**Mean RT in seconds**
PvN	3.779	.445	.6012
NvN	3.765	.452	.5821
Animal/non-animal	3.625	.399	.4217
ResPvN	-.154	.059	.000143
ResNvN	-.146	.066	.000140

The data given in Table 5.2 indicate that participants were slightly faster to categorise negative versus neutral words than positive versus neutral words. This difference was significant, $t(59)=2.36$, $p<.05$, $R^2=.09$. The ResPvN and ResNvN negative mean RTs indicate that participants were slower to correctly categorise the valence of words compared to the correct categorisation of animal and non-animal words. The difference between the mean RT of ResPvN and the mean RT of ResNvN was then tested. This difference was significant, $t(59)=-3.00$, $p<.01$, $R^2=.13$, indicating that participants were significantly faster at categorizing negative versus neutral words compared to positive versus neutral words after controlling for baseline RT.

The Effect of Suboptimal Priming on Reaction Times

It was hypothesised that the suboptimal priming of either a positive or a negative mood would influence RTs to positive and negative words respectively. To test this effect, a one-way between-groups Analysis of Variance was performed. To reiterate, each participant was randomly assigned to one of three priming conditions (positive priming:

PP; negative priming: NP; no priming: NoP). The assumption of homogeneity of variance was violated for both dependent variables (ResPvN and ResNvN), as indicated by a significant value on the Levene's test of equality of group variances (21.94, $p<.001$ and 32.39, $p<.001$ respectively). The Welch statistic is preferable to the F-statistic when the assumption of homogeneity of variance is violated, and as such, was used for these analyses. The Welch statistic for type of priming for ResPvN was not significant, Welch(2,33.82)=2.82, $p>.05$, $R^2=.14$, nor was the Welch statistic for type of priming for ResNvN, Welch(2,34.81)=3.32, $p=.05$. Thus the priming condition received did not significantly alter the speed of categorisation for positive and neutral words or negative and neutral words. The mean RTs for each priming condition are presented graphically in Figure 5.1 for ResPvN and Figure 5.2 for ResNvN.

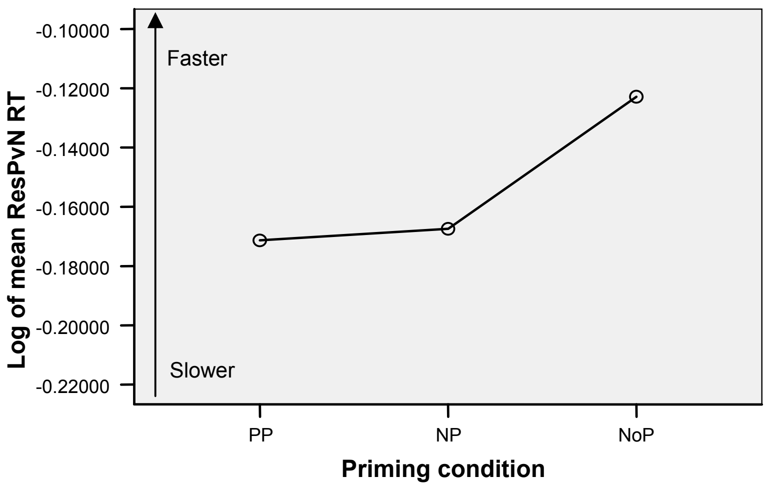


Figure 5.1: Log of mean ResPvN reaction time according to priming condition. The ordinate represents the log of mean ResPvN RT whilst the abscissa represents the priming condition (N=60).

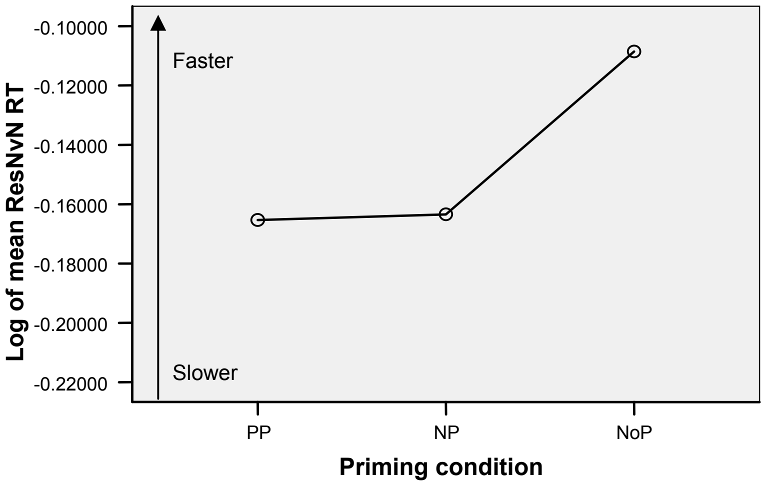


Figure 5.2: Log of mean ResNvN reaction time according to priming condition. The ordinate represents the log of mean ResNvN RT whilst the abscissa represents the priming condition (N=60).

An inspection of Figures 5.1 and 5.2 reveals that in each experimental task (ResPvN and ResNvN), there was trend toward faster RTs for individuals who did not receive priming (NoP). However, as mentioned above, these differences were not significant.

The Effect of Suboptimal Priming on State Affect Post-priming

To investigate whether suboptimal priming influenced state affect post priming (following the RT tasks), three univariate analyses of variance with planned contrasts were conducted to compare state PA (PANAS), state NA (PANAS), and state PACA for the groups that received suboptimal priming, and the group that did not receive suboptimal priming. The results of these analyses are presented in Table 5.3.

Table 5.3: Comparison of state affect post-priming for suboptimal priming and no-priming groups (N=60).

	PP ***M*** **(*n* = 21)**	**NP** ***M*** **(*n* = 19)**	**NoP** ***M*** **(*n* = 20)**	***F***	R^2	***P***
State PA post priming	55.15	52.90	48.75	.73 (*df*=2)	.03	>.05
State NA post priming	8.0	10.63	10.90	.48 (*df*=2)	.02	>.05
State PACA post priming	17.38	16.49	15.35	.81 (*df=2)*	.03	>.05

The results contained in Table 5.3 indicate that scores for state PA, state NA, and state PACA post-priming did not significantly differ between the suboptimal priming groups (PP and NP) and the no priming (NoP) group.

The Effect of Task Order on Reaction Times

To determine if the effect of task order (PvN task first, NvN task first) significantly influenced reaction times, a one-way between-subjects analysis of variance was conducted for both ResPvN and ResNvN. The assumption of homogeneity of variance was not violated, as indicated by non-significant Levene's statistics (ResPvN=2.15, p>.05; ResNvN=.48, p>.05). The analysis indicated no significant differences for the effect of task order on either ResPvN or ResNvN ($F(1,58)$=.94, p>.05, R^2=.02, and $F(1,58)$=.30, p>.05, R^2=.01, respectively). Thus, the effect of completing the PvN task first, or the NvN task first did not significantly alter participants subsequent RTs.

Correlations between Measured Variables for State Affect and Trait Affect

The relationships between the variables measured (age, gender, state affect, trait affect, personality, SWB, ResPvN, and ResNvN), in the form of bivariate correlations, are presented in Table 5.4 for trait affect, and Table 5.5 for state affect, in addition to means and standard deviations.

Table 5.4: Correlations between age, gender, trait affect, LS, PWI, ResPvN, and ResNvN (N=60).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.
1. Gender																														
2. Age	.22																													
3. PWI	.02	.15																												
4. Life Sat.	.05	.19	.70																											
5. ResPvN	.31	.16	-.16	-.15																										
6. ResNvN	.34	.21	-.24	-.18	.95																									
7. PA PANAS	.19	.21	.54	.44	-.27	-.30																								
8. NA PANAS	.09	-.24	-.33	-.26	.01	.08	-.22																							
9. Happy	.13	.11	.73	.62	-.12	-.20	.66	-.38																						
10. Content	.02	.20	.66	.67	-.22	-.27	.44	-.25	.67																					
11. Satisfied	.05	.09	.63	.59	-.37	-.40	.61	-.29	.75	.71																				
12. Pleased	.14	.19	.51	.36	-.24	-.28	.61	-.27	.53	.45	.53																			
13. Unhappy	.12	-.11	-.49	-.40	.12	.23	-.32	.79	-.57	-.41	-.44	-.35																		
14. Depressed	.01	-.17	-.53	-.44	.09	.19	-.26	.70	-.54	-.42	-.44	-.32	.76																	
15. Sad	.06	-.14	-.39	-.30	.02	.14	-.28	.78	-.54	-.40	-.44	-.29	.89	.73																
16. Gloomy	.10	-.05	-.36	-.30	.13	.25	-.26	.68	-.46	-.39	-.42	-.33	.72	.68	.82															
17. Discontent	-.04	-.11	-.47	-.48	-.02	.06	-.26	.59	-.56	-.49	-.44	-.24	.70	.60	.71	.65														
18. Annoyed	-.03	-.15	-.20	-.23	-.11	-.02	-.35	.57	-.34	-.27	-.31	-.22	.53	.50	.63	.56	.47													
19. Bored	-.12	-.23	-.26	-.17	-.02	.02	-.34	.59	-.25	-.17	-.26	-.30	.54	.40	.58	.52	.51	.65												
20. Tired	-.07	-.24	.02	.05	-.10	-.02	-.22	.37	-.12	.01	-.06	-.22	.22	.12	.40	.30	.22	.37	.33											
21. Sleepy	-.01	-.23	-.02	.01	-.08	.00	-.27	.46	-.15	-.02	-.09	-.26	.31	.19	.47	.38	.24	.44	.38	.90										
22. Flat	.04	-.16	-.44	-.26	.17	.29	-.49	.56	-.53	-.34	-.44	-.51	.63	.56	.67	.60	.66	.47	.51	.53	.59									
23. Fatigued	-.05	-.12	.04	.08	-.10	-.02	.10	.40	-.16	-.06	-.10	-.14	.31	.24	.49	.40	.28	.39	.27	.80	.78	.53								
24. At ease	.17	.17	.48	.39	-.02	-.09	.47	-.42	.57	.54	.46	.54	-.49	-.35	-.54	-.33	-.48	-.32	-.47	-.36	-.32	-.54	-.25							
25. Quiet	.10	.03	-.02	-.17	.33	.31	-.16	.22	-.07	-.01	-.06	.04	.26	.20	.16	.19	-.13	.11	.04	.04	.08	.11	-.06	.09						
26. Serene	.17	.18	.24	.17	.06	.07	.25	-.11	.26	.37	.30	.18	-.17	-.07	-.12	.01	-.04	-.16	-.08	.13	.15	.05	.07	.23	.31					
27. Calm	.38	.07	.23	.04	.16	.12	.33	-.23	.31	.22	.24	.41	-.19	-.11	-.21	-.06	-.22	-.30	-.29	-.25	-.25	-.28	-.22	.45	.20	.48				
28. Relaxed	.32	.11	.37	.20	.03	-.02	.46	-.33	.50	.29	.38	.55	-.29	-.28	-.33	-.23	-.30	-.29	-.17	-.44	-.45	-.42	-.41	.47	.12	.34	.75			
29.Extroversion	-.08	.23	.25	.16	-.26	-.36	.31	-.24	.37	.08	.21	.17	-.34	-.22	-.27	-.35	-.27	-.18	-.10	-.06	-.09	-.35	.01	.25	-.56	-.25	.04	.11		
30. Stability	.34	.22	.51	.50	.08	.06	.37	-.45	.47	.35	.36	.49	-.46	-.44	-.42	-.37	-.36	-.26	-.30	-.13	-.15	-.26	-.14	.43	-.02	.38	.42	.51	.07	
M	-	24.49	75.17	76.08	-.154	-.146	69.19	24.40	7.77	7.38	7.05	6.75	2.08	1.72	1.92	1.95	1.98	2.70	3.28	4.70	4.13	2.88	3.58	6.90	4.98	5.30	6.35	6.35	12.32	13.68
SD	-	8.92	10.68	11.65	.0592	.0658	11.35	13.83	1.25	1.51	1.38	1.19	1.64	1.72	1.57	1.83	1.69	1.88	2.20	2.12	2.16	1.94	2.13	1.66	1.94	1.99	1.74	1.94	4.34	3.19

Note: Correlations of .26 to .29 are significant at p <.05; Correlations of .30 to .43 are significant at p <.01; Correlations of .44 and above are significant at p<.001.

The correlations between the measured variables presented in Table 5.4 indicate a number of notable relationships. Firstly, as expected, trait happiness, contentment, and satisfaction are strongly related to PWI (*mean* r=.67) and LS (*mean* r=.63). However, somewhat unexpectedly, ResPvN and ResNvN were very highly correlated (r=.95), whilst trait happiness, contentment, satisfaction, and pleasure were negatively related with ResPvN (*mean* r=-.24) and ResNvN (*mean* r=-.29). Thus, regardless of the valence of words used in the different RT tasks, high scores on these positive trait affects were associated with slower RTs. This means that a person with a more positive, measured trait affect was more likely to have a slower RT. In addition, PWI and LS were weakly but negatively related to ResPvN (*mean* r=-.16) and ResNvN (*mean* r=-.21), indicating a trend towards inhibited RTs for individuals with high levels of SWB. Consistent with this result, extroversion (but not stability) was negatively related with ResPvN (r=-.26) and ResNvN (r=-.36). Thus, an individual who had high levels of measured trait positive affect, LS, SWB, or extroversion exhibited slower RTs. The correlations between age, gender, personality, SWB, ResPvN, and ResNvN for state affect are presented in Table 5.5.

Table 5.5: Correlations between age, gender, state affect, LS, PWI, ResPvN, and ResNvN (N=60).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.
1. Gender																														
2. Age	.22																													
3. PWI	.02	.15																												
4. Life Sat.	.05	.19	.70																											
5. ResPvN	.31	.16	-.16	-.15																										
6. ResNvN	.34	.21	-.24	-.18	.95																									
7. PA PANAS	.02	.09	.24	.13	-.18	-.22																								
8. NA PANAS	-.06	-.28	-.08	-.08	-.12	-.08	.05																							
9. Happy	-.16	-.14	.22	.19	-.20	-.22	.48	-.06																						
10. Content	.07	.28	.39	.34	-.33	-.32	.39	-.24	.40																					
11. Satisfied	.05	.01	.17	.17	-.32	-.30	.56	.04	.38	.51																				
12. Pleased	-.08	.09	.18	.05	-.32	-.30	.72	.15	.43	.41	.77																			
13. Unhappy	.01	-.04	-.22	-.29	.13	.17	-.07	.71	-.04	-.11	-.04	.08																		
14. Depressed	-.14	-.02	-.24	-.38	-.02	.01	.10	.49	.06	.01	.03	.22	.71																	
15. Sad	.02	-.17	-.07	-.05	.07	.08	.08	.75	-.10	-.18	.07	.13	.63	.51																
16. Gloomy	.09	-.05	-.08	-.08	.12	.14	-.01	.60	-.12	-.20	-.02	.10	.62	.45	.77															
17. Discontent	-.03	-.07	-.27	-.24	-.02	.12	.00	.64	-.03	-.29	.01	.10	.67	.53	.65	.76														
18. Annoyed	-.09	.02	-.12	-.22	.03	.01	-.01	.67	-.08	-.21	-.11	.13	.78	.64	.51	.53	.55													
19. Bored	-.12	-.07	-.26	-.03	-.20	.05	-.20	.50	.03	-.13	-.05	-.05	.47	.21	.29	.28	.34	.39												
20. Tired	-.08	-.07	.13	.35	-.22	-.15	-.06	.19	.19	.01	.14	.05	.10	-.15	.14	.14	.19	.05	.18											
21. Sleepy	-.12	-.22	.06	.20	.06	-.19	.04	.30	.11	-.05	.19	.06	.14	-.09	.20	.12	.24	.10	.10	.80										
22. Flat	.02	-.20	-.16	-.06	-.16	.11	-.15	.48	-.06	-.17	.03	-.04	.50	.32	.44	.57	.66	.34	.46	.36	.41									
23. Fatigued	.02	.11	.15	.35	-.10	-.11	.11	.20	.26	.07	.13	.14	.11	-.11	.22	.32	.33	.08	.21	.77	.65	.39								
24. At ease	.21	.15	.25	.37	-.03	-.03	.16	-.11	.30	.34	.07	.05	-.02	-.01	-.05	.03	-.22	-.04	.06	-.09	-.15	-.04	-.04							
25. Quiet	.10	-.01	.24	.23	.10	.04	-.07	.05	.03	.14	.01	.05	-.06	-.12	-.06	-.04	-.18	-.22	.18	-.02	.06	.19	.02	.25						
26. Serene	.07	.08	.21	.21	-.07	.08	.39	-.02	.09	.36	.48	.46	-.04	-.06	.05	.07	-.15	-.06	.00	.00	-.09	.01	.03	.10	.21					
27. Calm	.03	.02	.14	.07	-.08	-.15	.27	-.30	.33	.50	.19	.17	-.14	-.04	-.26	-.14	-.31	-.29	-.05	-.03	-.12	-.04	.04	.42	.48	.41				
28. Relaxed	.14	.03	.17	.20	-.14	-.18	.28	-.30	.29	.44	.22	.16	-.20	-.07	-.27	-.23	-.36	-.23	-.12	-.26	-.28	-.28	-.15	.52	.27	.32	.68			
29.Extroversion	-.08	-.23	.25	.16	-.26	-.36	.25	-.06	.32	-.06	-.06	-.04	-.12	-.07	-.04	-.10	-.13	-.01	.01	.19	.20	-.07	.15	.19	-.19	-.17	.08	.11		
30. Stability	.34	.22	.51	.50	.08	.06	.24	-.31	.13	.37	.25	.24	-.32	-.39	-.30	-.18	-.42	-.25	-.07	-.14	-.13	-.17	-.03	.41	.26	.34	.13	.25	.07	
M	-	24.49	75.17	76.08	-.154	-.146	61.42	9.28	7.22	7.12	6.62	5.78	.88	.63	.65	.63	1.28	.73	1.80	4.14	3.27	2.40	3.45	6.98	5.92	5.35	6.72	6.85	12.32	13.68
SD	-	8.92	10.68	11.65	.0592	.0658	15.13	9.13	1.66	1.39	1.75	2.22	1.26	1.07	1.13	1.13	1.45	1.13	1.93	2.40	2.20	2.07	2.40	1.80	2.29	2.13	1.86	1.97	4.34	3.19

Note: Correlations of .26 to .29 are significant at p <.05; Correlations of .30 to .43 are significant at p <.01; Correlations of .44 and above are significant at p <.001.

The data presented in Table 5.5 indicate that means for each affective state are much lower than the means for each affective trait (i.e., NA PANAS trait *M*=24.40; NA PANAS state *M*=9.28). The pattern of correlations between state affect, ResPvN, and ResPvN is similar to that observed for trait affect. In particular, the positive affective states of happiness, contentment, satisfaction, and pleasure were all negatively related with ResPvN (*mean r*=-.29) and ResNvN (*mean r*=-.29). Thus, consistent with results for trait positive affect, regardless of the valence of words used in each RT task, state positive affect was associated with slower RTs. However, in contrast with the results for trait affect, state happiness, contentment, and satisfaction were only weakly related to PWI (*mean r*=.26) and LS (*mean r*=.23).

The Association between <u>State Affect</u> and Reaction Times to Positive (ResPvN) and Negative (ResNvN) Words

As no differential effect of positive and negative suboptimal priming was found, testing of the mood congruency hypotheses proceeded by examining the pattern of bivariate correlations between state affect and RTs. It was hypothesised that under conditions of mood congruency (individuals high on positive affect and responding to positive word targets (PvN); and individuals high on negative affect and responding to negative word targets (NvN)), RTs and affect would be positively correlated (*faster* RTs). Conversely, under conditions of mood incongruency (individuals high on positive affect and responding to negative word targets (NvN); and individuals high on negative affect and responding to positive word targets (PvN)), RTs and affect would be negatively correlated (*slower* RTs). The correlations for state affect are presented previously in Table 5.5.

The pattern of correlations between state affect and ResPvN, and state affect and ResNvN, were very similar. The strongest correlations for ResPvN and ResNvN (respectively) were for the state affect adjectives of content (r=-.33, p<.01; r=-.32, p<.01), pleased (r=-.32, p<.01; r=-.30, p<.01), and satisfied (r=-.32, p<.01; r=-.30, p<.01). The negative correlations indicate that as state contentment, pleasantness, and satisfaction increased, RTs became slower for ResPvN *and* ResNvN. This means that individuals high on these state affects were slower to categorise words, regardless of word valence. To determine how much variance these positive affective states accounted for in ResPvN and ResNvN, the state affect adjectives of content, satisfied, and pleased were entered into two standard multiple regressions. The results of the standard multiple regression predicting ResPvN and ResNvN are presented in Table 5.6 and Table 5.7 respectively.

Table 5.6: Standard multiple regression of state affect on ResPvN (N=60).

Variable	***B***	***SE B***	***β***	***sr^2***
1. Content	-.010	.006	-.22	.04
2. Satisfied	-.003	.007	-.08	.00
3. Pleased	-.004	.005	-.16	.01
* p <.05; ** p <.01; *** p <.001				R^2 = .15*
				Adjusted R^2 = .11

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The results given in Table 5.6 indicate that state contentment, satisfaction, and pleasure do not significantly predict ResPvN (as indicated by non-significant beta weights). Together, state contentment, satisfaction, and pleasure only predict 15% variance in ResPvN. Although non-significant, the negative beta-weights indicate that increases in these state affects resulted in slightly slower RTs for categorizing positive versus neutral words. These three state affects were then entered into a standard multiple regression predicting ResNvN. The results for this analysis are presented in Table 5.7.

Table 5.7: Standard multiple regression of state affect on ResNvN (N=60).

Variable	B	$SE\ B$	β	sr^2
1. Content	-.010	.007	-.22	.04
2. Satisfied	-.002	.008	-.06	.00
3. Pleased	-.005	.006	-.16	.01
* p <.05; ** p <.01; *** p <.001				R^2 = .14*
				Adjusted R^2 = .09

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The data presented in Table 5.7 indicates that, as with ResPvN, the state affects of content, satisfied, and pleased did not significantly predict ResNvN. Together, these three state affects predicted only 14% of the variance in ResPvN. Although non-significant, the negative beta-weights indicate that increases in these variables resulted in slightly slower RTs for categorizing negative and neutral words.

Summary of Results for State Affect and Reaction Times to positive (ResPvN) and Negative (ResNvN) words

Testing revealed that regardless of word valence (positive or negative word targets), individuals with high state positive affect (contentment, satisfaction, and pleasure) recorded slower RTs. Thus the mood congruency effect was not detected in state affect.

The Association between Trait Affect and Reaction Times to Positive (ResPvN) and Negative (ResNvN) Words

It was hypothesised that RTs in the mood congruency conditions would be facilitated whilst RTs in the mood incongruency conditions would be inhibited. To test these hypotheses, the first step was to identify the significant correlations between trait affect and ResPvN and ResNvN, and extroversion and stability and ResPvN and ResNvN.

These correlations are given previously in Table 5.4. The analysis was conducted separately for ResPvN and ResNvN.

Trait Affect and Reaction Times to <u>*Positive Words*</u> *(ResPvN)*

It was hypothesised that positive affect would be positively correlated (faster RTs) with RTs to positive words, and negative affect would be negatively correlated (slower RTs) with RTs to positive words. The four strongest correlations observed between ResPvN and the trait affects were for satisfied (r=-.37, p<.01), quiet (r=.33, p<.01), PA (as measured by PANAS; r=-.27, p<.05), and extroversion (r=-.26, p<.05). The moderate negative correlations between ResPvN, satisfied, PA, and extroversion indicate that as these variables increased, the speed of categorization for positive versus neutral words *decreased*. Conversely, the positive correlation between quiet and ResPvN indicates that increases in this variable results in *faster* speed of categorizing positive versus neutral words.

As trait PA, measured using the PANAS, was found to significantly correlate with ResPvN, a hierarchical regression was conducted to determine the contribution of each PA PANAS item to the prediction of ResPvN. In addition, the variables that had a significant correlation with ResPvN (satisfied, quiet, and extroversion) were entered at step 2 to determine their relative predictive power in comparison with each other, and with the PA PANAS items. This regression is presented in Table 5.8.

Table 5.8: Hierarchical regression predicting ResPvN by 10 trait PA PANAS items and satisfied, quiet, and extroversion (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.24 n.s
1. Interested	.00	.01	.03	.00	
2. Excited	-.01*	.01	-.39	.07	
3. Strong	.00	.01	.01	.00	
4. Enthusiastic	-.01	.01	-.18	.01	
5. Proud	.01	.01	.15	.01	
6. Alert	.01	.01	.34	.04	
7. Inspired	.00	.01	-.02	.00	
8. Determined	-.01	.01	-.14	.01	
9. Attentive	-.01	.01	-.29	.03	
10. Active	.01	.01	.23	.03	
total unique variance = .20					
total shared variance = .04					
Step 2					.12*
1. Interested	-.00	.01	-.05	.00	
2. Excited	-.00	.01	-.11	.00	
3. Strong	.00	.01	.04	.00	
4. Enthusiastic	-.01	.01	-.19	.01	
5. Proud	.01	.01	.26	.04	
6. Alert	.02*	.01	.45	.07	
7. Inspired	.00	.01	.04	.00	
8. Determined	-.00	.01	-.08	.00	
9. Attentive	-.02*	.01	-.40	.06	
10. Active	.01	.01	.20	.02	
11. Satisfied	-.02***	.01	-.45	.10	
12. Quiet	.01	.01	.23	.02	
13. Extroversion	.00	.00	.01	.00	
additional unique variance =.12					
additional shared variance =.00					
* p <.05; ** p <.01; *** p <.001					R^2 = .37
n.s. = not significant					Adjusted R^2 = .19

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The hierarchical regression presented in Table 5.8 indicates that of the 10 trait PA PANAS items, only *excited* was a significant predictor of ResPvN. The beta-weight of -.39 indicates individuals high on trait excitement were slower to categorise positive versus neutral words. Following the addition of the trait affects of satisfied, quiet, and extroversion at step 2, excited no longer significantly predicted ResPvN, however, alert and attentive (both non-significant at step 1) became significant. Of the variables added at step 2, only satisfied significantly predicted ResPvN. The negative beta-weights for attentive and satisfied indicate that increases in these trait affects resulted in *slower* speed of categorisation for positive versus neutral words. Conversely, the positive beta weight for alert indicates that increases in trait alertness resulted in *faster* speed of categorisation for positive versus neutral words. Interestingly, extroversion is no longer significantly related with ResPvN.

The results of the hierarchical regression presented in Table 5.8, in which the variables alert and attentive shifted from non-significant at step 1 to significant at step 2 may be explained by negative suppression. That is, the variables added in step 2 may have enhanced the importance of *alert* and *attentive* in predicting ResPvN by virtue of suppression of irrelevant variance in these two trait affects. In addition, the shift from significance at step 1 to non-significant at step 2 for the variable *excited* can be explained by an increase in shared variance due to the addition of the variables satisfied, quiet, and extroversion at step 2.

To obtain a better estimate of the variance accounted for in ResPvN by the affects excited, satisfied, alert, and attentive, all four variables were entered into a standard multiple regression predicting ResPvN. This analysis is presented in Table 5.9.

Table 5.9: Standard multiple regression predicting ResPvN by excited, satisfied, alert, and attentive (*N*=60).

Variable	*B*	*SE B*	*β*	*sr*^{2}
1. Excited	-.01	.01	-.25	.04
2. Satisfied	-.01	.01	-.29	.05
3. Alert	.01*	.01	.33	.06
4. Attentive	-.01	.01	-.19	.02
* *p* =.05				R^2 = .23
				Adjusted R^2 = .17

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The data presented in Table 5.9 indicate that only *alert* significantly predicted ResPvN. The beta-weight of .33 indicates that increases in alertness resulted in faster classification of positive versus neutral words. The adjective satisfied, although contributing 5% unique variance to the prediction of ResPvN, failed to attain significance (p=.06). This result may be explained by suppression. That is, some or all of the variables in the hierarchical regression given in Table 5.7 that were not included in the standard regression in Table 5.9 were suppressor variables, enhancing the relation between satisfied and ResPvN.

Summary of Results for Trait Affect and Reaction Times to positive words (ResPvN)

In summary, increased trait alertness was associated with *faster* RTs to positive word targets, whereas increased trait satisfaction, extroversion, or PA (as measured by the PANAS) was associated with *slower* RTs to positive word targets. Thus, with the exception of trait alertness, individuals high on trait PA (satisfaction, extroversion, attentive) recorded slower RTs to positive word targets. This suggests a lack of mood congruency effect in trait affect for positive word targets.

Trait affect and Reaction Times to <u>Negative Words</u> (ResNvN)

It was hypothesised that negative affect would be positively correlated (faster RTs) with RTs to negative words (ResNvN), and positive affect would be negatively correlated (slower RTs) with RTs to negative words. The procedure used to test these hypotheses is identical to the procedures used in the previous section for ResPvN. Specifically, in the first step significant correlations were identified between ResNvN and affect and personality variables. This revealed a very similar pattern of results to ResPvN. The four strongest correlations observed for ResNvN were satisfied (r=-.40, p<.01), extroversion (*r*=-.36, *p*<.01), quiet (*r*=.31, *p*<.01), and trait PA (measured using PANAS; *r*=-.30, *p*<.05). The moderate negative correlations between ResNvN, satisfaction, extroversion, and trait PA indicate that as trait satisfaction, trait PA, and extroversion increased, the speed of categorization for negative versus neutral words *decreased*. However the positive correlation between quiet and ResNvN indicates that increases in trait quietness resulted in *faster* speed for categorizing negative versus neutral words.

The next strongest correlations for ResNvN were for flat (*r*=.29, *p*<.05), pleased (*r*=-.28, *p*<.05), and content (*r*=-.27, *p*<.01). The negative correlations between ResNvN, pleased, and content indicate *slower* RTs as scores on these variables increased. Conversely, the positive correlations between ResNvN and trait flatness indicate faster RTs for increased scores on this variable. Of interest, the correlations between ResNvN, gloomy (*r*=.25, *p*=.06), and unhappy (*r*=.23, *p*=.07), although non-significant, indicated a trend towards *faster* speed of categorisation of negative versus neutral words for increases in these negative affective traits.

As trait PA (measured using the PANAS), was found to significantly correlate with ResNvN, a hierarchical regression was conducted to determine the contribution of each PA PANAS item to the prediction of ResNvN. The variables that had a significant correlation with ResNvN (satisfied, extroversion, quiet, flat, pleased, and content) were entered at step 2 to determine their relative predictive power in comparison with each other, and with the PA PANAS items. This regression is presented in Table 5.10.

Table 5.10: Hierarchical regression predicting ResNvN by 10 trait PA PANAS items and satisfied, extroversion, quite, flat, pleased, and content (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.26 n.s.
1. Interested	-.00	.01	-.07	.00	
2. Excited	-.02*	.01	-.47	.09	
3. Strong	.00	.01	.05	.00	
4. Enthusiastic	.00	.01	-.09	.00	
5. Proud	.01	.01	.16	.02	
6. Alert	.01	.01	.22	.02	
7. Inspired	.00	.01	.06	.00	
8. Determined	-.01	.01	-.21	.02	
9. Attentive	-.01	.01	-.24	.02	
10. Active	.01	.01	.23	.03	
total unique variance = .20					
total shared variance = .06					
Step 2					.15 n.s.
1. Interested	-.01	.01	-.09	.00	
2. Excited	-.01	.01	-.20	.01	
3. Strong	.00	.01	.11	.00	
4. Enthusiastic	.00	.01	.03	.00	
5. Proud	.01	.01	.27	.04	
6. Alert	.01	.01	.33	.03	
7. Inspired	.00	.01	.01	.00	
8. Determined	-.01	.01	-.14	.01	
9. Attentive	-.02	.01	-.32	.04	
10. Active	.01	.01	.20	.02	
11. Satisfied	-.02*	.01	-.46	.07	
12. Extroversion	.00	.00	-.12	.01	
13. Quiet	.01	.01	.16	.01	
15. Flat	.00	.01	.11	.01	
16. Pleased	-.01	.01	-.11	.00	
17. Content	.01	.01	.12	.01	
additional unique variance =.11					
additional shared variance =.04					
* *p* <.05; ** *p* <.01; *** *p* <.001					R^2 = .41
n.s. = not significant					Adjusted R^2 = .19

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The hierarchical regression presented in Table 5.10 indicates that of the 10 trait PA PANAS items, only *excited* significantly predicted ResNvN. The beta weight of -.47 indicates that as trait excitement increased, the speed of categorizing negative versus neutral words decreased. Once the remaining six variables with significant correlations to ResNvN were entered at step 2, excited no longer significantly predicted ResNvN. At step 2, only *satisfied* was a significant predictor of ResNvN. The beta weight of -.46 for satisfied indicates that increased trait satisfaction was associated with slower RTs for the categorisation of negative versus neutral words.

The shift from significance at step 1 to non-significance at step 2 for the variable excited was a consequence of entering the additional variables at step 2, which consumed shared variance. To more precisely determine the predictive ability of excited and satisfied for ResNvN, another regression was conducted with excited and satisfied entered as the sole predictors of ResNvN. This regression is presented in Table 5.11.

Table 5.11: Standard multiple regression predicting ResNvN with excited and satisfied (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2
1. Excited	-.01	.01	-.26	.05
2. Satisfied	-.01	.01	-.25	.04
* *p* =.05				R^2 = .21
				Adjusted R^2 = .18

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

The results displayed in Table 5.11 indicate that once the shared variance due to the addition of extroversion, quiet, flat, pleased, and content (see Table 5.9) was removed, excited and satisfied no longer significantly predicted ResNvN. Together, these two variables predicted 21% of the total variance in ResNvN, and 5% (excited) and 4% (satisfied) of unique variance in ResNvN.

Summary of Results for Trait Affect and Reaction Times to Negative words (ResNvN)

Testing of the mood congruency hypothesis for ResNvN, as with ResPvN, indicated conflicting results. Whilst there was a trend towards a mood congruency effect in which trait negative affectivity (unhappiness, gloomy) facilitated faster RTs to negative word targets, this trend was not significant. In addition, the strongest correlations between trait affect and ResNvN occurred for the positive affective traits of satisfaction, extroversion, and trait PA (measured using the PANAS). Thus, individuals with high scores on these positive affective traits recorded slower RTs to negative word targets.

Overall Summary of Results Testing Association between State and Trait Affect and Reaction Times to Positive (ResPvN) and Negative (ResNvN) words

A summary of the results testing the association between state and trait affect and RTs to positive (ResPvN) and negative (ResNvN) words is given in Table 5.12.

Table 5.12: Summary of results testing the association between state and trait affect and RTs.

	ResPvN			***ResNvN***		
Predictor	**Pearson *r***	***P***	**High scores = faster or slower RT**	**Pearson *r***	***P***	**High scores = faster or slower RT**
State affect						
Satisfied	-.32	<.01	Slower	-.30	<.01	Slower
Content	-.33	<.01	Slower	-.32	<.01	Slower
Pleased	-.32	<.01	Slower	-.30	<.01	Slower
Trait affect						
Satisfied	-.37	<.01	Slower	-.40	<.01	Slower
Trait PA	-.27	<.05	Slower	-.30	<.05	Slower
Extroversion	-.26	<.05	Slower	-.36	<.01	Slower
Alert	.03	>.05	Neither	-.06	>.05	Neither
Attentive	-.12	>.05	Neither	-.15	>.05	Neither
Excited	-.37	<.01	Slower	-.41	<.01	Slower
Flat	.17	>.05	Neither	.29	<.05	Faster
Quiet	.33	=.01	Faster	.31	<.05	Faster
Pleased	-.24	=.07	Slower	-.28	<.05	Slower
Content	-.22	=.10	Slower	-.27	<.05	Slower

Note: negative signs indicate slower RTs; positive signs indicate faster RTs.

An examination of the results given in Table 5.12 reveals that high scores on state *or* trait positive affect (satisfied, content, pleased, trait PA, excited) or extroversion, are associated with slower RTs for *both* positive (ResPvN) and negative (ResNvN) word targets. This means that individuals scoring relatively high on state or trait positivity, or extroversion, were slower to correctly categorise words regardless of word valence. Thus, no mood congruency effects were detected in state or trait affect.

The Effect of Subjective Wellbeing on Reaction Times

It was hypothesised that high SWB would be associated with faster RTs to positive words (ResPvN) and slower RTs to negative words (ResNvN). The opposite was hypothesised for low SWB. To test these hypotheses the same procedure was used as for testing of state and trait affect and RTs. The bivariate correlations between PWI and LS, and ResPvN and ResNvN were investigated. This analysis yielded correlations ranging between -.15 to -.24. All of these correlations were non-significant. The negative correlations indicate that high scores on either LS or PWI inhibited RTs for *both* positive and negative words. The largest correlation found was between the PWI and ResNvN (r=-.24, p>.05). As scores on the PWI increased, participants were slower to categorise negative versus neutral words.

To investigate the relationship between SWB and RTs in more detail, the effects of high and low SWB on the experimental task (ResPvN and ResNvN) and the baseline RT task (animals vs. non-animals) were analysed using t-tests. As there are a number of t-tests for each group and RT task, the criterion α level was adjusted using the FDR procedure outlined in the beginning of section 5.3. High SWB scores were classified as scores of one standard deviation above the mean, whilst low scores were classified as scores of one standard deviation below the mean. These results are presented in Table 5.13.

Table 5.13: Mean RT for all experimental tasks for high and low SWB groups using *t*-tests.

	Animal v Non-animal				ResPvN				ResNvN			
Group	***M***	***SE***	**Diff.**	***P* (adjusted α)**	***M***	***SE***	**Diff.**	***P* (adjusted α)**	***M***	***SE***	**Diff.**	***P* (adjusted α)**
PWI High (n = 7)	3.80	.13			-.170	.02			-.160	.02		
PWI Low (n = 9)	3.47	.15	.327	.12 (.01)	-.138	.02	-.032	.20 (.02)	-.112	.02	-.048	.15 (.03)
LS High (n =12)	3.63	.13			-.167	.02			-.152	.02		
LS Low (n = 8)	3.45	.16	.175	.40 (.03)	-.124	.02	-.043	.16 (.04)	-.104	.02	-.048	.13 (.05)

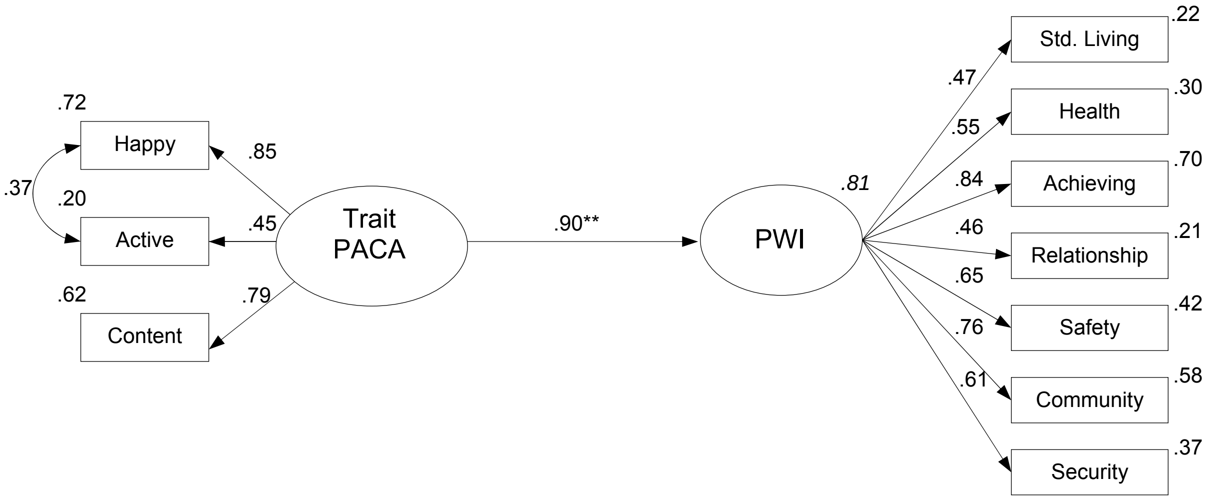
Note: For Animal v non-animal task, higher values represent slower RTs; for ResPvN and ResNvN tasks, larger negative values represent slower RTs.

The results given in Table 5.13, although non-significant, indicate that high scores on either the PWI or LS generally inhibit speed on the RT tasks. It is interesting to note that this effect was found not only for the experimental tasks, but also for the baseline measure of RT speed (animal vs. non-animal). This inhibition effect on RTs for individuals high on SWB is consistent with results obtained for state and trait affect. Overall, contrary to the hypotheses, the mood congruency effect was not detected in reports of subjective wellbeing.

The Relative Predictive Power of Trait PACA for Subjective Wellbeing Using Self-reports

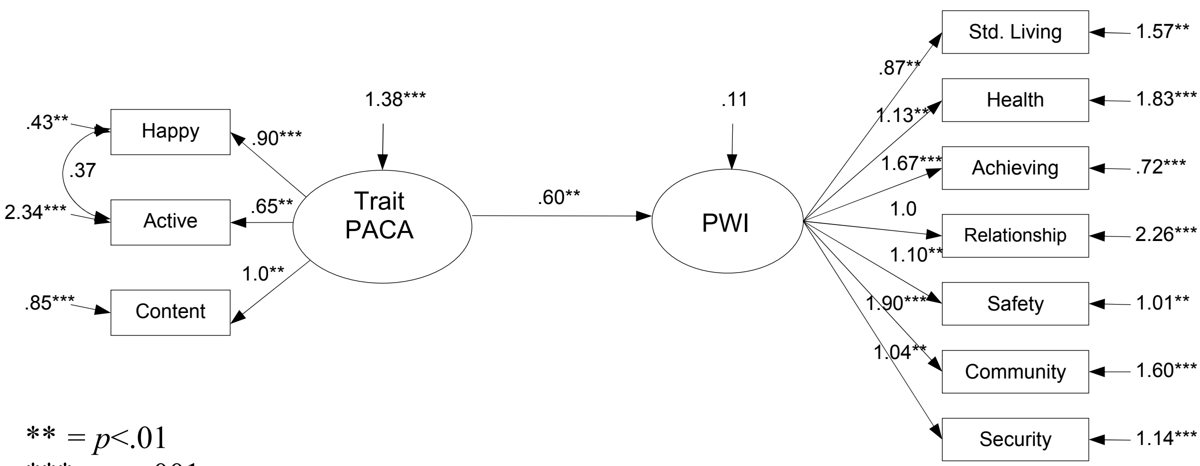
As self-reports of SWB, personality, and trait and state affect were collected in the current study, testing proceeded to determine, firstly, the utility of the trait PACA model in this sample; secondly, the relative predictive power of trait PACA, in comparison with PANAS trait PA, to PWI and LS; thirdly, the relative predictive power of trait PACA, compared with state PACA, state PA and state NA as measured by the PANAS, to PWI and LS; and lastly, the relative predictive power of trait PACA, in comparison with extroversion and stability, to PWI and LS.

As in Studies 1 and 2, the utility of the trait PACA model was tested using structural equation modelling. The model tested is identical to the models tested in Studies 1 and 2. The trait PACA model is presented in Figure 5.3 along with standardised regression paths, SMC (in italics), and correlations. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 5.4.



** = $p<.01$

Figure 5.3: Trait PACA model of SWB (Standardised; N=60).



** = $p<.01$
*** = $p<.001$

Figure 5.4: Trait PACA model of SWB (Unstandardised).

Absolute and relative fit indices for the trait PACA model are presented in Table 5.14.

Table 5.14: Absolute and relative fit indices for trait PACA model of SWB.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	76.05	28.05	31	>.05	.91	.89	1.0	.00	.81
Saturated	110.0	.000	0	-	-	1.0	1.0	-	-
Independence	280.39	260.39	45	<.001	5.79	.00	.00	.29	.00

The fit indices given in Table 5.14 indicate an excellent and absolute fit to the data. The result for the trait PACA model is consistent with results obtained in both Study 1 and Study 2. The standardised and unstandardised regression paths given in Figure 5.4 and Figure 5.5 indicate that trait PACA is a powerful determinant of PWI, accounting for 81% of the variance in PWI. The trait PACA model also demonstrates a higher degree of parsimony than the saturated model.

Comparing the Predictive Power of Trait PACA, PANAS PA and NA, State PACA, Extroversion, and Stability for SWB

Testing then proceeded to assess the predictive ability of trait PACA for PWI and LS, in comparison to the predictive ability of the trait and state PA and NA scales of the PANAS, and state PACA for PWI and LS. In the first regression, trait PACA was entered in step 1, followed by state PACA and trait and state PA and NA (PANAS) at step 2. The results of this analysis are presented in Table 5.15.

Table 5.15: Hierarchical regression predicting PWI with trait PACA, state PACA, and the trait and state scales of the PANAS (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.51***
1. Trait PACA	2.08***	.27	.72	.51	
total unique variance = .51					
Step 2					.05 n.s
1. Trait PACA	1.88***	.46	.65	.14	
2. State PACA	-.06	.37	-.02	.00	
3. Trait PA PANAS	.11	.16	.12	.00	
4. State PA PANAS	-.08	.12	-.11	.00	
5. Trait NA PANAS	-.19*	.09	-.25	.04	
6. State NA PANAS	.20	.13	.17	.02	
additional unique variance = .05					
* p <.05; ** p <.01; *** p <.001					R^2 = .56
n.s. = not significant					Adjusted R^2 = .51

The results contained in Table 5.15 reveal that trait PACA explained 51% unique variance in PWI. The beta weight of .72 indicates that high scores on trait PACA were associated with high scores on PWI. The addition of state PACA and the PANAS (trait and state) scales only increased the variance explained in PWI by a non-significant 5%. Moreover, the only other significant predictor of PWI was the trait NA scale of the PANAS. Higher trait NA scores resulted in slightly lower PWI scores. A comparison of trait NA and trait PACA indicates trait PACA to be 2.6 times more powerful in predicting PWI. These results illustrate the dominant influence of trait PACA in predicting PWI. This regression was repeated with LS as the dependent variable and the results are given in Table 5.16.

Table 5.16: Hierarchical regression predicting LS with trait PACA, state PACA, and the trait and state scales of the PANAS (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.44***
1. Trait PACA	2.10***	.31	.66	.44	
total unique variance = .44					
Step 2					.04 n.s.
1. Trait PACA	2.13***	.55	.67	.15	
2. State PACA	-.08	.45	-.03	.00	
3. Trait PA PANAS	.06	.19	.06	.00	
4. State PA PANAS	-.13	.14	-.17	.01	
5. Trait NA PANAS	-.15	.10	-.18	.02	
6. State NA PANAS	.16	.16	.13	.01	
additional unique variance =.04					
* p <.05; ** p <.01; *** p <.001					R^2 = .47
n.s. = not significant					Adjusted R^2 = .41

The results contained in Table 5.16 for LS as the DV are very similar to results for PWI as the DV (Table 5.17). Specifically, trait PACA predicted 44% variance in LS, whilst state PACA and the trait and state scales of the PANAS did not significantly predict LS. High scores on trait PACA were associated with higher LS scores. To further demonstrate the dominance of trait PACA in the prediction of PWI and LS, the PANAS scales and state PACA were entered into a hierarchical regression prior to trait PACA, allowing them to predict the maximum available variance in the DVs. This regression for PWI is displayed in Table 5.17.

Table 5.17: Hierarchical regression predicting PWI by PANAS scales, state PACA, and trait PACA (N=60).

Variable	B	$SE\ B$	β	sr^2	ΔR^2
Step 1					.31***
1. Trait PA PANAS	.62***	.14	.65	.25	
2. State PA PANAS	-.13	.10	-.19	.02	
total unique variance = .27					
total shared variance = .04					
Step 2					.12*
1. Trait PA PANAS	.58***	.13	.62	.21	
2. State PA PANAS	-.29*	.12	-.42	.07	
3. Trait NA PANAS	-.23*	.10	-.30	.06	
4. State NA PANAS	.22	.15	.19	.02	
5. State PACA	.74*	.36	.29	.04	
additional unique variance = .12					
Step 3					.14***
1. Trait PA PANAS	.11	.16	.12	.00	
2. State PA PANAS	-.08	.12	-.11	.00	
3. Trait NA PANAS	-.19*	.09	-.25	.04	
4. State NA PANAS	.20	.13	.17	.02	
5. State PACA	-.06	.37	-.02	.00	
6. Trait PACA	1.88***	.46	.65	.14	
additional unique variance = .14					

* p <.05; ** p <.01; *** p <.001 — R^2 = .56; Adjusted R^2 = .51

The results given in Table 5.17 indicate that, although the PANAS scales account for 31% of variance in PWI at step 1, once trait PACA is entered at step 3, the beta weight for the trait PA scale decreases from .65 to .12 and becomes non-significant. At step 3, trait PACA becomes the strongest predictor of PWI and adds a further 14% unique variance to the prediction of PWI. In addition, a comparison of the standardised coefficients for trait PA at step 1 and trait PACA at step 3 indicates trait PACA changes PWI by a factor of 5 in comparison to trait PA. The results for state PACA indicate that, although accounting for 4% unique variance at step 2, when trait PACA is entered in step 3, state PACA is no longer a significant predictor of PWI (β=-.02). In comparison, trait PACA is strongly predictive of PWI (β=.65). This analysis was repeated for LS as the dependent variable. The results of this analysis are given in Table 5.18.

Table 5.18: Hierarchical regression predicting LS by PANAS scales, state PACA, and trait PACA (*N*=60).

Variable	*B*	*SE B*	*β*	sr^2	ΔR^2
Step 1					.24***
1. Trait PA PANAS	.63***	.16	.61	.22	
2. State PA PANAS	-.21	.12	-.27	.04	
total unique variance = .24					
Step 2					.09 n.s.
1. Trait PA PANAS	.59***	.15	.58	.19	
2. State PA PANAS	-.38**	.14	-.49	.10	
3. Trait NA PANAS	-.19	.12	-.22	.03	
4. State NA PANAS	.18	.17	.14	.01	
5. State PACA	.82	.43	.30	.05	
additional unique variance = .09					
Step 3					.15***
1. Trait PA PANAS	.06	.19	.06	.00	
2. State PA PANAS	-.13	.14	-.17	.01	
3. Trait NA PANAS	-.15	.10	-.18	.02	
4. State NA PANAS	.16	.16	.13	.01	
5. State PACA	-.08	.45	-.03	.00	
6. Trait PACA	2.13***	.55	.67	.15	
additional unique variance = .15					
* *p* <.05; ** *p* <.01; *** *p* <.001					R^2 = .47
n.s. = not significant					Adjusted R^2 = .41

The results contained in Table 5.18 for LS as the DV indicate a very similar pattern to results for PWI as the DV (Table 5.16). Although trait PA accounts for a significant amount of variance in LS at step 1 (24%), it becomes non-significant once trait PACA is entered at step 3. In addition, trait PACA adds a further 15% unique variance, and is over 11 times more powerful in predicting LS in comparison to trait PA.

The final set of regression analyses compared the predictive ability of trait PACA to the predictive ability of extroversion and stability for PWI and LS. Trait PACA was entered in the first step of a hierarchical regression, with extroversion and stability entered at step 2. The results of the regression with PWI as the DV are presented in Table 5.19.

Table 5.19: Hierarchical regression predicting PWI with trait PACA and extroversion and stability (N=60).

Variable	B	$SE\ B$	β	sr^2	ΔR^2
Step 1					.51***
1. Trait PACA	2.08***	.27	.72	.51	
total unique variance = .51					
Step 2					.05*
1. Trait PACA	1.70***	.30	.59	.25	
2. Extroversion	.27	.22	.11	.01	
3. Stability	.76*	.34	.23	.04	
additional unique variance = .05					
* p <.05; ** p <.01; *** p <.001					R^2 = .56
n.s. = not significant					Adjusted R^2 = .54

The results displayed in Table 5.19 indicate that after accounting for trait PACA, only stability significantly and uniquely predicted PWI. However, stability predicted 4% unique variance, whereas trait PACA predicted 51% unique variance in PWI at step 1. This analysis was repeated with LS as the DV, and results are given in Table 5.20.

Table 5.20: Hierarchical regression predicting LS with trait PACA and extroversion and stability (N=60).

Variable	B	$SE\ B$	β	sr^2	ΔR^2
Step 1					.44***
1. Trait PACA	2.10***	.31	.66	.44	
total unique variance = .44					
Step 2					.04 n.s.
1. Trait PACA	1.72***	.35	.54	.22	
2. Extroversion	.07	.26	.03	.00	
3. Stability	.87*	.40	.24	.04	
additional unique variance = .04					
* p <.05; ** p <.01; *** p <.001					R^2 = .48
n.s. = not significant					Adjusted R^2 = .45

The results displayed in Table 5.20 for LS as the DV are almost identical to the results for PWI as the DV (Table 5.19). Extroversion did not significantly predict LS; however, stability added a significant 4% variance to the prediction of LS. In comparison, trait PACA predicted a unique 44% of variance in LS at step 1. Thus trait PACA is a more powerful determinant of LS than stability. The results for extroversion and stability in Table 5.19 and Table 5.20 are consistent with the results obtained in Studies 1 and 2.

Section 5.4: DISCUSSION

This study aimed to investigate differences in affective processing within a reaction time paradigm. It was hypothesised that individual differences in the speed of categorisation of positive and negative words would correlate with state and trait affectivity as well as with SWB. To test this hypothesis, individuals were suboptimally primed with positive and negative words (with the exception of a control group that received no priming). The results of the priming indicated no differential effect according to type of priming received. There was however, an overall effect of priming such that those who received priming of either mood were slower to categorise positive and negative words compared with those who received no priming (see Figure 5.1 and Figure 5.2). This result is unexpected and inconsistent with previous literature indicating differential effects of priming on various targets (Dimberg et al., 2000; Friedman et al., 2005; Murphy et al., 1995; Murphy & Zajonc, 1993; Ohman & Soares, 1994; Whalen et al., 1998). One possible explanation for this result is found within the suboptimal priming procedure used in this study. Whereas in previous research the prime has been presented immediately prior to presentation of the target (Murphy & Zajonc, 1993; Murphy et al., 1995; Ohman & Soares, 1994; Whalen et al., 1998), in this study the primes were presented all at once (during the lexical decision task). Thus, it may be that the passage of time between presentation of the suboptimal priming and presentation of the target words (approximately 5 minutes) dissipated the effects of suboptimal priming. Future research could modify the priming procedure by presenting the prime immediately prior to the target word. This will allow a further examination of whether suboptimal priming of a particular mood facilitates reaction times to subsequent target stimuli.

This study also examined the relation between SWB, state and trait affect, and RTs. It was hypothesised, in accordance with Bower (1981, 1987), that information congruent with one's affective state would be processed faster than incongruent information. By extension, it was also hypothesised that information congruent with a person's trait affectivity and SWB would be processed faster than incongruent information. However, the results only provided limited support for these hypotheses. The only affective states that correlated significantly with the RT tasks were satisfaction, contentment, and pleasure (see Table 5.5). Whilst it was expected that positive affective states would facilitate RTs to positive words, the opposite effect was found. Instead of facilitating RTs, these positive affective states inhibited RTs for both positive words *and* negative words. The inhibition effect of these positive affective states on RTs was not very large, with only 15% of variance accounted for in RTs for positive versus neutral words (see Table 5.6), and 14% of variance accounted for in RTs for negative versus neutral words (see Table 5.7).

The inhibition of reaction times was also found for trait affectivity. The positive affective traits of excitement, extroversion, satisfaction, pleasure, and contentment were all significantly negatively correlated with RTs (see Table 5.4), indicating slower RTs for higher scores on these trait affects. The effect size for the inhibition effect is indicated by the amount of variance accounted for in RTs for positive words (23%; see Table 5.9) and negative words (21%; see Table 5.11). Thus, the inhibition effect was slightly stronger for trait affect in comparison with state affect. There was also a trend for an inhibition effect on RTs for individuals with high SWB. An analysis of high and low scores on SWB indicated a trend toward slower RTs for individuals with high scores, and faster RTs for individuals with low scores (see Table 5.13). These results are inconsistent with the hypothesis that high SWB would be associated with faster RTs to positive words, and with previous literature that has reported mood congruency effects (Forgas, 1995; Forgas & Bower, 1987; Joorman & Siemer, 2004; Ruiz Caballero & Moreno, 1992; Schwarz & Clore, 1983; Siegle et al., 2001; Singer & Salovey, 1988).

An explanation of these inconsistent and unexpected results can be found within the type of RT task used in the current study. Individuals were asked to classify words into positive, negative, and neutral categories as accurately and as quickly as possible. This instruction, in combination with the type of task, may have resulted in a processing advantage for individuals who were low on state and trait positive affect and SWB. That is, individuals low on positive affect might have engaged in a different type of information processing compared with individuals high on positive affect. This possibility has been expanded upon by Fiedler (2000) in response to results that are incompatible with the mood congruency hypothesis. To account for this, Fiedler proposed a dual-force model in which a distinction is made between two complementary adaptive functions, accommodation and assimilation. According to Fiedler, to accommodate means to be responsive to the affordances of the stimuli. Successful accommodation results from maximising conservation of stimulus input and avoiding mistakes on stimulus-driven, reproductive tasks. Conversely, the function of assimilation is typically relied upon when tasks require creativity, active exploration, and the generation of novel information. Thus, accommodation is characterised as stimulus-driven, and assimilation is characterised as knowledge-driven. Accordingly, Fiedler hypothesised that assimilation is facilitated by positive mood, and accommodation is facilitated by negative mood. That is, tasks in which innovation and creativity are required would be better performed by an individual in a positive mood.

By contrast, tasks requiring the avoidance of mistakes and close attention to stimulus details would be facilitated by individuals in a negative mood. These predictions have been supported. Fielder, Nickel, Asbeck and Pagel (2003) found that recall performance was facilitated by positive mood under assimilation conditions, whereas recall performance under accommodation conditions was facilitated by negative mood.

Thus, the unexpected results of the current study can be explained by reference to Fiedler's (2000) dual-force model. The experimental task required participants to pay close attention to the stimulus details and avoid mistakes. These are precisely the conditions under which Fielder hypothesised performance would be facilitated by negative mood and inhibited by positive mood. An inspection of correlations and mean RTs for the positive versus neutral word task, and the negative versus neutral word task indicated that, for both state and trait affect, performance was facilitated by low positive affect and SWB, and inhibited by high positive affect and SWB (see Table 5.12 for affect and Table 5.13 for SWB). In addition, although not attaining significance at $p<.05$, the correlations between trait levels of gloom and unhappiness were associated with faster RTs for negative words ($r=.25$, $p=.06$ and $r=.23$, $p=.07$ respectively). Taken together, these results support the proposition contained within the dual-force model given by Fiedler in which negative mood facilitates accommodation. This proposition is also supported by Forgas (2000) who notes that tasks requiring close attention to detail are better performed in a negative affective state. Thus, although the results of the present study did not indicate a mood congruency effect, the results did support one part of Fiedler's dual-force model.

Whilst the reaction time results of the present study were unexpected, they do not invalidate the central argument of this thesis, that SWB is driven by trait PACA. The self-report data collected in the current study allowed a replication and extension of the tests of the trait PACA model contained in Studies 1 and 2, in addition to enabling a test of the heuristic hypothesis. The heuristic hypothesis asserts that affect is used as a heuristic when individuals make judgments of life satisfaction due to the demanding and abstract nature of the task (Schwarz & Strack, 1999). According to this hypothesis, state affect should be more strongly related with SWB than trait affect. However the results in the current study directly contradict this hypothesis. State affect was not significantly predictive of SWB after controlling for trait affect (see Table 5.15 for PWI and Table 5.16 for LS). In addition, trait PACA significantly and uniquely predicted SWB even after controlling for state affect (see Table 5.17 for PWI and Table 5.18 for LS). Therefore the heuristic hypothesis cannot account for the strong relationship between trait PACA and SWB.

Further support of the trait PACA model was provided using SEM. As in Studies 1 and 2, the trait PACA model provided an absolute fit to the data, accounted for a substantial amount of variance in SWB (81%) and was highly parsimonious (see Table 5.14). This result has now been replicated in four independent samples. In addition, trait PACA was directly compared with the predictive ability of the PANAS measures of trait and state positive and negative affect for SWB. The results were unequivocal. Trait PACA was the most powerful determinant of SWB even after allowing the state and trait PANAS scales, and state PACA, to consume the largest available amount of variance in SWB (see Table 5.17 for PWI and Table 5.18 for LS). Trait PACA was also compared with the predictive ability of extroversion and stability to SWB, and, as in Study 1 and Study

2, extroversion did not significantly predict SWB. Stability did significantly predict SWB, but only accounted for an additional 4 to 5% unique variance. In comparison, trait PACA predicted a unique 52% of variance in PWI (see Table 5.19) and 44% of variance in LS (see Table 5.20). Thus, in agreement with results from Studies 1 and 2, trait PACA was found to be a much stronger determinant of SWB than extroversion or stability.

Across four independent samples, trait PACA has been the strongest determinant of SWB, and an affective model of SWB, in which trait PACA is the sole predictor of SWB, has provided the best fit to the data. This is strong evidence that trait PACA drives SWB. However these results are based exclusively on retrospective self-reports, and as retrospective self-report data are particularly vulnerable to distortions of memory and judgmental biases (Feldman-Barrett, 1997; McFarland, Ross, & DeCourville, 1989; Ross, 1989; Wirtz, Kruger, Napa Scollon & Diener, 2003), the trait PACA model must be tested using a different methodology; one that avoids the problems associated with the use of retrospective self-reports. Indeed, Kahneman (1999) argues that global reports of subjective wellbeing are especially vulnerable to such distortions and biases, and as such, are not the best measure of SWB.

Kahneman's (1999) conclusion was formulated, in part, following research that indicated individuals' chose to endure a longer period of suffering, in comparison with a shorter period of suffering, when that longer period included a slight alleviation in suffering at the end. This is despite ratings of pain made at the time of the task indicating the longer pain condition involved more overall suffering than the shorter pain condition. Yet when asked to retrospectively report on both conditions, participants reported *lower* peak suffering and an enhanced ability to cope with the *longer* pain condition than the *shorter* pain condition. This counter-intuitive result was explained by reference to a recency effect. That is, the longer pain condition was retrospectively remembered more favorably because it ended on a less distressing note than the shorter pain condition. Similar retrospective biases have also been found in holidaymakers reports of their experiences. In a study conducted by Wirtz et al. (2003), individuals retrospectively reported significantly higher positivity ratings of their holiday compared with actual momentary reports of positivity during the holiday. Previous research (Robinson & Clore, 2002a) has hypothesised that such memory distortions and judgmental biases are related to the type of information used when making self-report assessments. When an individual is asked to retrospectively estimate a particular event or mood over a long time frame (longer than a few weeks), they will usually rely on semantic knowledge because episodic retrieval is too difficult. By contrast, when shorter time frames are involved, individuals will rely on episodic knowledge. Thus, retrospective biases and memory distortions arise from responses based on semantic knowledge, rather than episodic knowledge. The current study, in addition with Studies 1 and 2, have thus far relied on the use of trait self-reports which are characterised by instructions referring to extremely long time periods (i.e., "considering your life as a whole…"). This renders it likely that such data are contaminated by retrospective biases, and therefore, are somewhat unreliable. For stronger conclusions to be drawn regarding the efficacy of the trait PACA model of SWB, an alternative methodology must be used.

One particular methodology that provides an effective solution to the problems associated with retrospective self-reports is called Experience Sampling Methodology

(ESM). This involves the repeated measurement of a variable within the context of an individual's daily life. In a typical ESM study, an individual carries a device that sounds an alarm at random or fixed intervals throughout the day. When the alarm sounds, the individual fills out questionnaires that relate to their momentary experiences. Since the time lag between the signal and the response is very short, data are not contaminated by memory distortions or judgemental biases. ESM also has the added benefit of increased ecological validity, as it is able to capture the representation of experience (such as happiness or SWB) at, or close to its occurrence, and within the context of a person's everyday life. Thus, ESM offers an excellent alternative methodology with which to test the efficacy of the trait PACA model of SWB. This is the focus of Study 4.

CHAPTER 6: STUDY 4

Section 6.1: INTRODUCTION

Studies 1, 2, and 3 found that subjective wellbeing was driven by trait PACA, however these findings were based on retrospective global self-reports and it is now generally accepted that retrospective self-reports may be biased by memory distortions and judgmental processes (Robinson & Clore, 2002a). In particular, evidence suggests that individuals rely on semantic knowledge to inform retrospective judgments (Robinson & Clore, 2002a). For instance, retrospective judgments of trait affect are likely contaminated by how a particular individual perceives themselves. If the person characterises themselves as generally happy, then they are likely to report relatively high trait happiness, regardless of whether they actually experience high levels of happiness in their daily lives. Thus there may be a discrepancy between what people actually experience and what they report experiencing. This study has been designed to address this possible discrepancy by measuring affect and SWB using an alternative methodology to retrospective self-reports: Experience Sampling Methodology (ESM). This alternative methodology has been proposed to effectively solve problems associated with retrospective biases in self-report data. Using ESM enables a further, more stringent test of the PACA model of SWB.

Information Processing Strategies and Retrospective Self-reports

The discrepancy between what people report experiencing and what people actually experience (Robinson & Clore, 2002a) has been proposed to be due to differences in the use of information processing strategies when making self-report judgments. Specifically, Robinson and Clore (2002b) argue that when individuals are asked to give reports covering large time frames (for instance, “How happy were you this past year?”, or “How happy are you in general?”) episodic knowledge is inaccessible, and as such, semantic knowledge will be relied upon. By contrast, if an individual is asked to report on how happy they were yesterday, they are more likely to access episodic knowledge in forming a judgment. This hypothesis was explicitly tested by Robinson and Clore who used a reaction time paradigm to examine differences in knowledge retrieval for emotional self-reports. The authors measured the time it took for participants to report on their emotions for a varying width of time frames. For instance, participants reported on their momentary positive and negative emotions, their emotions over the past few hours, past few weeks, months, years, and in general. If an episodic knowledge strategy was being used, the authors expected to find a linear increase in the time it took participants to make a judgment. However, if participants were using a semantic knowledge strategy to answer questions covering larger time frames, then judgment latencies were expected to follow a curvilinear pattern.

To examine this hypothesis, Robinson and Clore (2002b) recruited three separate student samples, yielding 147 participants. The study was conducted on a computer, and, following the time frame instruction, an emotion word was presented on the screen. Participants were asked to press a button when they were ready to make a judgment of their felt intensity of that emotion over the relevant time period. The judgment latency was the time it took for the participant to hit the button. The results were collapsed across emotion valence to yield positive and negative emotion scales. The main effect of the time frame was significant for all three samples (sample 1: R^2=.10; sample 2:

R^2=.05; sample 3: R^2=.13). This effect did not differ according to emotional valence. Robinson and Clore found that judgment latencies increased linearly as time frames increased, before dropping off and flattening out for extremely long time frames. To further examine this relationship, the authors conducted several multiple regressions predicting the judgment latencies for each individual. They entered a linear time frame predictor in addition to a curvilinear time frame predictor in an ordinary multiple regression predicting judgment latencies. This analysis revealed a significant positive relation between the linear time frame and judgment latencies (β=.51, β=.25, β=.56 for samples 1, 2, and 3 respectively; B-weights not provided). However, there was also a significant curvilinear relation between judgment latencies and time frame (β=-.50, β=-.21, β=-.50 for samples 1, 2, and 3 respectively). Thus, judgment latencies were not only increasing linearly with longer time frames, but were also displaying a curvilinear pattern. To examine this in more detail, another set of regressions were conducted in which the same linear and curvilinear predictors were entered into multiple regressions predicting short time frames (moments, hours, days), and longer time frames (months, years, in general) separately. For the short time frames (moments, hours, days) the linear effect was significant (β=.11, averaged across participants and samples). However, for the longer time frames (months, years, in general), in two of the three samples there was no significant linear or curvilinear effect (in one of the samples, latencies significantly decreased, β=-.06, p<.05). Thus, across the shorter time frames, as the time frames increased (i.e., from moments to hours), individuals took longer to make a judgment. Yet this effect only occurred up to a point. When individuals were asked to make judgments over months, years, and in general, latencies flattened out and were not significantly different from one another. These results suggested that individuals were relying on episodic knowledge retrieval when this information was accessible in the shorter time frames, but abandoning this strategy and relying on semantic knowledge when the time frames became too long and episodic knowledge became inaccessible.

The results of the research conducted by Robinson and Clore (2002b) provides evidence to suggest that individuals rely on semantic knowledge to make judgments covering long time frames, such as those used in the trait affect judgments and SWB judgments of Studies 1, 2, and 3.

Influence of Retrospective Biases in Self-report Data

To effectively evaluate whether retrospective self-reports are biased, researchers need to measure the variable of interest both retrospectively, and at the time of its occurrence (ie., using momentary assessments). One study that has implemented this procedure was conducted by Napa Scollon et al. (2004). These authors examined cultural differences and retrospective biases in the reporting of positive and negative affect in five different cultural groups (European American, Asian American, Japanese, Indian, and Hispanic). A total of 416 college students completed global, recalled, and momentary reports of positive and negative emotion. In the momentary (ESM) phase, participants carried a Personal Data Assistant (PDA) for seven consecutive days. At five random intervals throughout the day, participants reported on current feelings of positive and negative emotions (the average response rate for the momentary questionnaires was 75%). Following the ESM phase, participants were asked to retrospectively report on their positive and negative emotions experienced over the past week. Positive emotions were assessed by the adjectives pride, affection, joy, and happiness whilst negative emotions were assessed by the adjectives irritation, guilt, sadness, and worry. The results of the study indicated that across all five cultural groups, and for both positive and negative emotion, global trait reports of emotion uniquely predicted retrospective reports of emotion, even after controlling for momentary emotion. The average beta weight across all cultural groups for global reports predicting recalled reports, was .37. In comparison, the average beta weight for momentary reports predicting recalled reports of emotion was .39. These results led Napa Scollon et al. (2004) to conclude that systematic biases in memory can be accounted for by a person's global self-concept (a form of semantic knowledge). As noted by the authors, this test of the influence of self-concept on memory was conservative, because participants in ESM studies are required to attend to emotional states up to 8 to 12 times per day for as long as 90 days (Feldman Barrett, 1997).

In a similar ESM study, Oishi (2002) examined European American and Asian American responses to daily life satisfaction. Each night for seven consecutive nights, 107 participants recorded how good or bad their day had been on a pencil and paper questionnaire. The author found that daily satisfaction did not differ by culture. However when participants were asked at the end of the seven days to retrospectively estimate how good or bad their week had been, significant differences between cultures emerged. European Americans, but not Asian Americans, significantly overestimated their daily satisfaction (R^2=.42). It is possible this overestimation was the result of semantic knowledge (cultural beliefs) being used in combination with episodic knowledge (actual daily satisfaction) to form retrospective judgments.

Systematic retrospective biases have also been found in holidaymakers reports of how enjoyable their holidays were (Wirtz et al., 2003). Wirtz et al. (2003) compared momentary, predicted, and remembered experiences of 41 students' spring break vacations. The participants estimated their overall subjective experience, positive affect, and negative affect two weeks prior to going on vacation, and again two to four days prior to going on vacation. For the entire period of their vacation students carried a PDA that sounded a signal at seven random intervals over a 13 hour period. The questions used for the momentary assessments were the same as those used for the students prospective estimates of subjective experience, with only the tense changing from future to present. At two to four days, and four weeks following the vacation, participants were asked to retrospectively estimate their average overall subjective experience and overall positive and negative affect for the vacation. In addition, at five weeks post-vacation, participants were asked whether they would like to take the same vacation again, presuming they had not already been. The results revealed systematic distortions of memory had occurred. Both predicted and remembered mean positive ratings and overall subjective experience were significantly higher than momentary reports of positive ratings and subjective experience (all Cohen's *d'*s>.61). Wirtz et al. then predicted the participants desire to repeat the holiday experience with actual, anticipated, and remembered experiences. This analysis indicated that remembered experience was the only significant predictor of the students desire to repeat the vacation. Actual experiences, and even anticipated experiences, were not important in predicting the students' willingness to take the same vacation again. Moreover, students' prior expectations of the vacation significantly influenced remembered experience above and beyond actual experience. This result supports the contention that individuals find it difficult to accurately report on their actual experience retrospectively, and that retrospective reports are biased in the direction of semantic knowledge.

From the evidence, it seems that the memory distortions and judgmental biases associated with retrospective self-reports are due to individuals beliefs about themselves. This proposition was tested by Feldman Barrett (1997) who proposed that personality might be one source of semantic knowledge that individuals use when making retrospective self-reports. Fifty six undergraduates completed pencil and paper ratings of affect three times a day for 90 days. The NEO-PI-R was used to assess extroversion and neuroticism. Following completion of the daily affect ratings, participants were asked to retrospectively estimate their average positive and negative affect over the past 90 days. Results indicated that momentary ratings of both positive and negative emotion predicted participants retrospective reports (β=.70, r=.63, and β=.57, r=.76, respectively). However, in line with Feldman Barrett's predictions, personality significantly and uniquely predicted retrospective estimates of emotion. Specifically, individuals who were high on extroversion overestimated the amount of positive emotion actually experienced (β=.21, r=.34) whilst individuals high on neuroticism overestimated the amount of negative affect actually experienced (β=.25, r=.38). This result is made even more remarkable by the fact that at the conclusion of the study (assuming 100% compliance) participants would have reported on their positive and negative emotional states 270 times over three months, which likely gave them far greater insight into their emotional lives compared to the average person. Thus the systematic memory distortions found in this study are likely an underestimate of memory distortions experienced in the general population. This likelihood is further increased by a consideration of the methodology used in the study. That is, the study used pencil and paper tests to record daily ratings of emotion which are known to be vulnerable to participant non-compliance (Broderick, Schwartz, Shiffman, Hufford, & Stone, 2003; Stone, Shiffman, Schwartz, Broderick & Hufford, 2002; however computerised assessment would probably have been prohibitively expensive at the time Feldman Barrett's study was conducted). A participant may have chosen to fill out the questionnaires just prior to handing them in, which makes it more likely that the questionnaires were filled out on the basis of semantic knowledge, and not episodic knowledge. This is likely to have enhanced the underestimation of the effect, making the systematic biases found by Feldman Barrett even more remarkable.

Advantages and Disadvantages of Using ESM as an Alternative Methodology to Retrospective Self-reports

ESM offers a number of advantages over retrospective self-reports, which have been demonstrated to suffer from retrospective biases. In a typical ESM study, an individual carries a PDA that sounds an alarm at random intervals throughout the day. When the alarm sounds, the individual fills out questionnaires on the PDA that relate to their momentary experiences. Since the time lag between the signal and the response is very short, data are not contaminated by memory distortions or judgemental biases. Accordingly, data obtained using ESM are likely to be more accurate than data obtained using retrospective self-reports. The use of ESM also increases ecological validity, as the representation of experience (such as happiness or life satisfaction) is captured at or close to its occurrence and within the context of a person's everyday life (Napa Scollon, Kim-Prieto, & Diener, 2003). In addition, using ESM allows the variable of interest to be studied across a variety of environmental, social, and psychological conditions as well as allowing an examination of the fluctuations in that variable across conditions and time (Stone, Shiffman & DeVries, 1999). Furthermore, retrospective reports obtained on a single occasion only allow for an examination of cross-sectional differences, whereas in ESM both longitudinal and cross-sectional differences can be examined. Napa Scollon et al. also note that a multi-method strategy may be used within ESM to investigate the differential effects of momentary measurement versus other types of measurement (such as recall).

The only significant disadvantage that may be associated with ESM is participant burden. That is, because signalling necessarily disrupts whatever activity the person is engaged in, a person might find participating in an ESM study irritating. A person might also find the task of filling out up to 12 assessments per day for two weeks onerous (Napa Scollon et al., 2003). However there is research to suggest that most people do not find it a burden to participate in an ESM study, nor do they find such participation increases their negativity (Cerin, Szabo, & Williams, 2001; Jamner, 2003). For example, Cerin et al. explicitly compared positive and negative emotions and cognitive anxiety in participants completing ESM reports, to participants completing retrospective reports. The authors of this study were testing the utility of ESM for studying the pre-competition emotions of athletes. In particular, the authors wanted to know whether ESM would increase anxiety and negativity in the athletes compared with more typical retrospective reports. Cerin et al. tested 66 professional male Tae-kwon-do practitioners in the build up to the English Championship. The participants were split into three equal groups. In the ESM group, participants were randomly signalled three times a day in the week leading up to the competition. They completed measures of positive and negative emotion in addition to cognitive and somatic measures of anxiety. The second group of participants (Repeated Measurements group; RM) were assessed on the same measures four times in the week leading up to the competition (7 days, 4 days, 1 day, and 1hr prior to competition). The third group provided retrospective estimates of their emotions and anxiety in the week before the competition (Retrospective Assessments group; RA).

The results of the study conducted by Cerin et al. (2001) indicated that the ESM and RM group did not differ in positive and negative emotions or anxiety, whereas anxiety and worry were significantly higher for the RA group (effect sizes not provided by the author). In this study, the use of ESM did not result in any more anxiety or negativity than the use of more conventional paper and pencil questionnaires. The results of this study are even more noteworthy when consideration is made of the nature of the participants sampled. These participants were athletes who were about to compete in a major championship, so it would be expected that if ESM does increase negative affectivity, it is likely to have been manifested in this group of participants. However, even up to an hour prior to competition, negative affect and anxiety were not significantly higher in the ESM group compared with the RM and RA groups.

Other research has also demonstrated that ESM is not experienced as burdensome or negative (Jamner, 2003). Jamner (2003) measured the inconvenience associated with participating in ESM research in two studies. The first study reported on results from 200 young adults who completed 50,000 momentary assessments. A majority of this sample (57%) reported weak to no inconvenience, whilst only 25% reported intense or strong inconvenience. In a second study of 400 adolescents who completed 140,000 momentary assessments, only 19% reported intense or strong inconvenience compared to 66% who reported weak to no inconvenience. These two results are remarkable when considering that, on average, most ESM studies only involve between 56 and 168 momentary assessments for studies running one to two weeks (Conner Christensen, Feldman Barrett, Bliss-Moreau, Lebo, & Kaschub, 2003). Based on the results of Jamner and Cerin et al. (2003) it is highly unlikely that a typical ESM study will increase negative affectivity or be experienced as inconvenient or burdensome.

Participant Compliance with Manual and Electronic Questionnaires

For ESM studies to be effective, participant compliance with the sampling protocol must be adhered to. If participants are non-compliant (i.e., by filling out questionnaires relating to momentary experiences retrospectively) then the resultant data are likely to suffer from the same memory distortions and judgmental biases associated with retrospective self-report data. Research has demonstrated that pencil and paper questionnaires used in ESM studies are particularly vulnerable to participant non-compliance (Broderick et al., 2003; Stone et al., 2002). Broderick et al. conducted a study in which 27 participants with chronic pain were given a daily diary to fill in over 24 days. Each participant was required to fill in the McGill Pain Questionnaire three times a day, corresponding with morning, afternoon, and evening. Participants wore a wrist watch that sounded an alarm to alert the participant to complete the questionnaire. The authors examined self-reported compliance with the sampling protocol by including a date and time item for each diary entry for the participant to complete. In addition, actual compliance with the sampling protocol was measured via photosensors unobtrusively attached to the diary. These sensors recorded the time and date for which the diary was opened. Thus self-reported compliance could be compared to actual compliance. The results indicated a large discrepancy between self-reported and actual compliance. Participants reported an overall compliance rate of 85%, whereas actual compliance was only 29%. In addition, only 48% of participants opened the diary at least once a day, and on 22% of days, the diary was not opened at all. Yet even on the days that the diary was not actually opened, 97% of participants earlier or later falsified at least one diary entry for that day. This indicates that entries were being completed either ahead of time, or hours and even days after the actual sampling moment. Such non-compliance is a serious problem for ESM studies, as it not only compromises the integrity of the data, but also undermines the whole rationale for conducting an ESM study. After reviewing other studies that have reported similar findings, Broderick et al. noted that non-compliance transcends patient characteristics, medical conditions, types of data collection and sampling burden. Subsequently the authors concluded that paper diary methodologies relying on self-reported compliance were seriously flawed.

As non-compliance with sampling protocol is a serious threat to the integrity of ESM studies, Stone et al. (2002) examined whether electronic diaries could adequately improve compliance. In this study the authors split 80 participants with chronic pain into two equal groups. One group was given a paper and pencil diary fitted with photosensors which indicated precisely when the diary was opened. The other group was given an electronic diary (a PDA) in which diary entries were completed on a touch screen. Both groups completed the same McGill Pain Questionnaire three times a day for 24 days. As in the Broderick et al. (2003) study, self-reported compliance for the paper diary group was indicated by time and date questions for each diary entry. Actual compliance (date and time that the diary was opened) was recorded by the photosensors. For the paper diary group, self-reported compliance was 90%, whereas actual compliance was only 11%. Furthermore, on 32% of days the diary was not opened at all, and yet self-reported compliance on these days was 92%. In addition, 75% of participants had at least one day where the diary was not opened, but diary entries for that day were completed. In comparison, the electronic diary group recorded an actual compliance rate of 94%. The results of this study, in conjunction with the results of Broderick et al.'s study, indicate that paper and pencil questionnaires relying on self-reported compliance should be avoided in ESM studies.

Fortunately the Stone et al. (2002) study indicates that computerised methods of data collection for ESM studies effectively solves the problem of participant non-compliance with the sampling protocol. There are also numerous other advantages associated with using computerised methods of data collection over pencil and paper methods. These include greater flexibility in item presentation (random ordering of questions minimises use of response sets); a reduction in the possibility of human error associated with data entry and management; the ability to record ancillary information (such as reaction times) to questions; and precisely controlled timing of questions (Conner Christensen & Feldman Barrett et al., 2003; Feldman Barrett & Barrett, 2001). After noting the advantages and disadvantages of computerised experience sampling, Conner Christensen and Feldman Barrett et al. concluded that computerised methods of data collection are always preferable to paper and pencil methods in ESM studies.

Using ESM to Investigate the Experience of Subjective Wellbeing

In another study that utilised ESM to avoid biases associated with retrospective reports, Schimmack (2003) investigated the predictive ability of specific affects for SWB. In this study, 127 participants were given a PDA to carry with them for seven days. During that time participants recorded their level of momentary pleasant affect and unpleasant affect at five random intervals throughout a 10 hour period. Participants also made additional ratings upon waking and prior to going to sleep. The items chosen to measure pleasant affect were happy, affectionate, proud, and excited, whilst the items chosen to measure unpleasant affect were sad, worried, guilty, and irritated. SWB was operationalised as life satisfaction (LS), and measured via a modified version of the Satisfaction With Life Scale (SWLS; Diener et al., 1985) in which the response format was changed from "in general" to "in the past month". This measure was then aggregated over three separate measurement occasions. The results of the study indicated that, of the separate affect items, only *happy* significantly predicted LS, accounting for 21% of unique variance (β=.38, r=.46). The average of the other pleasant affect items only accounted for an additional 1% variance, whilst the average of the unpleasant items predicted an additional 10% variance in LS. This led Schimmack to conclude that of the affect items measured, happiness was both necessary and sufficient to predict LS. However, Schimmack noted that future research should examine a broader range of affects to determine exactly which pleasant and unpleasant affects were necessary and sufficient for the prediction of LS. He also added that ESM was ideally suited to this purpose.

Although the study conducted by Schimmack (2003) goes some way toward redressing the over reliance on retrospective self-reports for affective judgments, it did not measure SWB momentarily. As such, the impact of changes in momentary affect on SWB could not be assessed. In addition, it is not possible to assess whether the SWB judgments were influenced by memory distortions and judgemental biases that have often been found in other retrospective self-reports (Conner Christensen, Wood, & Feldman

Barrett, 2003; Feldman Barrett, 1997; Oishi, 2002; Scollon et al., 2004; Wirtz et al., 2003).

Aims and Hypotheses

Studies 1, 2, and 3 of this thesis found a model of SWB based on trait PACA provided the strongest and most parsimonious explanation of SWB. However this conclusion was based exclusively on retrospective self-report data. Such data have been demonstrated to suffer from memory distortions and judgmental biases. As such, this study aims to test the PACA model of SWB using a methodology that effectively solves problems associated with retrospective self-reports; ESM. Using ESM will enable an accurate measure of each individual's baseline PACA, and the variation in baseline PACA, to be obtained. In addition, using ESM will provide an accurate estimate of each individual's SWB. In accordance with the PACA model, it is hypothesised that an individual's baseline level of PACA will provide the strongest and most parsimonious explanation of SWB.

This study adopts a multi-method strategy by measuring global trait self-reports of affect, SWB, and personality, and recall estimates of daily affect and SWB. This allows a direct comparison of the differential effects of momentary, global trait, and retrospective reports on affect and SWB. It is hypothesised that individuals will exhibit systematic memory distortions and judgmental biases in global trait self-reports of affect and SWB, and when retrospectively estimating daily affect and SWB.

Section 6.2: METHODOLOGY

Participants

Participants comprised a convenience sample of 60 individuals, however four participants were excluded due to extremely low response rates (<20%), giving a final total of 56 participants. Recruitment of participants was conducted through advertisements placed around the Deakin University Melbourne campus in addition to announcements made prior to Undergraduate and Postgraduate Psychology lectures. The age of participants ranged between 18 and 60, with a mean age of 23.28 years (*SD*=7.18). Males comprised 43% of the sample, whilst females comprised 57%. A majority of participants were in full-time study (85%) and part-time employment (74%), whilst only 4% were in full-time employment. In addition, a majority of participants were never married (76%) whilst 13% described their relationship as defacto or living together. The relationship status of participants was also reflected in the reported living arrangements, with 37% of participants living with one or both parents, and 33% living with adults who were neither their partner nor their parent. A majority of participants reported gross household incomes of below $15,000 (30%) whilst 20% reported a gross household income of $61,000 to $90,000. Each participant received $50 remuneration for the two weeks of participation.

Materials and Apparatus

Paper and Pencil Questionnaires

Participants completed five paper and pencil questionnaires prior to the ESM task. These consisted of a demographics questionnaire (gender, age, living arrangements, relationship status, work and study status, and household total annual gross income), two measures of SWB, a global trait affect questionnaire, and a questionnaire measuring extroversion and stability.

As in Studies 1, 2, and 3, the PWI was used as the primary measure of SWB (Cronbach's alpha for this sample =.71; see Chapter 3, section 3.1 for Cronbach's alpha's in previous research). An additional measure of SWB, the SWLS (Diener et al., 1985), was included to provide a further test of the trait PACA model of SWB. The SWLS is widely used in the SWB literature. It was developed by Diener et al. as a single factor, multi-item measure life satisfaction, which is hypothesised as the cognitive component of SWB. If trait PACA strongly predicts SWLS, this would provide further evidence that SWB is driven largely by trait PACA, and that affect should no longer be considered a component of SWB, but rather, a determinant of SWB. The SWLS comprises five items rated on a 1 to 7 Likert scale (1=strongly disagree, 4=neither agree nor disagree, 7=strongly agree). Examples of items include "In most ways my life is close to my ideal", and "I am satisfied with my life" (see Appendix I for a copy of this scale). The SWLS has demonstrated adequate reliability with Cronbach's alpha's of .83 in a sample of older adults (*N*=39) and .85 in a sample of college students (*N*=139; Pavot et al., 1991).

Participants also completed a self-report questionnaire measuring global trait affect. The trait affect items were chosen according to three criteria. These were: consistency with Studies 1, 2, and 3; previous research suggesting items to be good indicators of the representative quadrants of the circumplex model of emotion (Davern, 2004, Yik et al., 1999); and minimising the number of items as each item was also included in the ESM task. This resulted in 10 items being chosen. The items were happy, content, unhappy, and depressed for the pleasant-unpleasant dimension, and active, alert, annoyed, upset, tired, and relaxed for the activated-deactivated dimension. Participants were asked to rate each item according to the instruction, "Indicate to what extent you feel this way in general." Ratings were made on an 11-point end-defined unipolar scale (0-Not at all, 10-Extremely). A copy of this scale is included in Appendix J.

The TIPI was used as a brief measure of extroversion and stability. Cronbach's alpha's for the current sample were .79 for extroversion and .59 for stability (see Chapter 3, section 3.1 for Cronbach's alpha's in previous research).

Retrospective Questionnaires

Following the ESM task, two questionnaires were included to measure potential retrospective biases in the estimation of averaged momentary affect and SWB over the course of the two weeks. The ESM affect retrospective questionnaire (see Appendix K) asked participants to, "Please estimate, on average, how you have felt over the past two weeks. For example: On average, how upset did you feel over the past two weeks?" The items included were the same items that were asked on the global trait affect questionnaire. The PWI retrospective questionnaire (see Appendix L) asked participants

"Over the past two weeks, please estimate, on average, how satisfied you were with…" Responses were made on the same scale as the original PWI.

PDA Daily Electronic Questionnaires

The order of questionnaires remained constant for each participant. A schematic representation of the ordering of momentary questions on the PDA's is presented in Figure 6.1.

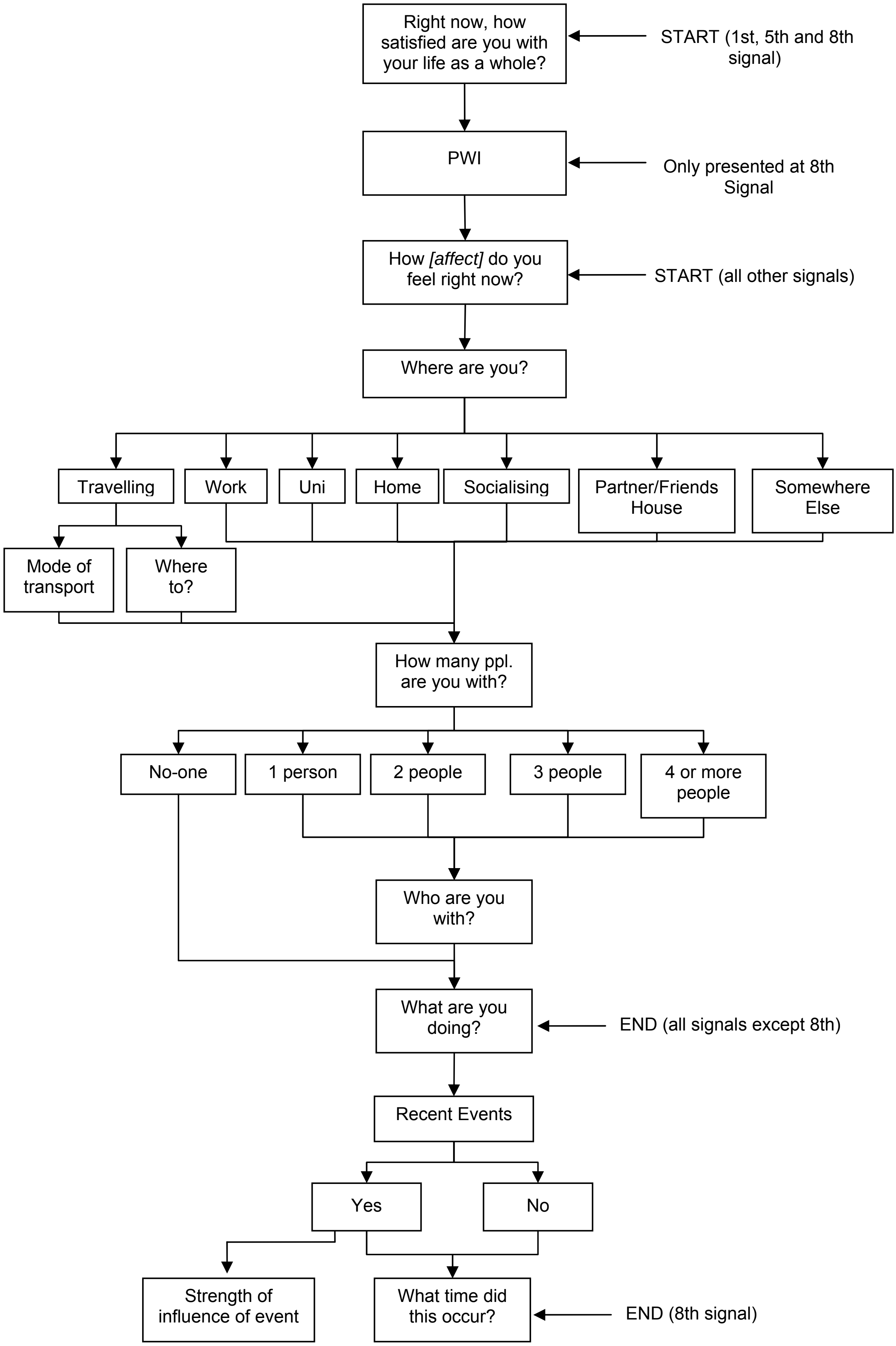


Figure 6.1: Schematic representation of order of PDA signals.

The first question that each participant completed on every day of the study was the life satisfaction (LS) question. To inform the participant of the nature of the question prior to completion, a screen was displayed with the message, “This question asks about how satisfied you are with your life as a whole.” The next screen presented the question, “Thinking about right now, how satisfied are you with YOUR LIFE AS A WHOLE?” Responses were made on an 11-point end-defined scale (0-Not at all, 10-Completely). Participants made their response by using the stylus to drag a vertical bar across a horizontal slider scale that was presented below the question on the PDA screen. This question was asked three times a day, at signals 1, 5, and 8 corresponding to morning, afternoon, and evening. At each relevant signal, the LS question was the first question presented to ensure that responses to subsequent questions did not influence the participant’s response to the LS question.

Following the LS question, participants received the affect question set. This question set consisted of 9 of the 10 global trait affect items asked at the beginning of participation in the study. The item depressed was excluded as it was considered unlikely to vary substantially over the course of the signalling period (12.5 hours) in the non-depressed normal sample recruited for this study. Prior to the affect question set, a screen was displayed with the message, “These items refer to your general everyday experiences”, signalling the start of the affect questions. Each question was asked in the following format: “How [AFFECT; i.e., HAPPY] do you feel right now?” Responses were made on an 11-point end-defined scale (0-Not at all, 10-Completely). The affect question set was asked at each signal (8 times per day), and, with the exception of the LS question, was the first question set presented.

Following the affect questions, participants completed a series of items designed to measure the context which the participant was in at the time of the signal. Whilst context was measured, it is not pertinent to this thesis and was measured only as part of further research (Blore & Stokes, 2008).

For the last signal of each day, participants completed the PWI questionnaire (which includes the LS question) following the context questions. A screen with the message, "These questions ask about how satisfied you are with your life", notified participants as to the nature of the upcoming questions. Each item was presented in the following format, "Thinking about right now, how satisfied are you with [PWI DOMAIN, i.e., YOUR STANDARD OF LIVING]?" Responses were made using the same 11-point scale as used for the LS question. The final question set was presented following the PWI at the end of each day. This question set asked about the occurrence and impact of any events that happened during that particular day. As with the context questions, the measurement of recent life events is not pertinent to this thesis, and was measured only as part of further research (Blore & Stokes, 2008).

ESM Apparatus

The PDA loaned to participants was a Palm Z22 (© Palm Inc., USA) running the Palm 5.4 Operating System (© Palm Inc., USA). The Z22 has a 200MHz processor, 20mb of internal memory, and a 160x160 color touchscreen. The questionnaires were constructed using the Purdue Momentary Assessment Tool (PMAT) developed by Weiss, Beal, Lucy, and MacDermid (2004). This program was chosen for its ease of use, functionality, and flexibility of options for the ESM study. Once the study was constructed using the PMAT, it was saved to a file and loaded onto each PDA with a unique participant identity.

Procedure

Following approval from the Deakin University Human Research Ethics Committee (DU-HREC EC 51-06), participants who indicated a willingness to take part in the study were invited to a laboratory session at the Deakin University Melbourne campus. In this session, participants received a Plain Language Statement (PLS) and an informed consent form. The PLS was given to the participants first to inform them of each aspect of the study. If the participants were still willing to take part, they read and signed the informed consent form. Following this, each participant received and completed a questionnaire packet, which contained the demographic questionnaire, the PWI, the global trait affect questionnaire, and the extroversion and stability scales of the TIPI. Once the questionnaire packet was completed, participants were each given a PDA and a charger, and were taken through its functions and use by the researcher. The PMAT program allows the other functions of the PDA to be disabled automatically, so participants required no prior familiarity with how to use a PDA. In addition, the PDA automatically turned itself on for each questionnaire and went into standby once the questionnaire was completed, thus requiring no intervention on the part of the participant. The researcher demonstrated how to fill in each questionnaire to ensure that each participant was able to complete the ESM part of the study. In addition, the researcher demonstrated how to disable the alarm for up to an hour if the participant was somewhere where an alarm would be considered disruptive (e.g., a lecture theatre or a cinema). The participants were instructed to charge the battery of the PDA every second day. Most participants complied, however a small minority of participants did not charge the PDA. This required the researcher to do a 'soft' reset in which the PDA was rebooted. No data was lost as a result of this resetting. Once the researcher was satisfied that each participant was competent in the use of the PDA, the PMAT program was started on each PDA.

Each participant carried the PDA with them for two consecutive weeks. The first day of the study was considered the day of the laboratory session. The PDAs were programmed to be signal contingent (signals occur randomly) rather than interval contingent (signals occur at regular intervals). The advantage of a signal contingent design is that it allows signals to be randomised throughout a given time period. This reduces the risk that participants will develop a habitual response set that is associated with prior knowledge of the sampling period (Napa Scollon et al., 2003). In addition, random signals allow for a broader range of daily life to be sampled. However, to prevent a scenario in which the participant is signalled for two questionnaires within a short space of time, a minimum spacing of signals was specified at 70 minutes apart. This allowed the signals to occur throughout the designated time period.

As only 20 PDAs were available, three groups of 20 participants each were recruited. The first group had the option of setting their own time period in which the signals occurred, however the time period had to be 12.5 hours. Thus, one participant could set the signal period to occur from 12pm to 12.30am whilst another could set the signal period for 9am to 9.30pm. This allowed the signals to be customized to suit each participant's circumstances; however a program error within PMAT resulted in the signals occurring at the same time each day as opposed to random times. This error was not bought to the experimenter's attention until halfway through the study period. As such, it was decided that the group would continue, but that for the analysis of results, a dummy coded variable would be created to specifically control for potential differences between the groups. The signalling time period for the second and third groups was defined by the experimenter 10am to 10.30pm. This period was chosen to minimise the possibility of signals occurring during the time that a participant could be sleeping.

The PDAs were programmed to signal participants eight times a day for 14 days. The order of the questionnaires at each signal were specified by the researcher such that: the first, fifth, and eighth signal of the day always included the life satisfaction question presented at the beginning of the questionnaire; and the eight signal always presented the PWI following the life satisfaction question, with the recent events question set at the end of the questionnaire. In addition, the affect question set always followed the life satisfaction question or the PWI, and the context question set was always presented following the affect question set (see Figure 6.1). This was done to ensure that the context questions did not influence the affect questions, the PWI questions, or the life satisfaction question, as previous research has shown that bringing attention to one's surroundings influences subsequent responses to affect and hedonic type questions (Schwarz & Clore, 1983). The LS question was asked three times a day, the PWI once a day, and the affect and context question sets were asked eight times a day.

On the fourteenth day of the study, participants were asked to attend another laboratory session to return the equipment and complete the SWLS, and the retrospective affect and SWB questionnaires. Following this, each participant received their remuneration.

Section 6.3: RESULTS

Data Preparation

Across all momentary questionnaires, the overall response rate was 72.5%. This is comparable with previous ESM research in which participants are signalled seven or more times per day (Conner Christensen & Wood et al., 2003). The missing data was dealt with using pairwise deletion. A missing values analysis was then conducted on retrospective questionnaire data. This analysis indicated less than 5% of cases contained missing data. As Tabachnick and Fiddell (2001) suggest that missing data of 5% or less can be ignored, the data was judged to be suitable for regression replacement (Tabachnick & Fiddell). This technique is a more sophisticated technique of data replacement than mean substitution and more objective than using prior knowledge (Tabachnick & Fidell). Data were then screened for multivariate and univariate outliers. No multivariate outliers were detected as assessed by Mahalanobis distance. Only one case was detected as a univariate outlier (on the PWI domain of safety), as indicated by a z-score exceeding four. Inspection of the raw score indicated a normal and expected response. Thus the case was retained.

The assumption of normality was assessed through inspection of expected normal probability plots of standardised residuals. Raw scores of skew and kurtosis were also analysed for each variable. Inspection of expected normal probability plots revealed no violation of the normality assumption. This was confirmed in the analysis of raw skewness and kurtosis scores. Following extensive Monte Carlo testing of the effects of skew and kurtosis, Curran et al. (1996) concluded that raw skewness scores of less than

2.0, and kurtosis scores of less than 7.0, are not likely to distort the results. As no skewness score exceeded 2.0, and no kurtosis score exceeded 7.0, it was concluded that the data did not violate the assumption of normality.

As in Studies 1, 2, and 3, testing proceeded by computing means, standard deviations, and correlations between all measured variables. Following this, the variability and stability in average levels of LS, PWI, and PACA was investigated in individuals across all 14 days of the study period and across each time signal (i.e., morning, afternoon, and evening for LS). Throughout, an averaged momentary (over the 14-day study period; henceforth mean state) measure of PACA is used to predict recalled, trait, and mean state measures of SWB.

Means, Standard Deviations, and Correlations between Variables

The means, standard deviations, and correlations for global trait PWI, global trait life satisfaction, SWLS, global trait affect, personality, and demographics are presented in Table 6.1.

Table 6.1: Correlations between global trait PWI, global trait life satisfaction, SWLS, global trait affect, personality, and demographics (N=53).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.
1. PWI																												
2. Std Living	.53																											
3. Health	.58	.34																										
4. Achieving	.60	.21	.18																									
5. Relationships	.63	.21	.43	.17																								
6. Safety	.57	.33	.15	.12	.41																							
7. Community	.67	.06	.13	.49	.23	.26																						
8. Security	.66	.28	.17	.42	.11	.22	.59																					
9. Life Sat.	.68	.45	.36	.41	.45	.36	.45	.43																				
10. SWLS	.39	.43	.25	.27	.20	.08	.21	.24	.43																			
11. Upset	-.35	-.23	-.26	-.34	-.29	-.33	-.11	.02	-.17	-.08																		
12. Alert	.20	.05	.01	.20	-.02	.25	.14	.27	.06	.00	-.09																	
13. Happy	.57	.35	.23	.18	.42	.42	.47	.35	.63	.15	-.28	.40																
14. Tired	-.28	-.16	-.31	.00	-.21	-.21	-.04	-.22	-.22	-.17	.30	-.06	-.11															
15. Content	.47	.26	.09	.23	.41	.32	.31	.34	.45	.11	-.14	.00	.39	-.06														
16. Annoyed	-.36	-.24	-.11	-.17	-.36	-.43	-.13	-.14	-.27	-.25	.54	-.27	-.39	.23	-.38													
17. Unhappy	-.45	-.39	-.24	-.32	-.18	-.34	-.32	-.17	-.43	-.32	.56	-.11	-.45	.17	-.18	.58												
18. Depressed	-.53	-.46	-.24	-.35	-.24	-.47	-.34	-.23	-.45	-.31	.56	-.01	-.43	.17	-.19	.35	.75											
19. Relaxed	.06	.21	.20	-.14	-.05	-.07	.02	.08	.30	.19	.01	.06	.23	-.15	-.02	.02	-.17	-.13										
20. Active	.27	.15	.21	.06	.14	.19	.18	.21	.46	.01	.05	.49	.49	-.06	.16	.00	-.16	-.11	.35									
21. Extroversion	.34	.13	.16	.12	.37	.24	.17	.22	.32	.16	-.15	-.08	.27	-.06	.49	-.37	-.22	-.24	.12	.09								
22. Stability	.40	.38	.17	.39	.02	.34	.20	.29	.56	.13	-.44	.18	.40	-.41	.12	-.23	-.34	-.39	.33	.24	.02							
23. Gender (K)	.14	.21	.02	.16	-.03	.15	.17	.22	.15	.13	.00	-.07	.11	.13	.09	-.09	-.22	-.31	-.19	-.12	.13	-.05						
24. Age	.04	-.13	-.01	.11	.09	.06	.21	-.20	-.02	.07	-.16	.14	.15	.10	-.04	-.03	-.04	-.18	-.03	.09	-.30	.07	-.09					
25. Living Arrange (K)	-.14	-.16	.05	-.01	-.16	.03	-.09	-.26	-.11	.00	.06	-.13	-.21	.01	-.05	.16	.10	.18	.14	.05	.08	-.03	-.34	-.13				
26. R'ship Status (K)	.07	-.06	.02	-.05	.24	-.07	.04	.17	.14	.07	-.01	.05	.07	-.11	.04	-.22	-.05	-.06	-.16	-.09	-.08	-.11	.21	.27	-.58			
27. Work/study status (K)	.07	-.04	.14	-.16	.19	.22	.13	.02	.06	-.11	-.03	-.16	.07	-.06	.06	.00	.09	-.09	.02	.19	-.08	-.07	.11	.22	-.29	.35		
28. Income (S)	.04	.19	-.19	.20	-.13	.01	.13	-.01	.02	.15	-.08	.14	.00	.18	.01	.07	-.15	-.27	-.14	-.18	-.15	.05	.29	.01	-.31	-.06	-.21	-
M	72.21	7.43	7.45	6.92	7.11	8.02	6.72	6.89	6.98	24.86	2.96	6.91	7.17	5.32	6.64	3.09	2.75	2.58	5.98	6.58	12.17	12.34	-	23.28	-	-	-	-
SD	10.85	1.42	1.91	1.66	2.04	1.61	1.93	1.9	1.54	5.28	1.87	1.74	1.49	1.95	1.48	2.17	1.86	2.36	1.99	1.63	3.88	3.53	-	7.18	-	-	-	-

Note: Correlations of .27 to .34 are significant at p <.05; correlations of .35 to .43 are significant at p <.01; and correlations of .44 and above are significant at p <.001; (K) = Kendall's Tau B; (S) = Spearman's Rho.

The correlations presented in Table 6.1 indicate that, consistent with Studies 1 and 2, the correlations between global trait PWI and the global trait affect adjectives happy and content were among the strongest observed. The correlations between the SWLS and global trait affect were small to moderate, ranging from .00 for active to -.32 for unhappy.

The means presented in Table 6.1 indicate that participants reported the highest satisfaction in the domain of safety, followed by health, and standard of living. The domains of safety and standard of living also received the highest satisfaction ratings in Studies 1 and 2 along with personal relationships. However, satisfaction with personal relationships was slightly lower in this sample compared to Studies 1 and 2. The mean global trait PWI score of 72.21 differs by less than 1 point from mean global trait PWI scores obtained in Studies 1 and 2. As recalled affect and SWB were analysed separately, the means, standard deviations, and correlations between mean state PWI, life satisfaction, affect, and recalled PWI, life satisfaction, affect, and SWLS are presented in Table 6.2.

Table 6.2: Correlations between mean state PWI, life satisfaction, affect, and recalled PWI, life satisfaction, affect, and SWLS (*N*=50).

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.
1. PWI-MS																							
2. Life Sat.- MS	.74																						
3. SWLS	.50	.59																					
4. Upset- MS	-.26	-.35	-.21																				
5. Alert- MS.	.37	.38	.22	-.24																			
6. Happy- MS	.59	.75	.56	-.43	.38																		
7. Tired- MS	-.18	-.05	.11	.30	-.25	-.14																	
8. Content- MS	.53	.76	.40	-.46	.46	.72	-.05																
9. Annoyed- MS	-.41	-.40	-.24	.69	-.17	-.37	.34	-.39															
10. Unhappy- MS.	-.35	-.43	-.22	.93	-.15	-.54	.31	-.50	.71														
11. Relaxed- MS	.35	.51	.30	-.29	.35	.58	-.20	.55	-.24	-.41													
12. Active- MS.	.55	.38	.26	-.01	.49	.40	-.39	.29	-.17	-.01	.27												
13. PWI-R	.78	.54	.61	-.16	.33	.47	-.01	.35	-.28	-.21	.20	.42											
14. Life Sat.-R	.47	.66	.57	-.34	.10	.63	.22	.51	-.25	-.42	.29	.11	.68										
15. Upset-R	-.22	-.43	-.15	.55	-.25	-.35	.05	-.47	.31	.50	-.22	.07	-.27	-.50									
16. Alert-R	.11	.27	.19	-.09	.72	.33	-.09	.31	.01	-.05	.33	.37	.30	.25	-.15								
17. Happy-R	.30	.56	.33	-.21	.08	.69	.07	.45	-.17	-.33	.35	.14	.47	.78	-.41	.38							
18. Tired-R	-.09	.00	.08	.33	-.28	-.15	.64	-.13	.19	.36	-.16	-.18	-.08	-.05	.27	-.21	-.08						
19. Content-R	.22	.47	.29	-.29	.24	.50	.09	.54	-.33	-.33	.32	.17	.34	.52	-.38	.37	.59	.00					
20. Annoyed-R	-.25	-.29	-.13	.26	-.25	-.21	-.01	-.49	.46	.23	-.20	-.02	-.27	-.33	.44	-.09	-.29	.25	-.23				
21. Unhappy-R	-.18	-.34	-.24	.42	.02	-.27	-.10	-.43	.27	.46	-.19	.23	-.33	-.53	.62	-.02	-.51	.11	-.42	.38			
22. Relaxed-R	.08	.27	.05	-.08	.06	.23	-.09	.11	-.14	-.16	.37	.17	.18	.32	-.01	.25	.39	.08	.46	.03	-.11		
23. Active-R	.26	.12	.27	.06	.20	.16	-.24	.02	-.21	.07	.14	.69	.38	.15	.17	.41	.19	-.11	.15	-.06	.05	.32	
M	65.65	65.42	24.76	1.79	5.70	6.15	4.26	5.77	2.30	2.08	5.73	5.09	68.14	6.58	3.30	6.46	6.84	5.02	6.30	2.54	2.82	6.14	6.44
SD	10.85	12.84	5.41	1.18	1.31	1.42	1.37	1.31	1.10	1.22	0.96	1.25	11.36	1.54	2.36	1.84	1.73	2.15	1.62	1.64	1.92	1.46	1.69

Note: Correlations of .27 to .36 are significant at p <.05; correlations of .37 to .43 are significant at p <.01; and correlations of .44 and above are significant at p <.001. R indicates recall measurement, MS indicates mean state measurement.

The correlations presented in Table 6.2 indicate moderate to strong correlations between SWLS, mean state PWI, LS, and mean state happiness, contentment, and activation. Surprisingly, the average correlation between mean state affect and recalled affect was not close to 1 (*M*=.57). The correlations between mean state affect and recalled affect, PWI, and LS are plotted in Figure 6.2.

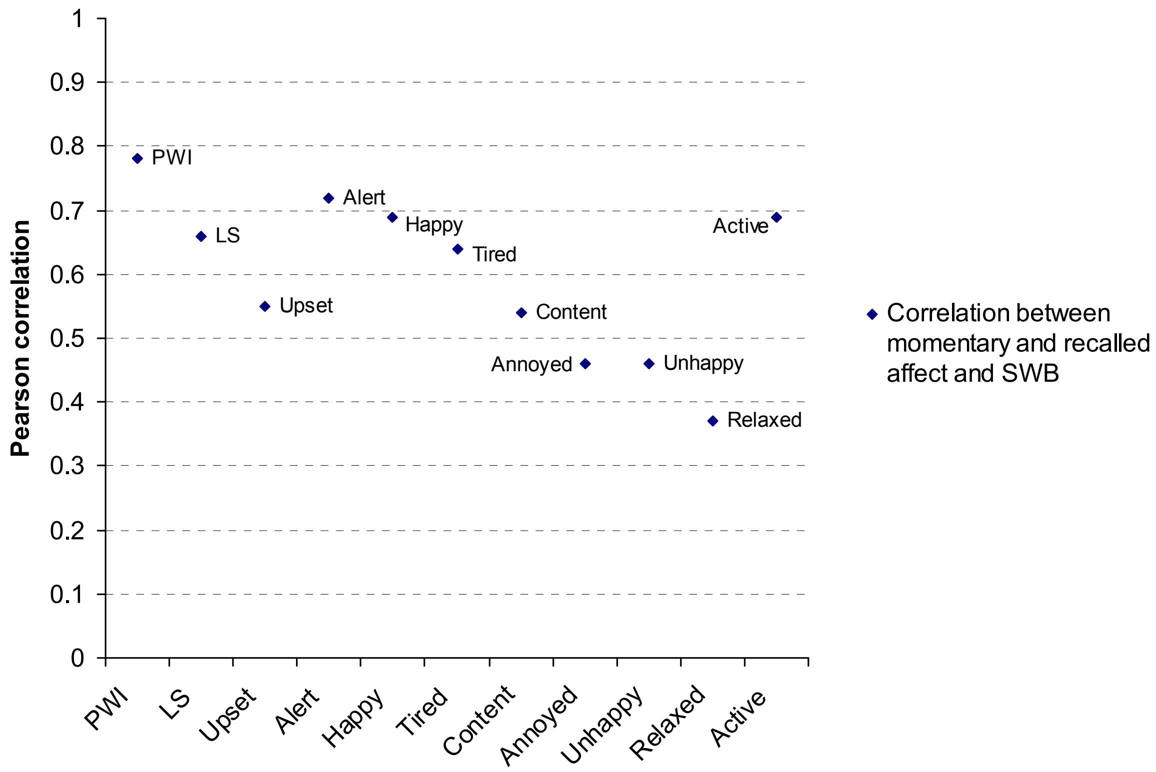


Figure 6.2: Average correlation between mean state affect and recalled affect, PWI, and LS. The ordinate reveals the Pearson correlation from 0 to 1 whilst the abscissa represents the relevant variable.

The correlations displayed in Figure 6.2 between mean state affect and recalled affect, PWI, and LS, ranged between .37 for relaxed to .78 for PWI. This data indicates participants' recalled estimate of their experienced affect and SWB over the 14 day study period was not an accurate reflection of the average of momentary experiences.

The stability and variability of daily LS and PWI was assessed in two ways. Firstly, average daily values of LS and PWI across all participants for each day of the 14 day study period were plotted (see Figure 6.3). Secondly, average LS scores across all participants at each of the three time signals over the 14 day study period (i.e., average LS across all participants and all days for signal 1) were plotted (see Figure 6.5). The plot of average daily LS and PWI across all participants for each day of the 14 day study is presented in Figure 6.3.

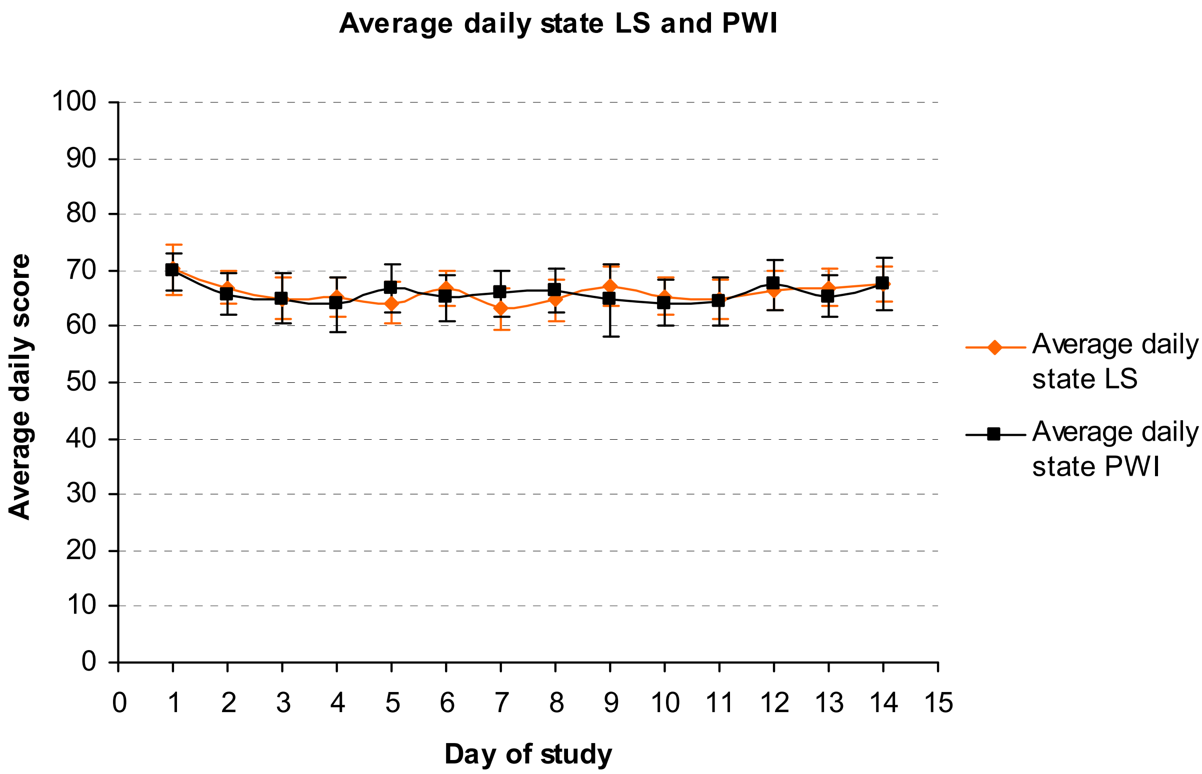


Figure 6.3: Average daily state LS and PWI across all participants (N=52) for each day of the 14 day study period. Error bars represent 95% Confidence Intervals (CI's) based upon Standard Errors (SE's) of the mean. The ordinate reveals life satisfaction and PWI scores ranging from 0 to 100, and the abscissa represents the day of the study. All cases were averaged for each day of the 14 day study period.

The data presented in Figure 6.3 illustrate the relative stability of average daily LS and PWI over the 14 days. During this period, average daily values did not exceed 70 or fall below 60. In addition, as shown in Figure 6.3, average daily PWI and average daily LS were very similar. In order to highlight the similarities and differences between average daily LS and PWI, these values are plotted over a restricted range (40 to 90), and are presented in Figure 6.4.

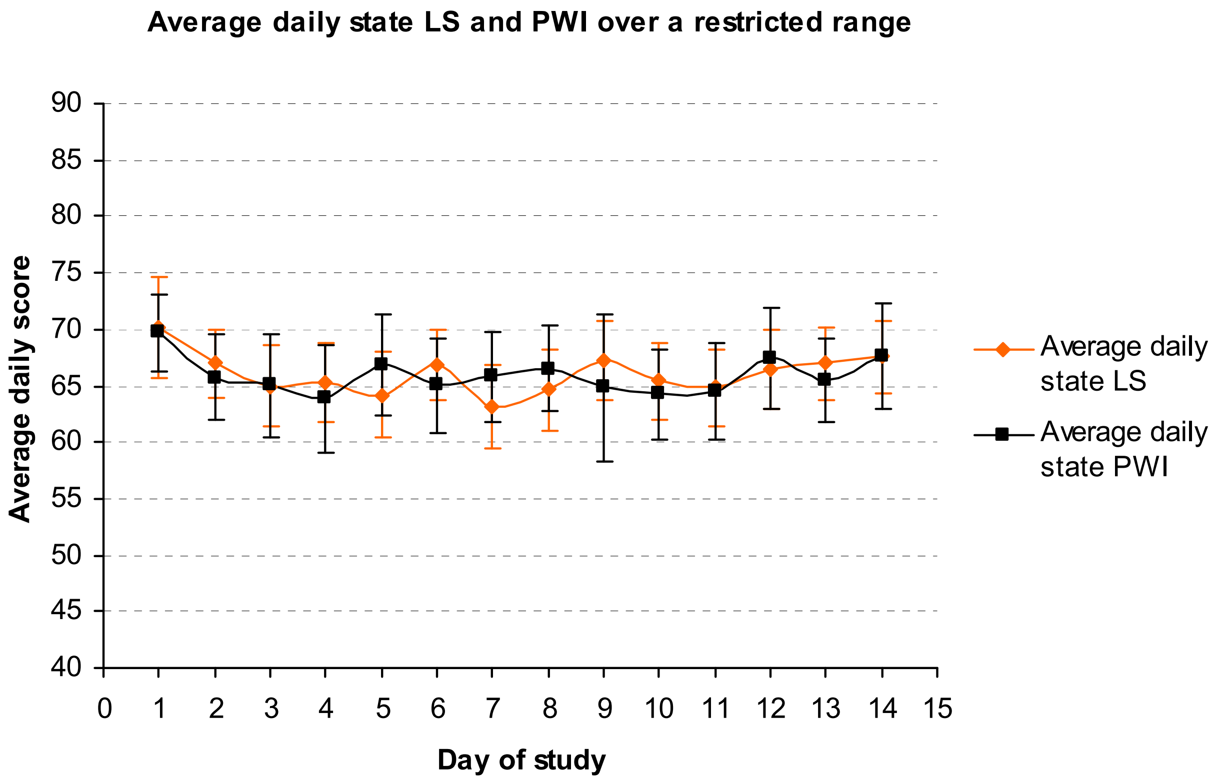


Figure 6.4: Average daily state LS and PWI across all participants (N=52) for each day of the 14 day study period over a restricted range of values (40 to 90). Error bars represent 95% Confidence Intervals (CI's) based upon SE's of the mean. The ordinate reveals life satisfaction and PWI scores ranging from 40 to 90, and the abscissa represents the day of the study. All cases were averaged for each day of the 14 day study period.

The data presented in Figure 6.4 illustrates the strong covariation between average daily state LS and average daily state PWI. The average LS scores across all participants for each time signal (signal 1, morning; signal 5, afternoon; and signal 8, evening) over the 14 day study period are plotted in Figure 6.5.

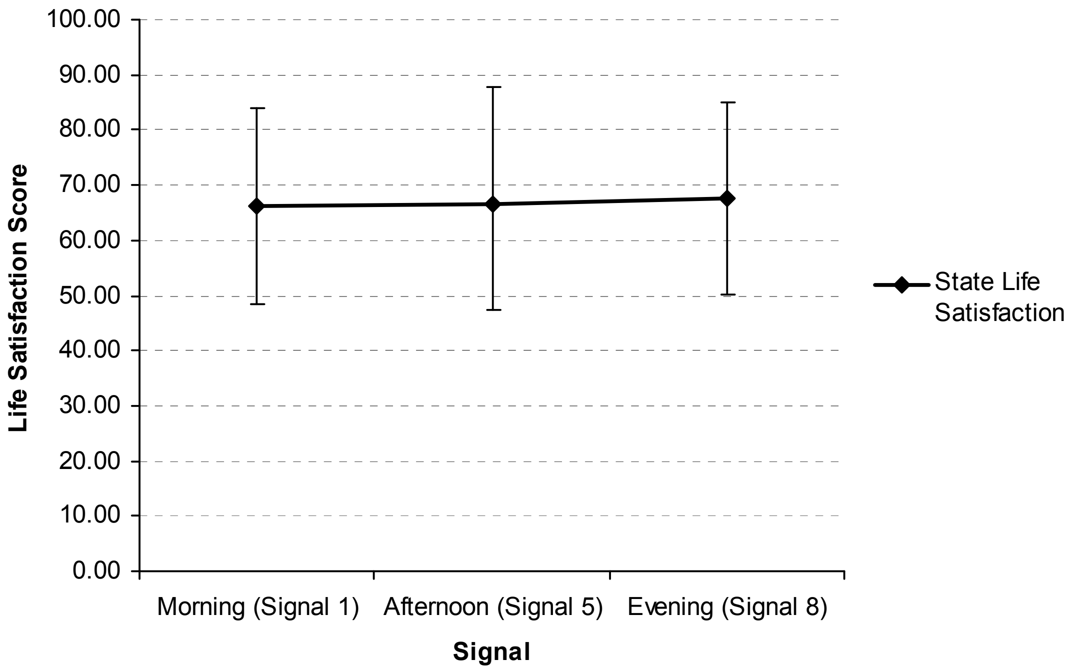


Figure 6.5: Average daily LS across all participants (N=52) and all 14 days of the study period for each time signal. Error bars represent 95% Confidence Intervals (CI's) based upon SE's of the mean. The ordinate reveals life satisfaction scores ranging from 0 to 100, and the abscissa represents the measurement time. All cases were averaged across all 14 days of the study period.

The data presented in Figure 6.5 reveal no appreciable variation in mean LS scores from the morning (signal 1), to the afternoon (signal 5), to the evening (signal 8). Thus, on average, within each day of the 14 day study period, LS remained relatively stable from the morning to the evening. However, the error bars, representing the variance in LS scores for 95% of participants (95%CI) at each signal, indicate appreciable variation in LS scores. It is interesting to note that this variance in LS scores is restricted to the positive range of the LS scale. To examine this variation in LS scores, a random sample of 10 individual's mean LS scores for each signal (morning, afternoon, evening) were plotted. To ensure an accurate estimate of mean LS, each individual must have recorded LS scores a minimum of 8 times for each signal across the 14 day study period (yielding a minimum total of 24 separate LS measurements). Of a possible 420 measurements of LS across these 10 people, 300 were recorded, yielding a response rate of 71% (comparable to the overall sample response rate of 72.5%). These average LS scores for 10 individuals at each signal across the 14 day study period are presented in Figure 6.6.

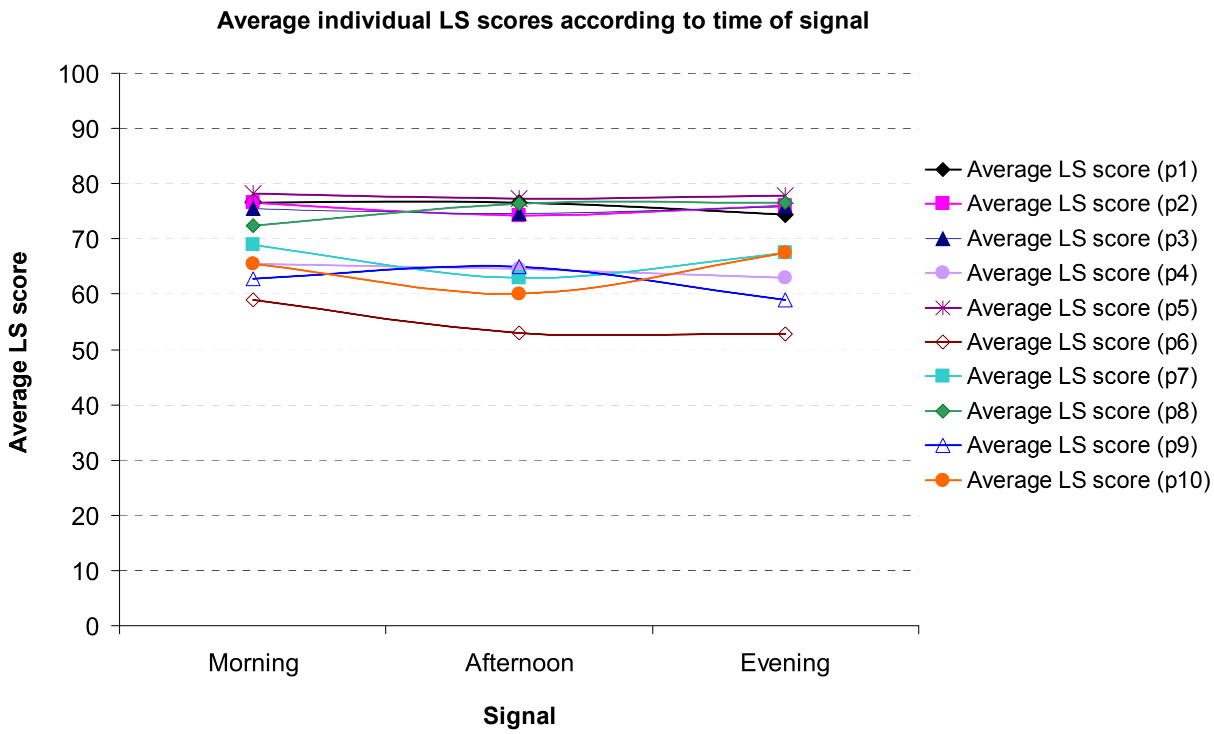


Figure 6.6: Average individual LS scores of a random sample of 10 individuals across 14 days for each signal time point (morning, afternoon, evening). The average LS scores were computed from a minimum of 8 separate measurements at each signal time point. The ordinate reveals life satisfaction scores ranging from 0 to 100, and the abscissa represents the measurement time. The scores for each individual were averaged across all 14 days of the study period.

In order to illustrate the differences and similarities for individual average LS scores across each signal, the data presented in Figure 6.6 are given over a restricted range (40 to 90) in Figure 6.7.

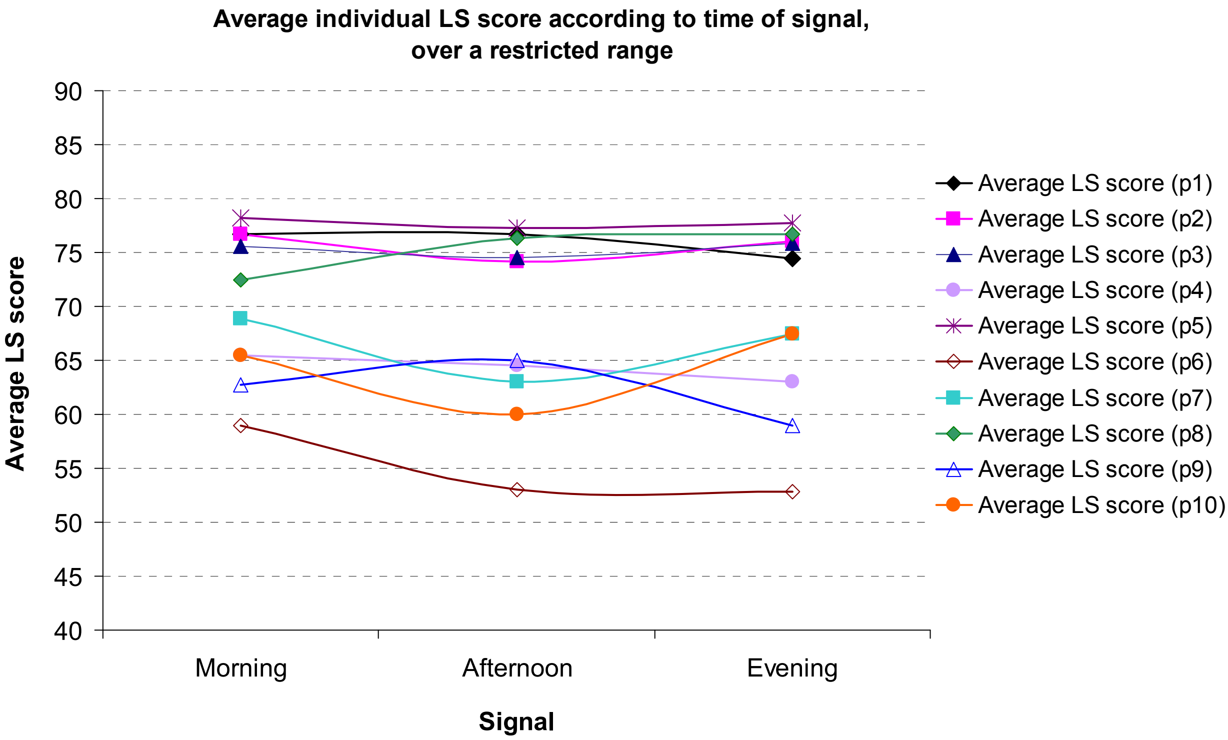


Figure 6.7: Average individual LS scores of a random sample of 10 individuals across 14 days for each signal time point (morning, afternoon, evening) over a restricted range (40 to 90). The average LS scores were computed from a minimum of 8 separate measurements at each signal time point. The ordinate reveals life satisfaction scores ranging from 40 to 90, and the abscissa represents the measurement time. The scores for each individual were averaged across all 14 days of the study period.

The data presented in Figures 6.6 and 6.7 for these 10 individuals indicates that, on average, over the 14 day study period (and a minimum of 24 separate LS measurements), individual LS scores varied within a maximum range of only 10 points. To further investigate the relative stability of LS, an analysis of individual means and standard deviations was undertaken, both within-persons and between-persons. Stability was considered to be demonstrated if the variance in LS within-persons was less than the variance between-persons. This analysis required the calculation of average *SD* within-persons, and average *SD* between-persons. In addition, as within-person variance is comprised of circadian variance, an estimate of average circadian variance was computed in order to control for daily fluctuations in LS. The components of variance used to determine stability in LS are given in Equation 6.1.

$$\sigma_{LS\ Total} = \sigma_{LS\ Avg\,Within-persons} + \sigma_{LS\ Avg\,Between-persons} \quad \therefore$$

$$\sigma_{LS\ Avg\,Between-persons} = \sigma_{LS\ Total} - \sigma_{LS\ Avg\,Within-persons} \qquad \text{(Eqn 6.1)}$$

$$\sigma_{LS\ Avg\,Within-persons} = \sigma_{Error} + \sigma_{LS\ Avg\,Circadian}$$

Thus, if $\sigma_{LS\ Avg\,Within-persons} < \sigma_{LS\ Avg\,Between-persons}$ after controlling for circadian variance, then LS will be considered stable over time. The circadian variance must be removed from the estimate of within person variability to remove systematic variance that is unrelated to stability. Each individual's mean LS score, standard error, overall standard deviation, and average daily (circadian) *SD* was then computed. This data is presented in Table 6.3.

Table 6.3: Overall mean LS, standard deviation, standard error, and average daily (circadian) standard deviation scores for each participant.

Participant Number (*n*)	**Overall *Mean* LS**	***S.E.***	**Overall *S.D.***	**Avg Daily *S.D.***	**Participant Number (*n*)**	**Overall *Mean* LS**	***S.E.***	**Overall *S.D.***	**Avg Daily *S.D.***	**Participant Number (*n*)**	**Overall *Mean* LS**	***S.E.***	**Overall *S.D.***	**Avg Daily *S.D.***
1 (35)	75.14	0.95	5.62	1.05	24 (20)	68.50	1.96	8.75	2.34	45 (16)	70.63	2.81	11.24	3.25
2 (36)	75.28	1.29	7.74	1.06	25 (19)	56.84	6.35	27.70	4.50	47 (36)	82.20	0.70	4.23	1.02
3 (32)	75.31	1.10	6.21	0.55	26 (39)	82.31	0.78	4.85	1.28	48 (38)	36.03	2.28	14.05	1.03
5 (16)	65.00	1.83	7.30	4.59	27 (30)	77.67	2.82	15.47	4.37	49 (19)	61.58	3.08	13.44	1.64
6 (39)	64.36	1.31	8.21	1.01	28 (31)	76.45	1.19	6.61	1.71	50 (34)	69.41	0.59	3.43	0.86
7 (37)	76.49	0.97	5.88	0.37	31 (40)	71.50	1.66	10.51	1.14	51 (20)	76.00	2.34	10.46	1.70
8 (25)	87.20	4.10	20.52	2.30	32 (29)	34.14	3.53	19.00	5.26	52 (15)	58.67	5.24	20.31	5.40
9 (33)	55.76	2.35	13.47	2.86	33 (24)	47.92	3.30	16.15	3.47	54 (30)	58.33	2.63	14.40	1.89
10 (23)	56.52	2.56	12.29	2.34	34 (29)	47.93	2.74	14.73	2.22	55 (27)	51.11	3.59	18.67	2.68
12 (32)	66.88	2.44	13.78	2.51	35 (26)	75.00	1.14	5.83	1.90	56 (36)	87.50	2.96	17.79	2.73
13 (29)	75.17	3.00	16.17	1.90	36 (36)	64.72	3.73	22.49	3.17	57 (35)	46.00	1.02	6.04	1.39
14 (29)	74.83	2.51	13.53	2.22	37 (24)	66.67	1.77	8.68	2.61	58 (36)	79.44	2.55	15.30	4.49
15 (36)	79.72	1.35	8.10	1.90	38 (22)	69.55	0.45	2.13	0.67	59 (22)	55.00	4.04	18.96	1.60
17 (30)	68.00	2.69	14.72	2.00	39 (35)	73.71	1.48	8.77	2.16	60 (23)	55.65	4.07	19.50	12.64
18 (19)	71.58	1.15	5.01	1.18	40 (27)	43.33	1.85	9.61	0.68					
19 (31)	74.84	2.89	16.10	5.33	41 (36)	43.06	1.53	9.20	0.47					
20 (18)	66.67	3.70	15.72	6.01	42 (15)	56.00	3.75	14.54	1.63					
22 (34)	77.35	0.88	5.11	0.46	43 (30)	51.00	1.47	8.03	2.74					
23 (36)	61.94	2.64	15.82	2.47	44 (16)	52.50	5.66	22.66	3.75					

Average Overall Mean LS = 65.28
Average Overall Within-person *SD* = 12.21
Average Within-person Daily *SD* = 2.51

Note: The (*n*) following participant number denotes the number of LS measurements for that participant.

The data presented in Table 6.3 indicates mean LS scores for each individual across the 14 day study period ranged from 34.14 to 87.5 (*M*=65.28). The variation in each individual's mean LS scores over the 14 day study period ranged from 2.13 to 27.7 (*mean SD*=12.21). In order to obtain an accurate estimate of stability in LS, average within-person variance (after controlling for circadian variance), must be compared to average between-person variance. Average between-person variance was obtained by subtracting total within-person variance (12.21) from the total variance in LS over all persons and all time points. The total variance in LS was 18.44 (*M*=65.92, *N*=1485). Thus between-person variance equals 6.23. To compute final within-person variance (controlling for circadian variance), the average circadian variance in LS of 2.51 (see Table 6.3) was subtracted from the average within-person LS *SD* (12.21). This gave a final estimate of within-person variance (controlling for circadian variance) of 9.70. Comparing within-person variance (9.70) to between-person variance (6.23) indicates there is more variation in LS within individuals than between individuals.

The relationship between mean LS scores and the variation in LS scores for each individual was then examined. This relationship is illustrated in an xy-plot of individual LS means and standard deviations given in Figure 6.8.

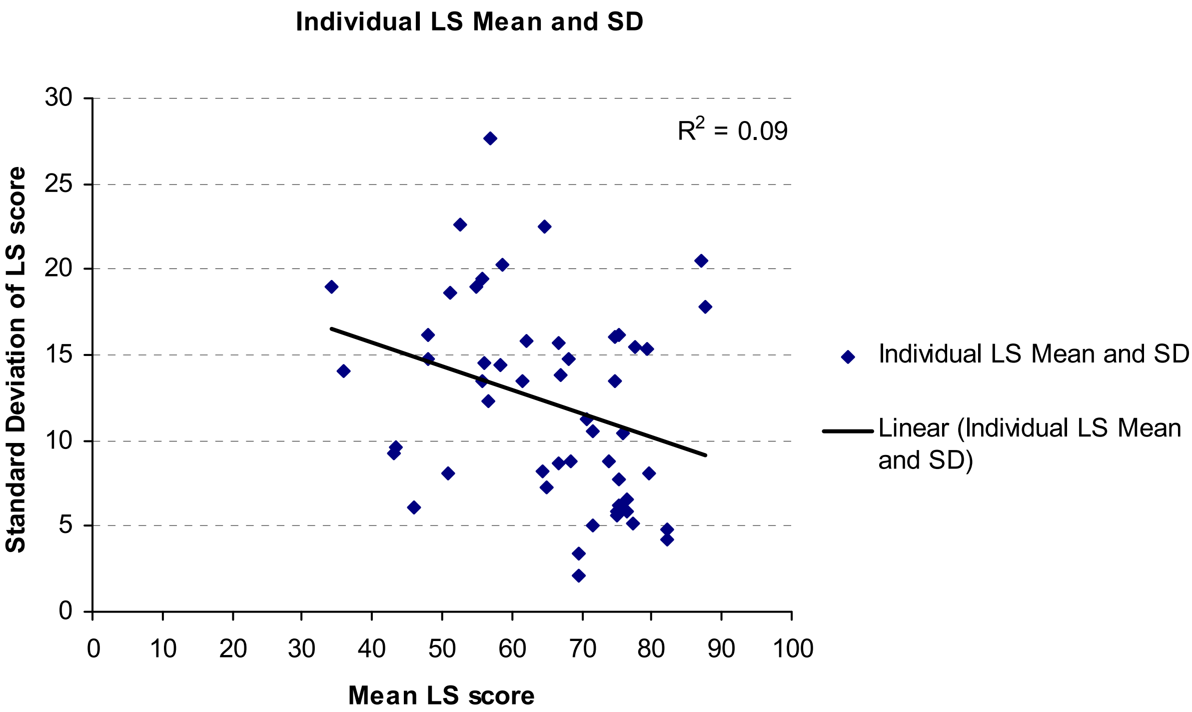


Figure 6.8: XY-plot of each individuals mean and standard deviation LS score across the 14 day study period (N=52). The correlation between individual LS means and standard deviations is r=.30 (R^2=.09). The ordinate reveals the standard deviation of mean life satisfaction scores and the abscissa represents mean life satisfaction scores averaged across all measurement time points.

The data presented in Figure 6.8 indicates an inverse relationship between individual mean LS scores and standard deviations. Thus, as mean LS scores increasd, the variation in LS decreased. This result is consistent with the prediction of homeostatic theory that the variance in SWB increases as scores fall below the individual's set-point (Cummins et al., 2002; Cummins, 2003; see Figure 2.2, Chapter 2). However, homeostatic theory also proposes that if an individual experiences excessively high levels of SWB, the homeostatic mechanism will work to pull the individual back toward their set-point (see Figure 2.2, Chapter 2). To demonstrate the operation of such a mechanism, variance in SWB must also *increase* as scores above the normal level of

SWB increases. To test this, individual mean LS scores and standard deviations were again plotted and analysed for evidence of a second order polynomial trend. Cutoff scores were chosen to maximise the variance explained by the polynomial function whilst being consistent with the theoretical prediction of homeostatic theory that homeostatic failure occurs for SWB scores of approximately 50 and below (Cummins et al., 2002). This analysis is presented in Figure 6.9.

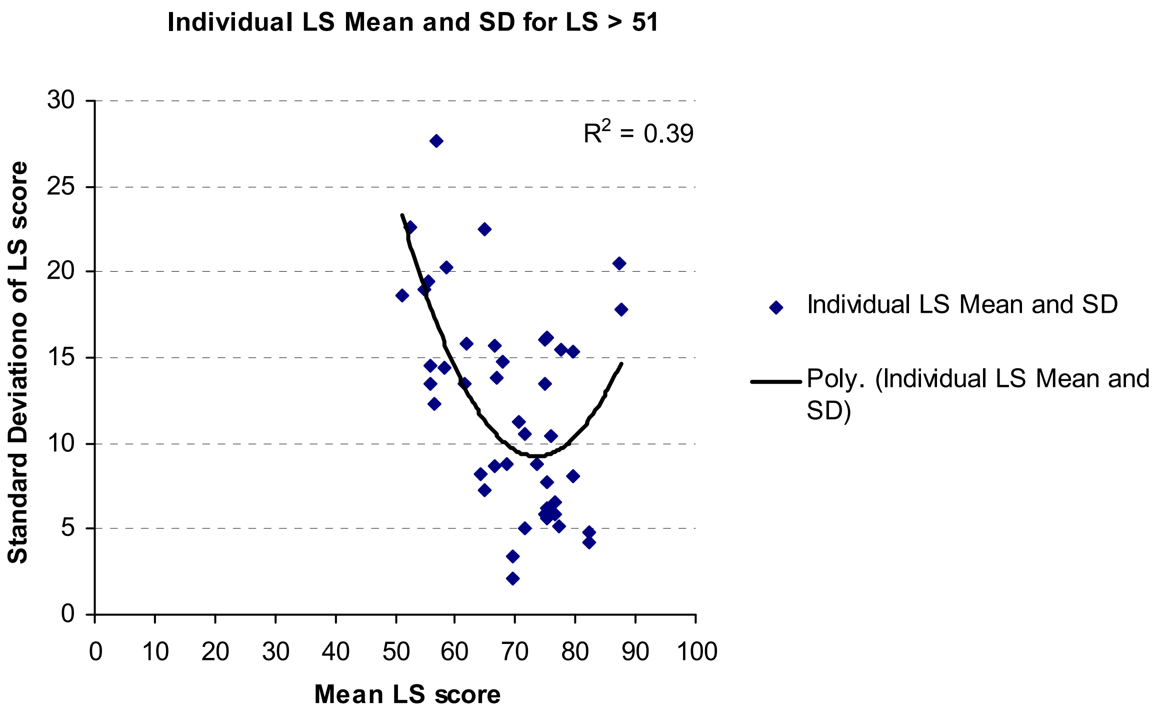


Figure 6.9: XY-plot of individual mean and standard deviation LS scores across 14 day study period over a restricted range (LS scores>51; N=44). The second order polynomial yields an R^2 of .39. The ordinate reveals the standard deviation of mean life satisfaction scores and the abscissa represents mean life satisfaction scores averaged across all measurement time points.

The data contained in Figure 6.9 indicate that variance in SWB increases either side of mean LS scores of approximately 72. Once mean scores approach 72, variance in LS decreases. This result suggests the operation of a homeostatic system. In order to verify this result, the linear trends in mean LS scores and standard deviations above and below 72 were analysed. These results are given in Figure 6.10 for LS mean scores below 72, and in Figure 6.11 for LS mean scores above 72.

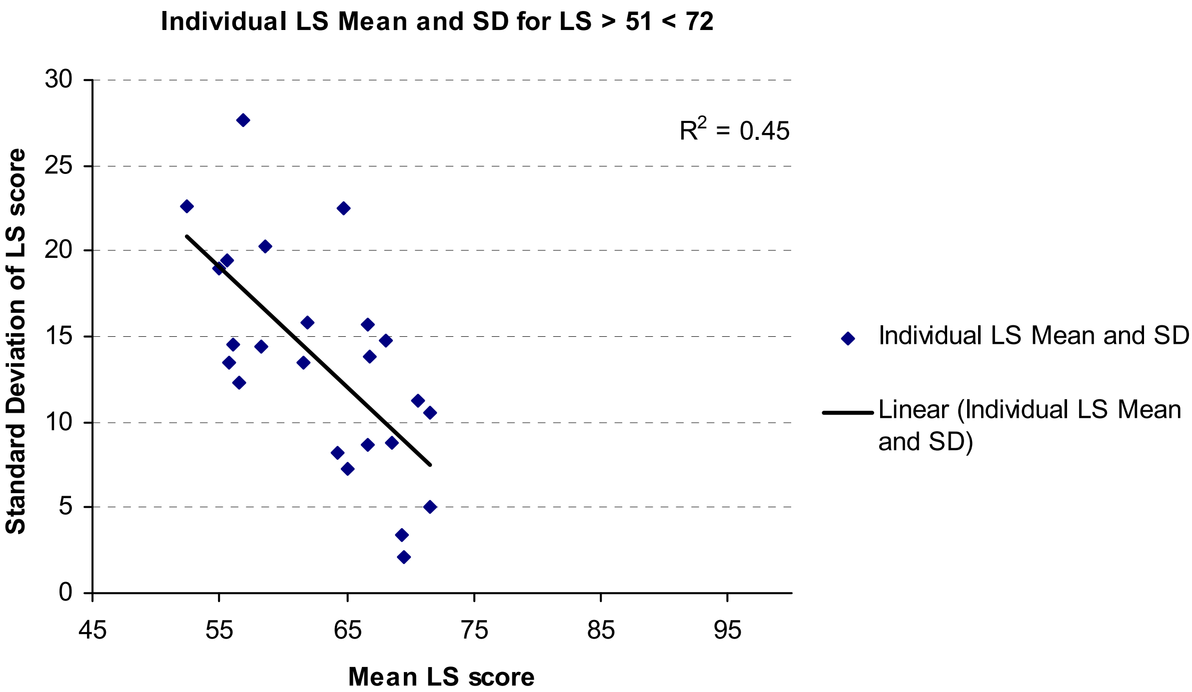


Figure 6.10: XY-plot of individual mean and standard deviation LS scores across 14 day study period demonstrating linearity over a restricted range (LS scores>51<72; N=24). The correlation between LS means and standard deviations is r=.67 (R^2=.45). The ordinate reveals the standard deviation of mean LS scores and the abscissa represents mean life satisfaction scores averaged across all measurement time points.

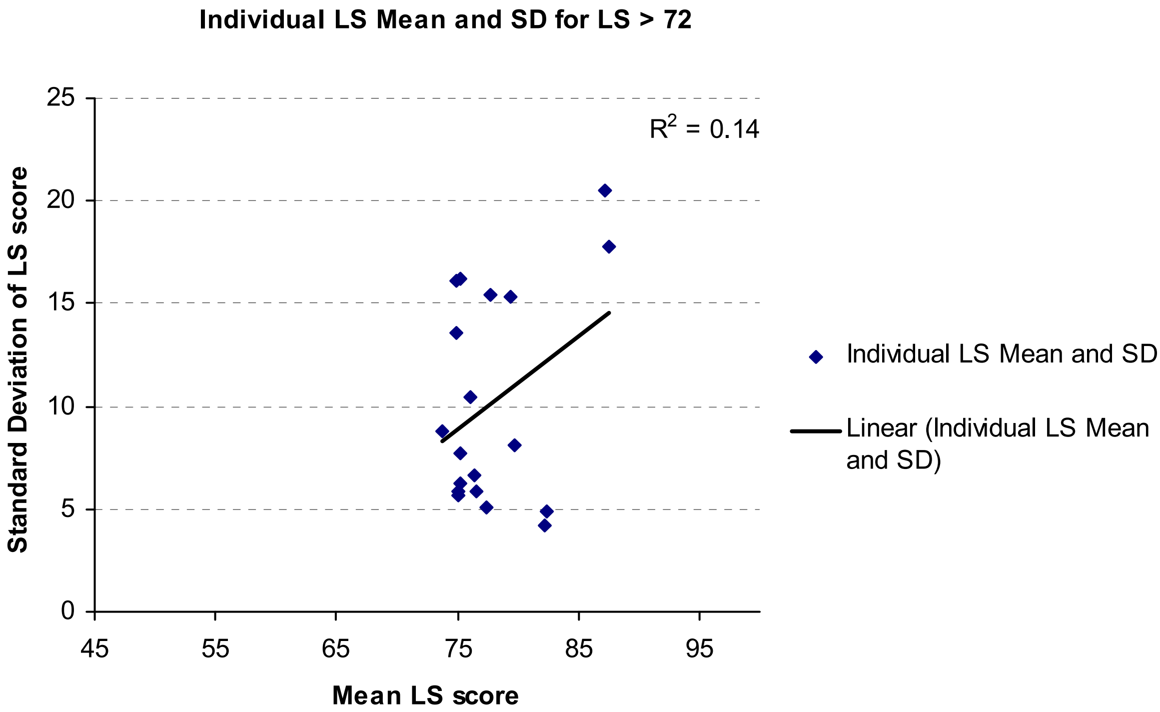


Figure 6.11: XY-plot of individual mean and standard deviation LS scores across 14 day study period demonstrating linearity over a restricted range (LS scores>72; N=19). The correlation between LS means and standard deviations is r=.37 (R^2=.14). The ordinate reveals the standard deviation of mean life satisfaction scores and the abscissa represents mean life satisfaction scores averaged across all measurement time points.

The data contained in Figures 6.10 and 6.11 further indicate that the variance in LS increases above and below a mean score of approximately 72. The analysis of stability in LS was repeated for PWI. This analysis proceeded by computing each individuals average PWI and *SD*. These data are presented in Table 6.4.

Table 6.4: Overall mean PWI and standard deviation scores for each participant.

Participant number (*n*)	Overall *M* PWI	Overall *M* *SD*	Participant number (*n*)	Overall *M* PWI	Overall *M* *SD*	Participant number (*n*)	Overall *M* PWI	Overall *M* *SD*
1 (13)	76.48	3.67	24 (7)	61.63	5.31	45 (7)	66.53	9.22
2 (13)	64.73	5.58	25 (5)	65.71	4.29	47 (12)	80.24	2.71
3 (12)	59.76	3.21	26 (13)	77.47	2.34	48 (13)	66.48	2.58
5 (4)	68.57	7.28	27 (11)	82.60	11.83	49 (5)	66.86	15.95
6 (14)	68.37	4.88	28 (11)	80.78	3.69	50 (13)	63.08	.98
7 (13)	66.70	3.89	31 (14)	71.63	2.37	51 (8)	69.11	14.37
8 (9)	74.29	7.07	32 (9)	44.44	11.30	52 (2)	69.29	1.01
9 (11)	58.44	5.87	33 (9)	50.16	17.22	54 (11)	67.01	7.04
10 (11)	55.84	7.04	34 (10)	52.86	6.17	55 (8)	63.21	7.74
12 (13)	65.16	8.11	35 (9)	72.54	3.63	56 (11)	79.87	6.89
13 (10)	76.29	10.61	36 (12)	48.57	10.66	57 (11)	50.91	4.05
14 (10)	76.14	6.80	37 (7)	77.76	4.73	58 (12)	72.74	5.00
15 (11)	82.99	7.21	38 (7)	73.27	1.59	59 (9)	40.48	5.89
17 (10)	56.29	7.71	39 (12)	61.31	7.64	60 (9)	63.65	6.23
18 (8)	73.93	2.26	40 (8)	50.00	7.40			
19 (12)	78.33	6.03	41 (12)	44.76	5.04	Avg Overall Mean PWI=65.88		
20 (4)	61.43	14.62	42 (5)	61.14	7.38	Avg Overall Within-person SD=6.69		
22 (14)	80.51	1.99	43 (8)	65.54	1.42			
23 (14)	48.06	19.41	44 (7)	60.00	11.03	Total SD=13.29		

Note: PWI was measured once per day. The (*n*) following participant number denotes the number of PWI measurements for that participant.

The data contained in Table 6.4 indicates mean PWI scores for each individual across the 14 day study period ranged from 40.48 to 82.99 (*M*=65.88). The variation in each individual's mean LS scores over the 14 day study period ranged from .98 to 15.95 (*mean SD*=6.69). In order to obtain an estimate of stability in PWI, average overall within-person variance (6.69) was compared to the average between-person variance. Average between-person variance was obtained by subtracting within-person variance (6.69) from the total variance in PWI over all time points (*N*=513) and all persons (total *SD*=13.29). Thus, between-person variance equals 6.6, which is slightly higher than the within-person variance of 6.69. This indicates that the variation in PWI within-persons is slightly higher than the variation in PWI between-persons. The relationship between mean PWI scores and the variation in PWI scores for each individual was then examined. This relationship is illustrated in an xy-plot of individual PWI means and standard deviations given in Figure 6.12.

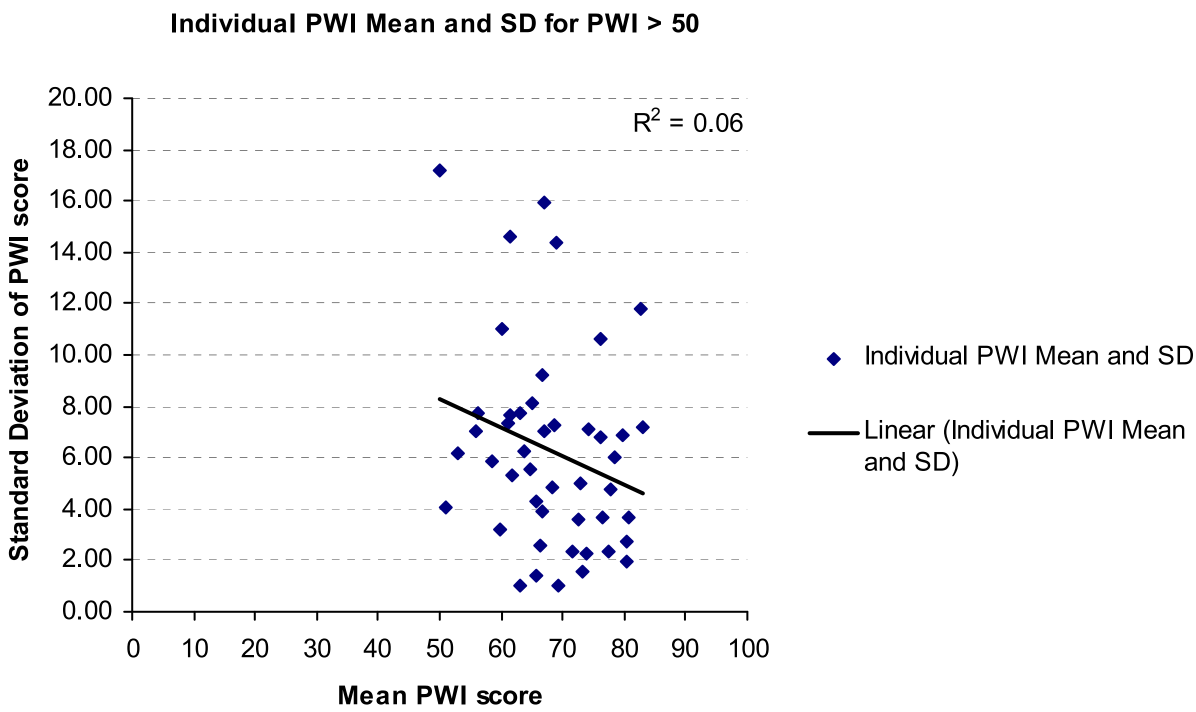


Figure 6.12: XY-plot of each individuals mean and standard deviation PWI score across 14 day study period (N=52). The correlation between PWI means and standard deviations is r=.24 (R^2=.06). The ordinate reveals the standard deviation of mean PWI scores and the abscissa represents mean PWI scores averaged across all measurement time points.

The data presented in Figure 6.12 indicates an inverse relationship between mean PWI and standard deviation. Thus, the variability in PWI decreases as mean scores increase. However, as for LS, PWI means and standard deviations were tested for evidence of increased variance above and below mean scores of approximately 72. This analysis is presented in Figure 6.13.

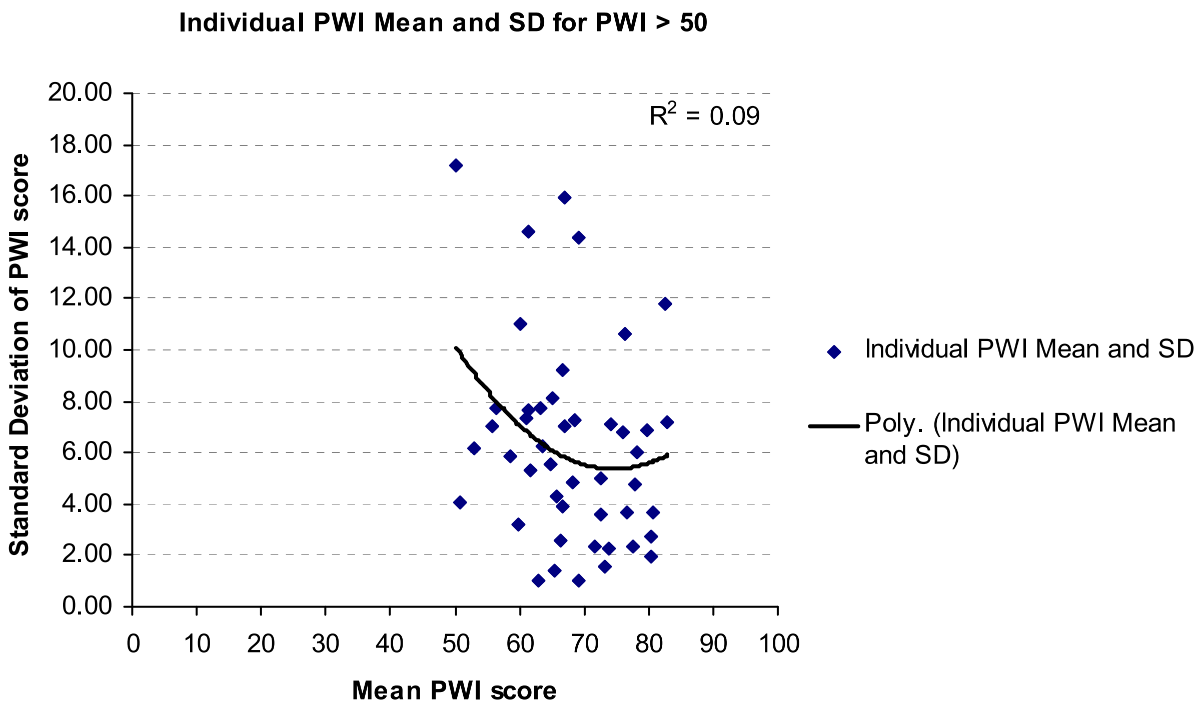


Figure 6.13: XY-plot of individual mean and standard deviation PWI scores across 14 day study period over a restricted range (PWI scores>50; N=46). The second order polynomial yields an R^2 of .09. The ordinate reveals the standard deviation of mean PWI scores and the abscissa represents mean PWI scores averaged across all measurement time points.

As for LS, the data presented in Figure 6.13 indicate a trend toward increased variance in PWI above and below a mean score of approximately 72. To verify this result, PWI means and standard deviations were tested for linear trends above and below scores of approximately 72. These analyses are presented in Figure 6.14 for PWI scores below 72 and Figure 6.15 for PWI scores above 72.

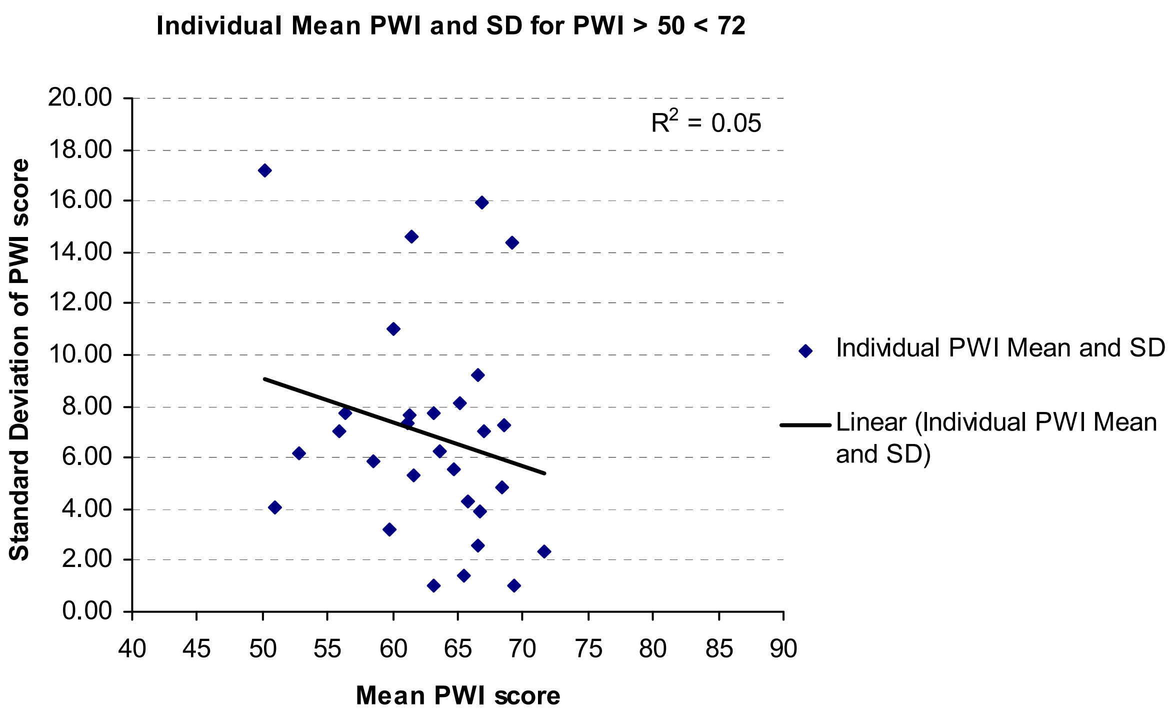


Figure 6.14: XY-plot of individual mean and standard deviation PWI scores across 14 day study period demonstrating linearity over a restricted range (PWI scores>50<72; N=29). The correlation between PWI means and standard deviations is r=.23 (R^2=.05). The ordinate reveals the standard deviation of mean PWI scores and the abscissa represents mean PWI scores averaged across all measurement time points.

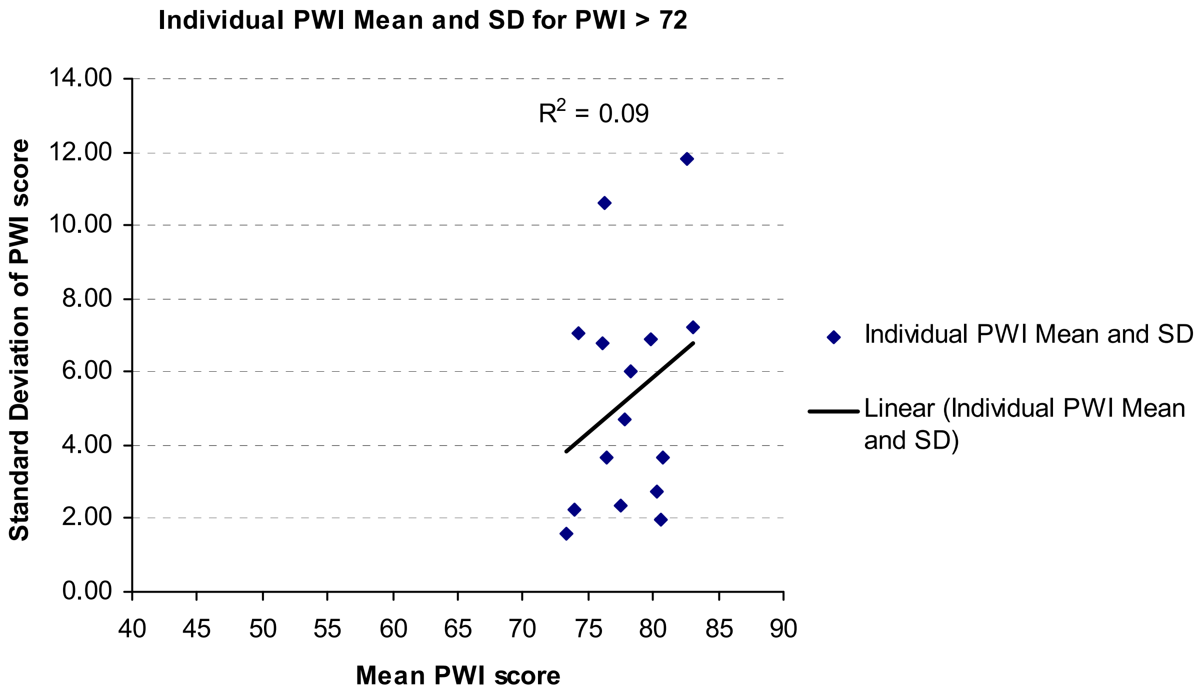


Figure 6.15: XY-plot of individual mean and standard deviation PWI scores across 14 day study period demonstrating linearity over a restricted range (PWI scores>72; N=17). The correlation between PWI means and standard deviations is r=.31 (R^2=.10). The ordinate reveals the standard deviation of mean PWI scores and the abscissa represents mean PWI scores averaged across all measurement time points.

The data contained in Figures 6.14 and 6.15 further demonstrate that above and below mean PWI scores of approximately 72, the variance in PWI increases, suggesting the operation of a homeostatic system.

Stability and Variability in Momentary Measures of PACA

Testing proceeded by examining average scores of happiness, contentment, and activity, which together form PACA. As with LS and PWI, individual PACA means and standard deviations were tested for evidence of increased variance above and below a particular mean score. The average scores for happiness, contentment, and activity, across all participants for each day of the 14 day study period, are plotted in Figure 6.16.

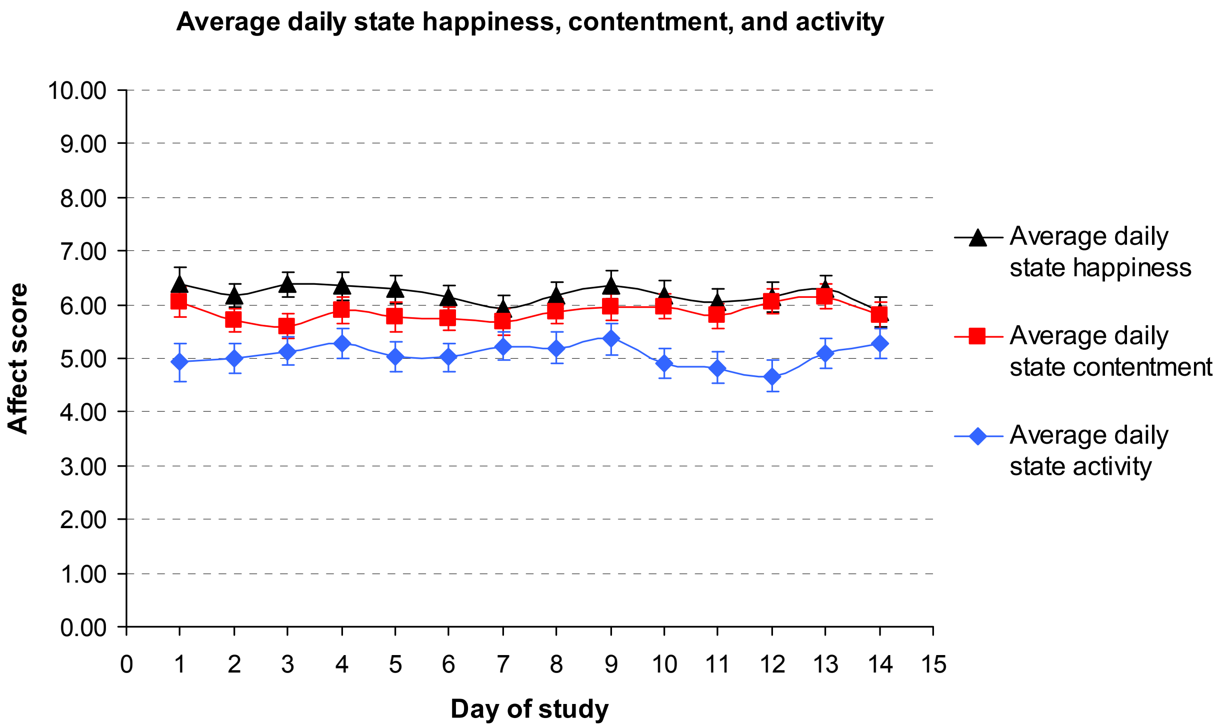


Figure 6.16: Average daily state happiness, contentment, and activity across all participants (N=52) for each day of the 14 day study period. Affect scores range from a minimum of 0 to a maximum of 10. The number of separate measurements of daily happiness, contentment, and activity ranged from a minimum of 181 (Day 1) to a maximum of 337 (Day 3). Error bars represent 95%CI's, based upon SE's of the mean. The ordinate reveals affect scores ranging from 0 to 10, and the abscissa represents the day of the study. All cases were averaged for each day of the 14 day study period.

In order to illustrate the differences and similarities between average daily happiness, contentment, and activity for each day of the 14 day study period, the data presented in Figure 6.16 are given over a restricted range (4 to 8) in Figure 6.17.

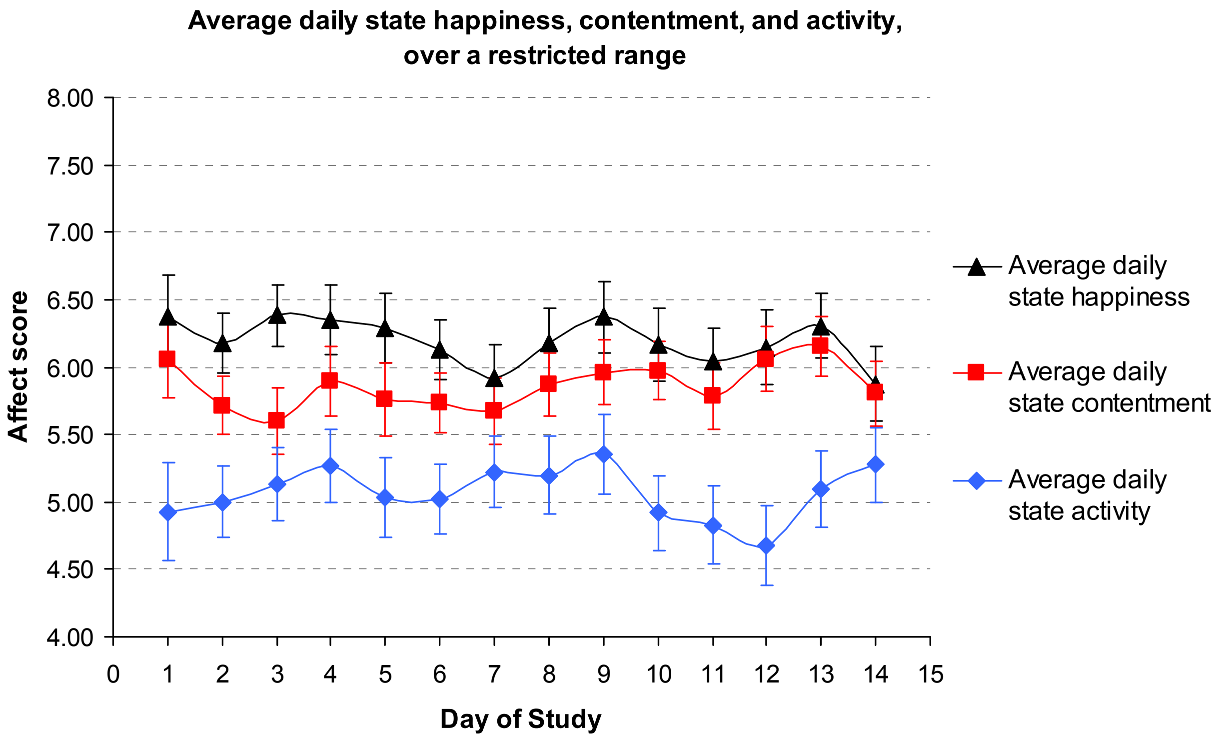


Figure 6.17: Average daily state happiness, contentment, and activity across all participants (N=52) for each day of the 14 day study period over a restricted range (4 to 8). The number of separate measurements of daily happiness, contentment, and activity ranged from a minimum of 181 (Day 1) to a maximum of 337 (Day 3). Error bars represent 95%CI's, based upon SE's of the mean. The ordinate reveals affect scores ranging from 4 to 8, and the abscissa represents the day of the study. All cases were averaged for each day of the 14 day study period.

The plot of average daily happiness, contentment, and activity presented in Figure 6.16 and Figure 6.17 indicate that, as with LS and PWI, average daily happiness and contentment exhibited little variation over the course of the study period, with average values not exceeding 6.5 or falling below 5.5. In addition, average daily activity, although consistently lower than happiness and contentment, displayed little variation over the 14 days. Average values for activity did not exceed 5.5, or fall below 4.5. The average happiness, contentment, and activity scores across all participants for each time signal (signal 1, morning; signal 5, afternoon; and signal 8, evening) over the 14 day study period are plotted in Figure 6.18.

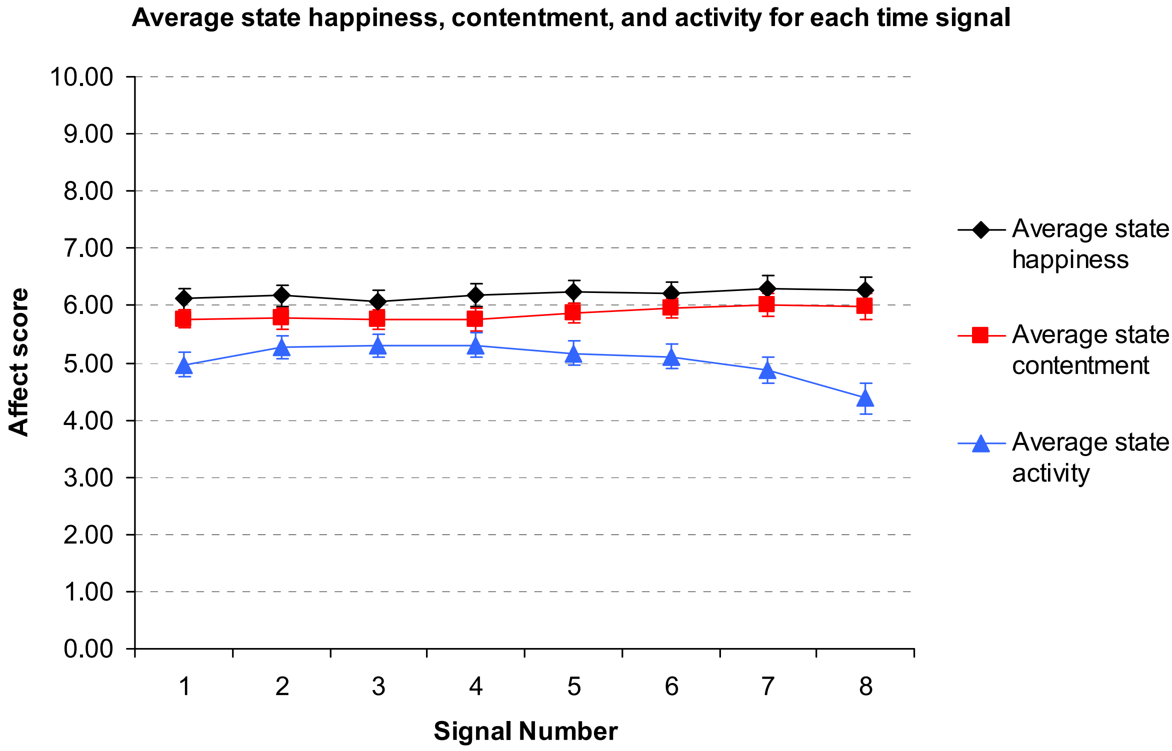


Figure 6.18: Average happiness, contentment, and activity scores across all individuals and all 14 days of the study period for each time signal. Error bars represent 95%CI's, based upon SE's of the mean. The ordinate reveals affect scores ranging from 0 to 10 and the abscissa represents the measurement time. All cases were averaged across all 14 days of the study period.

In order to illustrate the differences and similarities between average daily happiness, contentment, and activity according to each time signal, the data presented in Figure 6.12 is given over a restricted range (3 to 7) in Figure 6.19.

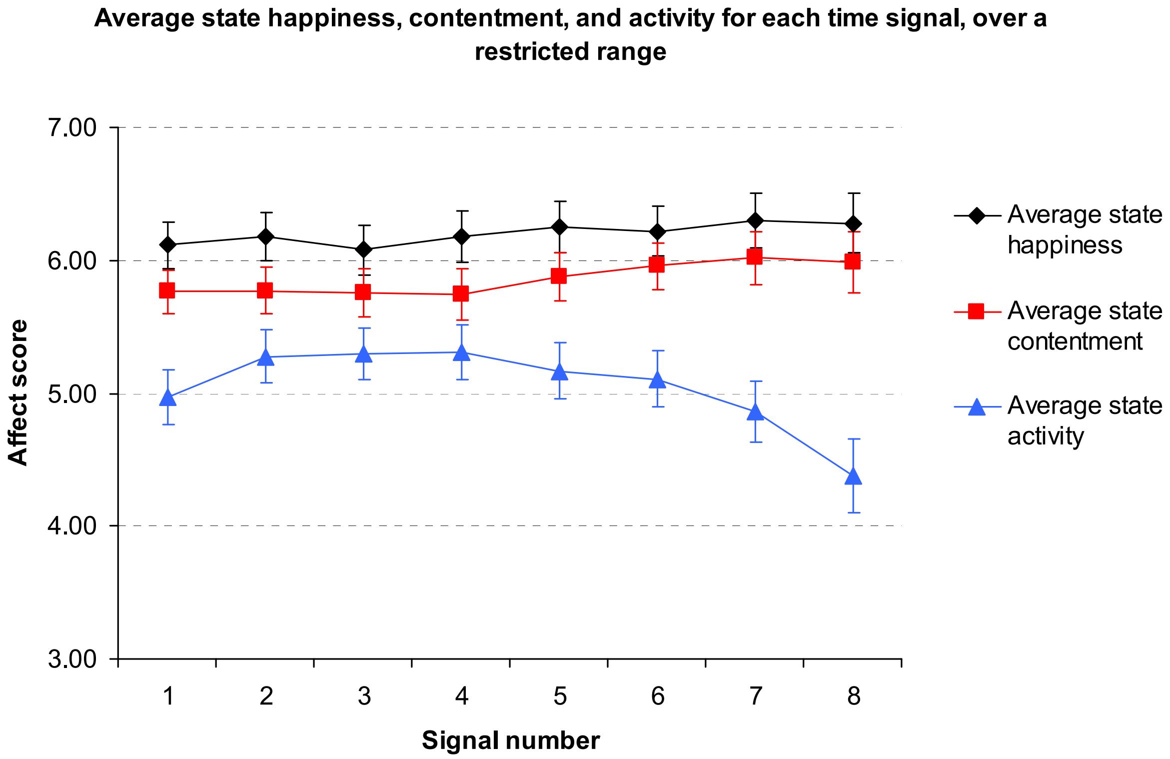


Figure 6.19: Average happiness, contentment, and activity scores across all individuals and all 14 days of the study period for each time signal over a restricted range (3 to 7). Error bars represent 95%CI's based upon SE's of the mean. The ordinate reveals affect scores ranging from 3 to 7 and the abscissa represents the measurement time. All cases were averaged across all 14 days of the study period.

The data presented in Figures 6.18 and 6.19 indicate that, on average, across all individuals, happiness and contentment remained stable over the course of the 12.5 hour signalling period. In comparison, activity showed a clear decline towards the end of the day. The small error bars indicate low variability in average happiness, contentment and activity over a typical day for 95% of the sample.

As evidence for the existence of a homeostatic mechanism was found in LS and PWI, this possibility is investigated for PACA. Individual PACA means and standard deviations are plotted for PACA scores above 15 (corresponding to 50%SM) in Figure 6.20.

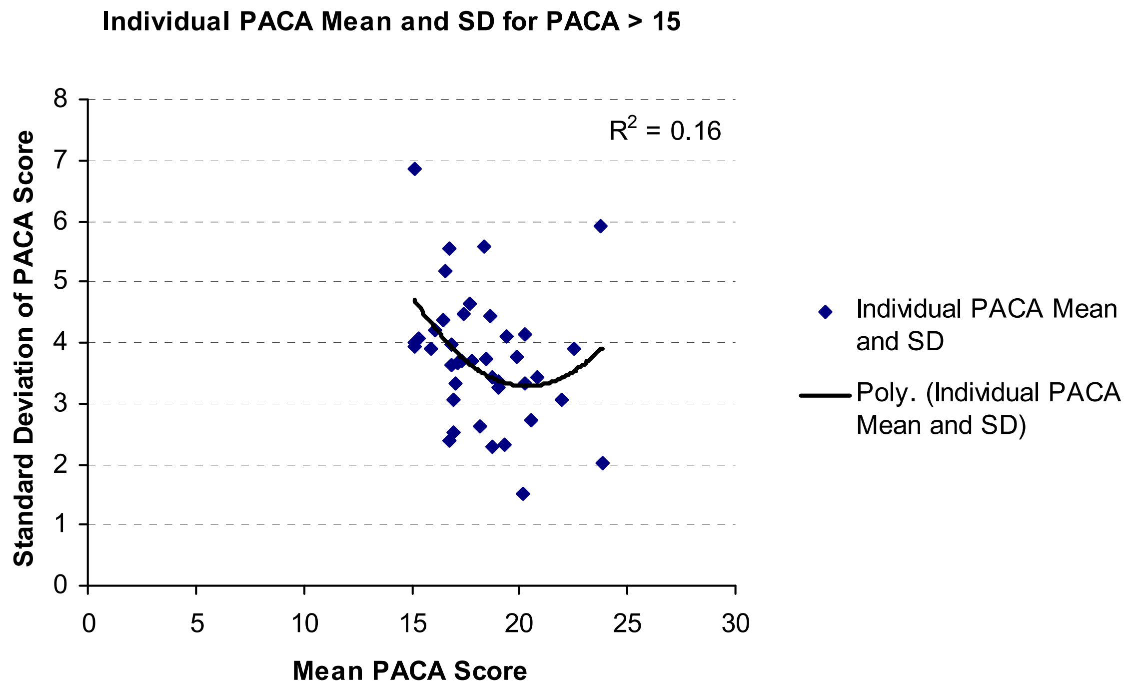


Figure 6.20: XY-plot of individual mean and standard deviation PACA scores across 14 day study period over a restricted range (PACA scores>15(50%SM); N=40). The second order polynomial yields an R^2 of .16. The ordinate reveals the standard deviation of mean PACA scores and the abscissa represents mean PACA scores averaged across all measurement time points.

The data contained in Figure 6.20 indicate that variance in PACA increases above and below a mean PACA score of approximately 20 (corresponding to 67%SM). To verify this relationship, scores above and below 20 were investigated for evidence of linear trends. These analyses are presented in Figure 6.21 for PACA scores below 20, and Figure 6.22 for PACA scores above 20.

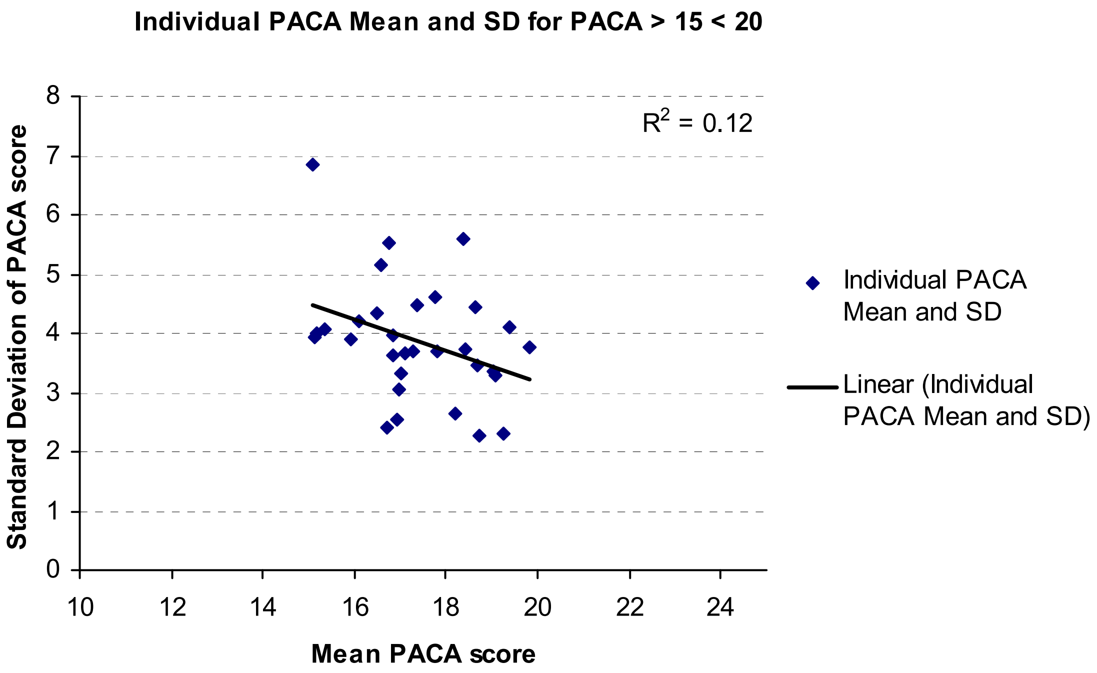


Figure 6.21: XY-plot of individual mean and standard deviation PACA scores across 14 day study period over a restricted range (PACA scores>15<20 (50 to 67%SM); N=31). The correlation between PACA means and standard deviations is r=.35 (R^2=.12). The ordinate reveals the standard deviation of mean PACA scores and the abscissa represents mean PACA scores averaged across all measurement time points.

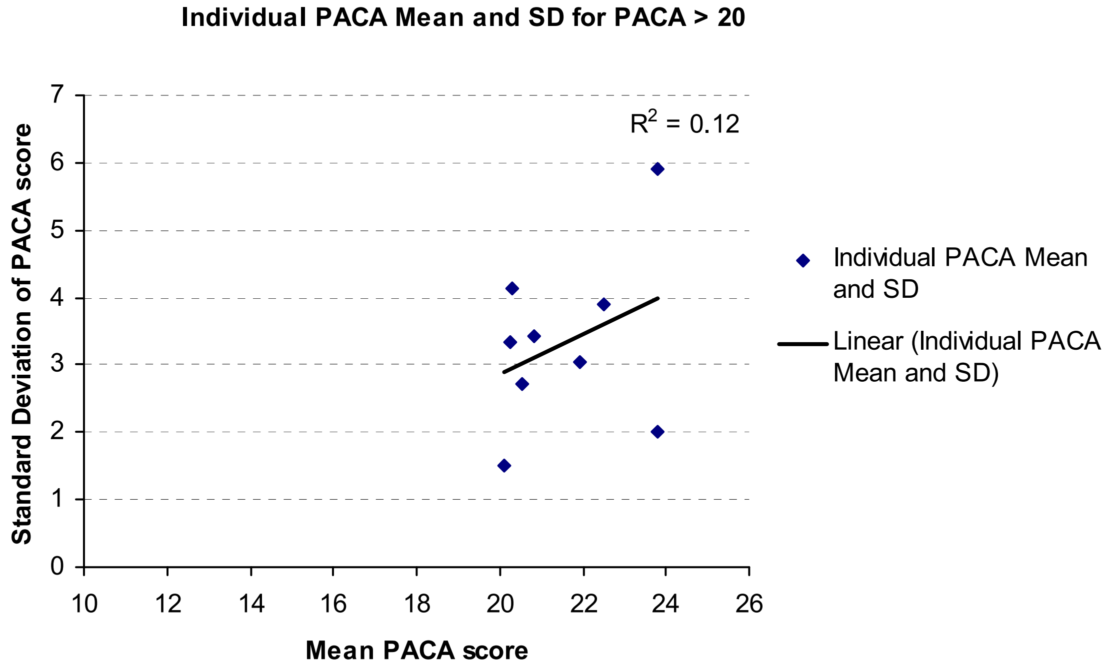


Figure 6.22: XY-plot of individual mean and standard deviation PACA scores across 14 day study period over a restricted range (PACA scores>20 (67%SM); N=9). The correlation between PACA means and standard deviations is r=.35 (R^2=.12). The ordinate reveals the standard deviation of mean PACA scores and the abscissa represents mean PACA scores averaged across all measurement time points.

The data contained in Figure 6.21 and Figure 6.22 further indicates that variance in PACA increases above and below a mean PACA score of approximately 20 (67%SM).

Multi-level Analysis of Momentary Measures of Subjective Wellbeing

Testing then proceeded to determine whether state PACA predicts state LS. As this is a repeated measures longitudinal design, Multi-Level Modelling (MLM) was used to analyse the results. MLM assumes data are clustered in groups (for repeated measures, the groups are the individuals). That is, there is one single outcome variable at the lowest level, and explanatory variables at all existing levels. This statistical technique has a number of advantages over standard Multiple Regression (MR). One of which is illustrated by comparing the application of ordinary MR and MLM to the current data. If ordinary MR was used to analyse the data, 56*(1*regression intercept, 1*residual variance and 1*regression slope) would have to be estimated, plus possible interactions (Hox, 2002). In MLM, instead of estimating 56 intercepts and 56 slopes (ordinary MR), an average intercept and an average slope is estimated, plus their variances across individuals. This approach greatly simplifies the analysis. Whilst this design could be addressed in a repeated measures MANOVA, it would fail to address the differences in intercepts and slopes together and would not provide the cross-level interaction.

Using MLM has a number of advantages. One considerable advantage of MLM is that it models different regression coefficients for each person at level 1 (the occasion, or within-persons level). This permits an examination of individual change over time. MLM is also not sensitive to missing data at level 1, thus the number of measurements per individual can vary. Higher levels can be added in MLM, allowing an investigation of the effects of varying types of group membership on individuals (Bryk & Raudenbush, 1992). Another advantage of MLM noted by Hox (2002) is that MLM allows a prediction of both between-person differences and within-person differences by including time varying and time constant explanatory variables in the MLM equation.

In repeated measures MLM, individuals are measured repeatedly over time. Consequently, the lowest level models time (or within-persons variance). The second level (the highest level in the current data), are the individuals themselves (or between-person variance). One can imagine a situation in which a third level is measured, for instance, schools. In such a situation it would be possible to examine the change in some variable over time, across individuals, and between schools.

The equation for MLM is very similar to the ordinary MR equation. In MLM the various subscripts and location of subscripts in the equation conveys important information. For instance, a subscript of “0” refers to the intercept, whilst the location of the subscript in the first position refers to level 1 of the equation. Similarly, the location of the subscript in the second position refers to level 2 of the equation.

The level 1 (within-persons) repeated measures MLM equation is presented in Equation 6.2.

$$\text{Level 1 Equation:} \quad Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti} \qquad \text{(Eqn 6.2)}$$

Where *t:* time point; *i: individual*
Y_{ti}: Applied to the current study, Y_{ti} is the life satisfaction (LS) score for an individual “*i”* at time point “*t”*.
π : regression coefficient (analogous to a β in ordinary MR).
π_{0i} : Intercept (average value of *Y* across all time points for each individual *i*).
T_{ti} : Time variable, indicating the time at which the LS measurement was taken for each individual *i*.
X_{ti} : Time *varying* covariate for each individual *i*. This is a level 1 explanatory variable, which explains within-person variation in Y_{ti}. For example, in the current study state PACA is used to explain within-person variation in LS. If π_{2i} is positive, then LS is higher for individuals high on PACA.
e_{ti} : Lowest level error. The variance of this error is expressed as σ_e^2 and is the variance within individuals.

In comparison to ordinary MR, MLM assumes that each individual has a different intercept coefficient π_{0i} , and a different slope coefficient π_{1i} (Hox, 2002). Because these coefficients are assumed to vary across individuals, they are often referred to as random coefficients (Hox, 2002). Applied to the current study, an individual with a high value on the intercept is predicted to have higher LS than an individual with a low value on the intercept. Similarly, the value of the slope coefficient indicates the degree to which state PACA influences LS. A higher value indicates a larger effect whereas a lower value indicates a smaller effect. Thus, variance in the slope coefficient for PACA (or time) indicates that the relationship between PACA and LS is not the same for every person. Across all individuals, the regression coefficients π_{1i} have a distribution with a particular mean and variance (Hox, 2002).

The level 2 (between-persons) equation is used to estimate *variation* in level 1 coefficients (π_{1i}) by introducing level 2 explanatory variables. That is, level 1 estimates the effect of PACA (and time) on within-person LS. Level 2 predicts the variability in these level 1 variables. This is achieved by using the level 2 explanatory variables (see Equation 6.3). For instance, extroversion and stability can be used to predict between-person variability in PACA.

Level 1Equation: $Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti}$ (Eqn 6.2)

Level 2 Equation: $\pi_{0i} = \beta_{00} + \beta_{01}Z_i + u_{0i}$ (Eqn 6.3)

Equation 6.3 represents the equation for explaining variation in the level 1 intercept (the level 1 equation gave the *average* LS score, the level 2 equation explains the *variation* in LS scores).

π_{0i}: The "π" corresponds with the level 1 equation. The subscript "*0i*" indicates we are modelling the intercept regression coefficient.

β_{00}: Intercept of the regression coefficient π_{0i}.

β_{01}: Level 2 regression coefficient for variable Z_i.

Z_i: Level 2 explanatory variable (for instance extroversion), which is a time *invariant* covariate. As this is a model of the intercept, if β_{01} is positive, then *average* LS is higher for individuals with higher scores on the IV.

u_{0i}: Error term at individual level. The variance of this residual error is given by $\sigma^2_{\mu_0}$, and is the variance between individuals on the average of the DV.

Equation 6.4 models the level 1 slope coefficient for *T* (time).

Level 1Equation: $Y_{ti} = \pi_{0i} + \pi_{1i} T_{ti} + \pi_{2i} X_{ti} + e_{ti}$ (Eqn 6.2)

Level 2 Equation: $\pi_{1i} = \beta_{10} + \beta_{11} Z_i + u_{1i}$ (Eqn 6.4)

π_{1i}: Level 1 regression coefficient for level 1variable T_{ti}.

β_{10}: Intercept of the regression coefficient π_{1i}.

β_{11}: Level 2 Regression coefficient for explanatory variable Z_i.

Z_i: Level 2 explanatory variable used to predict variation in the individual regression coefficient for Time.

u_{1i}: Error term at individual level. The variance of this residual error is given by $\sigma^2_{\mu_1}$

The final level 2 equation models the level 1 slope coefficient for *X* (PACA). This is presented in Equation 6.5.

$$\text{Level 1Equation:} \quad Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti} \qquad \text{(Eqn 6.2)}$$

$$\text{Level 2 Equation:} \quad \pi_{2i} = \beta_{20} + \beta_{21}Z_i + u_{2i} \qquad \text{(Eqn 6.5)}$$

π_{2i} : Level 1 regression coefficient for variable X_{ti}.

β_{20} : Intercept of the regression coefficient π_{2i}.

β_{21} : Level 2 Regression coefficient for variable Z_i.

Z_i : Level 2 explanatory variable. If Z_i were extroversion, and the coefficient β_{21} were positive, then the relationship between LS and PACA depends on the individual's level of extroversion. Thus, the effect of PACA on LS would be larger in more Extroverted individuals. This is also known as a cross-level moderation effect (Hox, 2002).

The full two level MLM equation is given in Equation 6.6.

$$\text{Level 1:} \quad Y_{ti} = \pi_{0i} + \pi_{1i}T_{ti} + \pi_{2i}X_{ti} + e_{ti} \qquad \text{(Eqn 6.6)}$$

$$\text{Level 2:} \quad \pi_{0i} = \beta_{00} + \beta_{01}Z_i + u_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}Z_i + u_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}Z_i + u_{2i}$$

The intra-class correlation (see Equation 6.7) is used to estimate how much variance in Y is within-persons, and how much variance in Y is between-persons (Hox, 2002).

$$\rho = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_e} \qquad \text{(Eqn 6.7)}$$

This statistic represents the proportion of individual level variance (or level 2 variance) compared to the total variance. Applied to the current study, this statistic indicates that 49% of the variance in LS is between-persons, and 51% of variance in LS is within-persons across time. This is somewhat consistent with the prior analysis of LS stability in which there was more variance in LS within individuals than between individuals.

Model Testing in Multi-Level Modelling

Multi-level modelling is an iterative procedure. When conducting MLM, the aim is to explain both within-person and between-person variation in the dependent variable. This is achieved by using a model building approach. The first model tested is the most basic model with no explanatory variables. This is called the intercept only model, or the null model. The error variance is used as a benchmark to compare the reduction in variance by the addition of an explanatory variable. The error variance at level 1 is indicated by σ_e^2, and at level 2 is indicated by $\sigma_{\mu_0}^2$.

The first step in MLM involves explaining the lowest level variance (within-persons variance) in the dependent variable. Level 1 explanatory variables (time varying covariates) are added one at a time in the hope that they are reducing error variance (σ_e^2). MLM also gives significance tests for the regression coefficient and the variation in that coefficient (the slope coefficient) of each variable added. A significant intercept coefficient indicates that individuals have different initial states whilst a significant slope coefficient means that individuals have different rates of change (Hox, 2002).

The next step involves adding level 2 explanatory variables (time invariant covariates) to explain between-person variance ($\sigma_{\mu 0}^2$). In repeated measures MLM, the intercept only model underestimates the person level variance (Hox, 2002). To correct for this, Hox suggests using the variance component of the model that includes the time variable as the benchmark for person level variance ($\sigma^2_{\mu 0}$). Applied to the current study, model 2, which includes the time variable, will be used as the benchmark to compare the increase or decrease in variance resulting from the addition of an explanatory variable. As in level 1, MLM gives the significance of the coefficient for the level 2 explanatory variable added, in addition to the significance of the slope coefficient.

The final step in MLM involves comparing the overall fit and parsimony of each model in which a variable is added or subtracted. Model fit is indicated by deviance, with lower values indicating a better fit to the data. Deviance is equivalent to -2 Log-likelihood, and reflects the significance of unexplained variance in the DV (Hox, 2002). The difference in deviance has a chi-square distribution with degrees freedom equal to the number of parameters in the models (Hox). As such, comparing the deviance of the model of interest with the deviance of the model to be compared indicates whether the model of interest fits the data significantly better than the compared model. In addition, the parsimony of each model is given by AIC. In MLM, AIC is equal to deviance + 2*number of estimated parameters (AIC=d+2q; Hox). Thus, AIC can also be used to compare models. The model with the lowest deviance is the model that explains the largest amount of variance in the DV whilst the model with the lowest AIC is the model with the most parsimony. Accordingly, the best model is considered the model that explains the largest amount of variance whilst also demonstrating parsimony.

According to the procedure outlined above, multi-level models were constructed to explain within-person variance in LS and tested using the program HLM (version 6.03; © Scientific Software International, Inc., USA). For each model tested, the group variable was included as a dummy variable to control for the effects of differences between group 1 (non-randomised PDA signals), and groups 2 and 3 (randomised PDA signals). This variable was constructed according to the procedure outlined by Hox (2002). That is, the non-randomised group was coded -0.5 and the randomised group was coded +0.5. This coding signifies that the intercept and variance components will be estimated for a value of zero on the group variable. This gives the average group result, disregarding the differences in signal randomisation between the groups. However, as the difference between -0.5 and +0.5 equals 1, the regression coefficient for the group variable indicates differences between the two groups (Hox, 2002).

The first model tested was the intercept only model. The next model tested included the time variable, which was free to vary between-persons. This means that each individual could have differing magnitudes of change in LS over time. State PACA was included in model 3 as an explanatory variable, whilst model 4 included state unhappiness. For model 3, if the coefficient of the explanatory variable was significant, it was retained for the following model (model 4). The results for these multi-level models are presented in Table 6.5.

Table 6.5: Multi-Level Modelling results for level 1 (Observations=1312).

	Coeff. π (*SE*)	**Variance of Coeff. π (*SD*)**	**Within-person Variance σ_e^2 (*SD*)**	**Between-person variance $\sigma_{\mu 0}^2$ (*SD*)**	**R^2 Within-persons**	**R^2 Between-persons**	**Deviance (*d*)**	**AIC**	**d_{m1} - d_{m2} (χ^2 test)**
Model 1 (null model)			170.25 (13.1)	164.73 (12.6)	0	0	10,606	10,610	
Intercept	64.07***(2.03)	-							
Group	6.67 (4.05)	-							
Model 1 Equation: $\text{LS} = 64.07 + 6.67 \times (\text{Group}) + 170.25$									
Model 2 (+Time)			159.89 (12.7)	210.86 (14.5)	.061	0	10,579	10,587	d_{m1} - d_{m2} = 27, *p*<.001
Intercept	64.05***(2.33)	-							
Group	6.46 (4.06)	-							
Time	.0007 (.0064)	.001***(.03)							
Model 2 Equation: $\text{LS} = 64.05 + 6.46 \times (\text{Group}) + .0007 \times (\text{Time}) + 159.89$									
Model 3 (+state PACA)			132.0 (11.5)	258.3 (16.1)	.23	0	10,275	10,287	d_{m2} - d_{m3} = 304, *p*<.001
Intercept	43.64***(2.91)	-							
Group	5.60 (2.74)	-							
Time	.0002 (.006)	.001***(.03)							
State PACA	1.27*** (.11)	.22*** (.47)							
Model 3 Equation: $\text{LS} = 43.64 + 5.60 \times (\text{Group}) + .0002 \times (\text{Time}) + 1.27 \times (\text{State PACA}) + 132.0$									
Model 4 (+state unhappiness)			124.19 (11.14)	243.16 (15.59)	.271	0	10,202	10,218	d_{m3} - d_{m4} = 73, *p*<.001
Intercept	50.50***(3.03)	-							
Group	4.90 (2.70)	-							
Time	-.001 (.005)	.001*** (.03)							
State PACA	1.02*** (.11)	.18*** (.42)							
State unhappiness	-1.07*** (.22)	.49* (.70)							
Model 4 Equation: $\text{LS} = 50.50 + 4.90 \times (\text{Group}) - .001 \times (\text{Time}) + 1.02 \times (\text{State PACA}) - 1.07 \times (\text{State Unhappiness}) + 124.19$									

Note: ***=*p*<.001; **=*p*<.01; *=*p*<.05.

The results contained in Table 6.5 indicate the differential effects of the explanatory variables on LS. These results will be addressed separately for each model. For the intercept only model, the intercept coefficient value of 64.07 is the average LS score for all persons across all occasions of measurement. The non-significant coefficient for the group variable indicates that there is no significant effect on LS for being in group 1 or groups 2 and 3. Adding the time variable in model 2 explained 6% of variance in LS within-persons. Although the coefficient for time was not a significant predictor of LS, there was significant variation in the time coefficient. This indicates that experience of LS over time varied between individuals.

For model 3, state PACA significantly predicted LS, explaining an additional 17% of within-person variation in LS. The coefficient value of 1.27 indicates that, on average, higher state PACA was associated with higher LS. However, the significant variance of the coefficient (.22) indicates that the relationship between state PACA and LS varied between individuals. For a person with a low state PACA coefficient, the effect of state PACA on LS was small. Conversely, for a person with a high state PACA coefficient, the effect of state PACA on LS was large. In MLM, this varying coefficient of .22 is assumed to be distributed normally (Hox, 2002). Thus the standard deviation of this coefficient can be obtained by deriving the square-root of the coefficient (.22), yielding a value of .47. As the coefficient is assumed to be normally distributed, the predicted range for the regression coefficients for 95% of the sample can be calculated using the formula: mean±1.96*SD. Applying this calculation yields a range of .35 to 2.19 for the state PACA regression coefficients. Furthermore, the 98%CI range is .06 to 2.48. This range indicates that the relationship between state PACA and LS is predicted to be positive for a majority of the sample. The regression slope of each individual for state PACA is presented in Figure 6.23.

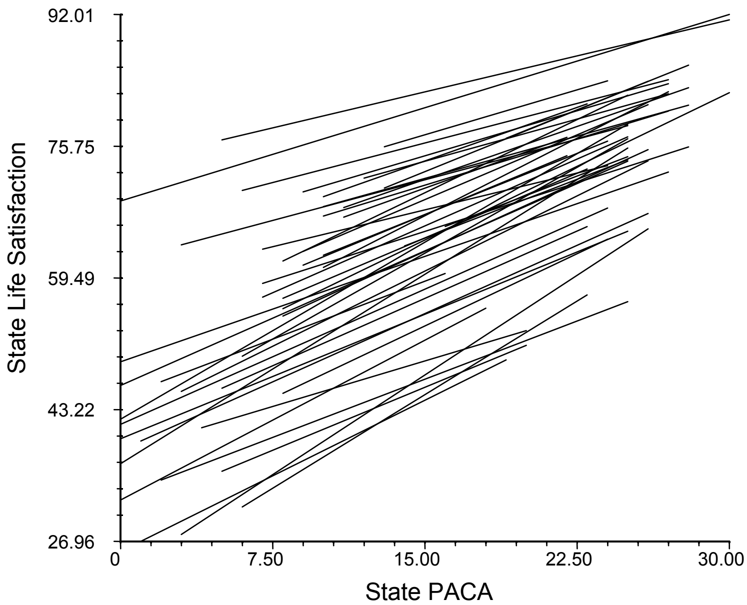


Figure 6.23: Individual regression slopes for state PACA (N=46). The ordinate represents state life satisfaction scores ranging from 26.96 to 92.01 whilst the abscissa represents state PACA scores, ranging from 0 to 30.

The individual regression slopes presented in Figure 6.23 indicate the positive relationship between state PACA and state LS for a majority of the sample. All regression slopes display a positive trend, however differences in the steepness of the slopes indicates variance in the relationship between state PACA and state LS.

The significant result for the chi-square deviance test comparing model 3 to model 2 indicates that model 3 fits the data significantly better than model 2. The lower AIC value also indicates model 3 to be more parsimonious than model 2. Thus, the MLM with state PACA as a within-persons explanatory variable provided a better fit to the data and was more parsimonious than the MLM with just the time variable.

In model 4, state unhappiness significantly predicted LS, explaining an additional 4% variance. The coefficient of -1.07 indicates that on average, high state unhappiness was associated with lower LS. The significant variance coefficient of .49 indicates the relationship between state unhappiness and LS was not the same for each individual. The range of the state unhappiness coefficients was calculated using the same procedure used to calculate the range for the state PACA coefficients. This gave a range of -2.44 to .30. Thus, for most individuals, the relation between state unhappiness and LS was negative. The regression slope of each individual for state unhappiness is presented in Figure 6.24.

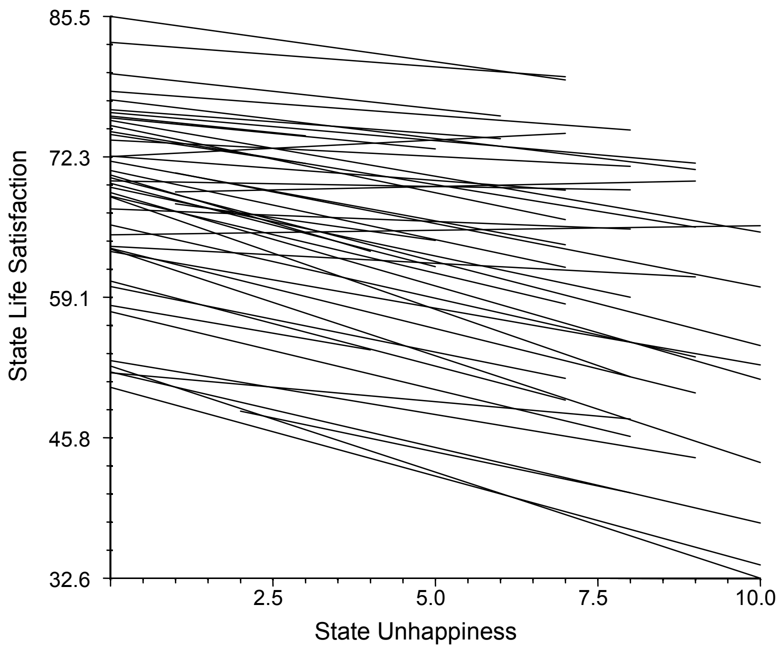


Figure 6.24: Individual regression slopes for state unhappiness (N=46). The ordinate represents state life satisfaction scores ranging from 32.6 to 85.5 whilst the abscissa represents state unhappiness scores, ranging from 0 to 10.

The individual regression slopes presented in Figure 6.24 indicate an overall negative relationship between state unhappiness and state LS. However, the small number of horizontal regression slopes indicates that for some individuals there was no relationship between state unhappiness and state LS.

The chi-square deviance test for model 4 compared to model 3 is significant, indicating a better fit to the data for model 4. Model 4 is also more parsimonious than model 3 as indicated by a lower AIC value. The remaining level 1 variables were tested in MLM but were non-significant, did not explain variance in LS, or decreased model fit and parsimony. As such, they were discarded from the model.

Testing then proceeded to explain between-person variation in LS by introducing level 2 time invariant explanatory variables into the MLM. As for testing in level 1, this was done on a variable by variable basis. The results of this testing are presented in Table 6.6 and Table 6.7.

Table 6.6: Multi-Level Modelling results for level 1(Observations=1312) and level 2 (N=46) for model 5 and model 6.

	Coeff. π (*SE*)	Variance of Coeff. π (*SD*)	Within-person Variance σ_e^2 (*SD*)	Between-person variance $\sigma_{\mu_0}^2$ (*SD*)	R^2 Within-persons	R^2 Between-persons	Deviance *(d)*	AIC	d_{m1} - d_{m2} (χ^2 test)
Model 5 *(+ global trait PWI)*			124.0 (11.1)	163.2 (12.8)	.27	.226	10,171	10,193	d_{m4} - d_{m5} = 31, p<.001
Intercept	8.80 (7.21)	-							
Trait PWI	*.58*** (.10)*	-							
Group	2.53 (2.04)	-							
Time	-.002 (.005)	.001*** (.03)							
State PACA	1.03*** (.11)	.19*** (.43)							
State unhappiness	-1.07*** (.22)	.61* (.78)							

Model 5 Equation:

Level 1: $\mathrm{LS} = \pi_{0i} + \pi_{1i} \times (\mathrm{Group}) + \pi_{2i} \times (\mathrm{Time}) + \pi_{3i} \times (\mathrm{State\ PACA}) + \pi_{4i} \times (\mathrm{State\ Unhappiness}) + 124.0$

Level 2: $\pi_{0i} = 8.80 + .58 \times (Trait\ PWI) + 163.2$

$\pi_{1i} = 2.53$

$\pi_{2i} = -.002$

$\pi_{3i} = 1.03$

$\pi_{4i} = -1.07$

	Coeff. π (*SE*)	Variance of Coeff. π (*SD*)	Within-person Variance σ_e^2 (*SD*)	Between-person variance $\sigma_{\mu_0}^2$ (*SD*)	R^2 Within-persons	R^2 Between-persons	Deviance *(d)*	AIC	d_{m1} - d_{m2} (χ^2 test)
Model 6 *(+ global trait depression)*			124.1 (11.1)	150.2 (12.3)	.27	.288	10,170	10,192	d_{m5} - d_{m6} = 1, p>.05
Intercept	19.59 (9.84)	-							
Trait PWI	*.46** (.12)*	-							
Trait Depression	*-.94 (.55)*	-							
Group	1.91 (2.04)	-							
Time	-.002 (.005)	.001*** (.03)							
State PACA	1.04*** (.11)	.19*** (.43)							
State unhappiness	-1.03*** (.22)	.57* (.75)							

Model 6 Equation:

Level 1: $\mathrm{LS} = \pi_{0i} + \pi_{1i} \times (\mathrm{Group}) + \pi_{2i} \times (\mathrm{Time}) + \pi_{3i} \times (\mathrm{State\ PACA}) + \pi_{4i} \times (\mathrm{State\ Unhappiness}) + 124.1$

Level 2: $\pi_{0i} = 19.59 + .46 \times (Trait\ PWI) - .94 \times (Trait\ Depression) + 150.2$

$\pi_{1i} = 1.91$

$\pi_{2i} = -.002$

$\pi_{3i} = 1.04$

$\pi_{4i} = -1.03$

Note: Level 2 predictors are presented in *italics;* ***=p<.001; **=p<.01; p<.05.

Table 6.7: Multi-Level Modelling results for level 1(Observations=1312) and level 2 (N=46) for model 7.

	Coeff. π (*SE*)	Variance of Coeff. π (*SD*)	Within-person Variance σ_e^2 (*SD*)	Between-person variance $\sigma_{\mu_0}^2$ (*SD*)	R^2 Within-persons	R^2 Between-persons	Deviance *(d)*	AIC	d_{m1} - d_{m2} (χ^2 test)
Model 7 *(+ extroversion)*			123.9 (11.1)	127.2 (11.3)	.27	.397	10,164	10,186	d_{m6} - d_{m7} = 6, p<.05
Intercept	15.64 (9.79)	-							
Trait PWI	*.41** (.12)*	-							
Trait Depression	*-1.04 (.54)*	-							
Trait Extroversion	*.64* (.25)*								
Group	.98 (2.0)	-							
Time	-.0014 (.005)	.0007*** (.03)							
State PACA	1.02*** (.11)	.17*** (.42)							
State unhappiness	-1.0*** (.22)	.58* (.76)							

Model 7 Equation:

Level 1: $LS = \pi_{0i} + \pi_{1i} \times (\text{Group}) + \pi_{2i} \times (\text{Time}) + \pi_{3i} \times (\text{State PACA}) + \pi_{4i} \times (\text{State Unhappiness}) + 123.9$

Level 2: $\pi_{0i} = 15.64 + .41 \times (\mathit{Trait\ PWI}) - 1.04 \times (\mathit{Trait\ Depression}) + .64 \times (\mathit{Trait\ Extraversion}) + 127.2$

$\pi_{1i} = .98$

$\pi_{2i} = -.0014$

$\pi_{3i} = 1.02$

$\pi_{4i} = -1.0$

Note: Level 2 predictors are presented in *italics;* ***=p<.001; **=p<.01; p<.05.

The results contained in Table 6.6 (for model 5 and model 6) indicate that the addition of global trait PWI to explain between-person variation in average LS in model 5 resulted in a better fit to the data than model 4 (Table 6.5). In addition, global trait PWI explained 23% of the between-person variation in LS. The significant coefficient of .46 indicates that average LS was higher for individuals with high scores on global trait PWI.

In model 6, depression did not significantly predict average LS. However the coefficient of -.94 indicates that higher depression results in lower average LS. The addition of depression in model 6 also increased the between-person variance explained in LS by 6%. The non-significant chi-square model test reveals that model 6 is not a significantly better fit to the data than model 5. However, this non-significance also indicates that the addition of depression did not decrease model fit, and as depression explains an additional 6% between-person variance in LS, it was retained in the model.

Adding trait extroversion as a predictor of average LS in model 7 (see Table 6.6) explained an additional 11% of between-person variance in LS. The coefficient of .64 indicates that increased extroversion was associated with higher average LS. The chi-square model test indicates that model 7 provides a significantly better fit to the data than model 6. Comparing the fit of model 7 to models 1 to 6 (Table 6.4 and Table 6.5) reveals that model 7 explains the most within-person and between-person variance in LS, provides the best fit to the data, and is the most parsimonious model tested.

Each of the remaining between-person variables were then entered into the MLM equation separately to predict variation in level 1 coefficients. The results for these analyses are presented in Table 6.8.

Table 6.8: Discarded level-2 variables used to predict variance in level 1 coefficients.

Predicting intercept (π_{0i})	Coeff. π (*S.E.*)	*P*	$R^2_{b/w}$	*D*	AIC	d_{m7} - d_{mi} (χ^2 test)
Gender	-1.77 (1.94)	>.05	.03 ↑	10,162↓	10,184↓	-2, *p*>.05
Age	.27 (.13)	<.05	.01 ↓	10,163↓	10,185↓	-1, *p*>.05
Income	.90 (.44)	=.05	.04 ↑	10,161↓	10,183↓	-3, *p*>.05
Upset	.47 (.76)	>.05	.02 ↓	10,164 -	10,186-	0, *p*>.05
Alert	.19 (.51)	>.05	.01 ↓	10,165↑	10,187↑	1, *p*>.05
Tired	-.25 (.52)	>.05	.00 -	10,165↑	10,187↑	1, *p*>.05
Annoyed	-1.0 (.48)	=.05	.04 ↑	10,161↓	10,183↓	-3, *p*>.05
Relaxed	-.17 (.47)	>.05	.00 -	10,165↑	10,187↑	1, *p*>.05
Stability	.03 (.34)	>.05	.00 -	10,166↑	10,188↑	2, *p*>.05
Happy	.88 (.72)	>.05	.03 ↓	10,163↓	10,185↓	-1, *p*>.05
Content	.64 (.82)	>.05	.01 ↓	10,164 -	10,186-	0, *p*>.05
Unhappy	-.52 (.75)	>.05	.02 ↓	10,164 -	10,186-	0, *p*>.05
Active	-.21 (.55)	>.05	.01 ↑	10,165↑	10,187↑	1, *p*>.05
SWLS	.53 (.19)	<.01	.02 ↓	10,161↓	10,183↓	-3, *p*>.05
PACA	.18 (.30)	>.05	.02 ↓	10,166↑	10,188↑	2, *p*>.05
MS PACA	1.55 (.22)	<.001	.08 ↓	10,142↓	10,164↓	22, *p*<.001

Predicting state PACA (π_{3i})	Coeff. π (*S.E.*)	*P*	$R^2_{b/w}$	*D*	AIC	d_{m7} - d_{mi} (χ^2 test)
Gender	-.02 (.09)	>.05	.00 -	10,169↑	10,191↑	5, *p*<.05
Age	.01 (.01)	<.05	.01 ↓	10,170↑	10,192↑	6, *p*<.05
Income	.03 (.02)	>.05	.01 ↓	10,169↑	10,191↑	5, *p*<.05
Upset	.04 (.03)	>.05	.02 ↑	10,163↓	10,185↓	-1, *p*>.05
Tired	.004 (.02)	>.05	.00 -	10,171↑	10,193↑	7, *p*<.05
Annoyed	-.03 (.02)	>.05	.03 ↓	10,170↑	10,192↑	6, *p*<.05
Relaxed	-.01 (.02)	>.05	.01 ↑	10,171↑	10,193↑	7, *p*<.05
Depressed	.06 (.04)	>.05	.05 ↑	10,168↑	10,190↑	4, *p*<.05
Stability	-.01 (.01)	>.05	.03 ↑	10,171↑	10,193↑	7, *p*<.05
Unhappy	-.01 (.03)	>.05	.02 ↓	10,171↑	10,193↑	7, *p*<.05
SWLS	.02 (.01)	<.05	.04 ↓	10,170↑	10,192↑	6, *p*<.05
Extroversion	.76 (.59)	>.05	.02 ↓	10,171↑	10,193↑	7, *p*<.05
PWI	-.02 (.01)	>.05	.08 ↑	10,170↑	10,192↑	6, *p*<.05

Predicting state unhappiness (π_{4i})	Coeff. π (*S.E.*)	*P*	$R^2_{b/w}$	*D*	AIC	d_{m7} - d_{mi} (χ^2 test)
Gender	-.80 (.41)	>.05	.02 ↓	10,162↓	10,184↓	-2, *p*>.05
Age	-.01 (.03)	>.05	.01 ↓	10,170↑	10,192↑	6, *p*<.05
Income	-.08 (.10)	>.05	.01 ↓	10,168↑	10,190↑	4, *p*<.05
Alert	.05 (.12)	>.05	.00 -	10,168↑	10,190↑	4, *p*<.05
Happy	-.05 (.14)	>.05	.00 -	10,168↑	10,190↑	4, *p*<.05
Content	.06 (.13)	>.05	.01 ↓	10,168↑	10,190↑	4, *p*<.05
Tired	.06 (.11)	>.05	.01 ↑	10,168↑	10,190↑	4, *p*<.05
Annoyed	.02 (.09)	>.05	.00 -	10,168↑	10,190↑	4, *p*<.05
Relaxed	.15 (.09)	>.05	.01 ↓	10,166↑	10,188↑	2, *p*>.05
Depressed	.15 (.09)	>.05	.01 ↓	10,166↑	10,188↑	2, *p*>.05

Predicting state unhappiness (continued) (π_{4i})	Coeff. π (*S.E.*)	*P*	$R^2_{b/w}$	*D*	AIC	d_{m7} - d_{mi} (χ^2 test)
Stability	-.03 (.06)	>.05	.00 -	10,169↑	10,191↑	5, *p*<.05
Active	.02 (.13)	>.05	.00 -	10,168↑	10,190↑	4, *p*<.05
Upset	.09 (.11)	>.05	.01 ↓	10,168↑	10,190↑	4, *p*<.05
Extroversion	-.06 (.05)	>.05	.01 ↑	10,168↑	10,190↑	4, *p*<.05
PWI	-.01 (.02)	>.05	.00 -	10,171↑	10,193↑	7, *p*<.05
PACA	.01 (.06)	>.05	.00 -	10,169↑	10,191↑	5, *p*<.05
MS PACA	.12 (.06)	<.05	.06 ↓	10,167↑	10,189↑	3, *p*>.05

Note: ↑↓ indicate change in value from benchmark comparison model (model 7, Table 6.6). For R^2, ↑ indicates an increase in variance explained; ↓ indicates a decrease in variance explained. For *D* and *AIC*, ↑ indicates a decrease in parsimony; ↓ indicates an increase in parsimony. Each variable was entered into the equation separately for testing. All level 2 predictors are global trait variables with the exception of mean state (MS) PACA. d_{mi} denotes the MLM model of interest which includes the level 2 predictor. $R^2_{b/w} = R^2$ between-persons.

The data contained in Table 6.8 indicates that each of the level 2 predictor variables were either not significant, decreased the variance explained in LS, or decreased model fit. Accordingly, these variables were not included in the final multi-level model. Of note, mean state PACA was a significant predictor of the level 1 intercept (average LS). The coefficient value of 1.55 indicates that a one unit increase in mean state PACA results in a 1.55 unit increase in average LS. The addition of mean state PACA also resulted in a significantly more parsimonious model. However, the variance explained in LS between-persons was reduced by .08. As such this variable was not included in the final multi-level model. Overall the data in Table 6.8 indicate a lack of moderation effects.

Substituting the unstandardised coefficients for each variable in model 7 into the level 1 and level 2 MLM equations gives the final MLM equation for state LS. The final equation is presented in Equation 6.8.

$$\begin{aligned} LS = (\ 15.64 + .41 \times \left(\mathit{Trait\ PWI}\right) - 1.04 \times \left(\mathit{Trait\ Depression}\right) + .64 \times \left(\mathit{Trait\ Extraversion}\right) + 127.2) \\ + .98 \times \mathit{(Group)} - 1.0 \times \mathit{(State\ Unhappy)} - .0014 \times \mathit{(Time)} + 1.02 \times \mathit{(State\ PACA)} + 123.89 \end{aligned} \quad \text{(Eqn 6.8)}$$

This equation indicates that for every unit increase in global trait PWI and extroversion, average LS increases by .41 and .64 points respectively. However for every unit increase in depression, average LS decreases by 1.04 points. In addition, for every unit increase in state unhappiness and time, LS decreases by 1.0 and .001 points respectively. For every unit increase in state PACA, LS increases by 1.02 points.

Together, the level 1 explanatory variables of time, state PACA, and state unhappiness predict 27% of variance in LS over time. The level 2 explanatory variables of global trait PWI, trait depression, and trait extroversion together predict 40% of variance in average LS between-persons.

Retrospective Biases in Global and Recalled Self-reports of Affect and SWB

The investigation of possible retrospective biases was conducted by comparing affect and SWB over each measured time frame. The time frames are: global trait (measured once at the beginning of the study); recall (on the 15th day of the study participants provided estimates of average affect and SWB over the previous 14 day study period); and mean state (average of all momentary measurements over 14 days of the study period). It is considered that the average of momentary affect and SWB provides a more accurate and reliable measure of an individual's trait affect and SWB, as momentary data are much less likely to be contaminated by retrospective biases. If this is correct, then both global trait reports and recalled reports should be significantly different from mean state reports. Mean differences between recalled affect, PWI, and LS, and mean state affect, PWI, and LS, are presented in Table 6.9. As there are a number of tests, the criterion alpha was adjusted using the FDR procedure (see Chapter 5, Section 5.3).

Table 6.9: Recalled PWI, LS, and affect compared to mean state PWI, LS, and affect.

	Variable	*M*	*SD*	Difference (R – MS)	*SD*	*T*	*df*	*P* (criterion α adjusted[1])
1.	Upset *R*	3.26	2.37	1.50	2.01	5.45	52	<.001 (.005)
	Upset *MS*	1.76	1.19					
2.	Alert *R*	6.50	1.80	.79	1.32	4.35	52	<.001 (.009)
	Alert *MS*	5.72	1.30					
3.	Happy *R*	6.81	1.69	.68	1.25	3.95	52	<.001 (.014)
	Happy *MS*	6.13	1.42					
4.	Tired *R*	5.05	2.10	.79	1.62	3.56	52	.001 (.018)
	Tired *MS*	4.26	1.36					
5.	Active *R*	6.44	1.65	1.36	1.30	7.60	52	<.001 (.023)
	Active *MS*	5.08	1.24					
6.	Annoyed *R*	2.52	1.64	.23	1.49	1.12	52	.27 (.027)
	Annoyed *MS*	2.29	1.09					
7.	Unhappy *R*	2.76	1.93	.68	1.77	2.80	52	.007 (.032)
	Unhappy *MS*	2.08	1.21					
8.	Content *R*	6.28	1.58	.51	1.43	2.62	52	.01 (.036)
	Content *MS*	5.77	1.30					
9.	Relaxed *R*	6.15	1.50	.42	1.53	2.00	52	.05 (.041)
	Relaxed *MS*	5.73	0.96					
10.	LS *R*	6.58	1.54	.04	1.30	0.24	52	.809 (.045)
	LS *MS*	6.54	1.28					
11.	PWI *R*	68.11	11.05	2.93	7.45	2.87	52	.006 (.05)
	PWI *MS*	65.17	11.29					

Note: R = recall measurement; MS = mean state measurement; [1]criterion alpha adjusted using FDR procedure.

The data contained in Table 6.9 indicate that individuals consistently overestimated their actual levels of affect and PWI. The only exceptions to this overestimation were for *annoyed, LS,* and *relaxed*. Mean differences between global trait affect, PWI, and LS and mean state affect, PWI, and LS are presented in Table 6.10.

Table 6.10: Global trait PWI, LS, and affect compared to mean state PWI, LS, and affect.

	Variable	*M*	*SD*	Difference (GT – MS)	*SD*	*t*	*df*	*P* (criterion α adjusted[1])
1.	Upset *GT*	2.96	1.87	1.20	1.90	4.60	52	<.001 (.005)
	Upset *MS*	1.76	1.19					
2.	Alert *GT*	6.91	1.73	1.19	1.91	4.53	52	<.001 (.009)
	Alert *MS*	5.72	1.30					
3.	Happy *GT*	7.17	1.49	1.04	1.64	4.61	52	<.001 (.014)
	Happy *MS*	6.13	1.42					
4.	Tired *GT*	5.32	1.95	1.06	1.82	4.25	52	<.001 (.018)
	Tired *MS*	4.26	1.36					
5.	Content *GT*	6.64	1.48	.87	1.51	4.21	52	<.001 (.023)
	Content *MS*	5.77	1.30					
6.	Annoyed *GT*	3.09	2.17	.81	2.25	2.60	52	.01 (.027)
	Annoyed *MS*	2.29	1.09					
7.	Unhappy *GT*	2.75	1.86	.67	2.14	2.28	52	.03 (.032)
	Unhappy *MS*	2.08	1.21					
8.	Relaxed *GT*	5.98	1.99	.25	1.81	1.01	52	.32 (.036)
	Relaxed *MS*	5.73	0.96					
9.	Active *GT*	6.58	1.63	1.50	1.92	5.69	52	<.001 (.041)
	Active *MS*	5.08	1.24					
10.	PWI *GT*	72.21	10.85	7.04	8.81	5.82	52	<.001 (.045)
	PWI *MS*	65.17	11.29					
11.	LS *GT*	69.81	15.38	4.40	12.64	2.53	52	.014 (.05)
	LS *MS*	65.42	12.84					

Note: GT = global trait measurement; MS= mean state measurement; [1]criterion alpha adjusted using FDR procedure.

The data in Table 6.10 indicate that global trait affect, PWI, and LS were consistently and significantly higher than actual levels of affect, PWI and LS. The only exception to this effect was for *relaxed*. In addition, the difference between global trait affect and SWB and mean state affect and SWB, was greater in almost all variables than the difference between recalled affect and SWB and mean state affect and SWB. The only exception to this was for the affects upset, unhappy, and relaxed.

The Prediction of Retrospective Biases in Subjective Wellbeing

The following analyses were conducted to determine whether the retrospective biases found in global trait measures and recalled measures of SWB (PWI and LS) could be predicted by global trait PACA, extroversion, and stability after controlling for mean state SWB. The analysis for global trait and recalled PWI is presented in Table 6.11.

Table 6.11: Hierarchical regression predicting global trait and recalled PWI with global trait and recalled PACA, extroversion, and stability after controlling for mean state PWI.

	Variable	*B*	*SE B*	*β*	*sr^2*	ΔR^2
DV: Global trait PWI						
Step 1	*MS* PWI	.61***	.10	.65	.42	.42***
Step 2	*MS* PWI	.49***	.10	.52	.22	.09**
	Global trait PACA	.98**	.34	.32	.09	
Step 3	*MS* PWI	.44***	.10	.46	.17	.05 n.s.
	Global trait PACA	.69	.35	.23	.04	
	Extroversion	.23	.28	.08	.01	
	Stability	.69*	.32	.24	.05	
			R^2= .56; Adjusted R^2=.52			
DV: Recalled PWI						
Step 1	*MS* PWI	.78***	.09	.78	.60	.60***
Step 2	*MS* PWI	.67***	.09	.67	.40	.08**
	Recalled PACA	.89**	.26	.30	.08	
Step 3	*MS* PWI	.69***	.10	.69	.37	.01 n.s.
	Recalled PACA	.92**	.27	.31	.09	
	Extroversion	-.29	.25	-.10	.01	
	Stability	-.01	.28	.00	.00	
			R^2=.69; Adjusted R^2=.66			

Note: MS = mean state measurement.

The data presented in Table 6.11 indicate that even after controlling for mean state PWI, global trait PACA and stability significantly predicted global trait PWI. Whilst mean state PWI accounted for 42% of the variance in global trait PWI, an additional 9% of variance was accounted for by global trait PACA. Stability also predicted a further 5% unique variance. Similarly, recalled reports of PWI were significantly and uniquely predicted by recalled PACA (8%) even after controlling for mean state reports of PWI. Extroversion and stability were not significantly predictive of recalled PWI. These analyses were repeated for global trait and recalled reports of LS. The results of these analyses are presented in Table 6.12.

Table 6.12: Hierarchical regression predicting global trait and recalled LS with global trait and recalled PACA, extroversion, and stability after controlling for mean state LS.

	Variable	B	$SE\ B$	β	sr^2	ΔR^2
DV: Global trait LS						
Step 1	*MS* LS	7.65***	1.23	.66	.44	.44***
Step 2	*MS* LS	5.49***	1.10	.48	.19	.19***
	Global trait PACA	2.10***	.42	.47	.19	
Step 3	*MS* LS	4.46***	1.05	.39	.11	.09**
	Global trait PACA	1.69***	.40	.38	.11	
	Extroversion	-.03	.34	-.01	.00	
	Stability	1.42	.37	.34	.09	
				R^2=.72; Adjusted R^2=.69		
DV: Recalled LS						
Step 1	*MS* LS	.75***	.13	.64	.41	.41***
Step 2	*MS* LS	.50***	.13	.42	.14	.15***
	Recalled PACA	.18***	.05	.44	.15	
Step 3	*MS* LS	.46**	.15	.39	.09	.01 n.s.
	Recalled PACA	.18***	.05	.44	.15	
	Extroversion	.03	.04	.08	.01	
	Stability	.01	.05	.01	.00	
				R^2=.57; Adjusted R^2=.53		

Note: MS = mean state measurement.

The results contained in Table 6.12 indicate that after controlling for mean state LS, global trait PACA and stability significantly and uniquely predicted global trait LS. Whilst mean state LS accounted for 44% of the variance in global trait LS, an additional 19% of variance was accounted for by global trait PACA. Stability also predicted a further 9% unique variance. Similarly, recalled reports of LS were significantly and uniquely predicted by recalled PACA (15%) even after controlling for mean state reports of PWI. Extroversion and stability did not significantly predict recalled LS.

The Relative Effect of Extroversion and Stability on Mean State Subjective Wellbeing

The following analyses were conducted to test the ability of extroversion and stability to predict unique variance in mean state SWB (PWI and LS) having controlled for mean state PACA. If extroversion and stability are important to SWB, then they should contribute unique variance following removal of the effects due to mean state PACA. The hierarchical regression predicting mean state PWI is presented in Table 6.13.

Table 6.13: Hierarchical regression predicting mean state PWI with extroversion and stability after controlling for mean state PACA.

	Variable	***B***	***SE B***	***β***	***sr^2***	**ΔR^2**
DV: *MS* PWI						
Step 1	*MS* PACA	2.38***	.36	.68	.46	.46***
Step 2	*MS* PACA	2.17***	.38	.65	.35	.03 n.s.
	Extroversion	.47	.31	.16	.02	
	Stability	.08	.35	.03	.00	
			R^2=.48; Adjusted R^2=.45			

Note: MS = mean state measurement.

The results contained in Table 6.13 indicate that extroversion and stability do not significantly predict mean state PWI after controlling for mean state PACA. This analysis is repeated with mean state LS as the DV. The results of this analysis are presented in Table 6.14.

Table 6.14: Hierarchical regression predicting mean state LS with extroversion and stability after controlling for mean state PACA.

	Variable	***B***	***SE B***	***β***	***sr^2***	**ΔR^2**
DV: *MS* LS						
Step 1	*MS* PACA	.34***	.03	.84	.70	.70***
Step 2	*MS* PACA	.31***	.03	.78	.50	.04*
	Extroversion	.06*	.03	.18	.03	
	Stability	.03	.03	.08	.00	
			R^2=.74; Adjusted R^2=.72			

Note: MS = mean state measurement.

The results contained in Table 6.14 indicate that extroversion predicted an additional 4% unique variance in mean state LS after controlling for mean state PACA. However, a comparison of the beta-weights for extroversion and mean state PACA reveals the effect of extroversion on mean state LS was minimal (β=.06, sr^2=.03) in comparison to the effect of mean state PACA (β=.31, sr^2=.50).

To further investigate the relation between SWB, extroversion, stability, and PACA, zero-order correlations between extroversion, stability, and SWB in each time frame (global trait, recalled, and mean state) were computed and compared with partial correlations controlling for global trait PACA and mean state PACA. These correlations, controlling for global trait PACA, are presented in Table 6.15.

Table 6.15: Pearsons and partial correlations between extroversion, stability, LS, PWI, and SWLS in each measured time frame (global trait, recalled, mean state), controlling for global trait PACA (*N*=48).

Variable	**Pearson *r* with extroversion**	**sr^2 (controlling for GT PACA)**	**Magnitude of reduction in Pearson *r***	**Pearson *r* with stability**	**sr^2 (controlling for GT PACA)**	**Magnitude of reduction in Pearson *r***
LS GT	.28	.09	.19	.60***	.51***	.09
LS R	.27	.25	.02	.18	.15	.03
LS *MS*	.35*	.25	.10	.39**	.28	.11
PWI GT	.27	.13	.14	.46**	.34*	.12
PWI R	.07	-.01	.08	.21	.13	.08
PWI *MS*	.21	.09	.12	.32*	.19	.13
SWLS	.11	.09	.02	.22	.21	.01

***p<.001; **p<.01; *p<.05

Note: GT=global trait measurement; R=recalled measurement; MS=mean state measurement.

The data contained in Table 6.15 indicate that the relationships between LS, PWI, and extroversion and stability were substantially reduced when the effects of global trait PACA were accounted for. The magnitude of reductions in the zero-order correlations for extroversion ranged from .02 to .19 (*M*=.10), whilst for stability ranged from .03 to .13 (*M*=.08). The largest reduction in the zero-order correlations was observed in the relationship between global trait LS and extroversion (from r=.28 to sr^2=.09). The zero-order and partial correlations between extroversion, stability, and SWB, controlling for mean state PACA, are presented in Table 6.16.

Table 6.16: Pearsons and partial correlations between extroversion, stability, LS, PWI, and SWLS in each measured time frame (global trait, recalled, mean state), controlling for mean state PACA (*N*=48).

Variable	Pearson *r* with extroversion	sr^2 (controlling for *MS* PACA)	Magnitude of reduction in Pearson *r*	Pearson *r* with stability	sr^2 (controlling for *MS* PACA)	Magnitude of reduction in Pearson *r*
LS GT	.28	.20	.08	.60***	.49**	.11
LS R	.27	.19	.08	.18	-.09	.09
LS *MS*	.35*	.35*	.00	.39**	.08	.31
PWI GT	.27	.21	.06	.46**	.33*	.13
PWI R	.07	-.05	.12	.21	-.02	.23
PWI *MS*	.21	.11	.10	.32*	.05	.27
SWLS	.11	.01	.10	.22	.01	.21

***p<.001; **p<.01; *p<.05

Note: GT=global trait measurement; R=recalled measurement; MS=mean state measurement.

The data contained in Table 6.16 indicates that the relationships between extroversion, stability, LS, PWI, and SWLS were substantially reduced when the effects of mean state PACA were accounted for. The reduction in zero-order correlations ranged from .00 to .12 for extroversion (*M*=.08), and .09 to .31 for stability (*M*=.19). The largest reduction in zero-order correlations occurred in the relationship between stability and mean state LS (from r=.39 to sr^2=.08).

PACA Model of SWB Using Mean State Measures of PACA and SWB

As results demonstrated that the global trait reports of affect and SWB were significantly different from mean state reports, the global trait reports should not be relied upon to test the efficacy of the PACA model of SWB. In addition, the application of MLM in the present study only took into account three out of eight possible measures of momentary PACA. To address this, SEM was utilised in which the PACA model was tested using averaged momentary (mean state) measures of PACA and SWB. Taking the average of every PACA and SWB momentary measure yields more stable, reliable, and accurate estimate of an individual's true baseline PACA and SWB, as fluctuations due to external influences (i.e., the environment, time of day) are controlled for. Using SEM also enabled a replication of results obtained in Studies 1, 2, and 3 with the more reliable measures of PACA and SWB.

SEMs were tested according to each measured time frame for PWI (global, recall, and mean state) and mean state LS. In each SEM, the predictor of SWB (PWI and LS) was always mean state PACA. A check of multi-collinearity was conducted through the examination of correlations between the constructs used in the SEMs (mean state PACA, global trait PWI, recalled PWI, mean state PWI, mean state LS, and SWLS). These correlations are presented in Table 6.17.

Table 6.17: Correlations between mean state PACA, PWI (global trait, recalled, and mean state), mean state LS, and SWLS (N=48).

Variable	1.	2.	3.	4.	5.	6.
1. *MS* PACA						
2. PWI-GT	.48					
3. PWI-R	.57	.59				
4. PWI-*MS*	.71	.74	.80			
5. LS-*MS*	.85	.63	.56	.72		
6. SWLS	.51	.40	.57	.50	.59	
M	16.91	72.53	68.96	65.77	65.17	66.60
SD	3.30	10.09	10.81	11.02	13.05	17.44

Note: All correlations are significant at p<.01; GT=global trait measurement; R=recalled measurement; MS=mean state measurement.

The correlations contained in Table 6.17 indicate the largest correlation, between mean state PACA and mean state LS, was .85. The average correlation between constructs was .62. As the criteria for multi-collinearity is considered to be correlations of .90 and higher (Predhazur, 1997; Tabachnick & Fidell, 2001), no multi-collinearity was deemed present. The mean state PACA model predicting mean state PWI is presented in Figure 6.25 along with standardised regression paths, SMC (in italics), and correlations. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 6.26.

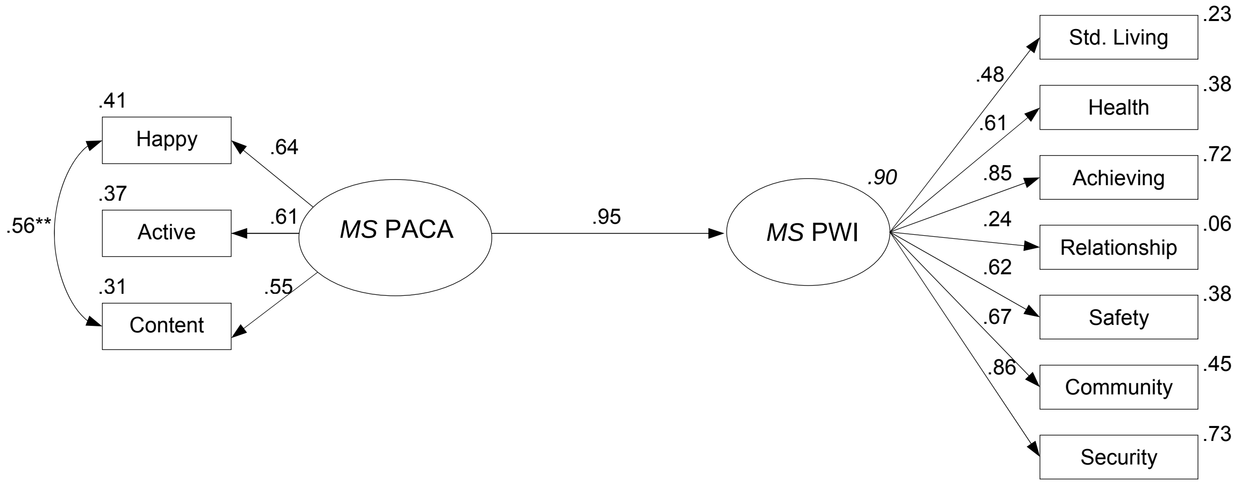


Figure 6.25: Mean state (MS) PACA model of SWB (Standardised; N=53).

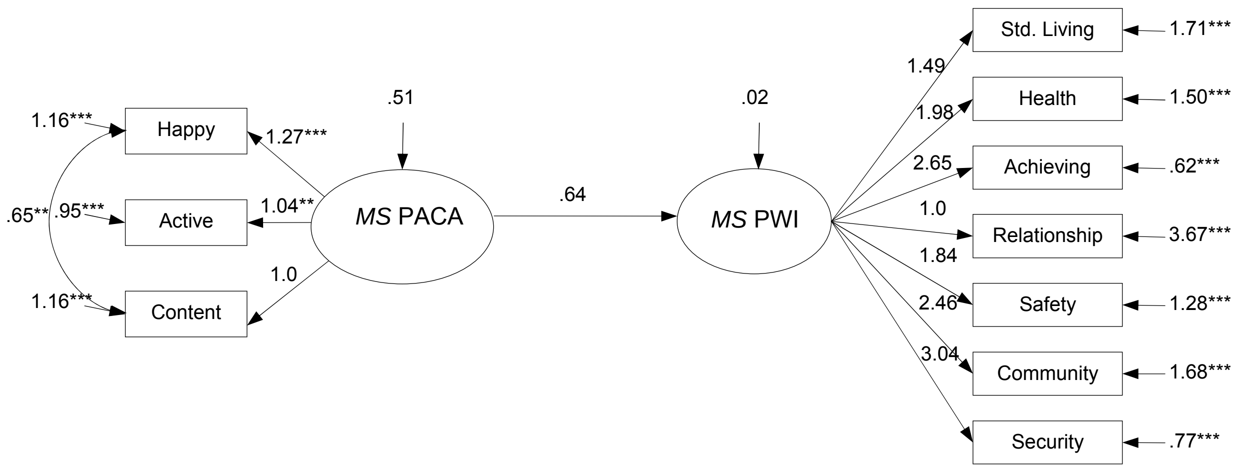


Figure 6.26: Mean state (MS) PACA model of SWB (Unstandardised).

Absolute and relative fit indices for the mean state PACA model are presented in Table 6.18.

Table 6.18: Absolute and relative fit indices for mean state PACA model of SWB.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	76.23	28.23	31	>.05	.91	.88	1.0	.00	.90
Saturated	110.0	.000	0	-	-	1.0	1.0	-	-
Independence	255.65	235.65	45	<.001	5.24	.00	.00	.29	.00

The fit indices contained in Table 6.18 reveal the mean state PACA model provides an absolute fit to the data, is parsimonious, and explains a substantial amount of variance in mean state PWI. The standardised and unstandardised regression paths and SMC given in Figure 6.25 and Figure 6.26 indicate that mean state PACA influences mean state PWI (β=.95, B=.64, p>.05), accounting for 90% of the variance. The mean state PACA model predicting mean state LS is presented in Figure 6.27 along with standardised regression paths, SMC (in italics) and correlations. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 6.28.

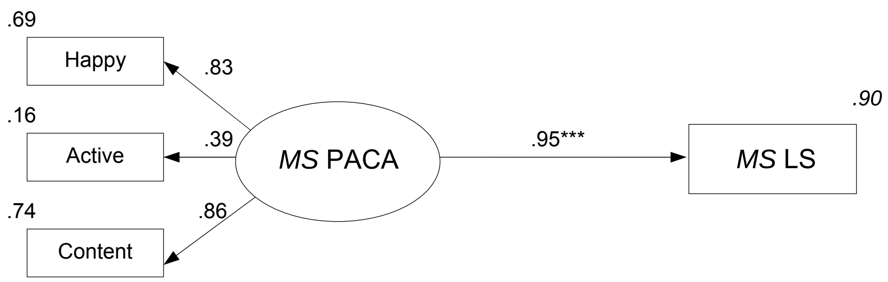


Figure 6.27: Mean state (MS) PACA model predicting mean state LS (Standardised; N=53).

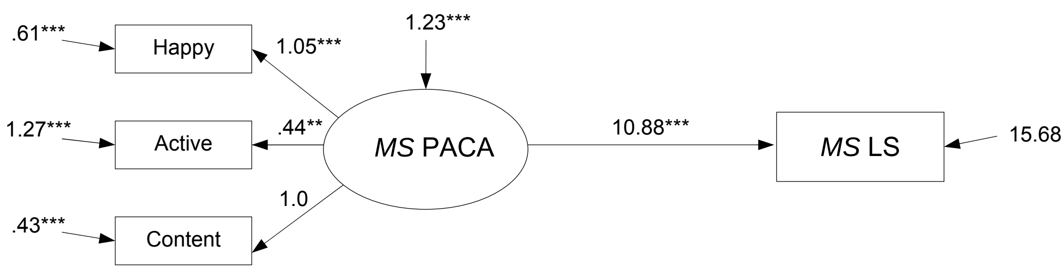


Figure 6.28: Mean state (MS) PACA model predicting mean state LS (Unstandardised).

Absolute and relative fit indices for the mean state PACA model predicting mean state LS are presented in Table 6.19.

Table 6.19: Absolute and relative fit indices for mean state PACA model predicting mean state LS.

Model	**AIC**	χ^2	***df***	***P***	χ^2/df	**NFI**	**CFI**	**RMSEA**	**SMC**
Specified	17.88	1.88	2	>.05	.94	.98	1.0	.00	.90
Saturated	20.0	.000	0	-	-	1.0	1.0	-	-
Independence	128.50	120.50	6	<.001	20.08	.00	.00	.61	.00

The fit indices given in Table 6.19 indicate that the mean state PACA model predicting mean state LS provides an absolute fit to the data, is highly parsimonious, and accounts for 90% of variance in mean state LS. The standardised and unstandardised regression weights given Figure 6.27 and Figure 6.28 indicate that mean state PACA strongly influences mean state LS (β=.95, B=10.88, p>.001).

Thereafter the PACA model was tested using an alternative measure of SWB to provide an additional assessment of the utility of the PACA model. This alternative measure of SWB is the SWLS, which has been proposed as a cognitive measure of life satisfaction (Diener et al., 1985). The mean state PACA model predicting SWLS is presented in Figure 6.29 along with standardised regression paths, SMC (in italics), and correlations. The unstandardised values for this model, including standard errors (in parentheses) are presented in Figure 6.30.

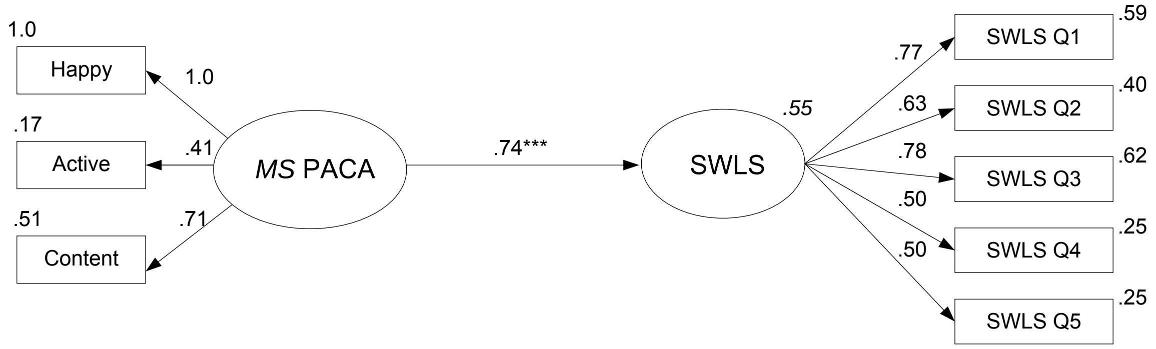


Figure 6.29: Mean state (MS) PACA model predicting SWLS (Standardised; N=53).

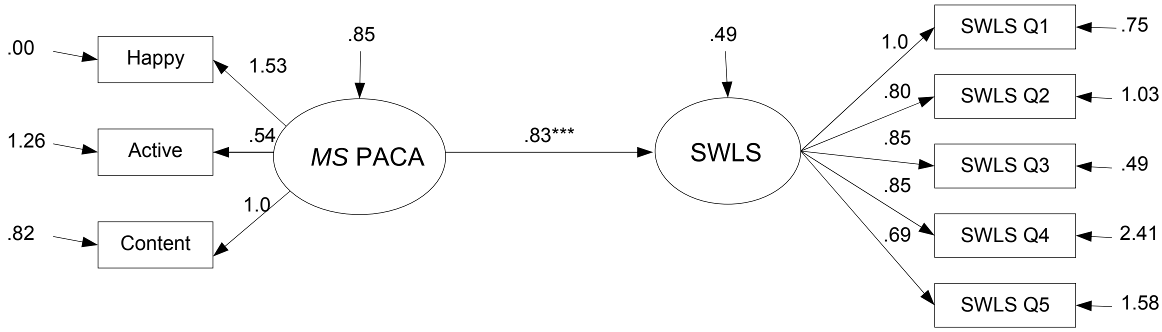


Figure 6.30: Mean state (MS) PACA model predicting SWLS (Unstandardised).

Absolute and relative fit indices for the mean state PACA model predicting SWLS are presented in Table 6.20.

Table 6.20: Absolute and relative fit indices for mean state PACA model predicting SWLS.

Model	AIC	χ^2	*df*	*P*	χ^2/df	NFI	CFI	RMSEA	SMC
Specified	61.71	27.71	19	>.05	1.46	.84	.94	.09	.55
Saturated	72.0	.000	0	-	-	1.0	1.0	-	-
Independence	194.13	178.13	28	<.001	6.36	.00	.00	.32	.00

The fit indices contained in Table 6.20 indicate an absolute fit to the data for the mean state PACA model predicting SWLS. Mean state PACA strongly predicted SWLS (β=.74, B=.83, *p*>.001), accounting for 55% variance. In addition, this model demonstrated a high degree of parsimony. A comparison of absolute and relative fit indices for all models tested is given in Table 6.21.

Table 6.21: Summary of absolute and relative fit indices for mean state PACA models predicting mean state PWI, mean state LS, and SWLS.

Predictor	**DV**	**AIC**	χ^2	***df***	***P***	χ^2/df	**NFI**	**CFI**	**RMSEA**	**SMC**
MS PACA	*MS* PWI	76.23	28.23	31	>.05	.91	.88	1.00	.00	.90
	MS LS	17.88	1.88	2	>.05	.94	.98	1.00	.00	.90
	SWLS	61.71	27.71	19	>.05	1.46	.84	.94	.09	.55

The absolute and relative fit indices contained in Table 6.21 indicate that all PACA models tested provided an absolute fit to the data and demonstrated a high degree of parsimony. Notably, 90% of the variance in mean state PWI and mean state LS was accounted for by mean state PACA. In addition, the PACA model with an alternate measure of SWB (the SWLS) provided an absolute fit to the data and accounted for 55% of variance.

Summary of Results

A plot of mean state LS and PWI indicated average daily values, across all days and all participants, did not fall below 60 or exceed 70 for the duration of the study. However, results indicated that the variability in mean state LS scores was higher within-persons than between-persons. Further investigation of the variance in SWB indicated that above and below mean values of approximately 72 (for LS or PWI), variance in SWB increased. An analysis of linear trends above and below mean scores of 72 confirmed this result.

A plot of mean state happiness, contentment, and activity (together forming PACA) demonstrated that average daily values, across all days and all participants, varied within a one-point range. The effect of time of day on mean state happiness and contentment was negligible whilst mean state activity showed a clear decline towards the end of the day. An analysis of the variance in PACA also revealed a similar pattern as that observed for SWB. Specifically, as mean PACA scores approached 20 (67%SM), the variance in PACA decreased.

Multi-level modelling revealed that state PACA and state unhappiness significantly predicted variation in state LS within-persons. Specifically, PACA predicted 17% of the variance in state LS within-persons. Significant variation in the PACA coefficient indicated the effect on state LS differed between people, however the 95%CI (.35 to 2.19) indicated the effect was positive for a majority of the sample. State unhappiness was significantly associated with state LS, explaining an additional 4% of variance within-persons. The 95%CI (-2.44 to .30) indicated the relationship between state LS and state unhappiness was negative for a majority of the sample. However, for some participants, there was no relationship between state unhappiness and state LS. Together, PACA and state unhappiness accounted for 27% of the variation in state LS within-persons. Variation in mean state LS between persons was found to be significantly predicted by trait PWI, trait depression, and trait extroversion. For trait PWI and trait extroversion, higher values were associated with higher average LS scores. Conversely, higher trait depression scores were associated with lower average LS scores. Together trait PWI, trait depression, and trait extroversion accounted for 40% of the variation in average LS between-persons. Further testing of level two variables predicting variation in LS between-persons indicated the variables were either not significant, decreased the variance explained, or decreased model fit. As such, they were not included in the final MLM model. The variables that comprised the final MLM model were PACA, state unhappiness, trait PWI, trait depression, and trait extroversion (in addition to time and group). This model was the most parsimonious model tested and predicted the largest amount of variance in LS, both within-persons, and between-persons.

An examination of retrospective biases in recalled and global trait measures of affect and SWB indicated a consistent and significant overestimation in comparison with mean state values (with the exception of the affects relaxed and annoyed). This overestimation effect was largest in global trait reports. Furthermore, a series of multiple regressions indicated that, even after controlling for mean state reports of SWB, PACA significantly and uniquely predicted global trait and recalled SWB. Testing of the PACA model of SWB, with mean state measures of SWB and PACA, replicated results obtained in Studies 1, 2, and 3. The PACA model consistently provided an absolute fit to the data, explained a substantial amount of variance in SWB, and demonstrated a high degree of parsimony.

Section 6.4: DISCUSSION

This study aimed to test the PACA model of SWB using a methodology (ESM) that yields more accurate and reliable data than retrospective global trait reports. In accordance with the PACA model, it was hypothesised that PACA would provide the strongest and most parsimonious explanation of SWB. Results supported this hypothesis. The application of MLM revealed state PACA significantly predicted variation in state LS within-persons (see Table 6.5). A plot of each individual's regression slope revealed the effect of state PACA on state LS was positive for a majority of the sample (see Figure 6.23). Furthermore, structural equation modelling indicated mean state PACA predicted 90% of the variance in mean state LS and PWI (see Table 6.21). These SEMs provided an absolute fit to the data and demonstrated a high degree of parsimony (see Table 6.21). The PACA model was also tested with an alternate measure of SWB (the SWLS). This model provided an absolute fit to the data. Mean state PACA accounted for 55% of the variance in SWLS (see Table 6.21), indicating significant affective processes operating in what are hypothesised as cognitive judgements of life satisfaction (Diener et al., 1985).

As retrospective reports have been found to be unreliable (Conner Christensen & Wood et al., 2003; Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Robinson & Clore, 2002a; Wirtz et al., 2003), using ESM enabled a more accurate and reliable estimate of individuals' PACA and SWB. This increased accuracy and reliability is due to the very short time lag between the question and the response. In addition, responses were made within the context of the individual's daily life, thereby providing a more accurate representation of an individual's actual experience. The examination of mean state reports of happiness, contentment, and activity (together forming PACA) across all persons, revealed PACA only varied within a one-point range over the 14 day study period (see Figure 6.16). Similarly, across all persons, SWB (as measured by LS and PWI) only varied within a one-point range over the 14 day study period (see Figure 6.3). Thus, on average, over 14 days individuals did not substantially vary in PACA or SWB. A further examination of the stability in SWB indicated that the variability within people was greater than the variability between people. A plot of individual mean LS and PWI scores and their standard deviations indicated that individuals became less variable as mean scores approached approximately 72 (see Figure 6.9 for LS and Figure 6.13 for PWI). This relationship was verified in an analysis of linear trends for mean scores above and below 72 for both LS (see Figures 6.10 and 6.11) and PWI (see Figures 6.14 and 6.15). Thus, the greatest degree of instability occurred for individuals with relatively high, and relatively low SWB scores. These results are consistent with the homeostatic model of SWB which posits increased variability in SWB for individuals experiencing a challenge to SWB homeostasis (Cummins, 2003; Cummins et al., 2002). Specifically, it is proposed that a homeostatic mechanism works to keep SWB within a narrow range by resisting change at upper and lower thresholds. If SWB increases or decreases substantially from the individual's set-point, homeostasis is said to be defeated, and control of SWB shifts towards the challenging agent (i.e., unemployment, ill-health, winning the lottery; Cummins et al., 2002; see Chapter 2, Figure 2.2).

An analysis of individual means and standard deviations for PACA revealed a similar pattern of results as that observed for SWB. Specifically, individuals became less variable as mean scores approached approximately 20 (67%SM; see Figure 6.20). This suggests that the homeostatic mechanism for SWB might be found in PACA. Indeed, the results of the present study, and of the three previous studies indicating PACA to be the strongest and most parsimonious predictor of SWB, makes it increasingly likely that the homeostatic mechanism for SWB operates through PACA.

The multi-level modelling results support this proposal, as PACA significantly predicted the variation in LS within-persons (see Table 6.5), accounting for 17% variance. (This result differs from the result obtained using SEM, however this is to be expected as MLM took into account three out of the eight possible daily measures of affect that were obtained in conjunction LS (LS measured three times daily) whereas SEM averaged all daily measures. Thus MLM had more variance to account for. In comparison, the PACA variable used in SEM was an average measure across the entire 14 day study period, taking into account every possible measure of PACA. This yields a more stable measure of PACA that is free from random noise variance, variance due to daily fluctuation, variance due to changes in the weather (Schwarz & Clore, 1983), and variance due to other environmental factors, all of which have been demonstrated to temporarily alter SWB (Forgas & Moylan, 1987; Schwarz et al., 1987). The results using this measure of PACA are considered following the discussion of MLM results.)

The effect of PACA on LS, as revealed in MLM, was positive; higher PACA was associated with higher LS. However, a significant variance coefficient indicated the strength of the relationship between PACA and LS was not the same for every individual. An examination of each individuals regression slope revealed the relationship between PACA and LS differed in magnitude; for some individuals the relationship was strong, for others it was relatively weak (see Figure 6.23). Despite this, the regression slopes indicated the relation between PACA and LS was positive for a majority of the sample. Individual differences in the magnitude of the relationship between PACA and LS were not explained adequately by any of the variables tested (see Table 6.8). However it is suggested that explanations for such differences need to be investigated in future research, ideally within an ESM framework.

Within-person variation in LS was also significantly predicted by state unhappiness. Higher unhappiness was related with lower LS. However unhappiness only accounted for an additional 4% variance in LS. As with PACA, the relationship between unhappiness and LS was not the same for every individual. An examination of the individual regression slopes revealed that, for a majority of the sample, the relationship was negative, differing only in magnitude (see Figure 6.24). However some individuals had horizontal regression slopes, indicating a lack of relationship between unhappiness and LS (see Figure 6.24). None of the variables tested adequately explained the individual differences in the relation between state unhappiness and LS (see Table 6.8). It is likely that the SWB of these individuals is resilient to changes in state unhappiness. This possibility, and potential explanations for such resilience, should be the subject of future research.

Between-person variation in mean state LS was significantly predicted by trait PWI (23% variance accounted for; see Table 6.6), mean state PACA (see Table 6.8), trait extroversion (11% variance accounted for; see Table 6.7) and trait depression (6% variance accounted for; see Table 6.6). Higher scores on trait depression were associated with lower mean state LS whilst higher scores on trait PWI, mean state PACA, and trait extroversion were associated with higher mean state LS. However, hierarchical regressions indicated that once mean state PACA had been accounted for, extroversion only predicted an additional 2% unique variance in mean state PWI (see Table 6.13) and 3% in mean state LS (see Table 6.14). Furthermore, partial correlations between extroversion and stability and three measures of SWB (PWI, LS, and SWLS) across three different time frames (global trait, recalled, and mean state), revealed that once the effects of PACA had been controlled for the relationships were substantially reduced (see Tables 6.15 and 6.16). This result replicates and confirms the results of Studies 1, 2, and 3, which found the influence of extroversion and stability on SWB was substantially reduced once the effects of PACA had been accounted for. These findings are also consistent with Davern (2004). Together these results suggest that previous research proposing a central role for personality in SWB (Brebner et al., 1995; Diener et al., 2003; Diener & Lucas, 1999; Headey & Wearing, 1989, 1992; Hills & Argyle, 2001; Myers & Diener, 1995; Vitterso, 2001) must be re-evaluated in light of the current findings.

The use of trait PWI to predict between-person variation in mean state LS may be criticised by some on grounds that the two constructs are circular. However trait PWI and mean state LS are separate, though overlapping, constructs. Trait PWI was developed to represent the first level deconstruction with LS. Trait PWI has also been found to account for between 48 and 52% of variance in LS (Cummins et al., 2004), leaving almost half the variance in LS unaccounted for. In addition, trait PWI was measured by global retrospective satisfaction judgements with various life domains, whereas mean state LS was measured by momentary satisfaction judgments of life as a whole.

The results of MLM uncover important attributes of the relationship between PACA and SWB in addition to the nature of SWB over time. However as mentioned previously, in the present study the application of MLM only incorporated the measures of affect taken in conjunction with the measures of LS. Thus, as affect was measured eight times per day, MLM excluded up to five daily measures of PACA. To address this, SEMs were specified and tested in which mean state measures of PACA were used to predict mean state measures of SWB.

The SEM results, incorporating the more reliable and accurate measures of SWB and PACA, demonstrated that when noise variance in PACA and SWB is controlled for, PACA accounts for 90% of the variance in SWB (LS or PWI; see Table 6.21), leaving only 10% of the variance in SWB unaccounted for. Furthermore, across three different measures of SWB (PWI, LS, SWLS), the PACA model provided an absolute fit to the data, explained a substantial amount of variance in SWB, and demonstrated a high degree of parsimony (see Table 6.21). These analyses demonstrate that baseline PACA is an extremely powerful predictor of the variation in baseline SWB. However these results also raise the possibility that SWB and PACA are multi-collinear. An examination of the correlations between mean state LS, mean state PWI, and mean state PACA (see Table 6.17) indicates the formal criterion for multi-collinearity (zero-order correlations of .90 and above; Predhazur, 1997; Tabachnick & Fidell, 2001) was not met (r=.71 and r=.85). Whilst the constructs are highly related, they are not collinear. Furthermore, Thompson (2004) argues that multi-collinearity is not as important as disconfirmability. This issue is highlighted by Cummins, Stokes, and Davern (2007) in a hypothetical example of a model which cannot be falsified. In this model, there are two cases of data over two variables. In such a situation, the "sums of squared unexplained goes to zero, because the degrees freedom unexplained (error) is zero, leaving no variance to be explained (p.7).” The authors went on to note that 100% of variance explained in a DV is only impressive “if there are sufficient degrees of freedom remaining to allow disconfirmability (p.463)”. Whilst the PACA model predicting mean state LS only has two degrees freedom remaining, the model predicting mean state PWI has 31 degrees freedom remaining, thereby allowing for the possibility of other disconfirmatory models.

An alternative explanation of the strong relationship observed between SWB and PACA would suggest that PACA and SWB are so similar as to be practically the same. Although this alternative explanation was covered earlier (see Chapter 3, section 3.3), it is necessary to return to again in light of the current findings, and in light of recent articles by Moum (2007) and Land (2007) criticising the relationship found between core affect and SWB by Davern et al. (2007) on these grounds. In Chapter 3 it was argued that the explanation of SWB by core affect is not tautological; it is an explanation in terms of another, lower order construct. This argument stands, and is bolstered when considering the nature of core affect as described by Russell (2003) in comparison with the nature of SWB. Core affect is an elementary affective tonicity. It is universal, primitive, and ubiquitous, and can be experienced without the presence of a known stimulus. There is now a large body of research supporting this conceptualisation of separate, but interacting systems of cognition and affect (Adolphs, Tranel, Damasio, & Damasio, 1994; Dimberg, et al., 2000; LeDoux, 1995a, 1995b, 1996; Murphy et al., 1995; Murphy & Zajonc, 1993; Ohman & Soares, 1994; Whalen, et al., 1998; Zajonc, 1980, 1984, 1998). In contrast with core affect, SWB is almost always measured as an evaluation of life satisfaction, whether with life as a whole, or across various domains.

Thus SWB is, of necessity, an object-related evaluation, whereas core affect is an elementary affective tonicity that can exist without being attributed to an object.

Moum (2007) and Land (2007) further criticise the relationship between core affect and SWB by suggesting that the items used to measure core affect and SWB are near identical, thereby accounting for the strong relationship. This criticism has been effectively dealt with by Cummins et al. (2007), however it will be reiterated here. In this thesis, PACA has been measured using the items happy, content, and active. In Studies 1, 2, and 3, these items were measured with the instruction, “Please indicate how each of the following describes your feelings when you think about your life in general.” In contrast, SWB was asked using the instruction, “Thinking about your own life and personal circumstances, please circle the number that best represents how satisfied you feel with your life. How satisfied are you with…” [your life as a whole, or, domain x]. In the current study the instructions were modified to represent the momentary time frame. Thus, momentary PACA was asked using the instruction, “How *[affect]* do you feel right now?” For SWB, the instruction was, “Thinking about right now, how satisfied are you with [your life as a whole, or, domain x]?” A consideration of these instructions indicates that the concepts of momentary or general feelings, and momentary or general life satisfaction judgments which specify concrete criteria (*life as a whole* or *domain x*), are very different. One is an evaluation, whereas the other is a representation of feelings. Whilst Land is correct in pointing out that items which have been used to measure SWB in previous research (happy, pleased, and delighted) lie quite close to the items used to measure PACA (happy, content, and active), this does not invalidate the results of this thesis, or of Davern et al. In both instances, SWB has been measured in two ways; through evaluations of life as a whole, and evaluations across various domains. In Davern et al., and in this thesis, variations in these evaluations were accounted for by PACA. In addition, whilst previous research may have used items such as happy, pleased, and delighted to measure SWB, it is argued here that such measurement is problematic as it confuses evaluations of life satisfaction with affective states. Taken together, the criticisms raised by Moum and Land do not invalidate the results of this thesis or of this study. In this study, a reliable and accurate measure of baseline PACA strongly predicted variation in two reliable and accurate measures of baseline SWB (mean state LS and mean state PWI). The invocation of PACA in the explanation of SWB is not tautological; it is an explanation of one concept (SWB) in terms of another, lower order concept (PACA).

Retrospective Biases in Self-reports of Affect and Subjective Wellbeing

Previous research has demonstrated that retrospective global self-reports are vulnerable to distortions of memory and judgmental biases (Robinson & Clore, 2002a), and as such, are an inaccurate reflection of an individual's actual experience (Conner Christensen & Wood et al., 2003; Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Robinson & Clore, 2002a; Wirtz et al., 2003). The results of this study confirmed the existence of retrospective biases in recalled and retrospective global reports of SWB and affect. Consistent with previous research (Wirtz et al., 2003), participants' recall estimates of their SWB and affect over the 14 day study period were consistently higher than the average of momentary levels of SWB and affect (see Table 6.9). This overestimation effect was also found in global trait reports of SWB and affect, with the magnitude of overestimation larger than in recalled reports (see Table 6.10). This increased magnitude in the overestimation effect for global trait reports is likely due to increased accuracy in recalling experiences as a result of the frequent daily attendance to affect and SWB over the course of the sampling period. However it is interesting to note that despite making, on average, 81 momentary judgments of affect and 31 judgments of SWB over 14 days, on the 15th day individuals still consistently overestimated their experiences of the past 14 days. In addition, even after controlling for actual SWB, trait PACA significantly predicted trait SWB, accounting for up to an additional 19% unique variance in trait SWB (see Tables 6.11 and 6.12). Similarly, after controlling for actual SWB, recalled PACA significantly predicted recalled SWB, accounting for up to an additional 15% variance (see Tables 6.11 and 6.12). These results demonstrate that an individual's perception of how happy, content, and active they believed themselves to be (semantic knowledge) predicted their trait and recalled reports of SWB, even after controlling for their actual reports of SWB. Together these results highlight the pervasive influence of semantic knowledge (in this instance, self-perceptions of happiness, contentment, and activity) when individuals are asked to make retrospective self-reports. These results are also consistent with previous research that has found semantic knowledge to be predictive of recalled self-reports after actual reports had been controlled for (Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Wirtz et al., 2003).

The overestimation of SWB in retrospective reports found in this study may help inform the debate regarding the existence of a cultural difference in the experience of SWB and emotion in Western and Asian individuals. On the basis of research finding that individuals from Asian cultures (i.e., Hong Kong, Japan) report lower SWB and pleasant affect than individuals from Western cultures (i.e., North America, Australia; Cummins, 1998; Diener, Diener & Diener, 1995; Kitayama, Markus, & Kurokawa, 2000; Lau et al., 2005), it has been suggested that individuals from Asian cultures underestimate their actual levels of SWB due to a cultural response bias (Lau et al., 2005). However, research conducted using ESM (Oishi, 2002) revealed that European Americans, but not Asian Americans, significantly overestimated their SWB compared to momentary daily ratings. This overestimation of SWB for Western individuals found by Oishi is consistent with the findings of the present study in which Australians significantly overestimated their SWB in comparison to momentary daily ratings. Taken together, these two results raise the possibility that the cultural difference in SWB observed by Cummins, Diener et al., Kitayama et al., and Lau et al. may not be due to a tendency by Asian individuals to under-estimate their SWB, but rather, due to a tendency by Westerners to retrospectively overestimate their SWB. However, as ethnicity was not measured in the current study, strong conclusions cannot be drawn. Future research should attempt to test this possibility further within an ESM paradigm by specifically measuring ethnicity in combination with momentary and retrospective reports of SWB.

The clear and consistent effect of semantic knowledge being used to inform retrospective self-reports should be taken into account by researchers when relying solely on this type of data. As mentioned previously, the results of this study, and previous research (Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Wirtz et al., 2003), have consistently demonstrated that retrospective reports do not correspond with momentary reports; and as momentary reports capture the representation of experience at or close to its occurrence and within the context of an individual’s daily life, momentary reports are more accurate, more reliable, and more valid than retrospective reports. Accordingly, retrospective reports should ideally be accompanied by momentary reports. Future research should examine precisely what semantic knowledge is relied upon when individuals make retrospective affective and SWB judgments. The results of this study suggest that trait PACA is one source of semantic knowledge that is used to inform retrospective global reports of SWB.

Conclusions

The results of the current study have wide-ranging implications. Firstly, as mentioned previously, they suggest that previous literature proposing personality and/or cognition as a central determinant of SWB (Brebner et al., 1995; Diener et al., 2003; Diener & Lucas, 1999; Headey & Wearing, 1989, 1992; Hills & Argyle, 2001; Michalos, 1985; Myers & Diener, 1995; Vitterso, 2001) is in need of revising. It is proposed that in future research, the variance due to PACA be used as a covariate to determine the unique contribution of personality and cognition to SWB. The results of this study, and of Studies 1, 2, and 3 suggest this contribution is minimal. Secondly, the results of Studies 1, and 2, which demonstrated that the PACA model of SWB was a powerful and parsimonious explanation of SWB, have been replicated using a more accurate, reliable, and ecologically valid measure of PACA and SWB. Thirdly, using an alternative measure of SWB (the SWLS), proposed by its developers to measure the cognitive component of SWB (Diener et al., 1985), did not alter the results. PACA predicted a substantial amount of variance in SWLS (55%) and the model tested provided an absolute fit to the data. This result provides further evidence that what are hypothesised as cognitive measures of SWB are largely influenced by PACA. Accordingly, affect should no longer be considered as a separate component of SWB (Diener, 1984, 1996), but rather as a lower order construct that strongly influences SWB. Finally, this study demonstrated that retrospective self-reports of affect and SWB are particularly vulnerable to memory distortions and judgmental biases. The results suggested that these retrospective reports are typically distorted by an individual's semantic knowledge. This is consistent with previous literature that has examined retrospective biases in self-reports (Conner Christensen & Wood et al., 2003; Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Robinson & Clore, 2002a; Wirtz et al., 2003). Accordingly, it is suggested that future research attempting to falsify the results of the current study utilise an ESM framework.

In conclusion, the results of this study provide further evidence that PACA powerfully influences SWB. These findings are important as they extend upon the findings of Studies 1, 2 and 3, and previous research (Schimmack, 2003), by measuring SWB and affect more accurately and reliably than has been done previously. This allowed a more stringent test of the utility of the PACA model of SWB. Results revealed that an individual's trait level of PACA (as measured by multiple random reports of momentary PACA over 14 days), strongly predicted an individual's trait level of SWB (as measured by multiple random reports of SWB over 14 days). Thus the trait PACA model of SWB is a comprehensive and parsimonious explanation of an individual's subjective satisfaction with life.

CHAPTER 7: OVERALL DISCUSSION

In the past 50 years there has been an exponential rise in the volume of research investigating an individual's self-perceived satisfaction with life. This research was borne out of a shift in the discipline of psychology away from an exclusive and narrow focus on illbeing, toward a broader, more encompassing focus on the factors that impact wellbeing. Since this time, there has been considerable progress in identifying the various factors that influence Subjective Wellbeing (SWB); however, there has also been a relative lack of progress in combining these influences into a comprehensive theoretical account of SWB. This thesis attempted to address this gap in knowledge by comparing and contrasting different theoretical models of SWB. These theories included a homeostatic model (Cummins et al., 2002), Multiple Discrepancies Theory (MDT; Michalos, 1985), and an affective-cognitive model (Davern, 2004; Davern et al., 2007).

Early research in subjective wellbeing identified a weak relationship between objective measures of quality of life (such as GDP and income), and subjective reports of life satisfaction (Andrews & Withey, 1976; Campbell et al., 1976; Easterlin, 1995; Max-Neef, 1995). This weak relationship has since been confirmed; increases in the GDP of Western industrialised countries since the 1970s were found to be relatively unrelated to subjective quality of life (Easterlin, 2005; Max-Neef, 1995). On an individual level, the influence of income on subjective wellbeing has been demonstrated to be negligible once a basic level has been met (see Chapter 1, Figures 1.1 and 1.2). As objective factors were found to correlate poorly with SWB, the search to understand the correlates of SWB shifted toward an analysis of dispositional influences, such as personality. However the review of literature conducted in Chapter 1 indicated that the major dimensions of personality, extroversion and neuroticism, often accounted for less than 30% of the variance in SWB. In a large meta-analysis of literature examining the relationship between personality and SWB (DeNeve & Cooper, 1998), the correlations between SWB and extroversion and neuroticism were only -.21 and .17 respectively. This weak relationship led to the proposal of other variables thought to account for the large amount of unexplained variance in SWB. Such variables included self-esteem, optimism, and perceived control, which were all found to correlate moderately with SWB (Compton, 2000; Cummins & Nistico, 2002; DeNeve & Cooper, 1998; Diener & M. Diener, 1995; Lucas et al., 1996). Whilst a number of studies identified correlates of SWB, there was a relative lack of theoretical progress in elucidating the mechanisms by which these variables influenced SWB. Notable exceptions to this lack of theoretical progress included homeostatic theory (Cummins et al., 2002), MDT (Michalos, 1985), and an affective-cognitive model (Davern, 2004; Davern et al., 2007). While each model had some empirical support, they had yet to be directly contrasted to each other, and as such, the efficaciousness of either one of the models could not be conclusively determined. Study 1 was conducted to address this question.

According to the homeostatic model (Cummins et al., 2002), SWB is hypothesised to be maintained around an individual set-point through the operation of personality in conjunction with a system of cognitive buffers (comprising self-esteem, perceived control, and optimism). Specifically, extroversion and neuroticism are proposed to directly, and indirectly (through the cognitive buffers), influence SWB. In contrast, MDT (Michalos, 1985) proposes that SWB is the direct result of a series of perceived gaps in relation to an individual's particular life circumstances. In both MDT and the homeostatic model, cognitions are central to the explanation of SWB. However, the affective-cognitive model (Davern, 2004; Davern et al., 2007) proposes that the driving force of SWB is not cognition, but affect. This model incorporated affect, cognition, and personality by proposing that affect directly influenced SWB, in addition to influencing the set of perceived discrepancies given by MDT. Affect was also proposed to directly influence personality, which in turn directly influenced SWB. Whilst the results of Study 1 indicated some support for each theory, none of the three models provided an adequate explanation of the data.

Further testing in Study 1 revealed that trait positive affect exerted a substantial influence on SWB. Specifically, the trait positive affects of happiness, contentment, and activity were found to predict a substantial amount of variance in SWB. The subsequent testing of an alternative theoretical model of SWB, in which these three affects combined to form a latent construct predicting SWB, revealed this model provided the best explanation of the data. Furthermore, once the shared variance due to trait happiness, contentment, and activity was accounted for, the relationships between SWB and each of the variables comprising homeostatic theory and MDT (extroversion, neuroticism, self-esteem, perceived control, optimism, perceived discrepancies) were greatly reduced. These findings were unexpected as a large body of previous research (Brebner et al., 1995; Compton, 2000; Cummins & Nistico, 2002; Diener & M. Diener, 1995; Emmons & Diener, 1985; Hills & Argyle, 2001; Lance et al., 1995; Lucas et al., 1996; Michalos, 1985; Staats et al., 1995; Vitterso, 2001) had concluded that the variables comprising homeostatic theory and MDT were strongly related to SWB. However these conclusions were reached on the basis of moderate zero-order correlations that did not account for the shared variance due to trait positive affect. The results of this thesis demonstrated that once this shared variance was removed, the correlations reduce dramatically.

It was then considered that trait happiness, contentment, and activity shared features of Russell's (2003) concept of "Core Affect". This concept was developed by Russell in response to the search for the primitive components associated with affect, valence, moods, and emotions. Core affect is a consciously accessible neurophysiological state comprised of a blend of hedonic (pleasantness-unpleasantness) and arousal (activation-deactivation) values. Russell considers core affect to be the primitive component associated with felt emotion and moods. It is simple, objectless, universal, and ubiquitous, existing prior to any attribution about its cause. Therefore core affect is not cognitive or reflective, as cognitive events are intrinsically about something (Russell, 2003). When applied to the results of Study 1, it becomes apparent that asking how happy, content, or active an individual felt in general reflects core affect. Together, trait happiness, contentment, and activity were proposed to form pleasant-activated core affect (PACA).

The results of Study 1 suggested that SWB did not comprise two separate components of life satisfaction and affect as previously hypothesised (Diener, 1984, 1996; Diener et al., 1999; Pavot et al., 1991). Rather, it is proposed that evaluations of life satisfaction, with life as a whole, and across various domains, comprise SWB. In contrast, PACA is a distinct, lower-order process that strongly influences these evaluations. This proposal is supported by research that has found affect to be independent, but related to cognitions (Adolphs et al., 1994; Dimberg et al., 2000; LeDoux, 1995a, 1995b, 1996;

Murphy et al., 1995; Murphy & Zajonc, 1993; Ohman & Soares, 1994; Whalen et al., 1998; Zajonc, 1980, 1984, 1998).

As the findings of Study 1 were inconsistent with a large body of previous research (Brebner et al., 1995; Compton, 2000; Cummins & Nistico, 2002; DeNeve & Cooper, 1998; Diener et al., 2003; Diener & M. Diener, 1995; Diener & Lucas, 1999; Emmons & Diener, 1985; Headey & Wearing, 1989, 1992; Hills & Argyle, 2001; Lance et al., 1995; Lucas et al., 1996; Michalos, 1985; Myers & Diener, 1995; Staats et al., 1995; Vitterso, 2001), replication of the results was necessary before strong conclusions could have been drawn regarding the utility of any of the theoretical models tested. This was provided in Study 2 in a test of the theoretical models in three independent samples. The results confirmed the findings of Study 1. The PACA model provided the best, simplest, and most comprehensive explanation of SWB. However, an alternative explanation of this result might suggest that PACA was used as a heuristic to inform life satisfaction judgments. Study 3 was conducted in an attempt to test this hypothesis. The use of a reaction time paradigm did not yield conclusive results. However the self-report data collected in conjunction with the RT data enabled an alternative test of the heuristic hypothesis. If the heuristic hypothesis were correct, then state PACA and state affect in general should have been more strongly related to SWB than trait PACA. In fact, the opposite was found. Even after allowing state PACA and state affect to consume the maximum available variance in SWB, trait PACA significantly and uniquely predicted a substantial amount of variance in SWB. Furthermore, state affect and state PACA accounted for no more than 6% of variance in SWB when the effects due to trait PACA were removed. The trait PACA model of SWB also provided an absolute and parsimonious fit to the data, replicating the results of Studies 1 and 2 in another independent sample.

Studies 1, 2, and 3 suggested that the trait PACA model of SWB was an efficacious and comprehensive explanation of SWB, however the results were based exclusively on retrospective self-reports. This is problematic as a large body of research has consistently found that retrospective self-reports are vulnerable to memory distortions and judgmental biases (Conner Christensen & Wood et al., 2003; Feldman Barrett, 1997; Napa Scollon et al., 2004; Oishi, 2002; Robinson & Clore, 2002a; Wirtz et al., 2003), and as such are an inaccurate representation of an individual's actual lived experience. Thus Study 4 was conducted using a methodology that would provide a more accurate and reliable measure of PACA and SWB, allowing a more stringent test of the trait PACA model. This alternative methodology (Experience Sampling Methodology, ESM) effectively solves problems of memory distortions and judgmental biases in retrospective self-reports. In an ESM study, individuals are signalled at different intervals throughout a day over multiple days. Due to the extremely short time lag between the signal and the response, data are much less likely to be contaminated by retrospective biases, thus providing an accurate measure of an individual's experience within the context of their daily lives. Using ESM enabled a baseline measure of PACA and SWB to be obtained by averaging each momentary assessment of affect and SWB over 14 days. Taking an average measure was important as previous research had indicated that fluctuations in affect due to environmental influences (watching a sad or happy movie, Forgas & Moylan, 1987) altered subsequent ratings of life satisfaction. Controlling for fluctuations in PACA and SWB allowed an accurate and reliable measure of PACA and SWB to be obtained, thereby enabling a more stringent and accurate test of the PACA model of SWB.

The results revealed that the PACA model, with the baseline measures of PACA and SWB, provided an absolute fit to the data, predicted 90% of variance in SWB, and demonstrated parsimony. This result is important as it confirms the results of Studies 1, 2, and 3 using more accurate and reliable measures of SWB and PACA. Importantly, although the homeostatic model failed to provide an adequate explanation of the data in Studies 1 and 2, one of the central predictions of the theory was supported in the results of Study 4. Specifically it was found that the variability in SWB was related to individual mean scores. Above and below scores of approximately 72, the variability in SWB increased. This is consistent with the hypothesised operation of a homeostatic mechanism working to maintain SWB within a relatively narrow range. Once SWB increases or decreases beyond this range, homeostasis is said to be challenged or defeated, and control of SWB shifts away from the homeostatic mechanism and toward the challenging agent, thereby increasing the variability in SWB.

The pattern of decreased variability around a specific mean score was also found in PACA. An increase in variability was found for individual mean scores above and below 67%SM. Based on these results in SWB and PACA, it is proposed that a homeostatic mechanism working to maintain stability in SWB is not determined by cognitions and personality as suggested by homeostatic theory (Cummins et al., 2002), but rather by baseline PACA. That is, individuals with a high baseline level of PACA are prone to experience higher levels of SWB than individuals with high levels of unpleasant core affect. Having a high level of PACA likely protects against reduced

SWB resulting from the experience of strong negative extrinsic influences. It is hypothesised that this protection occurs automatically, such that when strong negative extrinsic influences are experienced, the impact on SWB is minimal. This automatic protection functions through the general level of positivity (resultant from high PACA) permeating cognition and behaviour. In addition, the SWB of individuals with a high level of PACA is proposed to “bounce back” from the experience of negative influences that lower SWB. In contrast, a high unpleasant level of core affect is proposed to offer little protection against the destabilising influence of strong negative extrinsic conditions on SWB. This is likely due to the effect of a general level of unpleasant core affect permeating cognitions and behaviours. Specifically, negative cognitions and behaviours could form a feedback loop which reinforces the initial low level of SWB experienced as a result of the negative extrinsic conditions. Accordingly, individuals with high levels of baseline unpleasant core affect are prone to experiencing lower SWB. These theoretical proposals could be tested in an analysis of longitudinal data which includes individuals who have experienced strong negative extrinsic influences (i.e., dissolution of a valued relationship, illness or death of a loved one, long term unemployment). Such a study would ideally be conducted within an ESM framework as the results of this thesis confirm the unreliability of global trait measures of SWB and affect.

Whilst SWB was demonstrated to be relatively stable over the 14 day study period, the variation in SWB within-persons was significantly predicted by PACA and unhappiness. Thus, momentary SWB covaried with momentary PACA and unhappiness. Results also indicated that the magnitude of the relationships between PACA, unhappiness, and SWB varied across individuals (although remained predominantly positive and negative respectively). For some individuals, PACA strongly influenced SWB, whereas for others, the effect was weaker. Similarly, for some individuals, unhappiness was strongly negatively related to SWB, whilst for others, unhappiness and SWB were unrelated. Exactly what determines these individual differences should be the subject of future research. Such research could attempt to identify the characteristics of individuals who differ in core affective tonicity. It is likely that an individual's core affective tonicity is determined by a combination of genetic influences and environmental factors. Whilst individuals constantly seek out ways to alter their state core affect (through natural and synthetic means), it is an individual's trait core affect that provides the affective background to cognitions and behaviour. An investigation of these individual differences in trait core affect will likely provide a greater understanding of the determinants of core affect. Advances in neuroscience are also likely to help further understand the biological bases of core affect. One way to achieve this could involve mapping various core affect tonicities onto specific brain states. Initial work in this area (Hayward, 2008) has found that injury to the right parietal lobe (N=70) was associated with lowered PACA in comparison to non-injured individuals.

Using retrospective reports in conjunction with ESM reports in Study 4 confirmed the existence of retrospective biases in self-reported SWB and affect. Individuals were found to have consistently overestimated trait and recalled levels of affect and SWB. The use of semantic knowledge by individuals when making retrospective SWB judgments was also confirmed. Even after controlling for actual levels of SWB, semantic knowledge (self-perceptions of global trait happiness, contentment, and activity) significantly and uniquely predicted global trait, and recalled SWB. Thus, an individual's beliefs about how happy, content, and active they were in general led them to report higher levels of global trait SWB regardless of their actual level of SWB. These findings further suggest that retrospective global trait self-reports are unreliable as they are biased by self-perceptions and memory distortions. As such, the use of global trait reports, especially in the context of affect and SWB research, should be supplemented by momentary reports wherever possible.

The findings of Study 4, in conjunction with the findings of Studies 1, 2, and 3, provide strong evidence for the utility of the trait PACA model of SWB. Specifically, the findings suggest that an individual's trait level PACA powerfully influences their experience of satisfaction with life.

Overall, the results of this thesis strongly suggest that previous hypothesised structures of SWB, in which affect was seen as a component of SWB, are inadequate and in need of updating. Specifically, this thesis proposes that what was hypothesised previously as the cognitive component of SWB (life satisfaction) actually comprises SWB. In this proposal, affect, and in particular PACA, is not a component of SWB but a lower order process that heavily influences evaluations of life satisfaction (the higher order process). The distinction that Russell and Feldman Barrett (1999) make between PACA and evaluations helps to clarify this argument. Core affect is considered to be affect that is primitive and can be experienced independently of an object, therefore, independently of cognitive appraisal processes. In contrast, evaluations of life satisfaction, by necessity, require an object (i.e., one's life as a whole, or various life domains), and therefore involve higher order cognitive processes. Thus, evaluations of life satisfaction (the higher order process) are separate from, but highly influenced by PACA (the lower order process). This thesis also found that the influence of PACA was not restricted to judgments of life satisfaction. Comparative judgments of individuals' particular life circumstances (MDT) were also heavily influenced by PACA. The degree to which an individual rated themselves as generally happy, content, and active predicted close to three-quarters of the variation in these comparative judgments, such that individuals high on trait PACA reported the least disparity in their life circumstances. This serves to further highlight the pervasive influence of PACA. It is suggested that the influence of PACA may also extend into other facets of life, including cognitions and behaviour.

This thesis addressed a gap in the SWB literature by explicitly contrasting three theoretical models of SWB. This comparison revealed none of the theories provided an adequate explanation of the data. Further testing led to the development of an alternative theoretical model of SWB, the PACA model. In four separate studies the PACA model was confirmed as the best explanation of the data. This result has important implications for previous literature and for future research. Firstly, much of the previous literature proposing personality (Brebner et al., 1995; Emmons & Diener, 1985; Diener & Lucas, 1999; Headey & Wearing, 1989, 1992; Myers & Diener, 1995; Vitterso, 2001), cognition (self-esteem, optimism, perceived control; Compton, 2000; Cummins & Nistico, 2002; Cummins et al., 2002) or multiple discrepancies (Lance et al., 1995; Michalos, 1985; Staats et al., 1995) as important determinants of SWB must be re-interpreted in light of the current findings. Whilst future research should, as a minimum, control for the effects of PACA prior to assessing relationships between SWB and other variables, this thesis makes it clear that SWB is predominantly influenced by baseline PACA. As such, the goal of future research should not be to control for PACA and uncover further correlates of SWB, but rather, to investigate the psychological and behavioural correlates of PACA, as well as investigating individual differences in PACA. This will be more beneficial in furthering the understanding of SWB than identifying additional variables that only share a modest relationship with SWB.

The extent to which PACA has been found to permeate judgments that had previously been considered highly cognitive is somewhat surprising. However, these findings are important as they help to further advance psychology away from previous considerations of affect and emotions as outside the realm of psychology, and therefore not worthy to be studied, towards a greater understanding of the complex interaction and interdependence between affect and cognition. In this thesis, trait PACA was found to permeate judgments of self-esteem, perceived control, optimism, extroversion, stability, perceived discrepancies, and life satisfaction. The experience of subjective wellbeing is largely determined by trait levels of pleasant-activated core affect.

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APPENDIX A

Thinking about your own life and personal circumstances, please circle the number that best represents how satisfied you are with your life.

How satisfied are you with…

Your life as a whole?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your standard of living?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your health?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

What you are currently achieving in life?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your personal relationships?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

How safe you feel?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Feeling part of your community?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your future security?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

APPENDIX B

How much did these statements apply to you over the past week? 0 is not at all, and 10 is extremely.

	Not at all										Extremely
I found it hard to wind down	0	1	2	3	4	5	6	7	8	9	10
I was aware of dryness of my mouth	0	1	2	3	4	5	6	7	8	9	10
I couldn't seem to experience any positive feeling at all	0	1	2	3	4	5	6	7	8	9	10
I experienced breathing difficulty (eg, excessively rapid breathing, breathlessness in the absence of physical exertion)	0	1	2	3	4	5	6	7	8	9	10
I found it difficult to work up the initiative to do things	0	1	2	3	4	5	6	7	8	9	10
I tended to over-react to situations	0	1	2	3	4	5	6	7	8	9	10
I experienced trembling (eg, in the hands)	0	1	2	3	4	5	6	7	8	9	10
I felt that I was using a lot of nervous energy	0	1	2	3	4	5	6	7	8	9	10
I was worried about situations in which I might panic and make a fool of myself	0	1	2	3	4	5	6	7	8	9	10
I felt that I had nothing to look forward to	0	1	2	3	4	5	6	7	8	9	10
I found myself getting agitated	0	1	2	3	4	5	6	7	8	9	10
I found it difficult to relax	0	1	2	3	4	5	6	7	8	9	10
I felt down-hearted and blue	0	1	2	3	4	5	6	7	8	9	10
I was intolerant of anything that kept me from getting on with what I was doing	0	1	2	3	4	5	6	7	8	9	10
I felt I was close to panic	0	1	2	3	4	5	6	7	8	9	10
I was unable to become enthusiastic about anything	0	1	2	3	4	5	6	7	8	9	10
I felt I wasn't worth much as a person	0	1	2	3	4	5	6	7	8	9	10
I felt that I was rather touchy	0	1	2	3	4	5	6	7	8	9	10
I was aware of the action of my heart in the absence of physical exertion (eg, sense of heart rate increase, heart missing a beat)	0	1	2	3	4	5	6	7	8	9	10
I felt scared without any good reason	0	1	2	3	4	5	6	7	8	9	10
I felt that life was meaningless	0	1	2	3	4	5	6	7	8	9	10

APPENDIX C

These statements ask about the kind of person you are. Please indicate your agreement with each of the following statements.

1. I see myself as extraverted and enthusiastic.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

2. I see myself as anxious and easily upset.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

3. I see myself as reserved and quiet.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

4. I see myself as calm and emotionally stable.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

APPENDIX D

How much do you agree with the following statements?

On the whole, I am satisfied with myself.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

At times I think I am no good at all.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I feel that I have a number of good qualities.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I am able to do things as well as most other people.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I feel I do not have much to be proud of.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I certainly feel useless at times.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I feel that I'm a person of worth, at least on an equal plane with others.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I wish I could have more respect for myself.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

All in all, I am inclined to feel that I am a failure.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I take a positive attitude toward myself.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

APPENDIX E

How much do you agree with the following statements?

In uncertain times, I usually expect the best.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I'm always optimistic about my future.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

Overall, I expect more good things to happen to me than bad.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

APPENDIX F

When bad things happen to you how do you cope with them?
How much do you agree that when something bad happens....

I ask others for help or advice.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I look for different ways to improve the situation.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I use my skills to overcome the problem.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I remind myself that something good may come out of it.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I remind myself that I am better off than some others.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I remember that the situation will improve if I am patient.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I don’t do anything, as nothing can help.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I spend time by myself.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

I just let my feelings out so others know how I feel.

Strongly Disagree					Neutral					Strongly Agree
0	1	2	3	4	5	6	7	8	9	10

APPENDIX G

How happy do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How content do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How satisfied do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How unhappy do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How discontent do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How active do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How alert do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How excited do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How sleepy do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

How quiet do you generally feel?

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

APPENDIX H

Considering your life as a whole, how does it measure up to your general aspirations or what you want out of life? Generally, does life provide what you want fairly poorly, fairly well, etc.?

Provides nothing that you want					Provides half of what you want					Provides all that you want
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to the average for most people your own age and sex in this area? Generally, does your life offer you far less than what is offered the average person, more, etc.?

Far below average					About average					Far above average
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to the life you think you deserve? Generally, does your life offer you far less than you deserve, more, etc.?

Far less than you deserve					About what you deserve					Far more than you deserve
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to the life you think you need? Generally, does your life offer you far less now than you expected it would offer, more, etc.?

Far less than you need					About what you need					Far more than you need
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to what you expected about 3 years ago? Generally, does your life offer you far less now than you expected it would offer, more, etc.?

Far less than expected					About as expected					Far more than expected
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to what you expect in the next 5 years? Generally does your life offer you less now than you expect it will offer in 5 years, more, etc.?

Far more than it will offer (future is dark)					About what you expect in the future					Far less than it will offer (future is bright)
0	1	2	3	4	5	6	7	8	9	10

Considering your life as a whole, how does it measure up to the best in your previous experience? Generally, is your life these days running far below your previous best, above, etc.?

Far below previous best					Equals previous best					Far above previous best
0	1	2	3	4	5	6	7	8	9	10

APPENDIX I

Below are five statements with which you may agree or disagree. Using the 1-7 scale below, indicate your agreement with each item by placing the appropriate number on the line preceding that item. Please be open and honest in your responding. The 7-point scale is as follows:

1 = strongly disagree
2 = disagree
3 = slightly agree
4 = neither agree nor disagree
5 = slightly agree
6 = agree
7 = strongly agree

___ In most ways my life is close to my ideal.

___ The conditions of my life are excellent.

___ I am satisfied with my life.

___ So far I have gotten the important things I want in life.

___ If I could live my life over, I would change almost nothing.

APPENDIX J

This scale consists of a number of words that describe different feelings and emotions. Read each word and then mark the appropriate number in the space next to that word.

Indicate to what extent you feel this way **<u>in general</u>.** Use the following scale to record your answers.

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

______upset

______alert

______happy

______tired

______content

______annoyed

______unhappy

______depressed

______relaxed

______active

APPENDIX K

This scale consists of a number of words that describe different feelings and emotions. Read each word and then mark the appropriate number in the space next to that word.

Please estimate, on average, how you have felt **over the past two weeks.** For example: *On average, how upset did you feel over the past two weeks?*

Use the following scale to record your answers.

Not at All										Extremely
0	1	2	3	4	5	6	7	8	9	10

______upset

______alert

______happy

______tired

______content

______annoyed

______unhappy

______relaxed

______active

APPENDIX L

Thinking about your own life and personal circumstances, please circle the number that best represents how satisfied you are with your life.

<u>Over the past two weeks</u>, please estimate, on average, how satisfied you were with…

Your life as a whole?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your standard of living?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your health?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

What you are currently achieving in life?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your personal relationships?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

How safe you feel?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Feeling part of your community?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

Your future security?

Not at all Satisfied										Completely Satisfied
0	1	2	3	4	5	6	7	8	9	10

THE END