UNSW SYDNEY

Electrophysiological markers of mental wellbeing and ways to promote it

Author:
Chilver, Miranda

Publication Date:
2021

DOI:
https://doi.org/10.26190/unsworks/2059

License:
https://creativecommons.org/licenses/by/4.0/
Link to license to see what you are allowed to do with this resource.

Downloaded from http://hdl.handle.net/1959.4/100149 in https://unsworks.unsw.edu.au on 2024-03-29

Electrophysiological markers of mental wellbeing and ways to promote it

Miranda R. Chilver

A thesis in fulfilment of the requirements for the degree of Doctor of Philosophy

School of Psychology

Faculty of Science

University of New South Wales

Australia

November 2021

Thesis submission for the degree of Doctor of Philosophy

Thesis Title and Abstract | Declarations | Inclusion of Publications Statement | Corrected Thesis and Responses

Thesis Title

Electrophysiological markers of mental wellbeing and ways to promote it

Thesis Abstract

Mental wellbeing, a state of positive subjective experience and psychological functioning, is a key component of mental health. Despite this, little is known about how mental wellbeing is manifested in the brain, or how such neural associations covary with depression and anxiety symptoms. Thus, the aim of this thesis was to explore potential electrophysiological markers of wellbeing using electroencephalography (EEG) and event-related potentials (ERPs). To facilitate further investigation into the association between electrophysiology and wellbeing, a positive psychology intervention was also developed.

Following an introduction to the key topics, Chapter 2 examined the relationship between mental wellbeing and resting EEG power. This study identified a specific profile of resting EEG power that is associated with wellbeing, independent from depression and anxiety symptoms. Twin modelling clarified that this EEG profile shares a genetic correlation with mental wellbeing. Chapters 3 and 4 shift towards using ERPs to investigate how wellbeing and depression and anxiety symptoms are associated with emotional and cognitive processing. Chapter 3 reported that wellbeing was not significantly associated with emotion processing after accounting for depression and anxiety symptoms, which were significantly associated with alterations in emotion processing. In Chapter 4, no evidence was found for an association between wellbeing or depression and anxiety symptoms with cognitive ERPs, although associations with behavioural performance reported in previous studies were replicated. Finally, Chapter 5 reports on the effectiveness of an online positive psychology intervention which was found to significantly improve wellbeing, particularly subjective wellbeing. Although COVID-19 restrictions prevented the evaluation of causal links between wellbeing and EEG using this intervention, it is discussed for purposes of future research.

Together, this thesis provides one of the first investigations into the electrophysiological correlates of mental wellbeing. Resting EEG power was identified as the most promising avenue for future research aiming to establish endophenotype markers of mental wellbeing, with the task-related measures assessed here were not associated with wellbeing. A short and effective online intervention was developed that could be used to facilitate future investigations into the use of resting EEG as a predictor and marker of mental wellbeing.

Thesis submission for the degree of Doctor of Philosophy

Thesis Title and Abstract | Declarations | Inclusion of Publications Statement | Corrected Thesis and Responses

ORIGINALITY STATEMENT

☑ I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at UNSW or any other educational institution, except where due acknowledgement is made in the thesis. Any contribution made to the research by others, with whom I have worked at UNSW or elsewhere, is explicitly acknowledged in the thesis. I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

COPYRIGHT STATEMENT

☑ I hereby grant the University of New South Wales or its agents a non-exclusive licence to archive and to make available (including to members of the public) my thesis or dissertation in whole or part in the University libraries in all forms of media, now or here after known. I acknowledge that I retain all intellectual property rights which subsist in my thesis or dissertation, such as copyright and patent rights, subject to applicable law. I also retain the right to use all or part of my thesis or dissertation in future works (such as articles or books).

For any substantial portions of copyright material used in this thesis, written permission for use has been obtained, or the copyright material is removed from the final public version of the thesis.

AUTHENTICITY STATEMENT

☑ I certify that the Library deposit digital copy is a direct equivalent of the final officially approved version of my thesis.

Thesis submission for the degree of Doctor of Philosophy

Thesis Title and Abstract | Declarations | **Inclusion of Publications Statement** | Corrected Thesis and Responses

UNSW is supportive of candidates publishing their research results during their candidature as detailed in the UNSW Thesis Examination Procedure.

Publications can be used in the candidate's thesis in lieu of a Chapter provided:

- The candidate contributed **greater than 50%** of the content in the publication and are the "primary author", i.e. they were responsible primarily for the planning, execution and preparation of the work for publication.
- The candidate has obtained approval to include the publication in their thesis in lieu of a Chapter from their Supervisor and Postgraduate Coordinator.
- The publication is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in the thesis.

☑ The candidate has declared that **their thesis has publications - either published or submitted for publication - incorporated into it in lieu of a Chapter/s. Details of these publications are provided below.**.

Publication Details #1

Full Title:	Electroencephalography profiles as a biomarker of wellbeing: A twin study
Authors:	Miranda R. Chilver, Arielle S. Keller, Haeme R.P. Park, Javad Jamshidi, Arthur Montalto, Peter R. Schofield, C. Richard Clark, Eddie Harmon-Jones, Leanne M. Williams, Justine M. Gatt
Journal or Book Name:	Journal of Psychiatric Research
Volume/Page Numbers:	126, 114-121
Date Accepted/Published:	July 2020
Status:	published
The Candidate's Contribution to the Work:	MRC conducted the statistical analysis, wrote the first draft of the article, and edited the manuscript.
Location of the work in the thesis and/or how the work is incorporated in the thesis:	This article is included in lieu of Chapter 2.

Publication Details #2

Full Title:	Emotional face processing correlates with depression/anxiety symptoms but not wellbeing in non-clinical adults: An event-related potential study
Authors:	Miranda R. Chilver, Haeme R.P. Park, Peter R. Schofield, C. Richard Clark, Leanne M. Williams, Justine M. Gatt
Journal or Book Name:	Journal of Psychiatric Research
Volume/Page Numbers:	
Date Accepted/Published:	
Status:	submitted
The Candidate's Contribution to the Work:	MRC conducted the EEG data processing, the statistical analysis, wrote the first draft of the article, and edited the manuscript.
Location of the work in the thesis and/or how the work is incorporated in the thesis:	This article is included in Chapter 3, but has been edited to include components relating to the results and discussion of the twin analysis and heritability results.

Publication Details #3

Full Title:	Six-week online multi-component positive psychology intervention improves subjective wellbeing in young adults
Authors:	Miranda R. Chilver, Justine M. Gatt
Journal or Book Name:	Journal of Happiness Studies
Volume/Page Numbers:	
Date Accepted/Published:	September 2021
Status:	published
The Candidate's Contribution to the Work:	MRC conceptualised the study, created the materials, carried out recruitment & data collection, analysis, wrote the first draft of the paper, and edited the manuscript.
Location of the work in the thesis and/or how the work is incorporated in the thesis:	This article is included in lieu of Chapter 5.

Candidate's Declaration

I confirm that where I have used a publication in lieu of a chapter, the listed publication(s) above meet(s) the requirements to be included in the thesis. I also declare that I have complied with the Thesis Examination Procedure.

Acknowledgements

First and foremost, I would like to give a huge thanks to my supervisor, Dr Justine Gatt, who constantly provided her feedback and support to make this all possible. There were so many challenges along the way, and she was always there to push me forwards. I also extend my thanks to my co-supervisors, Dr Eddie Harmon-Jones and Dr Peter Schofield for supporting my candidature and their helpful feedback on my work. A special thanks also to Dr Lea Williams for her detailed advice and making time for me. I am also grateful to Twins Research Australia for the training they provided to assist with my statistical analyses, and their role in recruiting participants.

My PhD experience would not have been the same without my fellow lab members. To Haeme, thank you for always having time to talk, review my work, reassure me, and grab a coffee. You have been a life saver! To Arthur and Javad, thanks for sharing the PhD experience with me, struggles and victories both.

Deanna and Brondwyn, your friendship has been invaluable. You were there when I needed you most and pulled me through my toughest moments. I hope to return the favour.

Mom and dad, thanks for all the opportunities you provided me with, for never doubting me, and the endless support. To Clare, thanks for all the years of treating as your own daughter, for your concern and support and love. To my grandma, Evelyn, your love stretches across the ocean. Thank you for giving me a reason.

Finally, David, I am immeasurably lucky to have you in my life. For always making me laugh, for handling my stress, for listening to all my rants and all my joys, for supporting me in every way, thank you.

List of Publications

Chapter 2

Chilver, M. R., Keller, A. S., Park, H. R. P., Jamshidi, J., Montalto, A., Schofield, P. R., Clark, C. R., Harmon-Jones, E., Williams, L. M., & Gatt, J. M. (2020). Electroencephalography profiles as a biomarker of wellbeing: A twin study. *Journal of Psychiatric Research*, *126*, 114–121. https://doi.org/10.1016/j.jpsychires.2020.04.010

Chapter 3

Chilver, M. R., Park, H. R. P., Schofield, P. R., Clark, C. R., Williams, L. M., & Gatt, J. M. (in press). Emotional face processing correlates with depression/anxiety symptoms but not wellbeing in non-clinical adults: An event-related potential study. *Journal of Psychiatric Research*.

Chapter 5

Chilver, M. R., & Gatt, J. M. (2021). Six-week online multi-component positive psychology intervention improves subjective wellbeing in young adults. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-021-00449-3

Related publications

Jamshidi, J., Williams, L. M., Schofield, P. R., Park, H. R. P., Montalto, A., **Chilver, M. R.**, Bryant, R. A., Toma, C., Fullerton, J. M., & Gatt, J. M. (2020). Diverse phenotypic measurements of wellbeing: Heritability, temporal stability and the variance explained by polygenic scores. *Genes, Brain and Behavior*, *19*(8). https://doi.org/10.1111/gbb.12694

Park, H. R. P., **Chilver, M. R.,** Montalto, A., Jamshidi, J., Schofield, P. R., Williams, L. M., & Gatt, J. M. (2021). Associations between mental wellbeing and fMRI neural bases underlying responses to positive emotion in a twin sample. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291721002695

List of Presentations

Oral Presentations

Chilver, M.R., Park H.R.P., Schofield, P.R., Clark, R.C., Williams, L.M., Gatt, J.M. (2021). Electrophysiological markers of mental wellbeing. Oral presentation, NeuRA.

Gatt, J.M., **Chilver, M.R.,** French, B. (2020). Find the key to your mental resilience. Webinar, NeuRA Mental Health Week.

Chilver, M.R., Keller, A.S., Park, H.R.P., Jamshidi, J., Montalto, A., Schofield, P.R., Clark, R.C., Harmon-Jones, E., Williams, L.M., Gatt, J.M. (2020). EEG profiles as a biomarker of wellbeing: A twin study. Oral presentation, NeuRA Invited Seminar Series, Sydney, NSW.

Chilver, M.R., Gatt, J.M. (2020). Online multi-component positive psychology intervention improves life satisfaction in students. Oral presentation, Society of Mental Health Research Mental Health Week, online.

Chilver, M.R., Keller, A.S., Park, H.R.P., Jamshidi, J., Montalto, A., Schofield, P.R., Clark, R.C., Harmon-Jones, E., Williams, L.M., Gatt, J.M. (2019). EEG profiles of wellbeing: A twin study. Oral presentation, Society of Mental Health Research Annual Conference, Melbourne, VIC.

Chilver, M.R., Harmon-Jones, E., Schofield, P.R., Clark, R.C., Williams. L. M., Gatt, J.M. (2018). Uncovering the EEG profiles of mental wellbeing. Oral presentation, Sydney Post-Graduate Psychology Conference, Sydney, NSW.

Poster Presentations

Chilver, M.R., Gatt, J.M. (2021). Online positive psychology intervention outperforms active control: A randomised control trial. Poster presentation, International Positive Psychology Association 7th World Congress, online.

Chilver, M.R., Keller, A.S., Park, H.R.P., Jamshidi, J., Montalto, A., Schofield, P.R., Clark, C.R., Harmon-Jones, E., Williams, L.M., Gatt, J.M. (2021). Distinct electrophysiological markers of mental wellbeing and mental illness symptoms in non-clinical adults. Poster presentation, Society of Biological Psychiatry Virtual Meeting, online.

Chilver, M.R., Keller, A.S., Park, H.R.P., Jamshidi, J., Montalto, A., Schofield, P.R., Clark, C.R., Harmon-Jones, E., Williams L.M., Gatt, J.M. (2020). Using EEG and ERPs to understand wellbeing. Poster presentation, Biological Psychiatry Australia Annual Conference, online.

Chilver, M.R., Williams, L.M., Schofield, P.R., Clark, R., Harmon-Jones, E., Gatt, J.M. (2019). What EEG can tell us about wellbeing. Poster presentation, International Positive Psychology Association 6th World Congress, Melbourne, VIC.

Abstract

Mental wellbeing, a state of positive subjective experience and psychological functioning, is a key component of mental health. Despite this, little is known about how mental wellbeing is manifested in the brain, or how such neural associations covary with depression and anxiety symptoms. Thus, the aim of this thesis was to explore potential electrophysiological markers of wellbeing using electroencephalography (EEG) and event-related potentials (ERPs). To facilitate further investigation into the association between electrophysiology and wellbeing, a positive psychology intervention was also developed.

Following an introduction to the key topics, Chapter 2 examined the relationship between mental wellbeing and resting EEG power. This study identified a specific profile of resting EEG power that is associated with wellbeing, independent from depression and anxiety symptoms. Twin modelling clarified that this EEG profile shares a genetic correlation with mental wellbeing. Chapters 3 and 4 shift towards using ERPs to investigate how wellbeing and depression and anxiety symptoms are associated with emotional and cognitive processing. Chapter 3 reported that wellbeing was not significantly associated with emotion processing after accounting for depression and anxiety symptoms, which were significantly associated with alterations in emotion processing. In Chapter 4, no evidence was found for an association between wellbeing or depression and anxiety symptoms with cognitive ERPs, although associations with behavioural performance reported in previous studies were replicated. Finally, Chapter 5 reports on the effectiveness of an online positive psychology intervention which was found to significantly improve wellbeing, particularly subjective wellbeing. Although COVID-19 restrictions prevented the evaluation of causal links between wellbeing and EEG using this intervention, it is discussed for purposes of future research.

Together, this thesis provides one of the first investigations into the electrophysiological correlates of mental wellbeing. Resting EEG power was identified as the most promising avenue for future research aiming to establish endophenotype markers of mental wellbeing, with the task-related measures assessed here were not associated with wellbeing. A short and effective online intervention was developed that could be used to facilitate future investigations into the use of resting EEG as a predictor and marker of mental wellbeing.

Contents

Acknowledgements 3
List of Publications 4
List of Presentations 6
Oral Presentations 6
Poster Presentations 7
Abstract 8
List of figures 14
List of tables 16
List of abbreviations 17
Chapter 1: General Introduction 19
1.1. Mental wellbeing, mental illness, and mental health 21
1.1.1. Definitions of mental wellbeing 22
1.1.2. The dual factor model of mental health 24
1.2. Why promote mental wellbeing? 25
1.2.1. Mental wellbeing as a protective factor 26
1.2.2. Physical, economic, and productivity benefits 27
1.3. Explaining genetic vs environmental variance in mental wellbeing 27
1.4. Promoting wellbeing through positive psychology interventions 29
1.5. Using endophenotypes to improve positive psychology interventions 31
1.6. The TWIN-E Study 32
1.7. Resting EEG measures 34
1.6.1. Resting EEG in mental health 35
1.7. Event-related potentials 36
1.7.1. Emotion-related event related potentials 37
1.7.2. Cognitive event-related potentials 39
1.8. Thesis overview 42
1.9. References 46
Chapter 2: Identifying a resting EEG profile of wellbeing 69
2.1. Preamble 70
2.2. Abstract 71
2.3. Introduction 72
2.4. Methods & Materials 75
2.4.1. Participants 75

2.4.2. Procedure 75
2.4.3. EEG acquisition and processing 76
2.4.4. Statistical analyses 76
2.5. Results 80
2.5.1. Linear mixed models 81
2.5.2. Univariate twin analysis 85
2.5.3. Multivariate twin analysis 85
2.6. Discussion 88
2.7. References 93
Appendix A: Chapter 2 Supplementary Results 99
Chapter 3: Emotional face processing and mental health 117
3.1. Preamble 118
3.2. Abstract 119
3.3 Introduction 120
3.4. Materials and Methods 123
3.4.1. Design 123
3.4.2. Participants 124
3.4.3. Procedure 125
3.5. Results 130
3.5.1. ERP emotion pairwise comparisons 131
3.5.2. Associations between wellbeing and depression/anxiety symptoms with emotion processing 131
3.5.3. Univariate twin analysis 136
3.5.4. Multivariate twin analysis 137
3.6. Discussion 137
3.7. References 146
Appendix B: Chapter 3 Supplementary Results 153
Supplement 1: ERP emotion pairwise comparisons 154
Chapter 4: Cognitive processing and mental health 159
4.1. Introduction 160
4.2. Methods 165
4.2.1. Participants 165
4.2.2. Materials 165
4.2.3. Procedures 167

4.2.4. Statistical analysis 168
4.3. Results 169
4.3.1. Sample characteristics 169
4.3.2. Behavioural performance 169
4.3.2. Event-related potentials 172
4.3.3. Univariate heritability 176
4.4. Discussion 179
4.5. References 187
Chapter 5: Improving wellbeing with positive psychology interventions 196
5.1 Preamble 197
5.2. Abstract 198
5.3. Introduction 199
5.4. Materials and Methods 202
5.4.1. Design 202
5.4.2. Participants & Procedures 202
5.4.3. Measures 205
5.4.4. Data Analysis 207
5.5. Results 209
5.5.1. Participant characteristics 209
5.5.2. Intervention effects 211
5.6. Discussion 220
5.7. References 228
Appendix C: Chapter 5 Supplementary Results 235
Chapter 6: General Discussion 274
6.1. Resting EEG as a marker of mental wellbeing 275
6.2. Emotional face processing and mental health 278
6.3. Cognitive processing and mental health 281
6.4. Effectiveness of positive psychology interventions 284
6.5. Results summary and implications 287
6.6. Limitations 290
6.6.1. Sample characteristics 290
6.6.2. Study design 293
6.6.3. Statistical limitations 297
6.7. Future research directions 299

6.8. Conclusion 300
6.9. References.....302

List of figures

Figure 2.1 Association between the alpha, beta, delta (ABD) EEG interaction effect and wellbeing for the averaged central region in the eyes closed condition. Top panel (A) shows the interaction effect for different power levels in each EEG frequency band. High and low values for beta and delta are based on ± 1 standard deviation from the mean. Bottom panel (B) shows the strength of this association at each electrode site, whereby red indicates a larger standardised effect size and blue indicates smaller effect size using absolute values. **84**

Figure 2.2 Correlated factors model for wellbeing, the alpha, beta, delta (ABD) EEG interaction, and depression/anxiety symptoms. Single-headed arrows indicate the influence of additive genetic (A) or unique environmental (E) influence on each variable with standardised path coefficients. Double-headed arrows indicate genetic and environmental correlations between variables, with standard errors provided in parentheses. Solid lines indicate significant correlations, whereas dashed lines indicate non-significant correlations. For point estimates and corresponding confidence intervals, please refer to Table S9. .....**87**

Figure 3.1 The experimental task consisted of: (A) an unmasked condition where each emotional stimulus was presented for 500 msec as a blocked design (i.e., each emotion was presented eight times in a block, before moving to a new emotion block); and (B) a masked condition where each emotional stimulus was presented for 10 msec before being masked with a neutral stimulus for 150 msec. Task duration for each condition was 5 minutes and 8 seconds. ISI: interstimulus interval. **126**

Figure 3.2 Contrasts with significant associations with depression/anxiety symptoms after controlling for mental wellbeing in the unmasked condition. Graphs show participants in the lowest or highest tertile of depression/anxiety symptoms for the sake of illustration. (A) The Disgust and Happy waveforms for the N1. High Depression/Anxiety n = 140, Low Depression/Anxiety n = 143. .....**133**

Figure 3.3 Contrasts with significant associations with depression/anxiety symptoms in the masked condition. Graphs show participants in the lowest or highest tertile of depression/anxiety symptoms for the sake of illustration. (A) Happy, Fear, and Sad waveforms for the VPP. (B) Neutral, Fear waveforms for the N170. (C) Happy, Fear waveforms for the N170 and P250. High Depression/Anxiety n = 140, Low Depression/Anxiety n = 143.....**135**

Figure 4.1 Auditory oddball waveform comparing the P3b component for targets and non-targets at Pz. **173**

Figure 4.2 N-back waveform comparing targets, non-targets, and distractors at (a) FCz for the P3a component, and (b) Pz for the P3b component. **174**

Figure 4.3 Go/no-go waveform comparing go and no-go trials at FCz for the N2 and inhibitory P3a components **175**

Figure 5.1 CONSORT diagram of study participants.....**210**

Figure 5.2 Significant overall effects of the intervention relative to the active control group for (a) COMPAS-W Wellbeing, (b) COMPAS-W Positivity (moderated by COVID-19 restrictions), (c) COMPAS-W Own-worth, (d) Satisfaction with Life Scale (SWLS), (e) COMPAS-W Satisfaction, and (f) Perceived Stress Scale (PSS) scores. * indicates significantly larger improvements in the intervention group compared to the control group relative to baseline without accounting for COVID-19 restrictions. + indicates significantly larger improvements in the intervention group compared to the control group relative to baseline when accounting for COVID-19 restrictions. COMPAS-W scores have been normalised to a scale of 0 – 1 for comparative purposes.....**214**

Figure 5.3 Significant moderation effects of intervention effects at low baseline resiliency resources for (a) COMPAS-W Wellbeing and (b) log-transformed DASS-21 depression and anxiety total scores. Low resiliency was defined as a score less than 101 (N = 104, n = 54 in Intervention group) using the Resilience Resource Centre Adult Resilience Measure (RRC-ARM). * indicates significantly greater improvements in the intervention group compared to the control group relative to baseline. COMPAS-W scores were normalised to a scale of 0 – 1 for comparative purposes.....**218**

List of tables

Table 2.1 Participant characteristics in the current sample of twins (mean ± SD). **80**

Table 2.2 Linear mixed model results of EEG power with wellbeing scores in the central brain region for the eyes closed condition, covarying for age, sex, zygosity, education, and body mass index.....**82**

Table 2.3 Univariate heritability estimates in the averaged central brain region for the eyes closed condition, covarying for age, sex, and education **86**

Table 3.1 Summary of associations found in the unmasked condition.....**132**

Table 3.2 Summary of associations found in the masked condition.....**134**

Table 3.3 Univariate heritability by component and emotion for the masked condition.....**138**

Table 3.4 Univariate heritability by component and emotion for the unmasked condition..**139**

Table 4.1 Participant characteristics for participants completing at least one cognitive task **170**

Table 4.2 Behavioural performance for the auditory oddball, n-back, and go/no-go tasks..**170**

Table 4.3 Univariate heritability by task and component for select conditions.....**178**

Table 5.1 Descriptive statistics and t-tests comparing the intervention with the control group at baseline.....**211**

Table 5.2 Bivariate Pearson correlations between the survey measures at baseline.....**212**

List of abbreviations

ACE	A twin model estimating Additive genetics, Common environment, and unique Environment
ADE	A twin model estimating Additive genetics, Dominant genetics, and unique Environment
AIC	Akaike's Information Criterion
COMPAS-W	A composite wellbeing scale measuring Composure, Own-worth, Mastery, Positivity, Achievement, Satisfaction, and Wellbeing
DASS-21	Depression Anxiety Stress Scale, 21-item version
DASS-42	Depression Anxiety Stress Scale, 42-item version
DZ	Dizygotic
ECG	Electrocardiogram
EEG	Electroencephalography
ERN	Error Related Negativity
ERP	Event-Related Potential
fMRI	Functional Magnetic Resonance Imaging
ICC	Intra-class correlation
LPP	Late Positive Potential
MDD	Major Depressive Disorder
MZ	Monozygotic
PPI	Positive Psychology Intervention
PWB	Psychological Wellbeing
SWB	Subjective Wellbeing
TWIN-E	The Twin study in Wellbeing using Integrative Neuroscience of Emotion
VPP	Vertex Positive Potential

Chapter 1:
General Introduction

Historically, mental illness and mental wellbeing have been perceived as two ends of the same spectrum. This idea was challenged in the mid-twentieth century when Jahoda argued that the "absence of mental illness is not a sufficient indicator of mental health" (Jahoda, 1958, p. 15). Her stance aligned with the World Health Organization's constitutional definition of health as, "a state of complete physical, mental, and social wellbeing and not merely the absence of disease or infirmity" (World Health Organization, 1946). Despite the significant growth in the field of positive psychology, the neurological difference between an absence of mental illness and the presence of mental wellbeing remains largely unknown. This contrasts with the mental illness literature where countless studies have demonstrated cognitive, neurological, and genetic risk factors associated with a wide range of mental illnesses. Thus, it remains the case that mental illness is much better understood than mental wellbeing.

The primary aim of this thesis is to advance the current understanding of cognitive and neurological markers of mental wellbeing and how these relate to promoting wellbeing in the general population. Electroencephalography (EEG), which measures electrical activity from the scalp, is the primary tool of enquiry. EEG can reveal patterns in resting state brain activity, detect cognitive processes with high temporal sensitivity, and is known to be moderately to highly heritable (Anokhin et al., 2004; McLoughlin et al., 2014; Smit et al., 2005, 2007). Compared to other neurological measures, EEG is cost-effective and reliable, and is becoming increasingly available to the general public in the form of gel-free, wearable systems currently geared towards biofeedback games (Duvinage et al., 2013; McKenzie et al., 2017; Zabcikova, 2019). As such, EEG measures may provide a useful avenue of measuring and predicting mental wellbeing outcomes. The heritability of EEG makes it a viable candidate endophenotype: a physiological trait indicative of heritable risk (Gottesman &

Gould, 2003). However, to determine whether this avenue holds promise for predicting wellbeing, links between EEG measures and wellbeing must first be established.

This thesis first describes new results from the TWIN-E study (Gatt et al., 2012) exploring the associations that resting EEG power, and event related potentials (ERPs) capturing emotional face processing, attention, working memory, and inhibition have with mental wellbeing. The nature of these associations is described in terms of genetic relative to environmental variance using a classical twin design. Finally, to facilitate further investigation into the relationship between EEG markers and mental wellbeing, a positive psychology intervention was developed and assessed in a randomised control trial. This trial demonstrated that aspects of wellbeing can be altered in as short a timeframe as six weeks. Such an intervention may be used in an experimental design to assess whether responses to positive psychology interventions (PPIs) can be predicted by EEG markers previously found to be associated with wellbeing. While such an experiment could not be conducted within the constraints of the ongoing COVID-19 pandemic, similar interventions could be used to assess whether resting EEG can predict treatment response, or if changes in wellbeing are reflected in resting EEG.

1.1. Mental wellbeing, mental illness, and mental health

What exactly is mental wellbeing, and how does it differ from mental illness and mental health? Historically, psychologists primarily concerned themselves with defining, understanding, and treating mental illness with the assumption that eliminating mental illness would is synonymous with improving mental health. Mental illnesses are health conditions that can impact how a person thinks, acts, and feels, and are defined today using a specified set of criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders

(American Psychiatric Association, 2013). It is frequently assumed that individuals who do not meet the criteria for a mental illness are mentally healthy. However, this would be inconsistent with modern definitions of health, which indicate that health is the presence of a positive state of wellbeing, not just the absence of illness (World Health Organization, 1946). Based on this definition, mental illness and mental wellbeing are distinct components that contribute to mental health. As such, an understanding of mental *health* is incomplete without an understanding of mental *wellbeing*.

1.1.1. Definitions of mental wellbeing

Definitions of mental wellbeing have been debated since the mid-twentieth century when the inadequacy of using the absence of mental illness to define mental health was first called out (Jahoda, 1958). Despite the various approaches to defining and measuring mental wellbeing, the most prominent perspectives are based on two ancient philosophies: *hedonia*, which focuses on the experience of pleasure and happiness, and *eudaimonia*, which focuses on self-actualisation and living life according to specific values. Hedonia was first popularised by the ancient Greek philosopher Aristippus, who believed that the meaning of life was to maximise pleasurable experiences (Ryan & Deci, 2001). This idea has informed modern conceptualisations of 'subjective wellbeing', where wellbeing is defined subjectively by each individual (Diener, 1984; Kahneman et al., 1999). Diener proposed that subjective wellbeing consists of an affective component, referring to subjective experiences of positive and negative affect, and a cognitive component, referring to a cognitive appraisal of one's satisfaction with life (Diener, 1984). Although not free from criticism, this approach has been widely adopted within the field of positive psychology and is by far the most widely used approach to measuring wellbeing (Busseri & Sadava, 2011).

The next most prominent approach to defining and measuring mental wellbeing, referred to as ‘psychological wellbeing’, stems from Aristotle’s conceptualisation of eudaimonia in his work, *Nicomachean Ethics*. While some have interpreted Aristotle’s concept of eudaimonia as referring to the subjective experience of happiness (Bradburn, 1969), this perspective is largely taken to be oversimplified. Rather, Aristotle’s use of the term eudaimonia referred to achieving one’s full potential by living a virtuous life, not one’s immediate subjective experience (Ryan & Deci, 2001; Ryff, 1989; Waterman, 1993). This interpretation of eudaimonia formed the basis of the Psychological Wellbeing Scale (Ryff, 1989) which defines psychological wellbeing in terms of six components: self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life, and personal growth. Thus, while subjective wellbeing focuses on one’s affective experience and cognitive appraisal of one’s own life, psychological wellbeing focuses on a broader conceptualisation of positive psychological functioning and pre-defined values.

Although the modern concept of psychological wellbeing was developed in opposition to subjective wellbeing, a growing body of evidence indicates that these constructs are linked, demonstrated by moderate to high correlations between common indices of each (Disabato et al., 2016; Keyes et al., 2002). Based on this, measures of composite wellbeing, a conceptualisation encapsulating both hedonic and eudaimonic conceptions of wellbeing, have increased in popularity (Cooke et al., 2016). One such measure includes the COMPAS-W wellbeing scale, which consists of six subscales indexing Composure under stress, Own-worth, Mastery, Positivity, Achievement, and Satisfaction (Gatt et al., 2014). This scale was designed to provide an efficient measure of both subjective and psychological aspects of wellbeing, while also providing an overarching, composite wellbeing index from summing all items. Since its development, there has been growing support for hierarchical models of

wellbeing that construe general wellbeing as being made up of subjective and psychological wellbeing components (Disabato et al., 2016; Goodman et al., 2018). Measures such as the COMPAS-W provide an index of this overarching wellbeing construct.

The COMPAS-W was selected as the primary outcome measure for this thesis because it simultaneously captures different components of wellbeing instead of focusing only on subjective wellbeing or psychological wellbeing, allowing for a more holistic operationalisation of wellbeing than alternatives. It has been previously validated within the TWIN-E sample against other mental health measures and has shown strong internal and test-retest reliability over a 12-month period, indicating stability (Gatt et al., 2014). This is important for addressing the aims of this thesis in that a reliable and valid wellbeing measure is needed to identify stable electrophysiological markers of wellbeing.

1.1.2. The dual factor model of mental health

The development of wellbeing scales has facilitated further enquiry into the dual-factor model of mental health, the theory that mental illness and mental wellbeing form two distinct components of mental health. If mental wellbeing and mental illness were to represent opposing ends of a mental health spectrum, then individuals scoring high on mental wellbeing would necessarily show few signs of mental illness and vice versa. While mental wellbeing and illness are inversely correlated with each other (Keyes, 2002; Koivumaa-Honkanen et al., 2004; Routledge et al., 2016), a number of studies have demonstrated that wellbeing and mental illness symptoms can covary in unexpected ways (Greenspoon & Saklofske, 2001; Keyes, 2005; Routledge et al., 2016; Suldo & Shaffer, 2008). For instance, when combining measures of mental wellbeing and mental illness symptoms, individuals can be categorised into four groups: complete mental health, indicating high wellbeing but low

illness; a vulnerable or pure languishing group, indicating poor wellbeing and low illness; a symptomatic or ‘pure illness’ group, indicating high illness, but with moderate to high wellbeing; and a languishing with illness group, indicating high illness and low wellbeing (Keyes, 2005; Suldo & Shaffer, 2008). Of particular interest are those who experience moderate to high wellbeing despite mental illness, who make up approximately 13-16% of the population, and those who exhibit poor mental wellbeing in the absence of a mental illness, making up an additional 10-13% of the population (Keyes, 2005; Suldo & Shaffer, 2008). A limitation of these findings is that they apply a categorical approach to defining mental wellbeing and illness, which assumes that there is a qualitative difference between those with high compared to low levels of mental illness and wellbeing (Conway et al., 2021). Meta-analytic evidence suggests that such distinctions are uncommon in psychology, with most constructs being better captured by dimensional rather than categorical approaches to assessing mental health (Haslam et al., 2020). In this vein, studies using continuous measures of wellbeing find that about 30% of the variance between wellbeing and depression/anxiety symptoms is shared in opposing directions (Routledge et al., 2016). Thus, while mental wellbeing and mental illness are distinct constructs, they do appear to share some common variance, so it is worth acknowledging that the relationship between the two constructs is complex and difficult to tease apart empirically.

1.2. Why promote mental wellbeing?

Given that mental wellbeing is a component of mental health, promoting wellbeing is a necessary step towards improving mental health outcomes globally (World Health Organization, 1946). Mental wellbeing has inherent benefits, namely the experience of happiness that is widely sought out by the general public (Diener, 2000; Parks et al., 2012), and good mental wellbeing appears to protect against the negative effects of mental illness by

reducing susceptibility and promoting recovery (Grant et al., 2013; Iasiello et al., 2019; Keyes et al., 2002; Lamers et al., 2015). The effects of mental wellbeing promotion may also stem beyond mental health benefits; improvements in wellbeing have been associated with improved physical health, productivity, and income (Diener et al., 2017; Walsh et al., 2018).

1.2.1. Mental wellbeing as a protective factor

Various studies suggest that maintaining mental wellbeing during periods of stress and mental illness can mitigate their effects. Depressed individuals with at least moderate mental wellbeing reported significantly fewer days off work and significantly less limitation to their daily activities compared to depressed individuals with poor wellbeing (Keyes, 2002). A follow-up analysis of the same sample found that maintaining high wellbeing or improving wellbeing from low to moderate predicted recovery from mental illness over the next 10 years (Iasiello et al., 2019). Prospective studies have also supported the notion that wellbeing can protect against the development of mental illness (Grant et al., 2013; Lamers et al., 2015). One study found that the increase in depressive symptoms over the course of a one-year medical internship was attenuated in students who had higher wellbeing at the start of the internship compared to those with poorer wellbeing (Grant et al., 2013). Another study found that in a community sample, higher wellbeing indicated reduced risk of mental illness onset over the next year, even after accounting for risk factors including baseline mental illness symptoms and family history (Lamers et al., 2015). These studies suggest that wellbeing promotion could be used as a means of reducing the burden of mental illness by mitigating symptoms, improving chances of recovery, and preventing initial onset.

1.2.2. Physical, economic, and productivity benefits

In addition to the direct mental health benefits, a growing body of evidence indicates that wellbeing promotion has economic and physical health benefits (Diener et al., 2017; Kushlev et al., 2020; Walsh et al., 2018). For example, longitudinal studies have found that feelings of positive affect precede positive work outcomes including gaining and retaining employment (Côté et al., 2006; Haase et al., 2012; Luhmann et al., 2013), higher productivity (Miner & Glomb, 2010; Zelenski et al., 2008), and higher income (Binder & Coad, 2010; De Neve & Oswald, 2012; Diener & Seligman, 2002). Higher wellbeing has also been associated with better health-related outcomes including stronger immune function (Barak, 2006; S. Cohen et al., 2006) and improved cardiovascular health (Dockray & Steptoe, 2010; Howell et al., 2007; Tuck et al., 2017). Individuals with better wellbeing are also more likely to engage in positive health behaviours such as exercise and less likely to engage in negative health behaviours such as smoking (Boehm & Kubzansky, 2012; Kim et al., 2017; Sin, 2016). These health behaviours combined with improved immune and cardiovascular function may explain the observed association between higher subjective wellbeing and reduced risk of all-cause mortality and hospitalisation (Iwasa et al., 2006).

1.3. Explaining genetic vs environmental variance in mental wellbeing

Understanding why people experience different levels of wellbeing is key to understanding how it can be altered through intervention. One way of considering the variance in wellbeing is through comparing heritable versus environmental sources of variance in the population. A large number of studies have applied this approach using the classical twin design, which compares trait similarity within monozygotic twins who share 100% of their genetics, to that within dizygotic twins who share only 50% of their genetics on average (Verweij et al., 2012). Heritability can be inferred when monozygotic twins are

significantly more similar than dizygotic twins on a given trait. Studies applying this approach have estimated that wellbeing is moderately heritable and similar between subjective, psychological, and composite measures of wellbeing (Bartels et al., 2013; Keyes et al., 2010; Nes et al., 2008). A meta-analysis in 2015 estimated the heritability of subjective and psychological wellbeing at 32% and 36%, respectively (Bartels, 2015). The estimated heritability of the composite COMPAS-W wellbeing scale based on the TWIN-E sample was 48% (Gatt et al., 2014).

Previous work has interpreted the heritable component of wellbeing to represent the degree to which wellbeing has a 'set point' (Lyubomirsky et al., 2005). Here, the set point refers to a relatively stable level of wellbeing that a person tends to maintain throughout their life via the homeostatic process of hedonic adaptation (Headey & Wearing, 1989; Lyubomirsky, 2010). Although the heritable component of wellbeing has been associated with stability over time (Jamshidi et al., 2020; Nes et al., 2006), the assumption that genetics determine phenotypic outcomes on the individual level is not empirically supported (Harden, 2021; Visscher et al., 2008). A clear example of this can be seen when examining height. Despite estimates that heritable factors explain 80% of population variance in height, nutrition, disease, and socio-economic factors have also been demonstrated to have strong influences on height (Perkins, 2015). Thus, while heritable components of wellbeing might be associated with stability over time within a population, it does not indicate the degree to which an individual has the ability to change if appropriate interventions are in place. For instance, the heritability of resting EEG power is approximately 90% (Smit et al., 2005), yet neurofeedback interventions have successfully been used to alter EEG power through training (Kluetsch et al., 2014). Thus, the relationship between heritability and trait stability might indicate a lack of effective interventions, not that heritable trait components cannot be

changed. With the correct approach to intervention, environmental factors can be used to alter an individual's wellbeing (and other psychological phenotypes) on the individual level. The sections below describe common approaches to wellbeing intervention and how consideration of genetic predisposition towards certain levels of wellbeing might be used to improve outcomes.

1.4. Promoting wellbeing through positive psychology interventions

Positive psychology interventions (PPIs) provide a promising avenue for realising the benefits of mental wellbeing. PPIs refer to a range of interventions designed to promote wellbeing by increasing positivity and resources to cope with stressful situations (Bolier et al., 2013; Sin & Lyubomirsky, 2009). Commonly used PPI activities include acts of kindness, mindfulness, goal setting, and gratitude, though a wide range of activities exist (Sin & Lyubomirsky, 2009). PPIs can include programs focused on a single activity (e.g., acts of kindness), or a mix of activities delivered over a period of weeks or months. Both single and multi-component PPIs have been found to be effective in improving wellbeing in meta-analyses of randomised control trials with small to moderate effect sizes (Cohen's d = 0.2 – 0.4) (Bolier et al., 2013; Hendriks et al., 2020). However, these meta-analyses also revealed significant heterogeneity between studies indicating a need to better understand what makes PPIs most effective. Some investigations suggest that individual differences contribute to some of this heterogeneity and should be considered in intervention design (Lyubomirsky & Layous, 2013).

PPIs are proposed to work by teaching individuals to mimic the behaviours of happy individuals, resulting in increased positive emotions, thoughts, and behaviours (Lyubomirsky & Layous, 2013). However, active engagement with PPIs is necessary to gain the most

benefit (Lyubomirsky et al., 2005). Because individuals are more likely to actively engage in tasks they enjoy and believe are effective, good person-activity fit is necessary to obtain the full benefits of PPIs (Lyubomirsky & Layous, 2013; Proyer et al., 2015). The variety provided within multi-component PPIs may improve person-activity fit by increasing the likelihood that participants will enjoy and engage with at least some of the interventions, which they may continue to use beyond the intervention period (Proyer et al., 2015; Sheldon et al., 2013). Task variety might also help to reduce hedonic adaptation, potentially contributing to longer-lasting effects in multi-component PPIs compared to single-component variations (Lyubomirsky, 2010; Sanders et al., 2019; Sheldon et al., 2013).

Long-term improvements in wellbeing following participation in a PPI can be predicted by whether an individual initially responds well to the intervention in terms of symptom improvements; this is referred to as early reactivity (Cohn & Fredrickson, 2010; Proyer et al., 2015). This may be because individuals who experience positive effects early on are more likely to actively engage in the activity and continue practicing beyond the intervention period (Cohn & Fredrickson, 2010; Proyer et al., 2015). These individuals may have learned a stronger association between practising the intervention activities and improved mental wellbeing. However, it remains unclear why some individuals show early reactivity and others do not; when compared, these two groups did not differ in number of sessions attended or effort (Cohn & Fredrickson, 2010), and early reactivity itself is a better predictor of long-term outcomes than an individual's enjoyment or belief in the effectiveness of the intervention (Proyer et al., 2015). It is possible that individual differences stemming from heritable neuropsychological factors might play a role in predicting early reactivity.

1.5. Using endophenotypes to improve positive psychology interventions

Given evidence that the effectiveness of PPIs is impacted by individual differences, it is worth investigating whether these individual differences stem from heritable psychophysiological factors. To this end, candidate endophenotypes might be useful in quantifying these factors. Endophenotypes are physiological traits that confer heritable risk for complex phenotypes (Gottesman & Gould, 2003). They were originally proposed as a means to facilitate the discovery of key molecular genetic variants contributing to psychopathology and other complex traits because they were perceived as providing a link between the genotype and phenotype (Gottesman & Gould, 2003; Iacono et al., 2017; McLoughlin et al., 2014). Although this goal has failed to materialise after decades of research, traits identified as candidate endophenotypes can still provide valuable insight into genetic predisposition towards certain psychological phenotypes (Iacono et al., 2017; Yoon et al., 2015). For example, Yoon et al. (2015) found that the P3 ERP component could be used to predict risk of externalising disorders over a 12-year period, indicating long-term predictive value of this candidate endophenotype. Thus, candidate endophenotypes may still provide useful in understanding mental health trajectories. They might also be used to investigate neural pathways to mental wellbeing and as targets for novel interventions.

A current challenge in identifying candidate endophenotypes for mental wellbeing is the lack of established electrophysiological correlates of wellbeing. Electrophysiological measures, namely EEG and ERPs are particularly valuable in the search for endophenotypes given their cost-effectiveness relative to other neural measures and their moderate to high heritability (Iacono et al., 2017; McLoughlin et al., 2014). So far, alpha asymmetry is the strongest electrophysiological correlate of mental wellbeing. Alpha asymmetry has been used in cognitive science as an index of positive and negative mood, or more precisely, an

indicator of approach versus withdrawal motivation (Harmon-Jones & Gable, 2018). Typically, greater alpha power in the left compared to the right hemisphere is associated with negative moods and withdrawal motivation, while asymmetry towards the right hemisphere is associated with positive mood and approach motivation (Fingelkurts & Fingelkurts, 2015; Harmon-Jones & Gable, 2018). In line with this, alpha asymmetry towards the right hemisphere has also been associated with greater wellbeing, positivity, and emotion regulation (Alessandri et al., 2015; Papousek et al., 2011; Urry et al., 2004). Changes in alpha asymmetry have even been observed to correlate with responsiveness to PPIs (Xu et al., 2018). However, the potential of alpha asymmetry as a candidate endophenotype is limited due to its small to absent heritability of 0 to 0.27 (Anokhin et al., 2006). Therefore, the current thesis aims to explore alternative electrophysiological markers for wellbeing that could serve as candidate endophenotypes.

1.6. The TWIN-E Study

The current project is based on the TWIN-E study dataset, a longitudinal study investigating neural, cognitive, and behavioural correlates of mental wellbeing (Gatt et al., 2012). The full sample consists of over 1600 Australian twins with no history of mental illness, between the ages of 18 and 65. From this sample, a subset of 450 participants participated in the EEG phase of the study, who form the sample analysed here. The EEG phase included resting EEG power and four ERP tasks relating to emotion and cognitive processing. Specifically, the tasks included emotion recognition, an auditory oddball paradigm, a go/no-go paradigm, and an n-back paradigm. The tasks were developed by Brain Resource as part of an international database collection system and have been standardised and broadly used across various healthy and clinical groups (Gordon et al., 2005; Williams et al., 2004, 2005). The aim of including these tasks in the TWIN-E study was to investigate

how markers of emotional and cognitive functioning markers used in clinical research translate to mental wellbeing, to better understand optimal functioning (Gatt et al., 2012).

The primary outcome measure for the TWIN-E study is the COMPAS-W wellbeing scale, specifically designed as a composite measure of subjective and psychological wellbeing (Gatt et al., 2014). The six subscales measure Composure, indicating one's ability to cope under stress; Own-worth, indicating levels of self-esteem and autonomy; Mastery, indicating self-confidence and perceived control of one's environment; Positivity, indicating optimism and positive outlook; Achievement, indicating goal striving; and Satisfaction, indicating one's level of satisfaction with life, health, work, and relationships. The TWIN-E study also used the 42-item Depression, Anxiety, Stress Scale (DASS-42) to measure depression, anxiety, and stress symptoms within the sample (Lovibond & Lovibond, 1995). Previous work from the TWIN-E study assessed the overlap between COMPAS-W and DASS-42 scores, finding that they share 30% of their variance (Routledge et al., 2016). Thus, while they are distinct constructs, it is important to assess whether any identified wellbeing correlates are independent from or shared with non-clinical depression and anxiety symptoms.

The use of the twin design means that the TWIN-E study is particularly well-suited to identifying potential endophenotype markers of wellbeing. This is not only because the heritability of each electrophysiological correlate can be estimated, but because multivariate approaches can be used to assess whether the heritable (or environmental) components of each correlate drive each association. For an electrophysiological correlate of wellbeing to be considered a candidate endophenotype, its association with wellbeing should be driven by heritable components (Iacono et al., 2017). While resting EEG is known to be highly heritable with estimates as high as 0.90 (Smit et al., 2005), ERP heritability is more moderate

and variable between tasks. For instance, heritability estimates for early ERP components evoked by emotional face stimuli range from 0 to 0.64, and estimates may be emotion dependent (Anokhin et al., 2010; Shannon et al., 2013). In contrast, ERP components indexing attention, working memory, and inhibition, namely the P3 and N2 components, have more consistently been estimated to be moderately heritable across studies, with estimates typically ranging from 0.50 to 0.60 (Anokhin et al., 2004, 2017; Hall et al., 2006; Malone et al., 2014; Smit et al., 2007). Within the context of the TWIN-E study, it is possible to assess whether any associations between these tasks and wellbeing are due to shared heritable or environmental factors to clarify their potential as endophenotypes.

The following sections outline how each of the electrophysiological TWIN-E study measures might be related to mental wellbeing, depression and anxiety symptoms based on the existing research.

1.7. Resting EEG measures

Resting state EEG is measured in the absence of any assigned task to capture spontaneous brain activity. Power quantifies the amount of activity in a given frequency range within a specified time period and is usually extracted from the data using pre-determined frequency bands (M. X. Cohen, 2014). These bands usually include alpha (8–13 Hz), beta (13–30 Hz), delta (0.5–4 Hz), and theta (4–8 Hz). Each frequency band is involved in various cognitive functions, however, there are some examples of cognitive functions that are more strongly associated with certain frequencies than others (Knyazev, 2007). For instance, alpha power is dominant in waking adults and is hypothesised to capture self-referential processing (such as mind wandering about oneself or focusing on one's internal state) and inhibitory processes, especially inhibition of external stimuli (Klimesch, 2012;

Knyazev, 2007, 2013). Beta power has also been observed to increase at rest, but is associated with focused attention, where focus is targeted towards one's outward experience, rather than the inward focus associated with alpha power (Knyazev, 2013; Travis & Shear, 2010). Theta power has been linked to task-oriented attention and learning processes (Cavanagh & Shackman, 2015). Delta power, which is most prominent during deep sleep, may also be involved in learning via motivational purposes when more apparent in waking states (Knyazev, 2012).

1.6.1. Resting EEG in mental health

As discussed above, the most common resting EEG measure used in the context of mental health is alpha asymmetry. Greater alpha power in the right relative to the left hemisphere is associated with subjective and psychological wellbeing (Alessandri et al., 2015; Urry et al., 2004; Xu et al., 2018). While wellbeing studies have primarily focused on alpha asymmetry, studies from the broader mental health literature suggest that absolute resting EEG power may also be relevant. For instance, increases in alpha, beta, and theta power have been associated with the early stages of major depression, with alpha and theta power proposed to reflect decreased cortical activation implicated in depression and increased beta power reflecting associated anxiety symptoms (Grin-Yatsenko et al., 2009). Comparable studies associating absolute resting power with mental wellbeing, happiness, or life satisfaction have not yet been conducted to show whether specific patterns of resting EEG power are uniquely associated with mental illness and associated symptoms, or whether they may also reflect differences in wellbeing.

Interactions between EEG power bands might provide more nuanced information about how EEG relates to different mental states. Some studies suggest that coupling or

decoupling of different frequency bands, indicating positive or negative correlations between frequencies within an individual, can provide information about anxiety and stress symptoms (Knyazev et al., 2006; Schutter & van Honk, 2005; van Peer, 2008). Specifically, individuals with low trait anxiety tended to show increased alpha-delta coupling compared to individuals with high trait anxiety who showed decoupling (Knyazev et al., 2006). In addition, within the same study, participants who received negative feedback following a stressful task showed increased delta-beta coupling afterwards, regardless of trait anxiety level (Knyazev et al., 2006). Independent research has found that delta-beta coupling is positively correlated with salivary cortisol (Schutter & van Honk, 2005), and increases following experimental administration of cortisol in humans (van Peer, 2008). This research highlights the importance of considering the relationships between frequencies in clarifying how they relate to mental states. However, similar approaches remain to be tested with mental wellbeing.

1.7. Event-related potentials

In addition to resting EEG measures, task-related EEG measures called ERPs are another promising avenue for understanding heritable components of mental health (Gottesman & Gould, 2003; McLoughlin et al., 2014). ERPs are time-locked averages of EEG activity following the onset of a stimulus, such as an image or a sound (Woodman, 2010). The resulting ERP waveform reflects cognitive events occurring at specific timepoints relative to stimulus onset, measured in amplitude rather than frequency. Early ERP components occurring in the first 100-200 msec generally reflect sensory processing while later components reflect more elaborative processes including decision making and performance monitoring (VanRullen & Thorpe, 2001; Woodman, 2010). The TWIN-E Study included four ERP tasks including emotional and cognitive tasks similar to those that have been previously linked to mental illness (Bernat et al., 2020; Breukelaar et al., 2020; Bruder

et al., 2011; Gatt et al., 2012; Y. Zhang et al., 2007). Some behavioural research has also found associations between similar working memory tasks with positive affective states, suggesting a potential relationship between these functions and mental wellbeing (Pe et al., 2013; Storbeck & Maswood, 2016).

1.7.1. Emotion-related event related potentials

ERPs can provide useful insight into the early stages of emotion processing. Neural differentiation between different emotional facial expressions can be detected in ERPs from as early as 80 msec post-stimulus in the N1 and P1 components (Batty & Taylor, 2003; Carretié, 2014; Kiss & Eimer, 2008). ERPs can also detect subliminal face processing under backwards-masking paradigms that display an emotional expression for time periods too short to consciously perceive before masking with an alternative image (Liddell et al., 2005; Williams et al., 2004; Y. Zhang et al., 2007). Associations between mental health and emotional face processing have predominantly focused on mental illness, including depression and anxiety symptoms, with little focus on mental wellbeing. The studies that have been conducted in the realm of positive mood or wellbeing have mainly used behavioural methods without measuring ERPs. However, considering the behavioural associations previously reported between wellbeing and emotion processing, it would suggest that wellbeing would be similarly associated with the same tasks measured using ERPs during early processing of emotional faces.

Various ERP studies in clinical, subclinical, and at-risk populations have indicated that early stages of emotional face processing are altered in the presence of poor mental health (Chen et al., 2014; Dai et al., 2016; Dai & Feng, 2012; Hu et al., 2017; Jaworska et al., 2010; Watters et al., 2018; Williams et al., 2007; D. Zhang et al., 2016). Many of these

studies support a mood-congruency bias whereby stimuli reflecting one's current mood is processed more readily than mood-incongruent stimuli (Cavanagh & Geisler, 2006). In the earliest stages of visual processing captured by ERPs, patients with major depressive disorder (MDD) have been reported to show augmentation of the P1 component (Dai et al., 2016; D. Zhang et al., 2016), and occasionally a specific reduction in P1 amplitude in response to happy faces (Dai & Feng, 2012). An alteration of the N1 component in response to fearful faces has also been reported to be associated with depression and anxiety symptoms in unmasked and masked paradigms, respectively (Williams et al., 2007). The N170 and vertex positive potential (VPP) components that follow reflect face-specific processing (Batty & Taylor, 2003; Eimer, 2000) and are typically augmented in MDD patients for sad relative to happy or neutral faces, again supporting the mood congruency bias (Chen et al., 2014; D. Zhang et al., 2016). However, in some samples, especially subclinical groups, depression symptoms are associated with smaller amplitude differences between emotional expressions (Chen et al., 2014; Dai & Feng, 2012; Watters et al., 2018; Williams et al., 2007). This reduced differentiation has been suggested to reflect either less severe illness (e.g., Chen et al., 2014), or trait (rather than state) depression and anxiety (Watters et al., 2018). Similar patterns of reduced differentiation between emotions have been reported for the parietal P250 component (Hu et al., 2017; Jaworska et al., 2012), which is sensitive to emotional stimuli including scenes and faces (daSilva et al., 2016; Eimer & Holmes, 2007). While these studies indicate that depression/anxiety symptoms impact the early stages of cognitive processing, an understanding of what healthy processing looks like in individuals with high wellbeing is lacking.

Despite a lack of ERP studies examining the relationship between mental wellbeing and emotion recognition, behavioural studies have examined the effect of positive mood on

emotion recognition. Unlike the mental illness literature, which has predominantly used the mood-congruency bias to explain alterations in emotion recognition within clinical groups, mood manipulation studies have suggested that in the context of positive mood, a mood incongruency bias drives the effects (Schmid & Schmid Mast, 2010). Using mood induction procedures, one study reported that while sad participants were worse than neutral-mood participants at identifying happy faces and better at recognising sad faces, happy individuals only differed from the neutral-mood group on recognising sad faces less accurately (Schmid & Schmid Mast, 2010). Another study compared mood and temperament effects on emotion recognition, finding that while being in a happy mood did not lead to better accuracy in identifying happy faces, being more extraverted did (Yi et al., 2016). It is possible that more stable constructs, such as extraversion and wellbeing, might elicit a stronger positivity bias than more variable mood states. This would be consistent with the finding from the full TWIN-E sample that mental wellbeing was associated with faster reaction times for recognising happy faces (Routledge et al., 2018). This positivity bias was also examined in a subsample of the TWIN-E study using fMRI. In this study, individuals with higher wellbeing showed greater activation in the inferior frontal gyrus, a region previously associated with emotion recognition and regulation, for happy relative to neutral faces (Park et al., 2021). It is therefore expected that evidence of a positivity bias might also be found in early ERPs. If so, it is important to investigate how this bias relates to the negativity bias found in association with depression and anxiety symptoms.

1.7.2. Cognitive event-related potentials

In addition to emotion processing, the TWIN-E study examined potential links between cognitive function and mental wellbeing, specifically, working memory, attention, and inhibition. An analysis of the TWIN-E study's behavioural tasks revealed that wellbeing

was associated with improved working memory, inhibition, motor coordination, sustained attention, and cognitive flexibility (Routledge et al., 2017). This was in line with earlier research that found positive associations between wellbeing and global cognitive function (Llewellyn et al., 2008), working memory (Pe et al., 2013), and inhibition (Lee & Chao, 2012). It is also conceptually consistent with the broader positive psychology literature that has associated positive mood with improved cognitive function, namely increased attentional scope (Fredrickson, 2001; Putkinen et al., 2017; Vanlessen et al., 2014), improved cognitive control and inhibition (Dreisbach & Goschke, 2004; Vanlessen et al., 2015, 2016), and better working memory (Gray, 2001; Storbeck & Maswood, 2016). Only a few of these studies have used ERP measures to investigate the association between positive mood and cognition, and none have used ERPs to investigate the association between wellbeing and cognition. For instance, the P3b component, which is largely indicated to reflect attention allocation and working memory (Polich, 2007), has been used to assess whether positive mood alters attention allocation in line with the theory that positive moods broaden attentional scope (Fredrickson, 2001; Putkinen et al., 2017; Vanlessen et al., 2014). Specifically, P3b amplitudes were found to be larger during an auditory oddball task when participants were also completing a secondary visuospatial task (Vanlessen et al., 2014), but reduced when the secondary task was auditory (Putkinen et al., 2017). However, it remains unclear how either wellbeing or positive moods might alter P3b amplitude within an oddball task with no competing distractors.

The mood induction approach used by the above studies is limited in that it does not account for the potential effect of trait-like characteristics which might vary between studies depending on the sample. This might be particularly relevant for interpreting P3b effects because the P3b has been identified as a candidate endophenotype for broad psychopathology

risk (Bernat et al., 2020; Malone et al., 2014). In the context of the broader literature, it is notable that reduced P3b amplitudes have been proposed to indicate both positive emotions and psychopathology risk (Bernat et al., 2020; Putkinen et al., 2017). This highlights the need to clarify the contexts in which P3b amplitude is related to mental wellbeing and mental illness. One difference between positive mood studies and psychopathology studies is that the psychopathology literature tends to use simple two- or three-tone oddball tasks (Bernat et al., 2020; Bruder et al., 2011), whereas the positive mood studies to date have focused on attention allocation with more complex, dual-task settings (Putkinen et al., 2017; Vanlessen et al., 2014). The standard two-tone oddball paradigm used in the TWIN-E study provides an opportunity to assess whether wellbeing is positively correlated with P3b amplitude when there is no competing task, as would be expected if psychopathology risk is inversely associated with wellbeing.

In addition to the oddball paradigm, the TWIN-E study included two additional cognitive tasks known to evoke ERP components; the go/no-go paradigm, which indexes inhibitory function, and the n-back task, which indexes working memory and sustained attention (Gatt et al., 2012). The behavioural data from the TWIN-E study suggests that both inhibitory function and working memory are associated with better wellbeing (Routledge et al., 2017), however this is yet to been confirmed at the ERP level. Within an affective paradigm, wellbeing has been associated with better ability to retain positive information in working memory (Pe et al., 2013). Positive mood has also been suggested to boost general working memory performance, especially verbal memory (Storbeck & Maswood, 2016), but the effects of naturally occurring mood on working memory appear limited (Chung et al., 2021). However, the behavioural TWIN-E data suggests that composite wellbeing is

positively associated with better working memory performance (Routledge et al., 2017) and ERPs may be used to assess this effect on a neurological level (Watter et al., 2001).

Inhibition has also received attention in relation to its role in maintaining mental wellbeing. Inhibition of negative stimuli forms an important component of emotion regulation, but has been found to be impaired in depression (Joormann et al., 2011; Joormann & Gotlib, 2010). In comparison, inhibition has been found to be positively associated with mental wellbeing, even when non-emotional stimuli is used (Lee & Chao, 2012; Routledge et al., 2017). One ERP study examined inhibition in association with positive mood using an anti-saccade task, where participants had to look away from (instead of towards) a visual stimulus when it appeared on screen (Vanlessen et al., 2015). While the authors found no association between positive mood and P3a amplitude, happy individuals showed a larger N2 amplitude following target onset, suggesting greater inhibitory control in this group (Vanlessen et al., 2015). Examining the association between the inhibitory P3a and N2 components in the TWIN-E sample will help to clarify the degree to which mental wellbeing is associated with inhibitory function.

1.8. Thesis overview

In summary, the primary aim of the current thesis is to explore potential electrophysiological endophenotypes for mental wellbeing. This is done using the TWIN-E study dataset to test for associations between composite wellbeing with resting EEG and standardised ERP tasks. Heritability was then assessed for each measure and, if an association with wellbeing is observed, a multivariate heritability model was used to test whether the association was explained by shared heritability. The second key aim of this thesis was to develop a short positive psychology intervention that could be used to assess the

relationship between identified candidate endophenotypes with responsiveness to treatment. While the ongoing COVID-19 pandemic interfered with testing the endophenotypes in relation to treatment, the intervention developed here was shown to be effective in improving wellbeing and may be used in future research to test for associations between endophenotype markers and treatment response and help establish causality between resting EEG and wellbeing.

The following chapter, *Identifying a resting EEG profile of wellbeing*, presents a paper published in the *Journal of Psychiatric Research* detailing the relationship between resting EEG power and mental wellbeing (Chilver et al., 2020). This paper identified a novel relationship between mental wellbeing and a specific profile of resting EEG activity characterised by heightened alpha and delta power and reduced beta power. The association between this EEG profile and mental wellbeing was found to be driven by shared heritability, indicating its potential use in conveying genetic predisposition to mental wellbeing.

Chapter 3, *Emotional face processing and mental health*, presents a paper in submission to the *Journal of Psychiatric Research* (Chilver et al., in press) that has been edited to include additional heritability analyses. This chapter examined the association between emotional face processing, mental wellbeing, and depression/anxiety symptoms. Alterations in emotional face processing, namely the N170 component for fearful relative to happy faces, were associated with depression/anxiety symptoms, but not with wellbeing. Consistent with past research, the variation in this component was driven by environmental rather than heritable factors. Thus, emotion specific processing is not a candidate endophenotype for wellbeing but could be used as a state marker of depression/anxiety symptoms.

Chapter 4, *Cognitive processing and mental health*, describes an investigation into the association between cognitive ERPs, mental wellbeing, and depression/anxiety symptoms. Specifically, this chapter examined whether the P3b, P3a, and N2 components from the auditory oddball, n-back, and go/no-go paradigms are associated with mental health. The heritability of each component was also assessed. The results showed that although behavioural performance on the auditory oddball and n-back tasks were associated with mental wellbeing and depression/anxiety symptoms, none of the ERPs of interest were significantly associated with mental health. However, the heritability analysis aligned with past research indicating that these components are moderately heritable in the current sample.

Chapter 5, *Improving wellbeing with positive psychology interventions*, presents a paper published in the *Journal of Happiness Studies* regarding the effectiveness of a short online positive psychology intervention (Chilver & Gatt, 2021). The aim of this paper was to investigate whether a self-administered positive psychology intervention is effective over and above comparable active control tasks in improving mental wellbeing in as short a period as six weeks. The results from this randomised control trial indicated that subjective wellbeing improved more in the intervention group relative to the control group by the end of the intervention. Furthermore, individuals who participated in the intervention before the introduction of COVID-19 restrictions, and individuals with lower resiliency resources showed greater improvements in composite wellbeing relative to the control group. These moderation effects may be due to these groups having lower baseline wellbeing, leaving more room for improvement.

Finally, Chapter 6 presents a general discussion of the results, including a summary and discussion of the current thesis in relation to its aims is provided. The limitations, implications, and future research directions are also discussed.

1.9. References

Alessandri, G., Caprara, G. V., & De Pascalis, V. (2015). Relations among EEG-alpha asymmetry and positivity personality trait. *Brain and Cognition*, *97*, 10–21. https://doi.org/10.1016/j.bandc.2015.04.003

American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders* (Fifth Edition). American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890425596

Anokhin, A. P., Golosheykin, S., Grant, J. D., & Heath, A. C. (2017). Heritability of brain activity related to response inhibition: A longitudinal genetic study in adolescent twins. *International Journal of Psychophysiology*, *115*, 112–124. https://doi.org/10.1016/j.ijpsycho.2017.03.002

Anokhin, A. P., Golosheykin, S., & Heath, A. C. (2010). Heritability of individual differences in cortical processing of facial affect. *Behavior Genetics*, *40*(2), 178–185. https://doi.org/10.1007/s10519-010-9337-1

Anokhin, A. P., Heath, A. C., & Myers, E. (2004). Genetics, prefrontal cortex, and cognitive control: A twin study of event-related brain potentials in a response inhibition task. *Neuroscience Letters*, *368*(3), 314–318. https://doi.org/10.1016/j.neulet.2004.07.036

Anokhin, A. P., Heath, A. C., & Myers, E. (2006). Genetic and environmental influences on frontal EEG asymmetry: A twin study. *Biological Psychology*, *71*(3), 289–295. https://doi.org/10.1016/j.biopsycho.2005.06.004

Barak, Y. (2006). The immune system and happiness. *Autoimmunity Reviews*, *5*(8), 523–527. https://doi.org/10.1016/j.autrev.2006.02.010

Bartels, M. (2015). Genetics of wellbeing and its components satisfaction with life, happiness, and quality of life: A review and meta-analysis of heritability studies. *Behavior Genetics*, *45*(2), 137–156. https://doi.org/10.1007/s10519-015-9713-y

Bartels, M., Cacioppo, J. T., van Beijsterveldt, T. C. E. M., & Boomsma, D. I. (2013). Exploring the association between well-being and psychopathology in adolescents. *Behavior Genetics*, *43*(3), 177–190. https://doi.org/10.1007/s10519-013-9589-7

Batty, M., & Taylor, M. J. (2003). Early processing of the six basic facial emotional expressions. *Cognitive Brain Research*, *17*(3), 613–620. https://doi.org/10.1016/S0926-6410(03)00174-5

Bernat, E. M., Ellis, J. S., Bachman, M. D., & Hicks, B. M. (2020). P3 amplitude reductions are associated with shared variance between internalizing and externalizing psychopathology. *Psychophysiology*, *57*(7). https://doi.org/10.1111/psyp.13618

Binder, M., & Coad, A. (2010). An examination of the dynamics of well-being and life events using vector autoregressions. *Journal of Economic Behavior & Organization*, *76*(2), 352–371. https://doi.org/10.1016/j.jebo.2010.06.006

Boehm, J. K., & Kubzansky, L. D. (2012). The heart's content: The association between positive psychological well-being and cardiovascular health. *Psychological Bulletin*, *138*(4), 655–691. https://doi.org/10.1037/a0027448

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: A meta-analysis of randomized controlled studies. *BMC Public Health*, *13*(1), 119. https://doi.org/10.1186/1471-2458-13-119

Bradburn, N. M. (1969). *The structure of psychological well-being*. Aldine. http://www.jstor.org/stable/2093340?origin=crossref

Breukelaar, I. A., Erlinger, M., Harris, A., Boyce, P., Hazell, P., Grieve, S. M., Antees, C., Foster, S., Gomes, L., Williams, L. M., Malhi, G. S., & Korgaonkar, M. S. (2020). Investigating the neural basis of cognitive control dysfunction in mood disorders. *Bipolar Disorders*, *22*(3), 286–295. https://doi.org/10.1111/bdi.12844

Bruder, G. E., Kayser, J., & Tenke, C. E. (2011). *Event-related brain potentials in depression: Clinical, cognitive, and neurophysiological implications*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195374148.013.0257

Busseri, M. A., & Sadava, S. W. (2011). A review of the tripartite structure of subjective well-being: Implications for conceptualization, operationalization, analysis, and synthesis. *Personality and Social Psychology Review*, *15*(3), 290–314. https://doi.org/10.1177/1088868310391271

Carretié, L. (2014). Exogenous (automatic) attention to emotional stimuli: A review. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(4), 1228–1258. https://doi.org/10.3758/s13415-014-0270-2

Cavanagh, J. F., & Geisler, M. W. (2006). Mood effects on the ERP processing of emotional intensity in faces: A P3 investigation with depressed students. *International Journal of Psychophysiology*, *60*(1), 27–33. https://doi.org/10.1016/j.ijpsycho.2005.04.005

Cavanagh, J. F., & Shackman, A. J. (2015). Frontal midline theta reflects anxiety and cognitive control: Meta-analytic evidence. *Journal of Physiology-Paris*, *109*(1–3), 3–15. https://doi.org/10.1016/j.jphysparis.2014.04.003

Chen, J., Ma, W., Zhang, Y., Wu, X., Wei, D., Liu, G., Deng, Z., Zhang, Z., & Yang, L. (2014). Distinct facial processing related negative cognitive bias in first-episode and recurrent major depression: Evidence from the N170 ERP component. *PLoS ONE*, *9*(10), e109176. https://doi.org/10.1371/journal.pone.0109176

Chilver, M. R., & Gatt, J. M. (2021). Six-week online multi-component positive psychology intervention improves subjective wellbeing in young adults. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-021-00449-3

Chilver, M. R., Keller, A. S., Park, H. R. P., Jamshidi, J., Montalto, A., Schofield, P. R., Clark, C. R., Harmon-Jones, E., Williams, L. M., & Gatt, J. M. (2020). Electroencephalography profiles as a biomarker of wellbeing: A twin study. *Journal of Psychiatric Research*, *126*, 114–121. https://doi.org/10.1016/j.jpsychires.2020.04.010

Chilver, M. R., Park, H. R. P., Schofield, P. R., Clark, C. R., Williams, L. M., & Gatt, J. M. (in press). Emotional face processing correlates with depression/anxiety symptoms but not wellbeing in non-clinical adults: An event-related potential study. *Journal of Psychiatric Research*.

Chung, A., Busseri, M. A., & Arnell, K. M. (2021). Between-person variation in naturally occurring affect does not relate to working memory performance: A latent variable modelling study. *Psychological Research*. https://doi.org/10.1007/s00426-020-01387-0

Cohen, M. X. (2014). The discrete time Fourier transform, the FFT, and the convolution theorem. In M. X. Cohen, *Analyzing Neural Time Series Data*. The MIT Press. https://doi.org/10.7551/mitpress/9609.003.0016

Cohen, S., Alper, C. M., Doyle, W. J., Treanor, J. J., & Turner, R. B. (2006). Positive emotional style predicts resistance to illness after experimental exposure to rhinovirus or influenza A virus. *Psychosomatic Medicine*, 7.

Cohn, M. A., & Fredrickson, B. L. (2010). In search of durable positive psychology interventions: Predictors and consequences of long-term positive behavior change.

The Journal of Positive Psychology, *5*(5), 355–366. https://doi.org/10.1080/17439760.2010.508883

Cooke, P. J., Melchert, T. P., & Connor, K. (2016). Measuring well-Being: A review of instruments. *The Counseling Psychologist*, *44*(5), 730–757. https://doi.org/10.1177/0011000016633507

Conway, C. C., Krueger, R. F., HiTOP Consortium Executive Board, Cicero, D. C., DeYoung, C. G., Eaton, N. R., Forbes, M. K., Hallquist, M. N., Kotov, R., Latzman, R. D., Ruggero, C. J., Simms, L. J., Waldman, I. D., Waszczuk, M. A., Watson, D., Widiger, T. A., & Wright, A. G. C. (2021). Rethinking the diagnosis of mental disorders: Data-driven psychological dimensions, not categories, as a framework for mental-health research, treatment, and training. *Current Directions in Psychological Science*, *30*(2), 151–158. https://doi.org/10.1177/0963721421990353

Côté, S., Saks, A. M., & Zikic, J. (2006). Trait affect and job search outcomes. *Journal of Vocational Behavior*, *68*(2), 233–252. https://doi.org/10.1016/j.jvb.2005.08.001

Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. *British Journal of Clinical Psychology*, *42*(2), 111–131. https://doi.org/10.1348/014466503321903544

Dai, Q., & Feng, Z. (2012). More excited for negative facial expressions in depression: Evidence from an event-related potential study. *Clinical Neurophysiology*, *123*(11), 2172–2179. https://doi.org/10.1016/j.clinph.2012.04.018

Dai, Q., Wei, J., Shu, X., & Feng, Z. (2016). Negativity bias for sad faces in depression: An event-related potential study. *Clinical Neurophysiology*, *127*(12), 3552–3560. https://doi.org/10.1016/j.clinph.2016.10.003

daSilva, E. B., Crager, K., & Puce, A. (2016). On dissociating the neural time course of the processing of positive emotions. *Neuropsychologia*, *83*, 123–137. https://doi.org/10.1016/j.neuropsychologia.2015.12.001

De Neve, J.-E., & Oswald, A. J. (2012). Estimating the influence of life satisfaction and positive affect on later income using sibling fixed effects. *Proceedings of the National Academy of Sciences*, *109*(49), 19953–19958. https://doi.org/10.1073/pnas.1211437109

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*(3), 542–575. https://doi.org/10.1037/0033-2909.95.3.542

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American Psychologist*, *55*(1), 34–43. https://doi.org/10.1037/0003-066X.55.1.34

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Pressman, S. D., Hunter, J., & Delgadillo-Chase, D. (2017). If, why, and when subjective well-being influences health, and future needed research. *Applied Psychology: Health and Well-Being*, *9*(2), 133–167. https://doi.org/10.1111/aphw.12090

Diener, E., & Seligman, M. E. P. (2002). Very happy people. *Psychological Science*, *13*(1), 81–84. https://doi.org/10.1111/1467-9280.00415

Disabato, D. J., Goodman, F. R., Kashdan, T. B., Short, J. L., & Jarden, A. (2016). Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-

being. *Psychological Assessment*, *28*(5), 471–482. https://doi.org/10.1037/pas0000209

Dockray, S., & Steptoe, A. (2010). Positive affect and psychobiological processes. *Neuroscience & Biobehavioral Reviews*, *35*(1), 69–75. https://doi.org/10.1016/j.neubiorev.2010.01.006

Dreisbach, G., & Goschke, T. (2004). How positive affect modulates cognitive control: Reduced perseveration at the cost of increased distractibility. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(2), 343–353. https://doi.org/10.1037/0278-7393.30.2.343

Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., & Dutoit, T. (2013). Performance of the Emotiv Epoc headset for P300-based applications. *BioMedical Engineering OnLine*, *12*(1), 56. https://doi.org/10.1186/1475-925X-12-56

Eimer, M. (2000). The face-specific N170 component reflects late stages in the structural encoding of faces: *NeuroReport*, *11*(10), 2319–2324. https://doi.org/10.1097/00001756-200007140-00050

Eimer, M., & Holmes, A. (2007). Event-related brain potential correlates of emotional face processing. *Neuropsychologia*, *45*(1), 15–31. https://doi.org/10.1016/j.neuropsychologia.2006.04.022

Fingelkurts, A. A., & Fingelkurts, A. A. (2015). Altered structure of dynamic electroencephalogram oscillatory pattern in major depression. *Biological Psychiatry*, *77*(12), 1050–1060. https://doi.org/10.1016/j.biopsych.2014.12.011

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology. *American Psychologist*, *56*(3), 218–226. https://doi.org/10.1O37//0OO3-O66X.56.3.218

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Gatt, J. M., Korgaonkar, M. S., Schofield, P. R., Harris, A., Clark, C. R., Oakley, K. L., Ram, K., Michaelson, H., Yap, S., Stanners, M., Wise, V., & Williams, L. M. (2012). The TWIN-E Project in Emotional Wellbeing: Study protocol and preliminary heritability results across four MRI and DTI measures. *Twin Research and Human Genetics*, *15*(3), 419–441. https://doi.org/10.1017/thg.2012.12

Goodman, F. R., Disabato, D. J., Kashdan, T. B., & Kauffman, S. B. (2018). Measuring well-being: A comparison of subjective well-being and PERMA. *The Journal of Positive Psychology*, *13*(4), 321–332. https://doi.org/10.1080/17439760.2017.1388434

Gordon, E., Cooper, N., Rennie, C., Hermens, D., & Williams, L. M. (2005). Integrative Neuroscience: The role of a standardized database. *Clinical EEG and Neuroscience*, *36*(2), 64–75. https://doi.org/10.1177/155005940503600205

Gottesman, I. I., & Gould, T. D. (2003). The endophenotype concept in psychiatry: Etymology and strategic intentions. *American Journal of Psychiatry*, *160*(4), 636–645. https://doi.org/10.1176/appi.ajp.160.4.636

Grant, F., Guille, C., & Sen, S. (2013). Well-being and the risk of depression under stress. *PLoS ONE*, *8*(7), e67395. https://doi.org/10.1371/journal.pone.0067395

Gray, J. R. (2001). Emotional modulation of cognitive control: Approach–withdrawal states double-dissociate spatial from verbal two-back task performance. *Journal of Experimental Psychology: General*, *130*(3), 436–452. https://doi.org/10.1037/0096-3445.130.3.436

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research*, *54*, 81–108. https://doi.org/10.1023/A:1007219227883

Grin-Yatsenko, V. A., Baas, I., Ponomarev, V. A., & Kropotov, J. D. (2009). EEG power spectra at early stages of depressive disorders. *Journal of Clinical Neurophysiology*, *26*(6), 401–406. https://doi.org/10.1097/WNP.0b013e3181c298fe

Haase, C. M., Poulin, M. J., & Heckhausen, J. (2012). Happiness as a motivator: Positive affect predicts primary control striving for career and educational goals. *Personality and Social Psychology Bulletin*, *38*(8), 1093–1104. https://doi.org/10.1177/0146167212444906

Hall, M. H., Schulze, K., Rijsdijk, F., Picchioni, M., Ettinger, U., Bramon, E., Freedman, R., Murray, R. M., & Sham, P. (2006). Heritability and reliability of P300, P50 and duration mismatch negativity. *Behavior Genetics*, *36*(6), 845–857. https://doi.org/10.1007/s10519-006-9091-6

Harden, K. P. (2021). "Reports of my death were greatly exaggerated": Behavior genetics in the postgenomic era. *Annual Review of Psychology*, *72*(1), 37–60. https://doi.org/10.1146/annurev-psych-052220-103822

Harmon-Jones, E., & Gable, P. A. (2018). On the role of asymmetric frontal cortical activity in approach and withdrawal motivation: An updated review of the evidence. *Psychophysiology*, *55*(1). https://doi.org/10.1111/psyp.12879

Haslam, N., McGrath, M. J., Viechtbauer, W., & Kuppens, P. (2020). Dimensions over categories: A meta-analysis of taxometric research. *Psychological Medicine*, *50*(9), 1418–1432. https://doi.org/10.1017/S003329172000183X

Headey, B., & Wearing, A. J. (1989). Personality, life events, and subjective well-being: Toward a dynamic equilibrium model. *Journal of Personality and Social Psychology*, *57*(4), 731–739. https://doi.org/10.1037/0022-3514.57.4.731

Hendriks, T., Schotanus-Dijkstra, M., Hassankhan, A., de Jong, J., & Bohlmeijer, E. (2020). The efficacy of multi-component positive psychology interventions: A systematic review and meta-analysis of randomized controlled trials. *Journal of Happiness Studies*, *21*(1), 357–390. https://doi.org/10.1007/s10902-019-00082-1

Howell, R. T., Kern, M. L., & Lyubomirsky, S. (2007). Health benefits: Meta-analytically determining the impact of well-being on objective health outcomes. *Health Psychology Review*, *1*(1), 83–136. https://doi.org/10.1080/17437190701492486

Hu, B., Rao, J., Li, X., Cao, T., Li, J., Majoe, D., & Gutknecht, J. (2017). Emotion regulating attentional control abnormalities in major depressive disorder: An event-related potential study. *Scientific Reports*, *7*(1), 13530. https://doi.org/10.1038/s41598-017-13626-3

Iacono, W. G., Malone, S. M., & Vrieze, S. I. (2017). Endophenotype best practices. *International Journal of Psychophysiology*, *111*, 115–144. https://doi.org/10.1016/j.ijpsycho.2016.07.516

Iasiello, M., van Agteren, J., Keyes, C. L. M., & Cochrane, E. M. (2019). Positive mental health as a predictor of recovery from mental illness. *Journal of Affective Disorders*, *251*, 227–230. https://doi.org/10.1016/j.jad.2019.03.065

Iwasa, H., Kawaai, C., Gondo, Y., Inagaki, H., & Suzuki, T. (2006). Subjective well-being as a predictor of all-cause mortality among middle-aged and elderly people living in an urban Japanese community: A seven-year prospective cohort study. *Geriatrics and*

Gerontology International, *6*(4), 216–222. https://doi.org/10.1111/j.1447-0594.2006.00351.x

Jahoda, M. (1958). Clearing the air: Unsuitable conceptualizations of positive mental health. In *Current concepts of positive mental health* (pp. 10–21). Basic Books.

Jamshidi, J., Williams, L. M., Schofield, P. R., Park, H. R. P., Montalto, A., Chilver, M. R., Bryant, R. A., Toma, C., Fullerton, J. M., & Gatt, J. M. (2020). Diverse phenotypic measurements of wellbeing: Heritability, temporal stability and the variance explained by polygenic scores. *Genes, Brain and Behavior*, *19*(8). https://doi.org/10.1111/gbb.12694

Jaworska, N., Blier, P., Fusee, W., & Knott, V. (2012). The temporal electrocortical profile of emotive facial processing in depressed males and females and healthy controls. *Journal of Affective Disorders*, *136*(3), 1072–1081. https://doi.org/10.1016/j.jad.2011.10.047

Jaworska, N., Thompson, A., Shah, D., Fisher, D., Ilivitsky, V., & Knott, V. (2010). Electrocortical effects of acute tryptophan depletion on emotive facial processing in depression-prone individuals. *European Neuropsychopharmacology*, *20*(7), 473–486. https://doi.org/10.1016/j.euroneuro.2010.03.002

Joormann, J., & Gotlib, I. H. (2010). Emotion regulation in depression: Relation to cognitive inhibition. *Cognition & Emotion*, 19.

Joormann, J., Levens, S. M., & Gotlib, I. H. (2011). Sticky thoughts: Depression and rumination are associated with difficulties manipulating emotional material in working memory. *Psychological Science*, *22*(8), 979–983. https://doi.org/10.1177/0956797611415539

Kahneman, D., Diener, E., & Schwarz, N. (1999). *Well-being: Foundations of hedonic psychology*. Russell Sage Foundation. http://ebookcentral.proquest.com/lib/unsw/detail.action?docID=4416891

Keyes, C. L. M. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Behavior*, *43*(2), 207–222. http://dx.doi.org.wwwproxy1.library.unsw.edu.au/10.2307/3090197

Keyes, C. L. M. (2005). Mental illness and/or mental health? Investigating axioms of the Complete State Model of Health. *Journal of Consulting and Clinical Psychology*, *73*(3), 539–548. https://doi.org/10.1037/0022-006X.73.3.539

Keyes, C. L. M., Myers, J. M., & Kendler, K. S. (2010). The structure of the genetic and environmental influences on mental well-being. *American Journal of Public Health*, *100*(12), 2379–2384. https://doi.org/10.2105/AJPH.2010.193615

Keyes, C. L. M., Shmotkin, D., & Ryff, C. D. (2002). Optimizing well-being: The empirical encounter of two traditions. *Journal of Personality and Social Psychology*, *82*(6), 1007–1022. https://doi.org/10.1037/0022-3514.82.6.1007

Kim, E. S., Kubzansky, L. D., Soo, J., & Boehm, J. K. (2017). Maintaining healthy behavior: A prospective study of psychological well-being and physical activity. *Annals of Behavioral Medicine*, *51*(3), 337–347. https://doi.org/10.1007/s12160-016-9856-y

Kiss, M., & Eimer, M. (2008). ERPs reveal subliminal processing of fearful faces. *Psychophysiology*, *45*(2), 318–326. https://doi.org/10.1111/j.1469-8986.2007.00634.x

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Kluetsch, R. C., Ros, T., Théberge, J., Frewen, P. A., Calhoun, V. D., Schmahl, C., Jetly, R., & Lanius, R. A. (2014). Plastic modulation of PTSD resting-state networks and subjective wellbeing by EEG neurofeedback. *Acta Psychiatrica Scandinavica*, *130*(2), 123–136. https://doi.org/10.1111/acps.12229

Knyazev, G. G. (2007). Motivation, emotion, and their inhibitory control mirrored in brain oscillations. *Neuroscience & Biobehavioral Reviews*, *31*(3), 377–395. https://doi.org/10.1016/j.neubiorev.2006.10.004

Knyazev, G. G. (2012). EEG delta oscillations as a correlate of basic homeostatic and motivational processes. *Neuroscience & Biobehavioral Reviews*, *36*(1), 677–695. https://doi.org/10.1016/j.neubiorev.2011.10.002

Knyazev, G. G. (2013). EEG correlates of self-referential processing. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00264

Knyazev, G. G., Schutter, D. J. L. G., & van Honk, J. (2006). Anxious apprehension increases coupling of delta and beta oscillations. *International Journal of Psychophysiology*, *61*(2), 283–287. https://doi.org/10.1016/j.ijpsycho.2005.12.003

Koivumaa-Honkanen, H., Kaprio, J., Honkanen, R., Viinamäki, H., & Koskenvuo, M. (2004). Life satisfaction and depression in a 15-year follow-up of healthy adults. *Social Psychiatry and Psychiatric Epidemiology*, *39*(12), 994–999. https://doi.org/10.1007/s00127-004-0833-6

Kushlev, K., Heintzelman, S. J., Lutes, L. D., Wirtz, D., Kanippayoor, J. M., Leitner, D., & Diener, E. (2020). Does happiness improve health? Evidence from a randomized controlled trial. *Psychological Science*, *31*(7), 807–821. https://doi.org/10.1177/0956797620919673

Lamers, S. M. A., Westerhof, G. J., Glas, C. A. W., & Bohlmeijer, E. T. (2015). The bidirectional relation between positive mental health and psychopathology in a longitudinal representative panel study. *The Journal of Positive Psychology*, *10*(6), 553–560. https://doi.org/10.1080/17439760.2015.1015156

Lee, Y.-C., & Chao, H.-F. (2012). The role of active inhibitory control in psychological well-being and mindfulness. *Personality and Individual Differences*, *53*(5), 618–621. https://doi.org/10.1016/j.paid.2012.05.001

Liddell, B. J., Brown, K. J., Kemp, A. H., Barton, M. J., Das, P., Peduto, A., Gordon, E., & Williams, L. M. (2005). A direct brainstem–amygdala–cortical 'alarm' system for subliminal signals of fear. *NeuroImage*, *24*(1), 235–243. https://doi.org/10.1016/j.neuroimage.2004.08.016

Llewellyn, D. J., Lang, I. A., Langa, K. M., & Huppert, F. A. (2008). Cognitive function and psychological well-being: Findings from a population-based cohort. *Age and Ageing*, *37*(6), 685–689. https://doi.org/10.1093/ageing/afn194

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Luhmann, M., Lucas, R. E., Eid, M., & Diener, E. (2013). The prospective effect of life satisfaction on life events. *Social Psychological and Personality Science*, *4*(1), 39–45. https://doi.org/10.1177/1948550612440105

Lyubomirsky, S. (2010). *Hedonic adaptation to positive and negative experiences*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195375343.013.0011

Lyubomirsky, S., & Layous, K. (2013). How do simple positive activities increase well-being? *Current Directions in Psychological Science*, *22*(1), 57–62. https://doi.org/10.1177/0963721412469809

Lyubomirsky, S., Sheldon, K. M., & Schkade, D. (2005). Pursuing happiness: The architecture of sustainable change. *Review of General Psychology*, *9*(2), 111–131. https://doi.org/10.1037/1089-2680.9.2.111

Malone, S. M., Vaidyanathan, U., Basu, S., Miller, M. B., Mcgue, M., & Iacono, W. G. (2014). Heritability and molecular-genetic basis of the P3 event-related brain potential: A genome-wide association study: Genome-wide association study of P3 amplitude. *Psychophysiology*, *51*(12), 1246–1258. https://doi.org/10.1111/psyp.12345

McKenzie, E. D., Lim, A. S. P., Leung, E. C. W., Cole, A. J., Lam, A. D., Eloyan, A., Nirola, D. K., Tshering, L., Thibert, R., Garcia, R. Z., Bui, E., Deki, S., Lee, L., Clark, S. J., Cohen, J. M., Mantia, J., Brizzi, K. T., Sorets, T. R., Wahlster, S., … Mateen, F. J. (2017). Validation of a smartphone-based EEG among people with epilepsy: A prospective study. *Scientific Reports*, *7*(1), 45567. https://doi.org/10.1038/srep45567

McLoughlin, G., Makeig, S., & Tsuang, M. T. (2014). In search of biomarkers in psychiatry: EEG-based measures of brain function. *American Journal of Medical Genetics Part B: Neuropsychiatric Genetics*, *165*(2), 111–121. https://doi.org/10.1002/ajmg.b.32208

Miner, A. G., & Glomb, T. M. (2010). State mood, task performance, and behavior at work: A within-persons approach. *Organizational Behavior and Human Decision Processes*, *112*(1), 43–57. https://doi.org/10.1016/j.obhdp.2009.11.009

Nes, R. B., Czajkowski, N., R⊘ysamb, E., Reichborn-Kjennerud, T., & Tambs, K. (2008). Well-being and ill-being: Shared environments, shared genes? *The Journal of Positive Psychology*, *3*(4), 253–265. https://doi.org/10.1080/17439760802399323

Nes, R. B., Røysamb, E., Tambs, K., Harris, J. R., & Reichborn-Kjennerud, T. (2006). Subjective well-being: Genetic and environmental contributions to stability and change. *Psychological Medicine*, *36*(07), 1033. https://doi.org/10.1017/S0033291706007409

Papousek, I., Harald Freudenthaler, H., & Schulter, G. (2011). Typical performance measures of emotion regulation and emotion perception and frontal EEG asymmetry in an emotional contagion paradigm. *Personality and Individual Differences*, *51*(8), 1018–1022. https://doi.org/10.1016/j.paid.2011.08.013

Park, H. R. P., Chilver, M. R., Montalto, A., Jamshidi, J., Schofield, P. R., Williams, L. M., & Gatt, J. M. (2021). Associations between mental wellbeing and fMRI neural bases underlying responses to positive emotion in a twin sample. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291721002695

Parks, A. C., Della Porta, M. D., Pierce, R. S., Zilca, R., & Lyubomirsky, S. (2012). Pursuing happiness in everyday life: The characteristics and behaviors of online happiness seekers. *Emotion*, *12*(6), 1222–1234. https://doi.org/10.1037/a0028587

Pe, M. L., Koval, P., & Kuppens, P. (2013). Executive well-being: Updating of positive stimuli in working memory is associated with subjective well-being. *Cognition*, *126*(2), 335–340. https://doi.org/10.1016/j.cognition.2012.10.002

Perkins, J. M., Subramanian, S. V., Davey Smith, G., & Özaltin, E. (2016). Adult height, nutrition, and population health. Nutrition Reviews, 74(3), 149–165. https://doi.org/10.1093/nutrit/nuv105

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019

Proyer, R. T., Wellenzohn, S., Gander, F., & Ruch, W. (2015). Toward a better understanding of what makes positive psychology interventions work: Predicting happiness and depression from the person × intervention fit in a follow-up after 3.5 years. *Applied Psychology: Health and Well-Being*, *7*(1), 108–128. https://doi.org/10.1111/aphw.12039

Putkinen, V., Makkonen, T., & Eerola, T. (2017). Music-induced positive mood broadens the scope of auditory attention. *Social Cognitive and Affective Neuroscience*, *12*(7), 1159–1168. https://doi.org/10.1093/scan/nsx038

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2016). Shared versus distinct genetic contributions of mental wellbeing with depression and anxiety symptoms in healthy twins. *Psychiatry Research*, *244*, 65–70. https://doi.org/10.1016/j.psychres.2016.07.016

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2017). The shared and unique genetic relationship between mental well-being, depression and anxiety symptoms and cognitive function in healthy twins. *Cognition and Emotion*, *31*(7), 1465–1479. https://doi.org/10.1080/02699931.2016.1232242

Routledge, K. M., Williams, L. M., Harris, A. W. F., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2018). Genetic correlations between wellbeing, depression and anxiety symptoms and behavioral responses to the emotional faces task in healthy twins. *Psychiatry Research*, *264*, 385–393. https://doi.org/10.1016/j.psychres.2018.03.042

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, *52*(1), 141–166. https://doi.org/10.1146/annurev.psych.52.1.141

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081. https://doi.org/10.1037/0022-3514.57.6.1069

Sanders, C. A., Schueller, S. M., Parks, A. C., & Howell, R. T. (2019). Understanding long-term trajectories in web-based happiness interventions: Secondary analysis from two web-based randomized trials. *Journal of Medical Internet Research*, *21*(6), e13253. https://doi.org/10.2196/13253

Schmid, P. C., & Schmid Mast, M. (2010). Mood effects on emotion recognition. *Motivation and Emotion*, *34*(3), 288–292. https://doi.org/10.1007/s11031-010-9170-0

Schutter, D. J. L. G., & van Honk, J. (2005). Salivary cortisol levels and the coupling of midfrontal delta–beta oscillations. *International Journal of Psychophysiology*, *55*(1), 127–129. https://doi.org/10.1016/j.ijpsycho.2004.07.003

Shannon, R. W., Patrick, C. J., Venables, N. C., & He, S. (2013). 'Faceness' and affectivity: Evidence for genetic contributions to distinct components of electrocortical response to human faces. *NeuroImage*, *83*, 609–615. https://doi.org/10.1016/j.neuroimage.2013.06.014

Sheldon, K. M., Boehm, J., & Lyubomirsky, S. (2013). *Variety is the spice of happiness: The Hedonic Adaptation Prevention Model*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199557257.013.0067

Sin, N. L. (2016). The protective role of positive well-being in cardiovascular disease: Review of current evidence, mechanisms, and clinical implications. *Current Cardiology Reports*, *18*(11), 106. https://doi.org/10.1007/s11886-016-0792-z

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology*, *65*(5), 467–487. https://doi.org/10.1002/jclp.20593

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & de Geus, E. J. C. (2007). Genetic contribution to the P3 in young and middle-aged adults. *Twin Research and Human Genetics*, *10*(2), 335–347. https://doi.org/10.1375/twin.10.2.335

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & Geus, E. J. C. (2005). Heritability of background EEG across the power spectrum. *Psychophysiology*, *42*(6), 691–697. https://doi.org/10.1111/j.1469-8986.2005.00352.x

Storbeck, J., & Maswood, R. (2016). Happiness increases verbal and spatial working memory capacity where sadness does not: Emotion, working memory and executive control. *Cognition and Emotion*, *30*(5), 925–938. https://doi.org/10.1080/02699931.2015.1034091

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review*, *37*(1), 52–68. https://doi.org/10.1080/02796015.2008.12087908

Travis, F., & Shear, J. (2010). Focused attention, open monitoring and automatic self-transcending: Categories to organize meditations from Vedic, Buddhist and Chinese traditions. *Consciousness and Cognition*, *19*(4), 1110–1118. https://doi.org/10.1016/j.concog.2010.01.007

Tuck, N. L., Adams, K. S., Pressman, S. D., & Consedine, N. S. (2017). Greater ability to express positive emotion is associated with lower projected cardiovascular disease risk. *Journal of Behavioral Medicine*, *40*(6), 855–863. https://doi.org/10.1007/s10865-017-9852-0

Urry, H. L., Nitschke, J. B., Dolski, I., Jackson, D. C., Dalton, K. M., Mueller, C. J., Rosenkranz, M. A., Ryff, C. D., Singer, B. H., & Davidson, R. J. (2004). Making a life worth living: Neural correlates of well-being. *Psychological Science*, *15*(6), 367–372. https://doi.org/10.1111/j.0956-7976.2004.00686.x

van Peer, J. (2008). Cortisol administration enhances the coupling of midfrontal delta and beta oscillations. *International Journal of Psychophysiology*, *67*(2), 144–150. https://doi.org/10.1016/j.ijpsycho.2007.11.001

Vanlessen, N., De Raedt, R., Koster, E. H. W., & Pourtois, G. (2016). Happy heart, smiling eyes: A systematic review of positive mood effects on broadening of visuospatial attention. *Neuroscience & Biobehavioral Reviews*, *68*, 816–837. https://doi.org/10.1016/j.neubiorev.2016.07.001

Vanlessen, N., De Raedt, R., Mueller, S. C., Rossi, V., & Pourtois, G. (2015). Happy and less inhibited? Effects of positive mood on inhibitory control during an antisaccade task revealed using topographic evoked potential mapping. *Biological Psychology*, *110*, 190–200. https://doi.org/10.1016/j.biopsycho.2015.07.004

Vanlessen, N., Rossi, V., De Raedt, R., & Pourtois, G. (2014). Feeling happy enhances early spatial encoding of peripheral information automatically: Electrophysiological time-course and neural sources. *Cognitive, Affective, & Behavioral Neuroscience*. https://doi.org/10.3758/s13415-014-0262-2

VanRullen, R., & Thorpe, S. J. (2001). The time course of visual processing: From early perception to decision-making. *Journal of Cognitive Neuroscience*, *13*(4), 454–461. https://doi.org/10.1162/08989290152001880

Verweij, K. J. H., Mosing, M. A., Zietsch, B. P., & Medland, S. E. (2012). Estimating Heritability from Twin Studies. In R. C. Elston, J. M. Satagopan, & S. Sun (Eds.),

Statistical Human Genetics: Methods and Protocols (pp. 151–170). Humana Press. https://doi.org/10.1007/978-1-61779-555-8_9

Visscher, P. M., Hill, W. G., & Wray, N. R. (2008). Heritability in the genomics era—Concepts and misconceptions. *Nature Reviews Genetics*, *9*(4), 255–266. https://doi.org/10.1038/nrg2322

Walsh, L. C., Boehm, J. K., & Lyubomirsky, S. (2018). Does happiness promote career success? Revisiting the evidence. *Journal of Career Assessment*, *26*(2), 199–219. https://doi.org/10.1177/1069072717751441

Waterman, A. S. (1993). Two conceptions of happiness: Contrasts of personal expressiveness (eudaimonia) and hedonic enjoyment. *Journal of Personality and Social Psychology*, *64*(4), 678–691. https://doi.org/10.1037/0022-3514.64.4.678

Watter, S., Geffen, G. M., & Geffen, L. B. (2001). The n-back as a dual-task: P300 morphology under divided attention. *Psychophysiology*, *38*(6), 998–1003. https://doi.org/10.1111/1469-8986.3860998

Watters, A. J., Harris, A. W. F., & Williams, L. M. (2018). Electrocortical reactivity to negative and positive facial expressions in individuals with a family history of major depression. *Biological Psychology*, *136*, 127–135. https://doi.org/10.1016/j.biopsycho.2018.05.015

Williams, L. M., Kemp, A. H., Felmingham, K., Liddell, B. J., Palmer, D. M., & Bryant, R. A. (2007). Neural biases to covert and overt signals of fear: Dissociation by trait anxiety and depression. *Journal of Cognitive Neuroscience*, *19*(10), 1595–1608. https://doi.org/10.1162/jocn.2007.19.10.1595

Williams, L. M., Liddell, B. J., Rathjen, J., Brown, K. J., Gray, J., Phillips, M., Young, A., & Gordon, E. (2004). Mapping the time course of nonconscious and conscious

perception of fear: An integration of central and peripheral measures. *Human Brain Mapping*, *21*(2), 64–74. https://doi.org/10.1002/hbm.10154

Williams, L. M., Simms, E., Clark, C. R., Paul, R. H., Rowe, D., & Gordon, E. (2005). The test-retest reliability of a standardized neurocognitive and neurophysiological test battery: 'NeuroMarker'. *International Journal of Neuroscience*, *115*(12), 1605–1630. https://doi.org/10.1080/00207450590958475

Woodman, G. F. (2010). A brief introduction to the use of event-related potentials in studies of perception and attention. *Attention, Perception, & Psychophysics*, *72*(8), 2031–2046. https://doi.org/10.3758/BF03196680

World Health Organization. (1946). *Constitution of the World Health Organization*. https://www.who.int/about/governance/constitution

Xu, Y.-Y., Feng, Z.-Q., Xie, Y.-J., Zhang, J., Peng, S.-H., Yu, Y.-J., & Li, M. (2018). Frontal alpha EEG asymmetry before and after positive psychological interventions for medical students. *Frontiers in Psychiatry*, *9*, 432. https://doi.org/10.3389/fpsyt.2018.00432

Yi, C. Y., Murry, M. W. E., & Gentzler, A. L. (2016). Perception of emotional expressions in adults: The role of temperament and mood. *Journal of Individual Differences*, *37*(1), 16–23. https://doi.org/10.1027/1614-0001/a000183

Yoon, H. H., Malone, S. M., & Iacono, W. G. (2015). Longitudinal stability and predictive utility of the visual P3 response in adults with externalizing psychopathology: Longitudinal P3 investigation of EXT. *Psychophysiology*, *52*(12), 1632–1645. https://doi.org/10.1111/psyp.12548

Zabcikova, M. (2019). Visual and auditory stimuli response, measured by Emotiv Insight headset. *MATEC Web of Conferences*, *292*, 01024. https://doi.org/10.1051/matecconf/201929201024

Zelenski, J. M., Murphy, S. A., & Jenkins, D. A. (2008). The happy-productive worker thesis revisited. *Journal of Happiness Studies*, *9*(4), 521–537. https://doi.org/10.1007/s10902-008-9087-4

Zhang, D., He, Z., Chen, Y., & Wei, Z. (2016). Deficits of unconscious emotional processing in patients with major depression: An ERP study. *Journal of Affective Disorders*, *199*, 13–20. https://doi.org/10.1016/j.jad.2016.03.056

Zhang, Y., Hauser, U., Conty, C., Emrich, H. M., & Dietrich, D. E. (2007). Familial risk for depression and P3b component as a possible neurocognitive vulnerability marker. *Neuropsychobiology*, *55*(1), 14–20. https://doi.org/10.1159/000103571

Chapter 2: Identifying a resting EEG profile of wellbeing

Published as:

Chilver, M. R., Keller, A. S., Park, H. R. P., Jamshidi, J., Montalto, A., Schofield, P. R., Clark, C. R., Harmon-Jones, E., Williams, L. M., & Gatt, J. M. (2020). Electroencephalography profiles as a biomarker of wellbeing: A twin study. Journal of Psychiatric Research, 126, 114–121. https://doi.org/10.1016/j.jpsychires.2020.04.010

Author contributions

MRC is a PhD student with JMG as her primary supervisor. This work forms a component of her PhD dissertation. MRC conducted the statistical analysis, wrote the first draft of the article, and edited the manuscript. ASK cross-validated the results. JMG conceptualised the research focus on wellbeing biomarkers, guided analysis interpretation, and edited the first draft of the article. LMW conceptualised the twin study for funding by the Australian Research Council. LMW, PRS, CRC and JMG designed the twin study for implementation and acquired the data. All authors reviewed and edited the article and approved the final version of the paper.

2.1. Preamble

This chapter presents the first of three studies based on the TWIN-E dataset in the search for EEG candidate endophenotypes for wellbeing. Specifically, this chapter aimed to explore whether resting EEG measures, namely alpha, beta, theta, and delta power, are correlated with mental wellbeing, and to determine the extent to which any observed correlation is accounted for by shared genetic or environmental factors using multivariate twin analysis. A shared genetic association between wellbeing and resting EEG would support the use of resting EEG power as a candidate endophenotype for mental wellbeing.

2.2. Abstract

Alterations to electroencephalography (EEG) power have been reported for psychiatric conditions such as depression and anxiety, but not for mental wellbeing in a healthy population. This study examined the resting EEG profiles associated with mental wellbeing, and how genetics and environment contribute to these associations using twin modelling. Mental wellbeing was assessed using the COMPAS-W Wellbeing Scale which measures both subjective and psychological wellbeing. In 422 healthy adult monozygotic and dizygotic twins aged 18–61 years, we examined the association between mental wellbeing and EEG power (alpha, beta, theta, delta) using linear mixed models. This was followed by univariate and multivariate twin modelling to assess the heritability of wellbeing and EEG power, and whether the association was driven by shared genetics or environment. A significant association between wellbeing and an interaction of alpha, beta, and delta (ABD) power was found ($\beta = -0.33$, $p < 0.001$) whereby a profile of high alpha and delta and low beta was associated with higher wellbeing, independent of depression and anxiety symptoms. This finding was supported by a five-fold cross-validation analysis. A significant genetic correlation ($rG = -0.43$) was found to account for 94% of the association between wellbeing and the EEG power interaction. Together, this study has identified a novel EEG profile with a common genetic component that may be a potential biomarker of mental wellbeing. Future studies need to clarify the causal direction of this association.

2.3. Introduction

Mental health is often measured as the absence of mental illness because of the assumption that those without mental illness are mentally healthy. However, a study of over 3000 Americans found that 15% of individuals without a mental illness had lower wellbeing than individuals with major depression (Keyes, 2002). It is therefore important that mental health or 'wellbeing' be measured independently of mental illness symptoms and that its own unique markers are identified. Various twin and population studies have estimated that mental wellbeing is influenced almost equally by genetics and environment (Bartels, 2015; Gatt et al., 2014). This genetic component may be explained by differences in brain structure, function, or connectivity. Brain imaging methods such as electroencephalography (EEG) or functional magnetic resonance imaging (fMRI) can be used to understand the underlying neurobiology that contributes to wellbeing. Existing fMRI research has associated wellbeing with connectivity within the brain's default mode network (Luo et al., 2016), a network also associated with specific profiles of EEG spectral power at rest (Knyazev et al., 2011; Neuner et al., 2014). Despite evidence that resting brain networks are associated with wellbeing and that EEG power is a more cost-effective and accessible method of monitoring resting brain activity, research to date has not tested whether resting EEG power is an indicator of wellbeing. This study addressed this using a twin sample to explore the relationship between EEG and wellbeing and assessed whether this association was predominately environmental or genetic.

Resting EEG power measures spontaneous brain activity, largely unaffected by task demands (Fingelkurts & Fingelkurts, 2015). Both frontal alpha asymmetry (the difference in alpha power between the left and right hemisphere) and absolute resting power have been used to probe at the neural mechanisms underlying mental illnesses such as major depressive

disorder (Coburn et al., 2006; Fingelkurts & Fingelkurts, 2015). Alpha asymmetry towards the left hemisphere is thought to indicate less cortical activation in that region and has been associated with withdrawal motivation and depressive symptoms (Fingelkurts & Fingelkurts, 2015; Harmon-Jones & Gable, 2018). Differences in EEG absolute power have also been reported in individuals with major depressive disorder relative to controls, with depression characterised by patterns of increased alpha and beta power, and decreased delta and theta power (Fingelkurts & Fingelkurts, 2015). In comparison, the EEG literature on wellbeing is very limited. Some studies have suggested that alpha asymmetry towards the right hemisphere is indicative of higher wellbeing, although depressive symptoms were not accounted for (Alessandri et al., 2015; Urry et al., 2004). Thus, it is unclear whether this finding is simply reflecting the inverse association between wellbeing and depressive symptoms. No known attempts have been made to identify profiles of absolute EEG power with wellbeing. This was the focus of the current study.

Specifically, we explored whether resting absolute EEG power is associated with wellbeing and whether there is a genetic link. An exploratory method was chosen because previous research provides no strong rationale for a link between any specific frequency band and wellbeing, particularly when accounting for depression and anxiety symptoms. Wellbeing was operationalised using the composite COMPAS-W wellbeing scale (Gatt et al., 2014). This scale captures subjective wellbeing (SWB; happiness and life satisfaction) and psychological wellbeing (PWB; positive functioning and goal-driven behaviour) with six subscales: composure, own-worth, mastery, positivity, achievement, and satisfaction. Heritability of this scale has been estimated at 48% (Gatt et al., 2014), higher than estimates derived from either SWB (32%) or PWB (36%) alone (Bartels, 2015). In comparison, resting EEG power is much more heritable, with estimates of 80–90% depending on the frequency

band (Smit et al., 2005). Because EEG power is more heritable than default mode network connectivity with estimates of 10–54% (Korgaonkar et al., 2014; Xu et al., 2017), EEG power is more likely to be associated with wellbeing via a shared genetic correlation.

The twin model applied in the current study compares similarities in monozygotic twins who share 100% of their genetics with those of dizygotic twins who share approximately 50% of their genetics using univariate models. This method asserts that the increased similarity between monozygotic twins compared to dizygotic twins is due to their shared genetics, allowing the additive genetic (A), dominant genetic (D) or common environment (C), and unique environment (E) effects to be estimated (Verweij et al., 2012). The genetic and environmental correlations between two traits is estimated using cross-twin cross-trait correlations whereby the first trait in twin one is correlated with the second trait in twin two, and vice versa. The difference in these correlations when comparing monozygotic and dizygotic twins informs the fit of the multivariate model (Posthuma, 2009).

This study aimed to explore the association between wellbeing and EEG power in a large healthy twin sample using models that account for interactions between alpha, beta, delta, and theta power, as well as variation in depression/anxiety symptoms measured using the Depression Anxiety Stress Scale (DASS-42; Lovibond & Lovibond, 1995). The EEG profiles identified in this analysis were then tested for associations with lifestyle factors. To test previous wellbeing and EEG research findings (Urry et al., 2004), alpha asymmetry was also tested. Secondly, we determined the roles of genetics and environment in these relationships. Univariate twin models were used to estimate the heritability of each trait, followed by multivariate models to estimate shared genetic and environmental contributions between traits. Due to the high heritability of EEG power, associations between wellbeing and EEG power were predicted to be predominantly due to genetic correlations.

2.4. Methods & Materials

2.4.1. Participants

This study included 441 participants drawn from the TWIN-E project (Gatt et al., 2012) who agreed to participate in the EEG phase of the study. The full TWIN-E project sample includes a total of 1669 healthy adult same-sex twin pairs of European descent recruited through the Australian Twin Registry between 2009 and 2012. Participants were screened for previous and current physical and mental health.

Inclusion and exclusion criteria can be found in the study protocol (Gatt et al., 2012). A total of 422 participants, who had complete datasets available, were included in the analysis. The study was approved by the Human Research Ethics Committees of the University of Sydney (03–2009/11430), Flinders University (FCREC#08/09), and the University of New South Wales (HC14256).

2.4.2. Procedure

Participants completed an online test battery before attending the EEG recording session at either the Brain Dynamics Centre at the University of Sydney, NSW, Australia, or at Flinders University, Adelaide, SA, Australia. This included measures of mental health, lifestyle factors, and cognitive and emotional function (Gatt et al., 2012). The COMPAS-W wellbeing scale was used to measure wellbeing. This scale has been validated against other mental health measures and has demonstrated high internal reliability for wellbeing of 0.84 and test-retest reliability of 0.82 (Gatt et al., 2014). The DASS-42 (Lovibond & Lovibond, 1995) was used to measure depression and anxiety symptoms. This has been validated against other common depression and anxiety scales, including the Beck Depression and Anxiety

Inventories (Lovibond & Lovibond, 1995), and has very high internal reliability at 0.97 (Crawford & Henry, 2003).

2.4.3. EEG acquisition and processing

Resting EEG activity was recorded using a 26-electrode QuikCap and NuAmps DC amplifier with a sampling rate of 500 Hz. Impedances were kept below 5 kΩ. Recordings were made under an eyes open and eyes closed condition, each lasting a total of 2 min. Heart rate data was recorded simultaneously using an electrocardiogram (ECG) via an electrode on the left wrist. EEG and ECG recordings were made relative to virtual ground with a low-pass attenuation of 40 dB per decade above 100 Hz. A notch filter was applied to filter out line noise. EEG recordings were re-referenced offline to the linked mastoids for the resting power analysis, and to the average reference for the asymmetry analysis as used by Urry et al. (2004). The Gratton-Coles method was used to correct for eye movement artifacts with electrodes placed on the outside of each eye, and above and below the left eye (Gratton et al., 1983).

2.4.4. Statistical analyses

2.4.4.1. Pre-processing

Questionnaire data was checked for outliers and inconsistent responses prior to the analysis. DASS-42 scores were log transformed to normalise the score distribution.

2.4.4.2. EEG power

EEG power can be measured in either absolute or relative terms, whereby absolute power is the amplitude squared for each frequency, and relative power is each frequency's power as a proportion of total power. Absolute power was chosen for this study due to some

ambiguities in the quantification of relative power; that is, it is not clear whether an increase in relative power for a given frequency is caused by an increase in its absolute power, or a decrease in another frequency.

Resting power was calculated for each condition by dividing the 2min recordings into 4-s intervals and applying a Welch window prior to the Fast Fourier Transform. The power spectra were averaged for each electrode site in each of the two conditions over four frequency bands: delta (1.5–3.5 Hz), theta (4–7.5 Hz), alpha (8–13 Hz), and beta (14.5–30 Hz). A log transformation was applied to the resulting data to approximate a normal distribution. EEG power was averaged for frontal (F3, F4, F7, F8, Fp1, Fp2, Fz), central (CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, FC4), temporal (T3, T4, T5, T6) and parietal-occipital (O1, O2, Oz, P3, P4, Pz) regions to reduce the number of required models.

2.4.4.3. Alpha asymmetry

Alpha asymmetry was calculated for all frontal bilateral electrode pairs (Fp1-Fp2, F4–F3, FC4-FC3, F8–F7) using two different methods. The first method was a difference score between right and left log power used previously (Urry et al., 2004), and the second method used the difference score as a proportion of the total power from the same electrodes (right – left/right + left). Both methods were applied in the eyes open and eyes closed conditions.

2.4.4.4. Linear mixed models

The association between EEG power and wellbeing was assessed using linear mixed models in *R* with the *lme4* package (Bates et al., 2015). Models were specified with wellbeing as the criterion and EEG power in all four frequencies as predictors. To account for all possible interactions between the four EEG bands without increasing multi-collinearity, interaction

terms were calculated manually by multiplying each combination of frequency bands and regressing all lower-order terms on each interaction term for each participant (Burrill, 1997). The resulting residuals were then included in the models as the interaction terms, after multiplying by 100 to improve scaling. This method reduces the overlapping variances between multiple interactions produced from the same four frequency bands and improves the reliability of the results (Burrill, 1997). Similar models were used to assess the association between alpha asymmetry and wellbeing, with wellbeing as the criterion variable and each electrode pair as predictor variables with age, education, body mass index, and sex as covariates.

Statistical tests on the linear mixed model variables were conducted using the Satterthwaite method, an effective method for controlling the type 1 error rate in linear mixed models (Luke, 2017). A Bonferroni correction was used to control for multiple testing. Resting power models in each condition included 15 parameters (4 main effects, 6 two-way interactions, 4 three-way interactions, and 1 four-way interaction) across four different brain regions, resulting in an adjusted significance threshold of 0.05/60 = 0.0008 (8e-4). For the asymmetry analysis, the Bonferroni correction encompassed tests at 4 different electrode sites, resulting in an adjusted significance threshold of 0.05/4 = 0.0125.

Five-fold cross validation was used to determine whether EEG power was associated with wellbeing in held-out pairs of twins. After randomly assigning pairs of twins to one of five equal-sized groups, iterative linear mixed models with covariates (described above) were run to predict wellbeing in the held-out group. The results of this procedure were compared to a null model in which only the average wellbeing score within the four training folds was used to predict wellbeing in the held-out group for every individual.

2.4.4.5. Group-based analysis

To test whether the model-identified EEG profiles differentiated the wellbeing groups, as well as other underlying mechanisms for wellbeing, participants were assigned to groups based on whether their EEG profile was associated with high, moderate, or low wellbeing in the linear mixed model results. EEG profiles were then tested for a linear association with the COMPAS-W subscales, depression/anxiety symptoms, cognitive function (Routledge et al., 2017), emotion identification (Routledge et al., 2018), heart rate variability, and general lifestyle and nutrition variables (Gatt et al., 2012). For continuous variables, linear mixed models were used with each variable of interest included as the criterion. For ordinal variables (lifestyle), cumulative link mixed models were instead applied using the *ordinal R* package (Christensen, 2019). Tests were conducted using a Bonferroni correction.

2.4.4.6. Univariate twin analysis

Heritability of wellbeing, depression/anxiety, and the EEG measures was assessed using univariate twin analysis with the *OpenMx* package in *R* (Scheike et al., 2014). Where the intra-class correlation between monozygotic twins was double or more than the intra-class correlation between dizygotic twins, an ADE model was then tested, otherwise the ACE model was tested (Verweij et al., 2012). A, C, or D components were then dropped progressively from each model to find the most parsimonious model. Age, sex, and education were included as covariates in these twin models.

2.4.4.7. Multivariate twin analysis

The overlap in genetic and environmental variance between wellbeing, depression/anxiety, and EEG power was assessed using a correlated factors model with the

OpenMx R package (Neale et al., 2016) with covariates accounted for. Genetic and environmental correlations were tested by constraining them to zero in a new model, then comparing this model to the previously best-fit model using a chi-square difference test. A significant reduction in model fit resulting from constraining a correlation to zero indicated its significance (and therefore the correlation was retained in the model).

2.5. Results

Demographic information is provided in Table 2.1. Depression/anxiety symptoms were very low on average, and the average wellbeing was similar to the full TWIN-E Study sample. The obtained ratio of monozygotic to dizygotic twins is typical of volunteer twin samples, and arises from monozygotic twins having a higher participation rate than dizygotic twins when the same incentives are provided to both groups (Lykken et al., 1978).

Table 2.1 Participant characteristics in the current sample of twins (mean ± SD).

	Monozygotic (n = 292)	Dizygotic (n = 130)	Total (N = 422)
Age (years)	41.0 ± 12.2	37.8 ± 14.3	40.0 ± 13.0
Education (years)	14.8 ± 2.4	15.0 ± 2.2	14.9 ± 2.3
COMPAS-W (wellbeing)	99.7 ± 10.5	99.3 ± 9.6	99.5 ± 10.2
DASS-42 (anxiety/depression symptoms)	0.90 ± 0.42	0.98 ± 0.39	0.92 ± 0.41
Males	108 (37.0%)	40 (30.8%)	148 (35.1%)
Right-handed	256 (87.7%)	111 (85.4%)	367 (87.0%)
Sydney	188 (64.4%)	98 (75.4%)	286 (67.8%)

Notes: COMPAS-W = a composite measure of wellbeing (Gatt et al., 2014); DASS-42 = The Depression Anxiety Stress Scale (Lovibond & Lovibond, 1995); Participant data were collected in either Sydney or Adelaide, Australia.

2.5.1. Linear mixed models

With a significance threshold of $p = 0.0008$, only the three-way interaction between alpha, beta, and delta in the central region (electrodes CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, and FC4) in the eyes closed condition showed a significant relationship between EEG power and wellbeing (see Table 2.2). Although no additional main effects were significant at the corrected threshold in this analysis, there was a marginally significant negative association between beta power and wellbeing, and a marginally significant positive association between alpha power and wellbeing. Outcomes for all other regions and conditions can be found in Tables S1–7. No significant association was found between wellbeing and alpha asymmetry at any electrode site at the corrected significance threshold of $p < 0.0125$ irrespective of the asymmetry calculation used.

The significant three-way interaction between alpha, beta, and delta (ABD interaction) for the central region is shown in Fig. 2.1a. Fig. 2.1b demonstrates the standardised estimates of the interaction effect for each electrode site, including the central sites. Fig. 2.1b indicates that the interaction effect spreads bilaterally into the temporal regions when observing changes by electrode, despite the effect not showing statistical significance when averaging across the region. There was one clear EEG profile associated with higher wellbeing characterised by high delta, high alpha, and low beta power. This pattern was significant regardless of whether or not depression/anxiety symptoms were included in the model.

The results of the cross-validation procedure revealed that the ABD EEG model accounting for depression/anxiety symptoms is able to predict wellbeing in held-out pairs of twins (RMSE = 9.137) slightly better than a null model with predictions based solely on the mean wellbeing score (RMSE = 10.219). Importantly, on each fold of this cross-validation

Table 2.2 Linear mixed model results of EEG power with wellbeing scores in the central brain region for the eyes closed condition, covarying for age, sex, zygosity, education, and body mass index

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	111.78				2.12	0.034
Age	-0.01	-0.01	-0.13	0.11	-0.19	0.850
Education	0.40	0.09	0.00	0.18	2.04	0.042
Body mass index	-0.35	-0.16	-0.26	-0.06	-3.24	0.001
Zygosity	-0.14	-0.01	-0.10	0.09	-0.13	0.898
Sex	0.42	0.02	-0.08	0.12	0.39	0.698
Depression/anxiety symptoms	-10.20	-0.41	-0.50	-0.32	-9.24	**<2e-16**
Alpha	2.76	0.10	-0.03	0.23	1.56	0.119
Beta	-6.11	-0.14	-0.26	-0.02	-2.21	0.028
Delta	3.63	0.06	-0.08	0.21	0.84	0.404
Theta	-0.54	-0.01	-0.17	0.14	-0.19	0.852
A*B	-0.01	-0.00	-0.16	0.15	-0.06	0.949
A*T	-0.00	-0.00	-0.18	0.17	-0.04	0.969
A*D	0.07	0.05	-0.13	0.22	0.54	0.587
B*T	0.22	0.16	-0.05	0.37	1.47	0.143
B*D	-0.43	-0.18	-0.36	0.00	-1.98	0.048
T*D	0.05	0.03	-0.10	0.16	0.39	0.695
A*B*T	0.35	0.10	-0.05	0.24	1.30	0.193
A*B*D	-1.97	-0.33	-0.51	-0.14	-3.46	**6e-4**
A*T*D	0.12	0.02	-0.12	0.17	0.32	0.747
B*T*D	1.20	0.18	0.02	0.34	2.16	0.031

A*B*T*D	-1.11	-0.06	-0.15	0.02	-1.45	0.147
Random Effects						
σ^2				58.82		
$\tau_{00\ FamID}$				20.85		
Marginal R^2 / Conditional R^2				0.262 / 0.455		

Note: A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval, σ2 = within family variance, τ00 FamID = between family variance. Bolded p-values are significant at the Bonferroni corrected significance threshold of 0.0008 (8e-4). Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42). All EEG variables are based on the eyes closed condition averaged across the central brain region (electrodes CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, and FC4).

procedure, the ABD interaction remained significant, suggesting that the results hold in subsamples of this population.

Group-based analysis. The group-based analysis was conducted to test whether the two EEG profiles most associated with wellbeing in the linear mixed model were significantly associated with cognitive, emotional, or lifestyle variables that might explain the link between EEG power and wellbeing. The 'High ABD' profile associated with high wellbeing included individuals with above-average alpha (mean = 1.49, SD = 0.370) and delta (mean = 1.04, SD = 0.178) power and below average beta (mean = 1.13, SD = 0.227) power. Those with below-average alpha and delta and above-average beta were placed into a 'Low ABD' group (associated with low wellbeing), and everyone else was placed into a 'Moderate ABD' group (associated with moderate wellbeing). Based on this, 46 participants were placed in the Low ABD group, 346 were in the Moderate group, and 30 were in the High ABD group.

A significant linear trend verified that the groups derived from these specific EEG profiles were associated with wellbeing in the expected direction (β = 0.135, corrected *p* = 0.026), with significant effects also apparent for the COMPAS-W subscales composure (β =

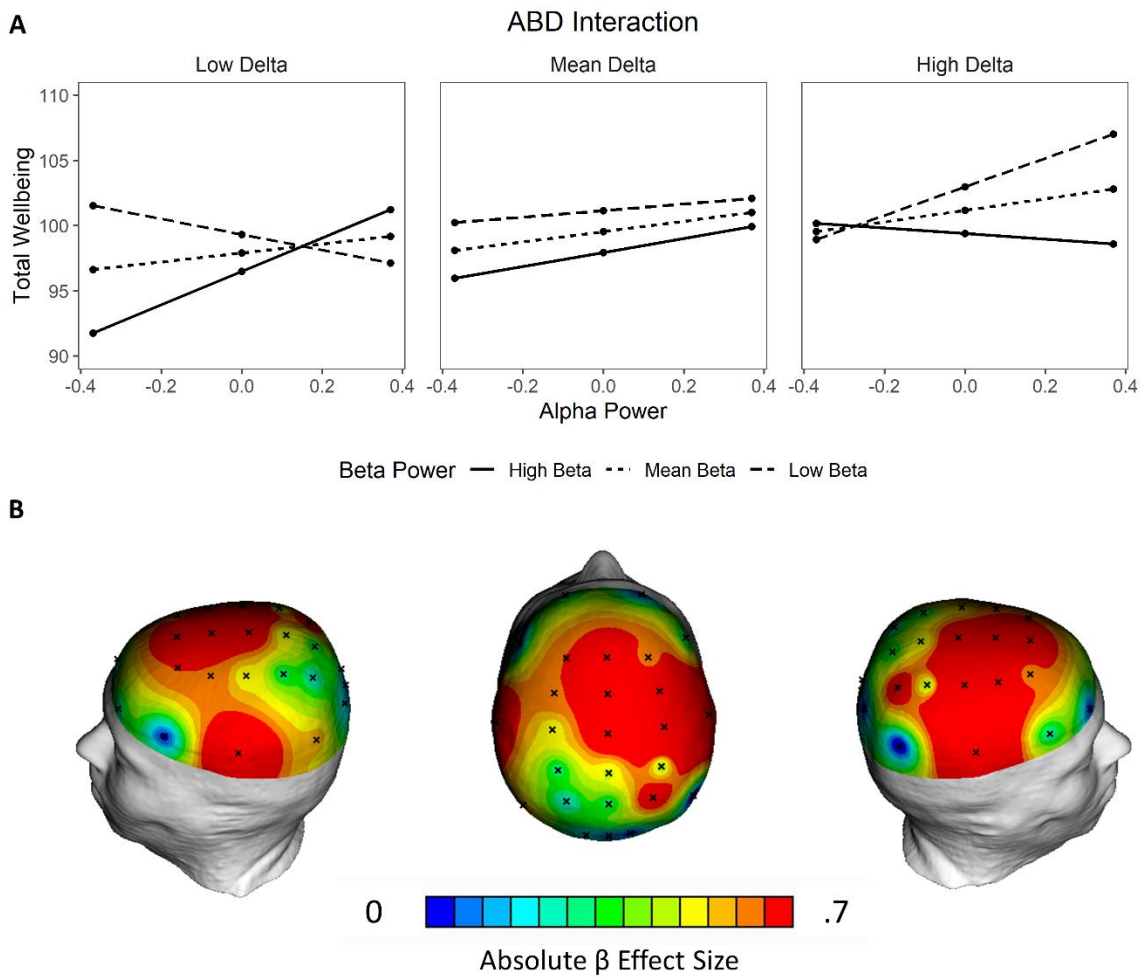


Figure 2.1 Association between the alpha, beta, delta (ABD) EEG interaction effect and wellbeing for the averaged central region in the eyes closed condition. Top panel (A) shows the interaction effect for different power levels in each EEG frequency band. High and low values for beta and delta are based on ± 1 standard deviation from the mean. Bottom panel (B) shows the strength of this association at each electrode site, whereby red indicates a larger standardised effect size and blue indicates smaller effect size using absolute values.

0.128, corrected $p = 0.018$) and satisfaction ($\beta = 0.131$, corrected $p = 0.008$). The EEG groups also showed a negative linear association with the DASS-42 depression subscale, but this effect was non-significant following correction ($\beta = -0.129$, corrected $p = 0.136$). Daily caffeine consumption, including coffee, soft-drink, and energy drinks ($\beta = -1.67$, corrected p

= 0.024), and weekly fast-food consumption (β = −2.42, corrected p = 0.019) were both lower in the High ABD profile compared to the Low ABD profile, consistent with a healthier lifestyle. No other significant associations were found.

2.5.2. Univariate twin analysis

Heritability estimates for the final models of wellbeing, depression/anxiety, and eyes closed EEG power at the central region are presented in Table 2.3. The AE model was the best fitting model for all variables (main and interaction variables). EEG power heritability estimates were similar across brain regions, ranging from 0.89–0.91 for alpha power, 0.72–0.86 for beta power, 0.77–0.83 for theta power, and 0.54–0.77 for delta power. The ABD interaction was of moderate heritability, estimated at 0.37. Heritability estimates for each region in each condition (eyes open and eyes closed) are provided in Table S8.

2.5.3. Multivariate twin analysis

Depression/anxiety symptoms and the EEG ABD interaction were both significantly associated with wellbeing and were therefore included in the correlated factors wellbeing model. All lower-order EEG power interaction terms were included in the model as covariates by regressing them from the mean. The final model is represented in Fig. 2.2. A significant genetic correlation of −0.43 was found between wellbeing and the ABD interaction (p = 0.002), accounting for 94% of the phenotypic correlation between these variables. The contribution of this genetic correlation to the total observed phenotypic correlation is calculated by multiplying the genetic correlation (−0.43) by the genetic path coefficients (or $\sqrt{h^2}$) for wellbeing (0.60) and the ABD interaction (0.69). Thus, the genetic correlation contributes −0.178 (CIs: 0.066 to −0.286) of the total phenotypic correlation of

Table 2.3 Univariate heritability estimates in the averaged central brain region for the eyes closed condition, covarying for age, sex, and education

Phenotype	ICC		Best Fit Model		Estimates			
	MZ	DZ	Model	*p*	A^2	C^2	D^2	E^2
Wellbeing	.428	.076	AE	.331	.393	-	0	.607
Depression/ Anxiety symptoms	.351	.261	AE	1	.325	0	-	.675
Alpha	.898	.363	AE	.150	.891	-	0	.109
Beta	.868	.381	AE	.543	.857	-	0	.143
Theta	.837	.414	AE	.636	.822	-	0	.178
Delta	.787	.652	AE	.060	.736	0	-	.264
A*B	.776	.034	ADE	.031	0	-	.752	.248
A*T	.756	.151	AE	.062	.742	-	0	.258
A*D	.597	.061	ADE	.014	0	-	.632	.368
B*T	.779	.181	AE	.159	.749	-	0	.251
B*D	.677	.167	AE	.052	.660	-	0	.340
T*D	.495	-.015	AE	.073	.421	-	0	.579
A*B*T	.621	-.065	ADE	.037	0	-	.586	.414
A*B*D	.402	.020	AE	.134	.376	-	0	.624
A*T*D	.405	.040	AE	.076	.398	-	0	.602
B*T*D	.400	.057	AE	.059	.406	-	0	.594
A*B*T*D	.283	.183	AE	.872	.307	0	-	.693

Note: ICC = intra-class correlation, MZ = monozygotic twins, DZ = dizygotic twins. Starting models were either ADE or ACE, where A = additive genetic, D = dominant genetic, C = common environment, E = unique environment. The ACE starting model was used if the ICC for MZ twins was greater than double the ICC for DZ twins. Squared model components indicate their contribution as a percentage of total variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42). EEG power interactions are indicated by an asterisk where A = alpha, B = beta, T = theta, D = delta. All EEG variables are based on the eyes closed condition averaged across the central brain region (electrodes CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, and FC4).

−0.193, or 93.7% of the total phenotypic correlation between these traits. Remaining confidence intervals can be found in Table S9. The environmental correlation between wellbeing and the ABD interaction term was non-significant (p = 0.751). Interestingly, there were significant genetic and environmental correlations between depression/anxiety symptoms and the ABD interaction, but in opposite directions. That is, there was a significant positive genetic correlation between depression/anxiety symptoms and the ABD interaction (p < 0.001), but a significant negative environment correlation between them also (p = 0.012). This resulted in a non-significant phenotypic correlation between depression/anxiety symptoms and the ABD interaction.

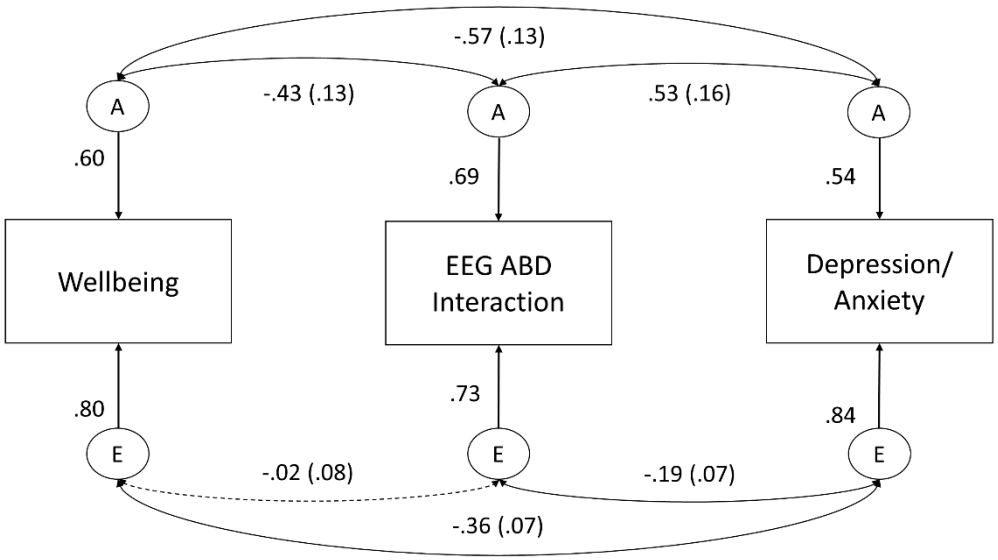


Figure 2.1 Correlated factors model for wellbeing, the alpha, beta, delta (ABD) EEG interaction, and depression/anxiety symptoms. Single-headed arrows indicate the influence of additive genetic (A) or unique environmental (E) influence on each variable with standardised path coefficients. Double-headed arrows indicate genetic and environmental correlations between variables, with standard errors provided in parentheses. Solid lines indicate significant correlations, whereas dashed lines indicate non-significant correlations. For point estimates and corresponding confidence intervals, please refer to Table S9.

2.6. Discussion

This was the first study to test and show an association between resting EEG power and wellbeing in a healthy sample, independent of depression/anxiety symptoms. Linear mixed models including interactions between EEG bands revealed a significant three-way interaction between alpha, beta, and delta power. A profile of high alpha and delta in combination with low beta was associated with elevated wellbeing. The univariate heritability analysis aligned with past estimates indicating moderate heritability of wellbeing and depression/anxiety symptoms, and high heritability of EEG power (Smit et al., 2005). In the multivariate heritability analysis, a significant genetic correlation between wellbeing and the ABD interaction accounted for 93.7% of their association.

The ABD interaction reported here indicates that the relative amplitudes of each band are relevant to mental wellbeing. Past studies have reported that alpha-delta coupling (i.e., positive correlation) and delta-beta coupling are associated with anxiety and stress levels (van Peer, 2008). Knyazev et al. (2006) examined resting EEG power in university students who were measured on trait anxiety using the State-Trait Anxiety Inventory and were randomly told that they either had good or poor performance on a go-no-go task. Participants with low trait anxiety had more alpha-delta coupling than those with high trait anxiety regardless of experimental condition. In contrast, there were no differences in beta-delta coupling between high and low trait anxiety groups. However, those who received negative feedback showed a significant increase in beta-delta coupling. This finding could indicate that beta-delta coupling is a sign of stress. This is supported by a study where cortisol administration in 40 male students increased beta-delta coupling, particularly for those with high behavioural inhibition which is associated with anxiety (van Peer, 2008). These past studies support the findings of the current study whereby associations between alpha, beta, and delta power were

associated with differences in wellbeing. The current study is differentiated from the previous studies by the association of three, instead of two, EEG bands, and the extension to wellbeing rather than negative symptoms. We also reported a direction of effect in means that are associated with higher wellbeing (namely, high alpha, high delta, low beta), whereas many of the previous studies focused on the presence/absence of the coupling correlation. It would be useful for future studies to explore this three-way (or four-way) EEG association in other phenotypes. Along with this, alternative methodologies could be used to provide a more in-depth evaluation of the current findings in relation to the functional roles of each frequency. For instance, source localisation conducted via low-resolution brain electromagnetic topography (Kozlowska et al., 2018) or simultaneous EEG and fMRI recordings (Neuner et al., 2014) could be used to improve understanding of the relationship between EEG power and underlying brain networks such as the default mode network. These and other methods may deepen our understanding of how EEG frequencies relate to wellbeing.

No significant association was found between alpha asymmetry and wellbeing, contrary to previous reports (Urry et al., 2004). Alpha asymmetry towards the right hemisphere (indicating greater cortical activity in the left hemisphere), particularly in frontal regions, is theorised to index approach motivation and is often associated with positive affect (Angus & Harmon-Jones, 2016), whereas the opposite pattern of asymmetry may predict depression (Olbrich & Arns, 2013). One possible explanation for the lack of an asymmetry effect in the current study is the lack of any emotional manipulation. Previous reports indicate that the power to detect associations between asymmetry and psychological traits (such as wellbeing) is weakened in the resting EEG paradigm due to the impact of uncontrolled or circumstantial variables (Harmon-Jones & Gable, 2018). Thus, an association between asymmetry and wellbeing may be detected in alternative paradigms.

A large meta-analysis of the heritability of SWB and PWB has estimated that around 35% of the variance in wellbeing is heritable (Bartels, 2015). The present study produced a similar estimate of 39.3%. The heritability of depression/anxiety symptoms was slightly lower than for wellbeing, at 32.5%, also similar to previous estimates (Sullivan et al., 2000). Finally, the heritability of the EEG power bands in the current study were very high, ranging from 70 to 90%. This study was the first to evaluate the heritability of the interactions between bands. Here it was found that the interaction terms had smaller heritable components compared to the raw EEG bands, ranging from 30 to 80%. The current study has thus replicated previous heritability estimates of wellbeing, depression/anxiety, and EEG power, but has also shown that interactions between the bands have larger environmental components than individual bands alone.

In the multivariate analysis, a genetic correlation accounted for 93.7% of the total correlation between wellbeing and the ABD EEG interaction ($r = 0.196$). Genetic correlations may indicate pleiotropy, which is when a single gene influences multiple traits. Pleiotropy can be biological whereby the gene directly impacts both traits, or mediated, whereby the gene causes trait A, and trait A causes trait B (Hackinger & Zeggini, 2017). However, genetic correlations can also arise from assortative mating and gene-gene correlations that were not accounted for in this study. Assortative mating refers to the tendency for individuals to mate with those who are genetically similar to themselves. This makes it more likely for gene-gene correlations to occur, whereby certain genes are more likely to occur together. Gene-gene correlations can also arise from the proximity of genes on a chromosome, as proximal genes are more likely to be inherited together. Thus, future research is needed to clarify whether pleiotropy is contributing to the genetic correlation between wellbeing and the ABD interaction. Regardless of the cause of the association between wellbeing and EEG, the

current study suggests that resting EEG power could be used as a biological predictor of wellbeing.

The primary limitation of this study is of the twin model itself, which relies on the equal environment assumption. This is the assumption that assumes that monozygotic and dizygotic twins experience the same level of environmental similarity. This assumption is violated if (i) monozygotic twins have more similar environments than dizygotic twins, (ii) the increased similarity impacts the trait of interest, and (iii) the increased environmental similarity is not itself due to genetic effects (Derks et al., 2006). Violating this assumption would inflate the genetic component of the model. While there is concern that this assumption is not always met in twin studies, it is unlikely to have a significant impact on heritability estimates (Felson, 2014). Other factors including assortative mating, as described earlier, and gene-environment correlations can also impact the estimation of genetic and environmental effects in the twin model, not accounted for here. Furthermore, the chosen sample of healthy twins of European descent may limit the generalisability of the study. This sample was selected to limit confounding effects of mental illness symptoms and treatment effects, and to minimise population stratification effects on genetic variants. However, the current models should be interpreted with these limitations in mind.

A final point for consideration is the use of absolute power instead of relative power, taken as a percentage of total power for the analysis. There is evidence indicating that skull thickness can have a small effect on measures of absolute power, although the majority of variance is explained by cortical activity (Hagemann et al., 2008). Despite this limitation, absolute power was chosen because relative power reduces the information captured. Specifically, relative power for all bands can be impacted by a change in a single frequency band as the total power changes. Absolute power is not impacted in this way. Furthermore,

the interactions reported in the current study were calculated within-subjects, limiting the already small impact of skull thickness on the results.

This study has made a significant contribution to our understanding of the relationship between wellbeing and EEG by providing evidence for a link between resting EEG power and wellbeing. An interaction between alpha, beta, and delta power was found to predict wellbeing whereby high alpha and delta power combined with low beta power was associated with elevated wellbeing. This interaction effect was supported using five-fold cross validation and may be an indicator of low trait anxiety and stress. The association between EEG power and wellbeing was found to be predominately genetic in nature, suggesting a common genetic pathway for both measures. Future research should aim to evaluate the relationship between EEG power and wellbeing to determine whether there are causal mechanisms underlying their association.

2.7. References

Alessandri, G., Caprara, G. V., & De Pascalis, V. (2015). Relations among EEG-alpha asymmetry and positivity personality trait. *Brain and Cognition*, *97*, 10–21. https://doi.org/10.1016/j.bandc.2015.04.003

Angus, D. J., & Harmon-Jones, E. (2016). On the neuroscience of approach and withdrawal motivation, with a focus on the role of asymmetrical frontal cortical activity. In S. Kim, J. Reeve, & M. Bong (Eds.), *Advances in Motivation and Achievement* (Vol. 19, pp. 37–63). Emerald Group Publishing Limited. https://doi.org/10.1108/S0749-742320160000019003

Bartels, M. (2015). Genetics of wellbeing and its components satisfaction with life, happiness, and quality of life: A review and meta-analysis of heritability studies. *Behavior Genetics*, *45*(2), 137–156. https://doi.org/10.1007/s10519-015-9713-y

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Burrill, D. F. (1997). *Modeling and interpreting interactions in multiple regression*. The Ontario Institute for Studies in Education Toronto.

Christensen, R. (2019). *ordinal—Regression models for ordinal data* (R Package Version 2019.3-9) [Computer software]. https://cran.r-project.org/web/packages/ordinal/ordinal.pdf

Coburn, K. L., Lauterbach, E. C., Boutros, N. N., Black, K. J., Arciniegas, D. B., & Coffey, C. E. (2006). The value of quantitative electroencephalography in clinical psychiatry: A report by the committee on research of the American Neuropsychiatric Association.

Journal of Neuropsychiatry and Clinical Neuroscience, *18*(4), 460–500. https://doi.org/10.1176/jnp.2006.18.4.460

Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. *British Journal of Clinical Psychology*, *42*(2), 111–131. https://doi.org/10.1348/014466503321903544

Derks, E. M., Dolan, C. V., & Boomsma, D. I. (2006). A test of the equal environment assumption (EEA) in multivariate twin studies. *Twin Research and Human Genetics*, *9*(3), 403–411. https://doi.org/10.1375/twin.9.3.403

Felson, J. (2014). What can we learn from twin studies? A comprehensive evaluation of the equal environments assumption. *Social Science Research*, *43*, 184–199. https://doi.org/10.1016/j.ssresearch.2013.10.004

Fingelkurts, A. A., & Fingelkurts, A. A. (2015). Altered structure of dynamic electroencephalogram oscillatory pattern in major depression. *Biological Psychiatry*, *77*(12), 1050–1060. https://doi.org/10.1016/j.biopsych.2014.12.011

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Gatt, J. M., Korgaonkar, M. S., Schofield, P. R., Harris, A., Clark, C. R., Oakley, K. L., Ram, K., Michaelson, H., Yap, S., Stanners, M., Wise, V., & Williams, L. M. (2012). The TWIN-E Project in Emotional Wellbeing: Study protocol and preliminary heritability results across four MRI and DTI measures. *Twin Research and Human Genetics*, *15*(3), 419–441. https://doi.org/10.1017/thg.2012.12

Gratton, G., Coles, M. G. H., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. *Electroencephalograhy and Clinical Neurophysiology*, *55*(4), 468–484. https://doi.org/10.1016/0013-4694(83)90135-9

Hackinger, S., & Zeggini, E. (2017). Statistical methods to detect pleiotropy in human complex traits. *Open Biology*, *7*(11), 170125. https://doi.org/10.1098/rsob.170125

Hagemann, D., Hewig, J., Walter, C., & Naumann, E. (2008). Skull thickness and magnitude of EEG alpha activity. *Clinical Neurophysiology*, *119*(6), 1271–1280. https://doi.org/10.1016/j.clinph.2008.02.010

Harmon-Jones, E., & Gable, P. A. (2018). On the role of asymmetric frontal cortical activity in approach and withdrawal motivation: An updated review of the evidence. *Psychophysiology*, *55*(1). https://doi.org/10.1111/psyp.12879

Keyes, C. L. M. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Behavior*, *43*(2), 207–222. http://dx.doi.org.wwwproxy1.library.unsw.edu.au/10.2307/3090197

Knyazev, G. G., Schutter, D. J. L. G., & van Honk, J. (2006). Anxious apprehension increases coupling of delta and beta oscillations. *International Journal of Psychophysiology*, *61*(2), 283–287. https://doi.org/10.1016/j.ijpsycho.2005.12.003

Knyazev, G. G., Slobodskoj-Plusnin, J. Y., Bocharov, A. V., & Pylkova, L. V. (2011). The default mode network and EEG alpha oscillations: An independent component analysis. *Brain Research*, *1402*, 67–79. https://doi.org/10.1016/j.brainres.2011.05.052

Korgaonkar, M. S., Ram, K., Williams, L. M., Gatt, J. M., & Grieve, S. M. (2014). Establishing the resting state default mode network derived from functional magnetic resonance imaging tasks as an endophenotype: A twins study. *Human Brain Mapping*, *35*(8), 3893–3902. https://doi.org/10.1002/hbm.22446

Kozlowska, K., Spooner, C. J., Palmer, D. M., Harris, A., Korgaonkar, M. S., Scher, S., & Williams, L. M. (2018). “Motoring in idle”: The default mode and somatomotor networks are overactive in children and adolescents with functional neurological symptoms. *NeuroImage: Clinical*, *18*, 730–743. https://doi.org/10.1016/j.nicl.2018.02.003

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Luke, S. G. (2017). Evaluating significance in linear mixed-effects models in R. *Behavior Research Methods*, *49*(4), 1494–1502. https://doi.org/10.3758/s13428-016-0809-y

Luo, Y., Kong, F., Qi, S., You, X., & Huang, X. (2016). Resting-state functional connectivity of the default mode network associated with happiness. *Social Cognitive and Affective Neuroscience*, *11*(3), 516–524. https://doi.org/10.1093/scan/nsv132

Lykken, D. T., Tellegen, A., & DeRubeis, R. (1978). Volunteer bias in twin research: The rule of two-thirds. *Social Biology*, *25*(1), 1–9. https://doi.org/10.1080/19485565.1978.9988312

Neale, M. C., Hunter, M. D., Pritikin, J. N., Zahery, M., Brick, T. R., Kirkpatrick, R. M., Estabrook, R., Bates, T. C., Maes, H. H., & Boker, S. M. (2016). OpenMx 2.0: Extended structural equation and statistical modeling. *Psychometrika*, *81*(2), 535–549. https://doi.org/10.1007/s11336-014-9435-8

Neuner, I., Arrubla, J., Werner, C. J., Hitz, K., Boers, F., Kawohl, W., & Shah, N. J. (2014). The default mode network and EEG regional spectral power: A simultaneous fMRI-EEG study. *PLoS ONE*, *9*(2), e88214. https://doi.org/10.1371/journal.pone.0088214

Olbrich, S., & Arns, M. (2013). EEG biomarkers in major depressive disorder: Discriminative power and prediction of treatment response. *International Review of Psychiatry*, *25*(5), 604–618. https://doi.org/10.3109/09540261.2013.816269

Posthuma, D. (2009). Multivariate Genetic Analysis. In Y.-K. Kim (Ed.), *Handbook of Behavior Genetics*. Springer New York. https://doi.org/10.1007/978-0-387-76727-7

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2017). The shared and unique genetic relationship between mental well-being, depression and anxiety symptoms and cognitive function in healthy twins. *Cognition and Emotion*, *31*(7), 1465–1479. https://doi.org/10.1080/02699931.2016.1232242

Routledge, K. M., Williams, L. M., Harris, A. W. F., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2018). Genetic correlations between wellbeing, depression and anxiety symptoms and behavioral responses to the emotional faces task in healthy twins. *Psychiatry Research*, *264*, 385–393. https://doi.org/10.1016/j.psychres.2018.03.042

Scheike, T. H., Holst, K. K., & Hjelmborg, J. B. (2014). Estimating heritability for cause specific mortality based on twin studies. *Lifetime Data Analysis*, *20*(2), 210–233. https://doi.org/10.1007/s10985-013-9244-x

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & Geus, E. J. C. (2005). Heritability of background EEG across the power spectrum. *Psychophysiology*, *42*(6), 691–697. https://doi.org/10.1111/j.1469-8986.2005.00352.x

Sullivan, P. F., Neale, M. C., & Kendler, K. S. (2000). Genetic epidemiology of major depression: Review and meta-analysis. *American Journal of Psychiatry*, *157*(10), 1552–1562. https://doi.org/10.1176/appi.ajp.157.10.1552

Urry, H. L., Nitschke, J. B., Dolski, I., Jackson, D. C., Dalton, K. M., Mueller, C. J., Rosenkranz, M. A., Ryff, C. D., Singer, B. H., & Davidson, R. J. (2004). Making a life worth living: Neural correlates of well-being. *Psychological Science*, *15*(6), 367–372. https://doi.org/10.1111/j.0956-7976.2004.00686.x

van Peer, J. (2008). Cortisol administration enhances the coupling of midfrontal delta and beta oscillations. *International Journal of Psychophysiology*, *67*(2), 144–150. https://doi.org/10.1016/j.ijpsycho.2007.11.001

Verweij, K. J. H., Mosing, M. A., Zietsch, B. P., & Medland, S. E. (2012). Estimating Heritability from Twin Studies. In R. C. Elston, J. M. Satagopan, & S. Sun (Eds.), *Statistical Human Genetics: Methods and Protocols* (pp. 151–170). Humana Press. https://doi.org/10.1007/978-1-61779-555-8_9

Xu, J., Yin, X., Ge, H., Han, Y., Pang, Z., Liu, B., Liu, S., & Friston, K. (2017). Heritability of the effective connectivity in the resting-state default mode network. *Cerebral Cortex*, *27*(12), 5626–5634. https://doi.org/10.1093/cercor/bhw332

Appendix A: Chapter 2 Supplementary Results

Supplementary material for

Electroencephalography power as a biomarker of wellbeing: A twin study

Miranda R. Chilver[1,2], Arielle S. Keller[3], Haeme R. P. Park[1,2], Javad Jamshidi[1,2], Arthur Montalto[1,2], Peter R. Schofield[1,4], C. Richard Clark[5], Eddie Harmon-Jones[2], Leanne M. Williams[3,6^] & Justine M. Gatt[1,2^*]

[1] Neuroscience Research Australia, Randwick, New South Wales, 2031, Australia

[2] School of Psychology, University of New South Wales, Sydney, New South Wales, 2052, Australia

[3] Department of Psychiatry and Behavioral Sciences, Stanford School of Medicine, Stanford University, Stanford, California 94305-5717, United States of America

[4] School of Medical Sciences, University of New South Wales, Sydney, New South Wales 2052, Australia

[5] College of Education, Psychology and Social Work, Flinders University, Bedford Park, South Australia 5042, Australia.

[6] Mental Illness Research Education and Clinical Centers VISN21, Veterans Administration Palo Alto Health Care System, California, 94304-151-Y, United States of America

***Corresponding author:** Dr Justine Gatt; Phone (+612 93991812); Postal address: Neuroscience Research Australia, Barker St, Randwick Sydney NSW 2031 Australia. E-mail address: j.gatt@neura.edu.au

^ Shared senior authorship

Key words: EEG, wellbeing, mental health, heritability, twins, alpha power

Tables S1-S8

Table S1 Linear mixed model results of EEG power with wellbeing scores in the frontal brain region, eyes closed condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	113.80				19.35	**<0.001**
Age	-0.03	-0.04	-0.15	0.07	-0.74	0.459
Education	0.44	0.10	0.01	0.19	2.23	0.026
Body mass index	-0.36	-0.17	-0.26	-0.07	-3.32	0.001
Zygosity	-0.14	-0.01	-0.10	0.09	-0.13	0.897
Sex	0.27	0.01	-0.09	0.11	0.25	0.803
Depression/anxiety	-10.35	-0.42	-0.51	-0.33	-9.20	**<0.001**
Alpha	1.82	0.06	-0.05	0.18	1.12	0.264
Beta	-4.51	-0.09	-0.19	0.02	-1.65	0.099
Delta	4.13	0.07	-0.05	0.19	1.13	0.260
Theta	-2.59	-0.06	-0.19	0.07	-0.89	0.375
A*B	-3.20	-0.02	-0.14	0.10	-0.36	0.717
A*T	4.29	0.04	-0.11	0.18	0.50	0.616
A*D	-4.14	-0.02	-0.16	0.11	-0.35	0.727
B*T	24.38	0.13	-0.02	0.28	1.66	0.098
B*D	-31.93	-0.10	-0.23	0.02	-1.63	0.103
T*D	0.93	0.00	-0.10	0.11	0.08	0.939
A*B*T	-15.02	-0.03	-0.14	0.09	-0.47	0.639
A*B*D	-91.45	-0.10	-0.23	0.02	-1.58	0.115
A*T*D	16.92	0.03	-0.08	0.13	0.49	0.626
B*T*D	66.40	0.06	-0.06	0.17	0.98	0.329
A*B*T*D	-239.70	-0.07	-0.15	0.01	-1.70	0.090
Random Effects						

σ^2	60.06
$\tau_{00\ FamID}$	20.21
Marginal R^2 / Conditional R^2	0.253 / 0.441

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the frontal brain region (average of electrodes F3, F4, F7, F8, Fp1, Fp2, Fz). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval,. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S2 Linear mixed model results of EEG power with wellbeing scores in the temporal brain region, eyes closed condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	110.94				19.47	**<0.001**
Age	-0.02	-0.02	-0.14	0.10	-0.32	0.746
Education	0.41	0.09	0.01	0.18	2.08	0.038
Body mass index	-0.35	-0.16	-0.26	-0.06	-3.21	0.001
Zygosity	0.04	0.00	-0.09	0.10	0.04	0.971
Sex	0.33	0.02	-0.09	0.12	0.29	0.769
Depression/anxiety	-10.20	-0.41	-0.50	-0.32	-9.22	**<0.001**
Alpha	2.33	0.08	-0.05	0.22	1.18	0.237
Beta	-4.64	-0.10	-0.21	0.01	-1.85	0.065
Delta	6.61	0.13	-0.04	0.29	1.48	0.139
Theta	-2.91	-0.08	-0.25	0.10	-0.87	0.387
A*B	-1.70	-0.01	-0.16	0.13	-0.19	0.847
A*T	-3.02	-0.03	-0.22	0.16	-0.30	0.763
A*D	0.95	0.01	-0.19	0.20	0.07	0.947
B*T	31.57	0.21	0.00	0.41	1.94	0.053
B*D	-35.64	-0.15	-0.32	0.01	-1.86	0.064
T*D	1.26	0.01	-0.12	0.14	0.12	0.906
A*B*T	6.41	0.02	-0.13	0.16	0.21	0.832
A*B*D	-119.84	-0.19	-0.35	-0.02	-2.22	*0.027*
A*T*D	-1.57	-0.00	-0.12	0.12	-0.05	0.958
B*T*D	96.21	0.13	-0.01	0.27	1.77	0.077
A*B*T*D	-170.37	-0.08	-0.17	0.00	-1.98	0.049

Random Effects	
σ^2	57.49
$\tau_{00\ FamID}$	22.52
Marginal R^2 / Conditional R^2	0.261 / 0.469

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the temporal brain region (average of electrodes T3, T4, T5, T6). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S3 Linear mixed model results of EEG power with wellbeing scores in the parietal-occipital brain region, eyes closed condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	113.80				19.35	**<0.001**
Age	-0.03	-0.04	-0.14	0.09	-0.74	0.459
Education	0.44	0.10	0.02	0.19	2.23	0.026
Body mass index	-0.36	-0.17	-0.25	-0.05	-3.32	0.001
Zygosity	-0.14	-0.01	-0.10	0.09	-0.13	0.897
Sex	0.27	0.01	-0.09	0.11	0.25	0.803
Depression/anxiety	-10.35	-0.42	-0.50	-0.32	-9.20	**<0.001**
Alpha	1.82	0.06	0.00	0.30	1.12	0.264
Beta	-4.51	-0.09	-0.26	-0.01	-1.65	0.099
Delta	4.13	0.07	-0.05	0.31	1.13	0.260
Theta	-2.59	-0.06	-0.27	0.10	-0.89	0.375
A*B	-3.20	-0.02	-0.16	0.17	-0.36	0.717
A*T	4.29	0.04	-0.24	0.16	0.50	0.616
A*D	-4.14	-0.02	-0.19	0.24	-0.35	0.727
B*T	24.38	0.13	-0.06	0.44	1.66	0.098
B*D	-31.93	-0.10	-0.33	0.09	-1.63	0.103
T*D	0.93	0.00	-0.18	0.11	0.08	0.939
A*B*T	-15.02	-0.03	-0.16	0.19	-0.47	0.639
A*B*D	-91.45	-0.10	-0.39	0.00	-1.58	0.115
A*T*D	16.92	0.03	-0.11	0.17	0.49	0.626
B*T*D	66.40	0.06	-0.09	0.22	0.98	0.329
A*B*T*D	-239.70	-0.07	-0.10	0.07	-1.70	0.090

Random Effects	
σ^2	60.06
$\tau_{00\ FamID}$	20.21
Marginal R^2 / Conditional R^2	0.253 / 0.441

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the parietal-occipital brain region (average of electrodes O1, O2, Oz, P3, P4, Pz). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S4 Linear mixed model results of EEG power with wellbeing scores in the frontal brain region, eyes open condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	113.04				18.85	**<0.001**
Age	-0.06	-0.07	-0.19	0.04	-1.24	0.218
Education	0.39	0.09	0.00	0.18	1.91	0.057
Body mass index	-0.32	-0.14	-0.24	-0.05	-2.88	0.004
Zygosity	-0.14	-0.01	-0.10	0.09	-0.13	0.900
Sex	0.46	0.02	-0.08	0.12	0.41	0.684
Depression/anxiety	-10.34	-0.42	-0.51	-0.33	-9.16	**<0.001**
Alpha	0.66	0.02	-0.13	0.16	0.23	0.817
Beta	-1.09	-0.02	-0.13	0.08	-0.43	0.670
Delta	4.82	0.08	-0.06	0.21	1.12	0.262
Theta	-4.18	-0.07	-0.24	0.09	-0.86	0.388
A*B	6.36	0.04	-0.12	0.19	0.49	0.626
A*T	-4.24	-0.02	-0.19	0.14	-0.29	0.770
A*D	-26.30	-0.11	-0.28	0.05	-1.36	0.174
B*T	12.90	0.06	-0.15	0.26	0.55	0.586
B*D	-3.93	-0.01	-0.16	0.13	-0.18	0.857
T*D	15.00	0.05	-0.08	0.19	0.77	0.443
A*B*T	6.56	0.01	-0.10	0.12	0.18	0.860
A*B*D	-68.59	-0.07	-0.22	0.09	-0.87	0.385
A*T*D	47.63	0.06	-0.07	0.18	0.90	0.368
B*T*D	25.08	0.02	-0.13	0.17	0.27	0.788
A*B*T*D	-330.20	-0.08	-0.17	0.00	-1.95	0.052

Random Effects	
σ^2	58.91
$\tau_{00\ FamID}$	23.27
Marginal R^2 / Conditional R^2	0.234 / 0.451

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the frontal brain region (average of electrodes F3, F4, F7, F8, Fp1, Fp2, Fz). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S5 Linear mixed model results of EEG power with wellbeing scores in the central brain region, eyes open condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	113.90				17.70	**<0.001**
Age	-0.03	-0.03	-0.16	0.09	-0.52	0.602
Education	0.41	0.09	0.00	0.18	2.03	0.043
Body mass index	-0.36	-0.17	-0.27	-0.07	-3.30	0.001
Zygosity	-0.23	-0.01	-0.11	0.09	-0.20	0.839
Sex	0.38	0.02	-0.09	0.12	0.33	0.741
Depression/anxiety	-10.40	-0.42	-0.51	-0.33	-9.19	**<0.001**
Alpha	1.27	0.04	-0.12	0.20	0.49	0.626
Beta	-4.41	-0.10	-0.23	0.02	-1.57	0.118
Delta	3.22	0.05	-0.10	0.20	0.67	0.506
Theta	-0.73	-0.02	-0.20	0.17	-0.16	0.871
A*B	1.22	0.01	-0.17	0.19	0.11	0.914
A*T	-1.78	-0.02	-0.20	0.17	-0.16	0.874
A*D	-7.97	-0.05	-0.25	0.16	-0.44	0.664
B*T	10.50	0.06	-0.18	0.30	0.49	0.623
B*D	-14.70	-0.05	-0.22	0.11	-0.64	0.521
T*D	2.98	0.01	-0.15	0.18	0.15	0.883
A*B*T	-3.03	-0.01	-0.14	0.12	-0.11	0.912
A*B*D	-83.79	-0.13	-0.34	0.08	-1.17	0.243
A*T*D	9.06	0.02	-0.15	0.18	0.20	0.844
B*T*D	119.45	0.14	-0.08	0.37	1.23	0.220
A*B*T*D	-149.85	-0.07	-0.16	0.01	-1.63	0.105

Random Effects	
σ^2	59.87
$\tau_{00\ FamID}$	22.64
Marginal R^2 / Conditional R^2	0.232 / 0.443

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the central brain region (average of electrodes CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, FC4). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S6 Linear mixed model results of EEG power with wellbeing scores in the temporal brain region, eyes open condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	116.03				20.25	**<0.001**
Age	-0.04	-0.05	-0.17	0.07	-0.84	0.400
Education	0.37	0.08	-0.01	0.18	1.83	0.067
Body mass index	-0.39	-0.18	-0.28	-0.08	-3.48	0.001
Zygosity	-0.22	-0.01	-0.11	0.09	-0.19	0.846
Sex	0.51	0.02	-0.08	0.13	0.44	0.657
Depression/anxiety	-10.24	-0.41	-0.50	-0.32	-9.04	**<0.001**
Alpha	-1.06	-0.03	-0.19	0.13	-0.38	0.702
Beta	-3.31	-0.08	-0.19	0.02	-1.58	0.114
Delta	2.97	0.05	-0.11	0.22	0.60	0.548
Theta	1.15	0.02	-0.19	0.23	0.20	0.841
A*B	-5.85	-0.05	-0.23	0.13	-0.51	0.608
A*T	-6.65	-0.05	-0.23	0.14	-0.51	0.612
A*D	-9.31	-0.05	-0.27	0.16	-0.49	0.622
B*T	40.99	0.21	-0.03	0.45	1.69	0.093
B*D	-26.99	-0.11	-0.28	0.05	-1.32	0.186
T*D	8.14	0.03	-0.13	0.20	0.41	0.679
A*B*T	-26.08	-0.05	-0.18	0.08	-0.80	0.422
A*B*D	-11.91	-0.02	-0.19	0.16	-0.18	0.855
A*T*D	1.75	0.00	-0.11	0.12	0.05	0.961
B*T*D	80.34	0.08	-0.10	0.26	0.89	0.377
A*B*T*D	-286.40	-0.09	-0.17	-0.01	-2.14	0.033

Random Effects	
σ^2	57.41
$\tau_{00\ FamID}$	24.68
Marginal R^2 / Conditional R^2	0.239 / 0.468

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the temporal brain region (average of electrodes T3, T4, T5, T6). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S7 Linear mixed model results of EEG power with wellbeing scores in the parietal-occipital brain region, eyes open condition.

	Total Wellbeing					
Predictors	*B*	*β*	*95% CI Low*	*95% CI High*	*Statistic*	*p*
(Intercept)	113.59				18.90	**<0.001**
Age	-0.01	-0.02	-0.14	0.10	-0.31	0.760
Education	0.42	0.10	0.01	0.18	2.11	0.036
Body mass index	-0.40	-0.18	-0.28	-0.08	-3.62	**<0.001**
Zygosity	-0.43	-0.02	-0.12	0.08	-0.39	0.698
Sex	0.78	0.04	-0.07	0.14	0.67	0.502
Depression/anxiety	-10.31	-0.42	-0.50	-0.33	-9.21	**<0.001**
Alpha	-0.70	-0.03	-0.19	0.13	-0.33	0.739
Beta	-5.36	-0.12	-0.24	0.00	-1.93	0.054
Delta	2.96	0.06	-0.11	0.22	0.67	0.503
Theta	3.88	0.08	-0.12	0.29	0.80	0.426
A*B	-1.23	-0.01	-0.19	0.16	-0.14	0.889
A*T	-6.07	-0.06	-0.25	0.13	-0.63	0.530
A*D	-2.61	-0.02	-0.22	0.18	-0.21	0.837
B*T	36.08	0.20	-0.04	0.44	1.62	0.106
B*D	-32.05	-0.14	-0.31	0.03	-1.58	0.114
T*D	-3.92	-0.02	-0.17	0.13	-0.26	0.798
A*B*T	-39.30	-0.10	-0.24	0.03	-1.52	0.130
A*B*D	-50.69	-0.10	-0.28	0.09	-1.04	0.297
A*T*D	-2.03	-0.00	-0.13	0.13	-0.07	0.946
B*T*D	129.99	0.16	-0.02	0.33	1.76	0.079
A*B*T*D	-118.74	-0.06	-0.15	0.02	-1.46	0.144

Random Effects	
σ^2	58.90
$\tau_{00\ FamID}$	21.97
Marginal R^2 / Conditional R^2	0.248 / 0.452

Notes: Linear mixed model output predicting wellbeing from EEG power with covariates (age, sex, zygosity, education, body mass index) for the parietal-occipital brain region (average of electrodes O1, O2, Oz, P3, P4, Pz). A = alpha power, B = beta power, D = delta power, T = theta power. Interactions are indicated by asterisk. B = non-standardised coefficients, β = standardised coefficient, 95% CI = standardised 95% confidence interval. P-values in bold indicate significance at the corrected threshold. Under random effects, σ2 = within family variance, τ00 FamID = between family variance. Wellbeing was measured using the COMPAS-W and depression/anxiety symptoms was measured using the Depression Anxiety Stress Scale (DASS-42).

Table S8 Univariate heritability estimates for alpha, beta, theta, and delta power by region and condition.

Phenotype	ICC		Best Fit Model		Estimates			
	MZ	DZ	Model	*p*	A^2	C^2	D^2	E^2
Frontal eyes closed								
Alpha	.903	.345	AE	.152	.895	-	0	.105
Beta	.868	.229	AE	.113	.759	-	0	.241
Theta	.792	.439	AE	.696	.774	0	-	.226
Delta	.787	.481	AE	.221	.544	0	-	.456
Central eyes closed								
Alpha	.898	.363	AE	.150	.891	-	0	.109
Beta	.868	.381	AE	.543	.857	-	0	.143
Theta	.837	.414	AE	.636	.822	-	0	.178
Delta	.787	.652	AE	.060	.736	0	-	.264
Temporal eyes closed								
Alpha	.913	.404	AE	.261	.908	-	0	.093
Beta	.735	.361	AE	.834	.720	-	0	.280
Theta	.851	.456	AE	1	.837	0	-	.163
Delta	.791	.608	AE	.330	.744	0	-	.256
Parietal-occipital eyes closed								
Alpha	.898	.404	AE	.154	.891	-	0	.109
Beta	.847	.358	AE	.308	.833	-	0	.167
Theta	.849	.459	AE	1	.832	0	-	.168
Delta	.824	.623	AE	.445	.774	0	-	.226
Frontal eyes open								
Alpha	.870	.465	AE	.925	.866	0	-	.134
Beta	.657	.279	AE	1	.618	-	0	.383
Theta	.758	.512	AE	.262	.722	0	-	.278
Delta	.653	.403	AE	1	.584	0	-	.416
Central eyes open								
Alpha	.906	.494	AE	.688	.900	0	-	.100
Beta	.839	.491	AE	.575	.818	0	-	.182

Theta	.840	.585	AE	.408	.815	0	-	.185
Delta	.841	.650	AE	.487	.793	0	-	.207
Temporal eyes open								
Alpha	.916	.536	AE	.476	.911	0	-	.089
Beta	.612	.442	AE	.396	.627	0	-	.373
Theta	.856	.604	AE	.283	.833	0	-	.167
Delta	.776	.628	AE	.486	.717	0	-	.283
Parietal-occipital eyes open								
Alpha	.919	.485	AE	.929	.912	0	-	.088
Beta	.831	.488	AE	.683	.814	0	-	.186
Theta	.848	.577	AE	.611	.824	0	-	.176
Delta	.805	.615	AE	1	.750	0	-	.250

Notes. Model fit indices for univariate models. ICC = intra-class correlation, MZ = monozygotic twins, DZ = dizygotic twins. Starting models were either ADE or ACE, where A = additive genetic, D = dominant genetic, C = common environment, E = unique environment. The ACE starting model was used if the ICC for MZ twins was greater than double the ICC for DZ twins. Squared model components indicate their contribution as a percentage of total variance. Frontal = average of F3, F4, F7, F8, Fp1, Fp2, Fz; Central = average of CP4, CPz, CP3, Cz, C4, C3, FCz, FC3, FC4; Temporal = average of T3, T4, T5, T6; Parietal-occipital = average of O1, O2, Oz, P3, P4, Pz.

Table S9 Point estimates and confidence intervals for correlated factors model components.

Variable	Genetic Component	Lower bound	Point estimate	Upper bound	Environment Component	Lower bound	Point estimate	Upper bound
Wellbeing	h^2	0.227	0.3649	.491	e^2	.509	.6351	.777
Depression/anxiety	h^2	0.151	0.2949	0.426	e^2	0.574	0.7051	0.849
ABD interaction	h^2	0.339	.4718	.585	e^2	0.414	0.5282	0.660
r(Wellbeing, Depression/anxiety)	*rG*	-.297	-.186	-0.071	*rE*	-0.354	-0.242	-0.146
r(Wellbeing, ABD interaction)	*rG*	-0.286	-0.178	-0.066	*rE*	-0.107	-0.014	0.076
r(Depression/anxiety, ABD interaction)	*rG*	0.086	0.196	0.300	*rE*	-0.216	-0.119	-0.026

Notes. Point estimates are calculated from values indicated in Figure 2.2. For e^2 (unique environment) and h^2 (heritability), values are calculated by taking the square of the path coefficients (e.g., wellbeing $h^2 = .60^2 = 0.36$). For rG (correlation due to genetics) and rE (correlation due to environment), values are calculated by multiplying the path coefficients for each trait by the genetic or environmental correlation between the traits (e.g., genetic r(wellbeing, ABD interaction) = .60*-.43*.69 = -.178). ABD interaction = the interaction between alpha, beta, delta power. Wellbeing refers to the total score on the COMPAS-W. Depression/anxiety refers to the total score on the DASS-42.

Chapter 3:
Emotional face processing and mental health

Submitted as:

Chilver, M.R., Park, H.R.P., Schofield, P.R., Clark, C.R., Williams, L.M., Gatt, J.M. (under review). Emotional face processing correlates with depression/anxiety symptoms but not wellbeing in non-clinical adults: An event-related potential study. *Journal of Psychiatric Research*.

This submission has been edited to include components relating to the results and discussion of the heritability components.

Author contributions:

MRC is a PhD student with JMG as her primary supervisor. This work forms a component of her PhD dissertation. MRC conducted the EEG data processing, the statistical analysis, and wrote the first draft of the article. HRPP assisted in data analysis and interpretation, and in revising the manuscript. JMG conceptualised the research focus on wellbeing biomarkers, guided analysis interpretation, and edited the first draft of the article. LMW conceptualised the twin study for funding by the Australian Research Council. LMW, PRS, CRC and JMG designed the twin study for implementation and acquired the data. All authors reviewed and edited the article and approved the final version of the paper.

3.1. Preamble

Chapter 2 showed that resting EEG can be used to predict mental wellbeing independently from depression/anxiety symptoms. This could be an indicator that spontaneous thought patterns, such as mind wandering, differs in individuals with high compared to low wellbeing. The next aim of this thesis was to investigate whether task-based measures, that is, event-related potentials (ERPs) can be used to predict mental wellbeing. Specifically, Chapter 3 focused on whether emotional face processing is associated with differences in mental wellbeing. Given the substantial research base focused on emotional face processing in clinical and subclinical depression and anxiety, this chapter also tested whether emotional face processing is associated with depression/anxiety symptoms within the current non-clinical sample. This allowed for a more complete picture of how emotional processing relates to mental health.

3.2. Abstract

Whilst alterations in emotional face processing, as indicated by event-related potentials (ERPs), are associated with depression and anxiety symptoms in clinical and non-clinical samples, it has remained unclear whether they are related to mental wellbeing. The current study aimed to address this question in a non-clinical sample. The analysis included 402 adult twins from the TWIN-E study. The COMPAS-W and the Depression Anxiety Stress Scale (DASS-42) were used to measure mental wellbeing and depression/anxiety symptoms, respectively. Participants viewed facial expressions under Unmasked (conscious) and Masked (subliminal) conditions while ERPs were recorded. The associations of emotion processing with mental wellbeing and depression/anxiety symptoms were assessed using multivariate linear mixed models. There was a strong association between depression/anxiety symptoms and the N170 amplitude difference for the Fear – Happy contrast in the Masked condition after controlling for wellbeing scores ($B = 0.34$, $p < .001$). Specifically, higher depression/ anxiety symptoms were associated with a lack of differentiation between fearful and happy faces. No associations were found between emotional face processing and mental wellbeing scores. These results indicate that even within a non-clinical sample, alterations in emotional ERPs, namely the N170, reflect differences in depression/anxiety symptoms rather than differences in wellbeing. Furthermore, this effect was limited to automatic processing, rather than conscious processing of emotional stimuli, suggesting the observed differences apply only to the subconscious pathway.

3.3 Introduction

Mental wellbeing describes a complete state of positive psychological functioning, positive mood, and life satisfaction (Gatt et al., 2014). Although mental wellbeing and mental illness are often viewed as two ends of the same spectrum, multiple studies have demonstrated they are mostly independent of each other. In a study of over 3000 American adults, representative of the general population, mental wellbeing was found to share only 28% of its variance with mental illness (Keyes, 2005). This finding was replicated in the TWIN-E study (Gatt et al., 2012), involving an Australian sample with no history of mental illness, in which mental wellbeing shared 30% of its variance with depression, anxiety, and stress symptoms (hereinafter referred to as depression/anxiety symptoms) (Routledge et al., 2016). Thus, mental wellbeing is correlated with but independent of depression/anxiety symptoms in both clinical and non-clinical samples. Given that they share some variance, it is important to identify the neurophysiological correlates that are unique to mental wellbeing and/or depression/anxiety symptoms. However, little research has aimed to differentiate neurological markers for these constructs in this way.

Alterations to emotion recognition have been repeatedly associated with depression/anxiety symptoms in clinical and non-clinical samples using behavioural measures, functional magnetic resonance imaging (fMRI) and event-related potentials (ERPs). In clinical samples, Major Depressive Disorder (MDD) has been associated behaviourally and neurologically with a bias towards negative and especially sad facial expressions (Chen et al., 2014; Dai et al., 2016; Dai & Feng, 2012; Weightman et al., 2014; Zhang et al., 2016). For example, behavioural studies have reported that MDD patients are slower to recognise positive expressions and are more likely to misidentify neutral expressions as sad expressions compared to controls (Weightman et al., 2014). Meanwhile,

ERP studies have reported enhanced neural responses reflected in the P1, N170, and vertex positive potential (VPP), consistent with a bias towards negative expressions (Chen et al., 2014; Dai & Feng, 2012; Zhang et al., 2016). However, some studies have also reported reduced neural differentiation between expressions in MDD and subclinical depression, whereby positive and negative expressions are processed similarly to each other. Some have proposed that a lack of differentiation may serve as a trait-like marker of vulnerability in subclinical cases, whereas a negativity bias may reflect a state-like effect of the disorder in clinical states (e.g., Watters et al., 2018). Others have suggested the difference may be related to the severity of illness in clinical groups (e.g., Chen et al., 2014). Notably, however, both effects may be observed in the same sample. Zhang et al. (2016) reported that while MDD patients showed enhanced N170 amplitude to sad faces relative to controls, N170 amplitudes for sad and happy faces did not differ *within* the MDD group. Thus, further work is necessary to clarify the underlying cause of these differential effects.

Our previous work has primarily focused on non-clinical samples. One study examined the differential effects of depression and anxiety on emotion processing, finding that high trait *anxiety* was associated with enhanced N1 and reduced VPP amplitudes in response to *subliminal* presentations of fearful faces, whereas high *depression* was associated with enhanced N1 and reduced VPP amplitudes in response to *conscious* presentations of fearful faces (Williams et al., 2007). In a more recent study, unaffected individuals with familial risk for MDD showed a lack of neural differentiation between emotional expressions compared to controls, as indexed by the VPP (Watters et al., 2018). To test whether wellbeing might also play a role in emotion processing, the TWIN-E study examined behavioural responses in identifying emotional faces. The results showed a potential positivity bias in those with high wellbeing, indicated by faster reaction times for happy faces

compared to those with low wellbeing (Routledge et al., 2018). A subset of these participants also participated in a functional magnetic resonance imagining (fMRI) study that found wellbeing was positively associated with activation in the inferior frontal gyrus (IFG) for happy relative to neutral faces (Park et al., 2021), a region previously associated with emotional face processing (Jabbi & Keysers, 2008) and emotion regulation (Grecucci et al., 2013). These results suggest that mental wellbeing, similarly to depression/anxiety symptoms, may also be associated with alterations in how emotional stimuli are processed, but whether these alterations are reflected in ERPs remains to be examined.

Within the full TWIN-E study, the association between wellbeing and shorter reaction times was predominantly explained by shared heritable factors (82%), as was the relationship with depression/anxiety symptoms (79%; Routledge et al., 2018). These results suggest that similar genes may influence both emotion recognition and mental health. Within the fMRI sample, IFG activation during emotion recognition was somewhat heritable (20%) but its association with wellbeing was fully explained by environmental factors (Park et al., 2021). Whether electrophysiological correlates of emotion processing are more heritable than fMRI correlates is unclear. One study reported that ERPs indexing emotional processes are moderately heritable (42-64%), however, these estimates may be inflated by the heritability of face processing more generally (Anokhin et al., 2010). A later study sought to estimate the heritability of emotion-specific processing by regressing out variance shared between neutral and fearful faces (Shannon et al., 2013). While this approach found no evidence that fear-specific processing is heritable, the authors only examined fearful faces and no other emotional expressions (Shannon et al., 2013). Furthermore, no studies have yet tested the heritability of subconscious emotion processing that can be detected by ERPs within a backwards-masking paradigm (Liddell et al., 2004, 2005).

Based on these research gaps, the primary aim of the current study was to examine whether mental wellbeing is associated with alterations in ERP indices of emotional face processing independently of depression/anxiety symptoms. We chose to focus on the N1, P1, N170, VPP, and P250 components given their use in previous research assessing the association between emotion processing mental health in both clinical and non-clinical samples (Chen et al., 2014; Dai & Feng, 2012; Hu et al., 2017; Jaworska et al., 2010, 2012; Watters et al., 2018; Williams et al., 2007; Zhang et al., 2016). Because emotional facial expressions can be processed with or without conscious awareness via an alternative subcortical pathway (Liddell et al., 2005) with differential associations with depression/anxiety symptoms (Williams et al., 2007), we included a masked and unmasked task condition. This could help clarify whether specific processing streams are impacted by mental wellbeing. Finally, the current study sought to estimate the heritability of emotion-specific processing for happy, sad, fearful, angry, and disgusted expressions within the masked and unmasked conditions. This was used to determine whether any associations identified between either wellbeing or depression/anxiety symptoms with emotional face processing were explained by heritable or environmental factors.

3.4. Materials and Methods

3.4.1. Design

This study formed part of the TWIN-E study, a multi-component longitudinal twin study (Gatt et al., 2012). The initial phase of the TWIN-E study was carried out online and included a battery of self-report questionnaires measuring physical and psychological health, and standardized cognitive tests. A subset of the online sample opted to participate in the EEG phase of the study, which consisted of standardized psycho-physiological activation

tasks described previously (see Gatt et al., 2012), including the emotional ERP paradigm reported here.

The analysis aimed to assess whether wellbeing and depression/anxiety symptoms are associated with distinct components of emotion processing under masked and unmasked conditions. The design includes three within-subject factors (Emotion, Masked *vs* Unmasked Condition, and Component) and two continuous between-subjects factors that covary (wellbeing and depression/anxiety symptoms). Because the study was conducted in a twin sample, a linear mixed model was used to account for family ID. Due to differences in event timing, the masked and unmasked conditions were not compared. A multivariate mixed model approach allowed for both wellbeing and depression/anxiety symptoms to be tested in the same model as predictors of ERP amplitude for each emotion condition. Further details on statistical analysis are provided in section 2.3.4.

3.4.2. Participants

A subsample of 438 participants from the TWIN-E study (Gatt et al., 2012) participated in this ERP task. Recruitment was conducted through the Australian Twin Registry, now known as Twins Research Australia. All participants were either monozygotic or dizygotic, same-sex twins between the ages of 18 and 61. Twin pairs with a current, past, or family history of psychiatric disorder were excluded from the study. Further details of inclusion and exclusion criteria can be found in the study protocol (Gatt et al., 2012).

This study was carried out in accordance with the Declaration of Helsinki and approved by the Human Research Ethics Committees of the University of Sydney (03-2009/11430), Flinders University (FCREC#08/09), and the University of New South Wales (HC14256). All participants provided written informed consent prior to participation.

3.4.3. Procedure

After completing the online phase of the TWIN-E study which included the COMPAS-W and DASS-42 questionnaires (see below), participants attended the recording session onsite at either the Brain Dynamics Centre at the University of Sydney, NSW, Australia, or Flinders University, Adelaide, SA, Australia. The median time between the online and EEG session was 91 days.

3.4.3.1. Questionnaires

The 26-item COMPAS-W questionnaire was used to measure mental wellbeing. The COMPAS-W was designed to provide an overall measure of both subjective and psychological components of mental wellbeing and includes six subscales: composure, own-worth, mastery, positivity, achievement, and satisfaction (Gatt et al., 2014). The 42-item Depression Anxiety Stress Scale (DASS-42) was used to measure depression/anxiety symptoms (Lovibond & Lovibond, 1995). It was chosen because it has been validated and widely used to measure depression and anxiety symptoms in non-clinical samples (Crawford & Henry, 2003).

3.4.3.2. Emotion paradigm

The emotion paradigm, illustrated in Figure 3.1, included the presentation of six basic emotional facial expressions (neutral, happy, sad, angry, disgusted, and fearful) using images selected from a previously validated and standardised series (Gur et al., 2002) and altered to be centrally positioned at eye level and to have equivalent luminance and brightness (Watters et al., 2018). Each expression was depicted by eight different actors, half of whom were male, for a total of 48 images.

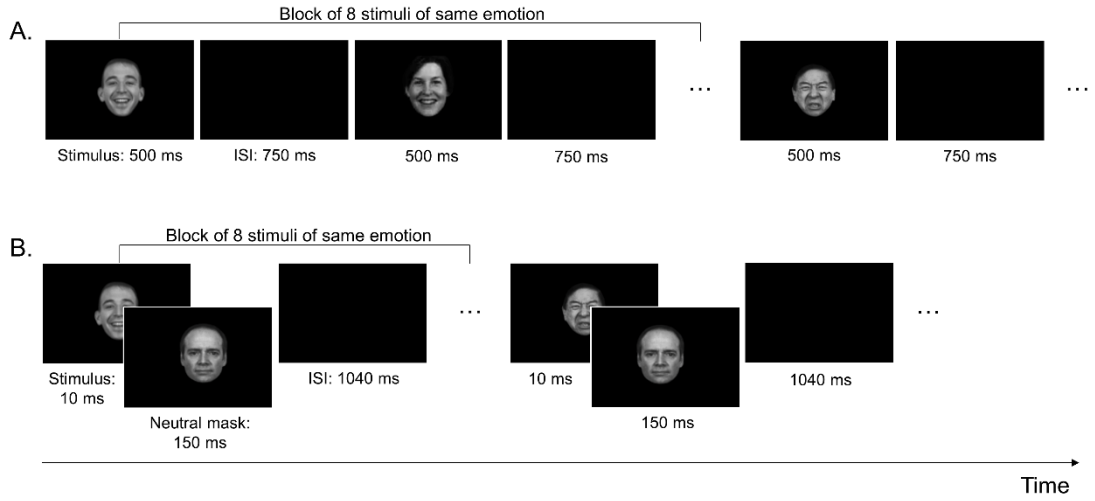


Figure 2.1 The experimental task consisted of: (A) an unmasked condition where each emotional stimulus was presented for 500 msec as a blocked design (i.e., each emotion was presented eight times in a block, before moving to a new emotion block); and (B) a masked condition where each emotional stimulus was presented for 10 msec before being masked with a neutral stimulus for 150 msec. Task duration for each condition was 5 minutes and 8 seconds. ISI: interstimulus interval.

The experiment included two viewing conditions, masked and unmasked. For both conditions, a block design was adopted, with each block consisting of eight trials of different faces portraying the same emotion (e.g., eight different happy faces were presented as a block before moving onto another emotion). For the unmasked condition, each trial was presented for 500 msec, followed by an interstimulus interval of 750 msec. For the masked condition, each trial consisted of an emotional face presented for 10 msec, immediately followed by a neutral face for 150 msec, then followed by an interstimulus interval of 1040 msec. The stimulus presentation timing for each condition was selected based on a prior signal detection study where displays over 170 msec were identified consistently above chance (discrimination threshold) while identification of displays presented for 10 msec did not differ from chance (Williams et al., 2004). For both masked and unmasked conditions, there were 192 trials in total showing each emotional expression 32 times, presented as four blocks

of eight emotional faces. Participants were told they would be asked about the stimuli later in the experimental session but were not required to behaviourally respond to the stimuli. The same protocol has been employed in similar independent studies (Watters et al., 2018; Williams et al., 2007).

3.4.3.3. EEG acquisition and ERP processing

EEG data was recorded using a 26-electrode QuikCap and NuAmps DC amplifier at a sampling rate of 500 Hz (electrodes included Fp1, Fp2, Fz, F3, F4, F7, F7, FC3, FC4, FCz, C3, C4, Cz, CP3, CP4, CPz, T3, T4, T5, T6, P3, P4, Pz, O1, O2, and Oz). Data was recorded relative to the virtual ground with impedances kept below 5 kΩ. BrainVision Analyzer v2.1 was used for processing the data offline. First, the data was down sampled to 250 Hz and a 0.01 – 30 Hz Butterworth filter applied (Luck, 2005). The data was re-referenced offline to the common average. Ocular artefacts were corrected using a semi-automatic infomax ICA procedure, followed by manual inspection of the data. Trials with remaining artefacts exceeding a min-max excursion of 50 microvolts were excluded from further analysis. Single ERP trial data was constructed from 1000 msec segments, which included a 200 msec pre-stimulus and an 800 msec post-stimulus period, each baseline corrected to the 200 msec pre-stimulus interval before being averaged by condition. Participants with fewer than 10 artefact-free trials in any experimental condition were excluded from the analysis, meaning each participant had 10 to 32 trials included per emotion in each condition.

The frontocentral N1 and parietal P1 components have been shown to reflect processing of low-level visual features that may be relevant to distinguishing between emotional and neutral expressions (Batty & Taylor, 2003) and were examined based on previous evidence that these components may be altered to specific emotional expressions in

clinical and sub-clinical samples (Dai & Feng, 2012; Jaworska et al., 2010; Williams et al., 2007; Zhang et al., 2016). Based on prior research, the N1 was measured from the Cz electrode (Williams et al., 2007) and the P1 was measured from the average of the O1 and O2 electrodes (Dai & Feng, 2012; Jaworska et al., 2010; Zhang et al., 2016). The following N170 and VPP components capture face-specific processing (Eimer, 2000; Luo et al., 2010) and are also reportedly sensitive to emotional expressions (Hinojosa et al., 2015; Luo et al., 2010). Consistent with the literature (Hinojosa et al., 2015), the N170 was measured from the T5 and T6 electrodes, which are placed in the same position as the P7 and P8 electrodes, while the VPP was measured from Cz. The posterior P250 component, measured from the T5 and T6 electrode sites, was also included. This emotion-sensitive component sometimes referred to as the P2 (daSilva et al., 2016; Eimer & Holmes, 2007), has previously shown reduced emotional differentiation in clinical samples (Hu et al., 2017; Jaworska et al., 2012).

The following components were analysed with time windows selected from the peaks in grand-averaged waveforms for the masked and unmasked conditions, respectively, ± 20 msec: N1, calculated as the mean voltage between 88-128 msec in the unmasked condition, and 84-124 msec in the masked condition; P1, calculated as the mean voltage between 84-124 msec in the unmasked condition, and 80-120 msec in the masked condition; N170 and VPP, both calculated as the average voltage between 140-180 msec in the unmasked condition, and 136-176 msec in the masked condition; and P250, calculated as the mean voltage from 216-256 msec in the unmasked condition, and 232-272 msec in the masked condition. Separate time windows were used for the masked and unmasked conditions due to the differences in event timing between the two conditions.

3.4.3.4. Statistical analyses

All statistical analyses were carried out in *R* (R Core Team, 2020). Evidence of emotional differentiation in the behavioural and ERP components was assessed using linear mixed models specified using the *lme4* package (Bates et al., 2015) to account for twin relatedness, followed by Tukey-adjusted pairwise comparisons using the *emmeans* package (Lenth, 2020). Masked and unmasked conditions were evaluated separately due to differences in the event timing. Random effects were specified such that each participant ID was nested within family ID to account for family relatedness in the within- by between-subjects design.

Multivariate linear mixed models were used to evaluate the association between emotion-specific processing and mental wellbeing and/or depression/anxiety symptoms. Models were based on difference scores calculated for each participant between emotional – neutral expressions and between negative – happy expressions. Difference scores were entered as criterion variables in the multivariate models while COMPAS-W and DASS-42 scores were entered as predictors, first in separate models, then combined in a single model to determine whether any identified associations were specific to one outcome or the other. Age, sex, and zygosity were also included as covariates in all models, and family ID was included as the random effect. Models were fit using the *MCMCglmm* package in *R* (Hadfield, 2010) which uses a Markov chain Monte Carlo to fit the model under a Bayesian framework. Variance-covariance matrices were derived from data collected in a different sample (Gatt et al., 2007), but with low confidence. The simulations were run with 20,000 iterations, a burn-in of 3,000 iterations, and a thinning interval of 10. Models were carried out separately for each ERP component. Following the analysis, a Benjamin-Hochberg procedure (Benjamini & Hochberg, 1995) was used to control the False Discovery Rate (FDR) at .05 across a total of

45 tests (9 emotion contrasts x 5 ERP components) for each of the two viewing conditions for each outcome (mental wellbeing and depression/anxiety symptoms). Because we were interested in associations with wellbeing and depression/anxiety symptoms that were independent of each other, this correction was only assessed for the models including both wellbeing and depression/anxiety.

Univariate heritability of each of the emotion contrasts was assessed using the *OpenMx* package in *R* (Scheike et al., 2014). When monozygotic twins had an intra-class correlation of at least double that of dizygotic twins, the ADE model was tested, otherwise the ACE model was tested (Verweij et al., 2012). When intra-class correlations were negative for dizygotic twins, the ACE model was chosen as the starting model. A, C, or D components were then progressively dropped from the model to identify the most parsimonious model on the basis of AIC and a chi-square test. Age, sex, and education were included as covariates in the heritability analysis. Further, multivariate models were planned where significant heritability was found for contrasts that were also associated with either mental wellbeing or depression/anxiety symptoms.

3.5. Results

Of the 438 participants, 36 were excluded due to having fewer than ten trials remaining for any given Emotion condition once trials with artefacts had been removed. Of the remaining 402 participants, 42 of the 125 dizygotic twins were male and 103 of the 277 monozygotic twins were male. Participants were aged from 18 to 61 years (M = 39.97, SD = 12.72). COMPAS-W (M = 99.98, SD = 9.99) and DASS-42 scores (raw M = 11.13, SD = 10.59; log-transformed M = 0.92, SD = 0.41) were similar to the larger TWIN-E sample (Gatt et al., 2014).

3.5.1. ERP emotion pairwise comparisons

To assess whether the ERP components of interest were sensitive to differences in emotional expressions, Tukey-corrected pairwise comparisons were used to compare amplitudes between each emotion for each component. The results are detailed in the Supplementary Materials. Means and standard deviations for ERP amplitudes are provided in Table S1. Some emotion-specific effects were found for all components other than the N1 for the masked and unmasked conditions and are shown in Table S2.

3.5.2. Associations between wellbeing and depression/anxiety symptoms with emotion processing

In each condition, nine emotion contrasts were tested, including each emotional expression relative to Neutral, and each *negative* expression (Fearful, Sad, Angry, and Disgusted) relative to Happy. Associations with mental wellbeing and depression/anxiety symptoms were first tested separately without co-varying for the other, before being entered into a combined model to check if any identified associations were unique to one variable.

3.5.2.1. Unmasked condition

In the Unmasked condition, only differences between negative facial expression and Happy expressions showed significant associations with mental wellbeing and depression/anxiety symptoms, and only for the N1 and VPP components as described below. A summary of significant contrasts is provided in Table 3.1.

N1. No significant associations were found between wellbeing and differences in N1 amplitude. However, higher depression/anxiety symptoms were associated with larger amplitudes for Disgusted relative to Happy expressions, and this effect for depression/anxiety

symptoms remained when covarying for mental wellbeing, illustrated in Figure 3.2. When controlling the FDR at .05, this association was not significant.

Table 3.1 Summary of associations found in the unmasked condition

Wellbeing Model	**N1**		**VPP**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**
Fearful - Happy	0.00	0.748	0.01*	0.021
Disgusted - Happy	0.00	0.814	0.01*	0.009
Angry - Happy	0.00	0.993	0.01*	0.016
DASS Model	**N1**		**VPP**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**
Fearful - Happy	-0.14	0.162	-0.30*	0.007
Disgusted - Happy	-0.24*	0.018	-0.23	0.061
Sad - Happy	-0.10	0.311	-0.25*	0.035
DASS in Combined Model	**N1**		**VPP**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**
Disgusted - Happy	-0.29*	0.005	-0.19	0.105

Notes. * indicates significance at $p < 0.05$. None of the unmasked associations survived FDR correction for 45 tests. Only contrasts with at least one significant association are shown.

VPP. Without covarying for depression/anxiety symptoms, mental wellbeing was associated with larger VPP amplitudes for Disgusted, Fearful, and Angry expressions relative to Happy expressions. When covarying for depression/anxiety symptoms, no associations with mental wellbeing remained significant. Lower depression/anxiety symptoms were associated with larger amplitudes for Fearful, and Sad expressions relative to Happy expressions, neither of which remained significant when covarying for wellbeing.

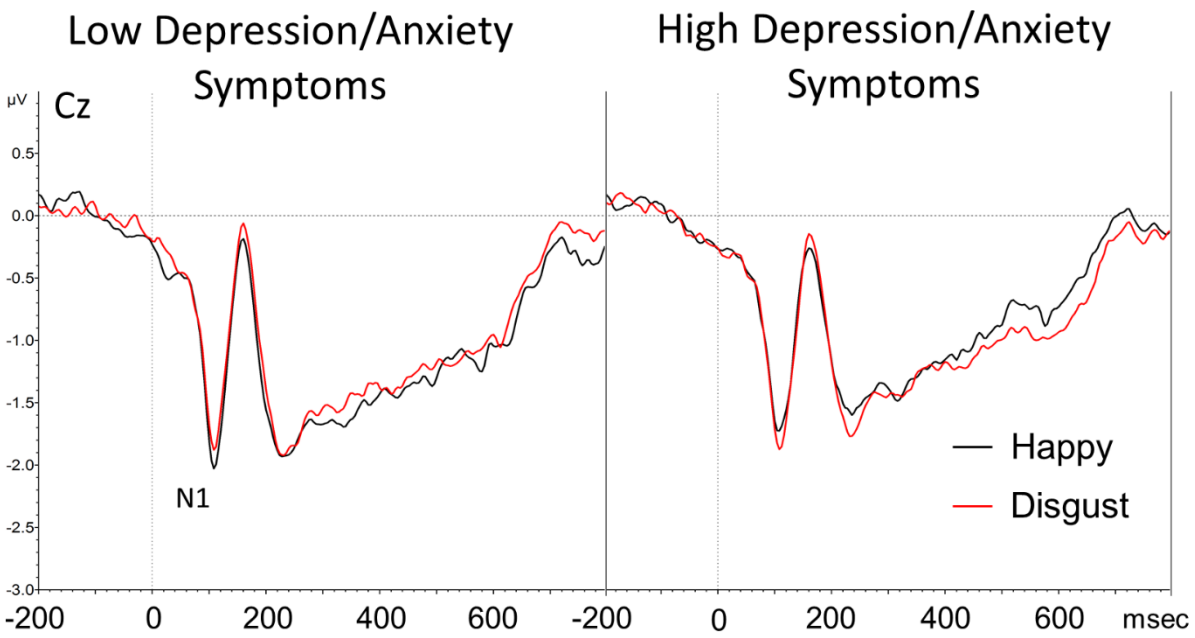


Figure 3.2 Contrasts with significant associations with depression/anxiety symptoms after controlling for mental wellbeing in the unmasked condition. Graphs show participants in the lowest or highest tertile of depression/anxiety symptoms for the sake of illustration. (A) The Disgust and Happy waveforms for the N1. High Depression/Anxiety n = 140, Low Depression/Anxiety n = 143.

3.5.2.2. Masked condition

In the Masked condition, associations between wellbeing and depression/anxiety symptoms were found for the VPP, N170, and P250 components as described below. A summary of significant contrasts is provided in Table 3.2.

VPP. Without covarying for depression/anxiety symptoms, higher wellbeing was associated with larger VPP amplitudes for Sad, Fearful, Angry, and Disgusted expressions relative to Happy expressions. None of these associations remained significant when covarying for depression/anxiety symptoms. Lower depression/anxiety symptoms were similarly associated with larger VPP amplitudes for Sad, Fearful, Disgusted, and Angry expressions relative to Happy expressions. Only the associations with Sad and Fearful

relative to Happy expressions remained significant when covarying for mental wellbeing, shown in Figure 3.3A. Neither association was significant after controlling the FDR at .05.

Table 3.2 Summary of associations found in the masked condition

Wellbeing Model	**VPP**		**N170**		**P250**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Fearful - Happy	0.01*	0.002	-0.00	0.597	-0.00	0.986
Sad - Happy	0.01*	0.001	-0.00	0.589	-0.00	0.880
Disgusted - Happy	0.01*	0.005	-0.00	0.745	-0.00	0.394
Angry - Happy	0.01*	0.004	-0.00	0.326	-0.00	0.781
DASS Model	**VPP**		**N170**		**P250**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Fearful - Neutral	-0.10	0.342	0.22*	0.026	0.03	0.790
Fearful - Happy	-0.32*	0.001	0.30*	0.001	0.22*	0.044
Sad - Happy	**-0.36***	**0.001**	0.20	0.064	0.12	0.293
Disgusted - Happy	-0.31*	0.005	0.20	0.052	0.25*	0.026
Angry - Happy	-0.27*	0.014	0.05	0.587	0.07	0.512
DASS in Combined Model	**VPP**		**N170**		**P250**	
Contrast	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Fearful - Neutral	-0.10	0.342	0.26*	0.014	0.08	0.487
Fearful - Happy	-0.25*	0.031	**0.34***	**0.001**	0.28*	0.040
Sad - Happy	-0.29*	0.016	0.21	0.064	0.16	0.186

Notes. * indicates significance at $p < 0.05$. Bold indicates significance after FDR correction for 45 tests. Only contrasts with at least one significant association are shown.

N170. No associations were found between N170 amplitudes and wellbeing. Lower depression/anxiety symptoms were associated with larger absolute N170 amplitudes for Fearful relative to Happy and Neutral faces. Both associations were retained when covarying for mental wellbeing, shown in Figures 3.3B and 3.3C. Only the association between depression/anxiety symptoms and Fearful relative to Happy faces remained significant when controlling the FDR at .05 ($p = .0006 < p = .0011$).

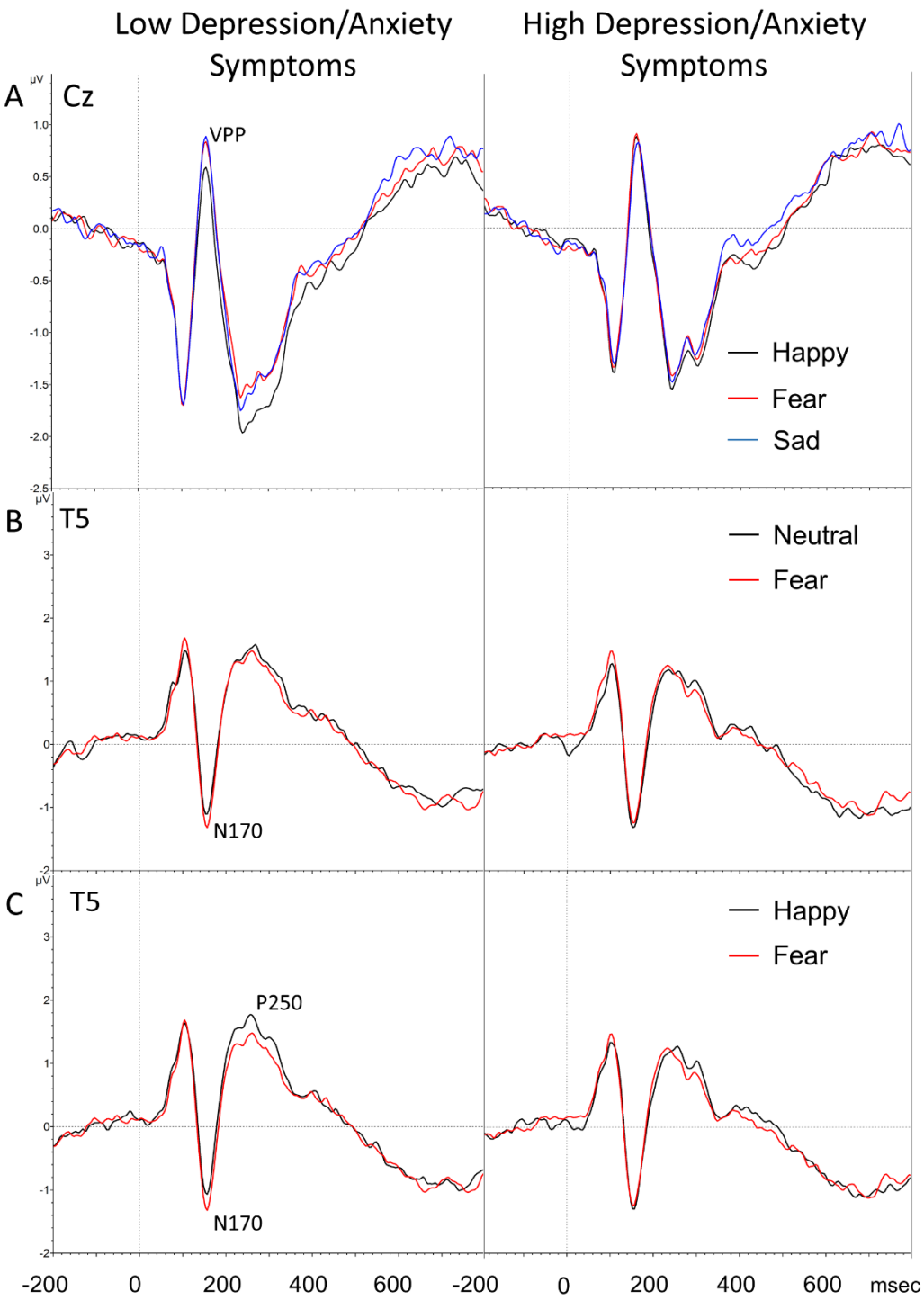


Figure 3.3 Contrasts with significant associations with depression/anxiety symptoms in the masked condition. Graphs show participants in the lowest or highest tertile of depression/anxiety symptoms for the sake of illustration. (A) Happy, Fear, and Sad waveforms for the VPP. (B) Neutral, Fear waveforms for the N170. (C) Happy, Fear waveforms for the N170 and P250. High Depression/Anxiety n = 140, Low Depression/Anxiety n = 143.

P250. No associations were found between P250 amplitudes and wellbeing. Lower depression/anxiety symptoms were associated with smaller amplitudes for Fearful and Disgusted faces relative to Happy faces. The association with Fearful relative to Happy expressions remained significant when covarying for wellbeing, illustrated in Figure 3.3C. This effect did not remain significant when controlling the FDR at .05.

3.5.3. Univariate twin analysis

Table 3.3 presents the intra-class correlations and univariate heritability estimates for for the Unmasked condition, and Table 3.4 presents the same measures for the Masked condition. In both cases, only contrasts for which either the AE or CE model was deemed to be the best fit was reported. In all remaining models (not shown), the E model was the best fit, attributing all variance to unique environmental effects.

3.5.3.1. Unmasked condition

Within the Unmasked condition, there was evidence for the CE model for the Happy – Sad contrast for both the P1 and N170 components. Here, common environmental factors accounted for approximately 14% of the variance in this contrast, with the remaining variance accounted for by unique environmental factors. In comparison, additive genetics accounted for 18.8% and 20.9% of the variance in the Neutral – Disgust contrast for the N170 and P250 components, respectively.

3.5.3.2. Masked condition

Within the Masked condition, there was evidence for the CE model for the Neutral – Happy contrast for the VPP component whereby 24.2% of variance was attributed to common environmental factors. In comparison, additive genetic factors were found to

account for 26.0% and 18.7% of the variance in the Neutral – Angry and Neutral – Sad contrasts for the VPP, respectively. In addition, the Neutral – Sad and Happy – Sad contrasts for the N170 were also partially explained by additive genetics, which accounted for 22.8% and 17.8% of the variance in these contrasts, respectively.

3.5.4. Multivariate twin analysis

As the Happy – Fear N170 contrast in the Masked condition was the only contrast to be significantly associated with mental health outcomes (i.e., depression/anxiety symptoms) after FDR correction, and this contrast was fully explained by unique environmental factors, it was not necessary to conduct a multivariate twin analysis.

3.6. Discussion

Mental wellbeing and depression/anxiety symptoms are distinct but correlated constructs and cannot be regarded as tails of the same continuum (Keyes, 2005; Routledge et al., 2016). Despite extensive research into emotional correlates of mental health, no study, to the best of our knowledge, has yet investigated the independent effects of wellbeing and depression/anxiety symptoms on emotion processing within the same sample. To this end, we aimed to examine whether electrophysiological correlates of emotional face processing may show unique associations with mental wellbeing or depression/anxiety symptoms, and whether such associations would differ depending on the type of emotion processing (conscious vs. automatic). We found a strong association between depression/anxiety symptoms and the N170 amplitude difference for the Fear – Happy contrast in the masked condition. Importantly, this association was significant after controlling for the participants' wellbeing levels, suggesting that individuals with high levels of depression/anxiety show deficits in differentiating negative (fear) and positive (happy) emotions, *regardless* of

Table 3.3 Univariate heritability by component and emotion for the masked condition

Phenotype	ICC		Model fit					Parameter estimates		
	MZ	DZ	Model	-2LL	AIC	Comparison	p-value	A (CI)	C or D (CI)	E (CI)
P1	0.136	0.228	ACE	1120.109	1136.109	vs. saturated	NA	0	0.144	0.856
Happy-Sad									(< 0.01, 0.28)	(0.72, 0.99)
			CE	**1120.109**	**1134.109**	**vs. ACE**	**1**	**-**	**0.144**	**0.856**
									(< 0.01, 0.28)	**(0.72, 0.99)**
			E	1123.922	1135.922	vs. CE	0.051	-	-	1
N170	0.158	0.119	ACE	1057.197	1073.197	vs. saturated	NA	0	0.142	0.858
Happy-Sad								(< .01, 0.15)	(< 0.01, 0.28)	(0.70, > 0.99)
			CE	**1057.197**	**1071.197**	**vs. ACE**	**1**	**-**	**0.142**	**0.858**
									(< 0.01, 0.28)	**(0.72, > 0.99)**
			E	1060.884	1072.884	vs. CE	0.054	-	-	1
N170	0.290	-0.252	ACE	950.823	966.823	vs. saturated	NA	0.188	0	0.812
Neutral-Disgust								(< 0.01, 0.36)	(< 0.01, 0.14)	(0.50, 0.99)
			AE	**950.823**	**964.823**	**vs. ACE**	**1**	**0.188**	**-**	**0.812**
								(0.01, 0.36)		**(0.64, 0.99)**
			E	954.988	966.988	vs. AE	0.041	-	-	1
P250	0.213	0.074	ADE	1075.091	1091.091	vs. saturated	NA	0	0.229	0.771
Neutral-Disgust									(< 0.01, 0.37)	(0.63, > 0.99)
			AE	**1075.395**	**1089.395**	**vs. ADE**	**0.581**	**0.209**	**-**	**0.791**
								(0.03, 0.37)		**(0.63, 0.97)**
			E	1080.614	1092.614	vs. AE	0.022	-	-	1

Notes. ICC = Intraclass correlation; MZ = monozygotic twins; DZ = dizygotic twins; starting models were either ACE or ADE where A = additive genetic, D = dominant genetic, C = common environment, E = unique environment. Parameter estimates indicate their contribution as a percentage of total variance. Models in bold letters represent the best fit based on AIC.

Table 3.4 Univariate heritability by component and emotion for the unmasked condition

Phenotype	ICC		Model fit					Parameter estimates		
	MZ	DZ	Model	"-2LL"	AIC	Comparison	p-value	A (CI)	C or D (CI)	E (CI)
VPP	0.214	0.291	ACE	877.74	893.74	vs. saturated	NA	0.036	0.214	0.749
Neutral-Happy								(< 0.01, 0.29)	(< 0.01, 0.42)	(0.58, > 0.99)
			CE	**877.757**	**891.757**	**vs. ACE**	**0.895**	**-**	**0.242**	**0.758**
									(0.10, 0.37)	**(0.63, 0.90)**
			E	888.679	900.679	vs. CE	< 0.001	-	-	1
VPP	0.206	0.149	ACE	922.495	938.495	vs. saturated	NA	0.26	0	0.74
Neutral-Angry								(0.07, 0.43)		(0.57, 0.93)
			AE	**922.495**	**936.495**	**vs. ACE**	**1**	**0.26**	**-**	**0.74**
								(0.07, 0.43)		**(0.57, 0.93)**
			E	929.642	941.642	vs. AE	0.007	-	-	1
VPP	0.231	-0.136	ACE	921.166	937.166	vs. saturated	NA	0.187	0	0.813
Neutral-Sad								(0.01, 0.35)		(0.65, 0.99)
			AE	**921.166**	**935.166**	**vs. ACE**	**1**	**0.187**	**-**	**0.813**
								(0.01, 0.35)		**(0.65, 0.99)**
			E	925.42	937.42	vs. AE	0.039	-	-	1
N170	0.298	-0.207	ACE	966.825	982.825	vs. saturated	NA	0.228	0	0.772
Neutral-Sad								(0.06, 0.38)		(0.62, 0.93)
			AE	**966.825**	**980.825**	**vs. ACE**	**1**	**0.228**	**-**	**0.772**
								(0.07, 0.38)		**(0.62, 0.93)**
			E	974.298	986.298	vs. AE	0.006	-	-	1
N170	0.239	-0.169	ACE	932.995	948.995	vs. saturated	NA	0.178	0	0.822
Happy-Sad								(0.01, 0.33)		(0.67, 0.99)
			AE	**932.995**	**946.995**	**vs. ACE**	**1**	**0.178**	**-**	**0.822**
								(0.01, 0.33)		**(0.67, 0.99)**
			E	937.456	949.456	vs. AE	0.035	-	-	1

Notes. ICC = Intraclass correlation; MZ = monozygotic twins; DZ = dizygotic twins; starting models were either ACE or ADE where A = additive genetic, D = dominant genetic, C = common environment, E = unique environment. Parameter estimates indicate their contribution as a percentage of total variance. Models in bold letters represent the best fit based on AIC.

whether they had high or low wellbeing. The association was also found to reflect unique environmental factors linked with both traits. Contrary to our hypothesis, we did not find evidence of a link between wellbeing (independent of depression/anxiety) and emotion-related ERPs.

Previous studies investigating electrophysiological correlates of conscious and automatic emotional face processing in clinical populations have reported either a heightened response to negative faces, or diminished differentiation between negative and positive faces (Chen et al., 2014; Jaworska et al., 2012; Zhang et al., 2016). Within the masked paradigm, we observed weaker differentiation between fearful and happy faces in relation to high depression/anxiety levels in a large sample of healthy community adults. Such a link is broadly in line with previous work from the authors utilising the same emotion paradigm in trait anxiety and depression in a non-clinical sample (Williams et al., 2007) and in first-degree relatives of proband parents with MDD (Watters et al., 2018). While in Williams et al., (2007), trait anxiety and depression were associated with enhanced N1 and reduced VPP amplitudes to masked and unmasked fearful faces, respectively, the latter study reported reduced differentiation between negative and positive faces (Watters et al., 2018), similar to what is observed in the current study. However, despite multiple studies reporting a strong association between Sad – Happy amplitude difference and clinical depression/anxiety symptoms (Dai et al., 2016; Dai & Feng, 2012; Zhang et al., 2016), here we observed the same association only with a Fear – Happy amplitude difference. More specifically, a visual inspection of the waveforms showed that the reduced neural differentiation between the two emotions in those with higher depression/anxiety symptoms was driven by an increased neural response to Happy faces compared to individuals with lower depression/anxiety symptoms. Given previous research establishing fearful faces as a prominent threat signal

(Ekman et al., 1972) one interpretation of this is that these cases show a reduced ability to automatically distinguish between threatening and non-threatening stimuli, causing non-threatening stimuli (i.e., happy faces) to be processed as potential threats.

Out of the five components-of-interest tested in the current study, only the N170 component was found to be significantly related to mental health measures (i.e., depression/anxiety levels). The N170 has been widely shown to be sensitive to faces and familiar objects (Bentin et al., 1996), and appears to be modulated by various aspects of face-related features (for review, see Schindler & Bublatzky, 2020), including emotional expression (Hinojosa et al., 2015). This indicates that the N170 may be involved in a perceptual processing of facial features that include emotional expressions (Schyns et al., 2009). A more recent review has also suggested that passive viewing paradigms, as used in the current study, may amplify the effect of emotion on the N170, potentially due to a lack of other confounding factors such as a motor response (Schindler & Bublatzky, 2020). The authors proposed that such designs allow for a more in-depth focus on emotion-specific features that give rise to larger N170 amplitude modulations as a function of emotion. When taken together with research that show attenuated emotion-related ERPs in individuals at familial risk for depression (e.g., Watters et al., 2018), the current findings add to the idea that atypical differentiation between negative and positive/neutral emotions is evident in non-clinical individuals with higher levels of depression/anxiety symptoms, and manifest as a *lack* of differentiation between fearful and happy faces in the current sample. Importantly, this association is present even after individual wellbeing levels are accounted for, suggesting that the link between atypical N170 amplitude difference and depression/anxiety levels exist regardless of mental wellbeing, even in non-clinical (and otherwise healthy) participants. This is particularly pertinent as much of mental health research focuses on the healthy vs.

illness dichotomy. The current results suggest that mental wellbeing is only associated with alterations in electrophysiological markers of emotion processing to the extent that wellbeing is associated with depression/anxiety symptoms within healthy samples.

The current study also examined the effect of masked vs. unmasked presentation of emotional faces on the association between emotion processing and wellbeing, as well as with depression/anxiety symptoms. Despite previous findings linking depression symptoms with altered *conscious* processing of emotional faces (e.g., Watters et al., 2018; Williams et al., 2007), the only significant link we observed was for depression/anxiety symptoms in the masked paradigm, indicating altered *automatic* processing. Specifically, depression/anxiety symptoms were associated with reduced differentiation in the Fear – Happy N170 contrast. This is consistent with evidence suggesting that within healthy populations, the N170 is enhanced for negative (e.g., angry, fearful) compared to non-negative (e.g., happy, neutral) emotions in masked paradigms (Kiss & Eimer, 2008; Zotto & Pegna, 2015). However, the results suggest that this pattern is altered in participants with high depression/anxiety symptoms who are otherwise healthy as the amplitude difference typically observed between fearful and happy faces was lost. This is more in line with what has been reported in individuals with MDD (Zhang et al., 2016). Furthermore, as one of the few studies that have tested both masked and unmasked conditions within the same sample of participants (also see Williams et al., 2007), it is interesting to note that the *conscious* processing of facial expressions did not differ as a function of depression/anxiety levels in healthy participants when wellbeing levels are controlled for. Here, we speculate that in non-clinical populations, any potential associations between negative and positive emotion processing with depression/anxiety levels may only be present (or observable) for subconscious processes. This might reflect alterations to the automatic orienting response that is triggered especially

for threat-related stimuli (Liddell et al., 2004; Tamietto & de Gelder, 2010) in individuals with higher levels of depression/anxiety symptoms.

The second aim of the current study was to assess the heritability of each emotion contrast to clarify whether emotion-specific processing is heritable. Consistent with a previous study that assessed the heritability of fear-specific processing (Shannon et al., 2013), most emotions showed no evidence of heritability in the current study. There were, however, some exceptions. Within the unmasked condition, there was a significant heritable component to disgusted face processing within the N170 and the P250 components (0.19 and 0.21, respectively). In contrast, within the masked condition, there was a significant heritable component to sad face processing within the VPP and N170 components (0.19 and 0.23, respectively), and for the angry face processing in the VPP component (0.26). This suggests that the heritability of emotion specific processing differs between emotions and according to visual pathways (conscious vs. subconscious; see Liddell et al., 2005, 2004). In addition to these heritable components, a common environment component was found for sad relative to happy face processing in the unmasked paradigm for the P1 and N170 components, and for happy relative to neutral faces in the masked paradigm for the VPP component. This suggests that shared environmental features, such as the prenatal environment or parenting styles, might contribute to the processing of sad and happy faces. As this was the first study to assess the heritability of emotion-specific processing for non-fearful expressions, further replication of these results is warranted. In addition, while none of the contrasts with significant heritability were associated with either mental wellbeing or depression/anxiety symptoms in the current sample, the processing of sad, happy, and disgusted faces have been associated with clinical depression and anxiety in clinical samples (Chen et al., 2014; Watters et al., 2018; Zhang et al., 2016). Thus, while the association between the fear-happy contrast and

depression/anxiety symptoms found in the current sample is best explained by environmental factors, it is possible that a genetic correlation could play a role in clinical groups.

A limitation of the present study is that, compared to other ERP studies of emotional face processing, there were fewer trials per emotion, reducing the signal-to-noise ratio. However, this methodological choice enabled a larger sample size to be obtained, as well as being able to collect both masked and unmasked conditions of the experiment. Furthermore, the same paradigm has been used successfully in previous work (e.g., Watters et al., 2018; Williams et al., 2007). A further limitation was the lack of behavioural data during the ERP recording. As such, it is unclear whether greater neural differentiation translates to better conscious ability to distinguish between emotional expressions, or vice versa. However, using a passive viewing paradigm meant we did not need to account for certain confounding factors, such as a motor response or higher-level decision-making processes (i.e., deciding between response options). It is also important to note that this sample had low levels of depression/anxiety symptoms relative to the general population, making it unclear whether the linear effects reported here would extend to samples with a greater variability of symptoms. On this note however, our finding of an association between such symptoms and the N170 suggests that this component could be a more sensitive indicator of depression/anxiety symptoms compared to low levels of wellbeing.

In conclusion, the current study indicates that, within a non-clinical sample, increased depression/anxiety symptoms rather than decreased mental wellbeing accounts for alterations in neural differentiation between emotional expressions. More specifically, heightened, non-clinical depression/anxiety symptoms were associated with a lack of neural differentiation, indicated by ERP amplitude, between fearful and happy expressions. Furthermore, this difference was limited to automatic processing of facial expressions, rather than conscious

awareness and processing of such stimuli and appears to be driven by unique environmental factors. Future research using longitudinal designs could explore whether the degree of neural differentiation between fearful and happy faces in non-clinical samples changes as symptom levels change or if a lack of N170 differentiation between these emotions is a risk factor for future mental illness to better understand the nature of this association.

3.7. References

Anokhin, A. P., Golosheykin, S., & Heath, A. C. (2010). Heritability of individual differences in cortical processing of facial affect. *Behavior Genetics*, *40*(2), 178–185. https://doi.org/10.1007/s10519-010-9337-1

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Batty, M., & Taylor, M. J. (2003). Early processing of the six basic facial emotional expressions. *Cognitive Brain Research*, *17*(3), 613–620. https://doi.org/10.1016/S0926-6410(03)00174-5

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological)*, *57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Bentin, S., Allison, T., Puce, A., Perez, E., & McCarthy, G. (1996). Electrophysiological studies of face perception in humans. *Journal of Cognitive Neuroscience*, *8*(6), 551–565. https://doi.org/10.1162/jocn.1996.8.6.551

Chen, J., Ma, W., Zhang, Y., Wu, X., Wei, D., Liu, G., Deng, Z., Zhang, Z., & Yang, L. (2014). Distinct facial processing related negative cognitive bias in first-episode and recurrent major depression: Evidence from the N170 ERP component. *PLoS ONE*, *9*(10), e109176. https://doi.org/10.1371/journal.pone.0109176

Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. *British Journal of Clinical Psychology*, *42*(2), 111–131. https://doi.org/10.1348/014466503321903544

Dai, Q., & Feng, Z. (2012). More excited for negative facial expressions in depression: Evidence from an event-related potential study. *Clinical Neurophysiology*, *123*(11), 2172–2179. https://doi.org/10.1016/j.clinph.2012.04.018

Dai, Q., Wei, J., Shu, X., & Feng, Z. (2016). Negativity bias for sad faces in depression: An event-related potential study. *Clinical Neurophysiology*, *127*(12), 3552–3560. https://doi.org/10.1016/j.clinph.2016.10.003

daSilva, E. B., Crager, K., & Puce, A. (2016). On dissociating the neural time course of the processing of positive emotions. *Neuropsychologia*, *83*, 123–137. https://doi.org/10.1016/j.neuropsychologia.2015.12.001

Eimer, M. (2000). The face-specific N170 component reflects late stages in the structural encoding of faces: *NeuroReport*, *11*(10), 2319–2324. https://doi.org/10.1097/00001756-200007140-00050

Eimer, M., & Holmes, A. (2007). Event-related brain potential correlates of emotional face processing. *Neuropsychologia*, *45*(1), 15–31. https://doi.org/10.1016/j.neuropsychologia.2006.04.022

Ekman, P., Friesen, W. V., & Ellsworth, P. (1972). *Emotion in the Human Face* (P. Ekman, W. V. Friesen, & P. Ellsworth, Eds.; Vol. 11). Pergamon. https://doi.org/10.1016/B978-0-08-016643-8.50006-9

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Gatt, J. M., Clark, C. R., Kemp, A. H., Liddell, B. J., Dobson-Stone, C., Kuan, S. A., Schofield, P. R., & Williams, L. M. (2007). A genotype-endophenotype-phenotype

path model of depressed mood: Integrating cognitive and emotional markers. *Journal of Integrative Neuroscience*, *06*(01), 75–104. https://doi.org/10.1142/S0219635207001398

Gatt, J. M., Korgaonkar, M. S., Schofield, P. R., Harris, A., Clark, C. R., Oakley, K. L., Ram, K., Michaelson, H., Yap, S., Stanners, M., Wise, V., & Williams, L. M. (2012). The TWIN-E Project in Emotional Wellbeing: Study protocol and preliminary heritability results across four MRI and DTI measures. *Twin Research and Human Genetics*, *15*(3), 419–441. https://doi.org/10.1017/thg.2012.12

Grecucci, A., Giorgetta, C., Bonini, N., & Sanfey, A. G. (2013). Reappraising social emotions: The role of inferior frontal gyrus, temporo-parietal junction and insula in interpersonal emotion regulation. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00523

Gur, R. C., Sara, R., Hagendoorn, M., Marom, O., Hughett, P., Macy, L., Turner, T., Bajcsy, R., Posner, A., & Gur, R. E. (2002). A method for obtaining 3-dimensional facial expressions and its standardization for use in neurocognitive studies. *Journal of Neuroscience Methods*, *115*(2), 137–143. https://doi.org/10.1016/S0165-0270(02)00006-7

Hadfield, J. D. (2010). MCMC Methods for Multi-Response Generalized Linear Mixed Models: The **MCMCglmm** *R* Package. *Journal of Statistical Software*, *33*(2). https://doi.org/10.18637/jss.v033.i02

Hinojosa, J. A., Mercado, F., & Carretié, L. (2015). N170 sensitivity to facial expression: A meta-analysis. *Neuroscience & Biobehavioral Reviews*, *55*, 498–509. https://doi.org/10.1016/j.neubiorev.2015.06.002

Hu, B., Rao, J., Li, X., Cao, T., Li, J., Majoe, D., & Gutknecht, J. (2017). Emotion regulating attentional control abnormalities in major depressive disorder: An event-related potential study. *Scientific Reports*, *7*(1), 13530. https://doi.org/10.1038/s41598-017-13626-3

Jabbi, M., & Keysers, C. (2008). Inferior frontal gyrus activity triggers anterior insula response to emotional facial expressions. *Emotion*, *8*(6), 775–780. https://doi.org/10.1037/a0014194

Jaworska, N., Blier, P., Fusee, W., & Knott, V. (2012). The temporal electrocortical profile of emotive facial processing in depressed males and females and healthy controls. *Journal of Affective Disorders*, *136*(3), 1072–1081. https://doi.org/10.1016/j.jad.2011.10.047

Jaworska, N., Thompson, A., Shah, D., Fisher, D., Ilivitsky, V., & Knott, V. (2010). Electrocortical effects of acute tryptophan depletion on emotive facial processing in depression-prone individuals. *European Neuropsychopharmacology*, *20*(7), 473–486. https://doi.org/10.1016/j.euroneuro.2010.03.002

Keyes, C. L. M. (2005). Mental illness and/or mental health? Investigating axioms of the Complete State Model of Health. *Journal of Consulting and Clinical Psychology*, *73*(3), 539–548. https://doi.org/10.1037/0022-006X.73.3.539

Kiss, M., & Eimer, M. (2008). ERPs reveal subliminal processing of fearful faces. *Psychophysiology*, *45*(2), 318–326. https://doi.org/10.1111/j.1469-8986.2007.00634.x

Lenth, V. R. (2020). *emmeans: Estimated marginal means, aka least-squares means* (1.5.0) [Computer software]. https://CRAN.R-project.org/package=emmeans

Liddell, B. J., Brown, K. J., Kemp, A. H., Barton, M. J., Das, P., Peduto, A., Gordon, E., & Williams, L. M. (2005). A direct brainstem–amygdala–cortical ‘alarm’ system for

subliminal signals of fear. *NeuroImage*, *24*(1), 235–243. https://doi.org/10.1016/j.neuroimage.2004.08.016

Liddell, B. J., Williams, L. M., Rathjen, J., Shevrin, H., & Gordon, E. (2004). A temporal dissociation of subliminal versus supraliminal fear perception: An event-related potential study. *Journal of Cognitive Neuroscience*, *16*(3), 479–486. https://doi.org/10.1162/089892904322926809

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Luck, S. J. (2005). *An introduction to the event-related potential technique*. MIT Press.

Luo, W., Feng, W., He, W., Wang, N.-Y., & Luo, Y.-J. (2010). Three stages of facial expression processing: ERP study with rapid serial visual presentation. *NeuroImage*, *49*(2), 1857–1867. https://doi.org/10.1016/j.neuroimage.2009.09.018

Park, H. R. P., Chilver, M. R., Montalto, A., Jamshidi, J., Schofield, P. R., Williams, L. M., & Gatt, J. M. (2021). Associations between mental wellbeing and fMRI neural bases underlying responses to positive emotion in a twin sample. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291721002695

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2016). Shared versus distinct genetic contributions of mental wellbeing with depression and anxiety symptoms in healthy twins. *Psychiatry Research*, *244*, 65–70. https://doi.org/10.1016/j.psychres.2016.07.016

Routledge, K. M., Williams, L. M., Harris, A. W. F., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2018). Genetic correlations between wellbeing, depression and anxiety symptoms and behavioral responses to the emotional faces task in healthy twins. *Psychiatry Research*, *264*, 385–393. https://doi.org/10.1016/j.psychres.2018.03.042

Scheike, T. H., Holst, K. K., & Hjelmborg, J. B. (2014). Estimating heritability for cause specific mortality based on twin studies. *Lifetime Data Analysis*, *20*(2), 210–233. https://doi.org/10.1007/s10985-013-9244-x

Schindler, S., & Bublatzky, F. (2020). Attention and emotion: An integrative review of emotional face processing as a function of attention. *Cortex*, *130*, 362–386. https://doi.org/10.1016/j.cortex.2020.06.010

Schyns, P. G., Petro, L. S., & Smith, M. L. (2009). Transmission of facial expressions of emotion co-evolved with their efficient decoding in the brain: Behavioral and brain evidence. *PLoS ONE*, *4*(5), e5625. https://doi.org/10.1371/journal.pone.0005625

Shannon, R. W., Patrick, C. J., Venables, N. C., & He, S. (2013). 'Faceness' and affectivity: Evidence for genetic contributions to distinct components of electrocortical response to human faces. *NeuroImage*, *83*, 609–615. https://doi.org/10.1016/j.neuroimage.2013.06.014

Tamietto, M., & de Gelder, B. (2010). Neural bases of the non-conscious perception of emotional signals. *Nature Reviews Neuroscience*, *11*(10), 697–709. https://doi.org/10.1038/nrn2889

Verweij, K. J. H., Mosing, M. A., Zietsch, B. P., & Medland, S. E. (2012). Estimating Heritability from Twin Studies. In R. C. Elston, J. M. Satagopan, & S. Sun (Eds.), *Statistical Human Genetics: Methods and Protocols* (pp. 151–170). Humana Press. https://doi.org/10.1007/978-1-61779-555-8_9

Watters, A. J., Harris, A. W. F., & Williams, L. M. (2018). Electrocortical reactivity to negative and positive facial expressions in individuals with a family history of major depression. *Biological Psychology*, *136*, 127–135. https://doi.org/10.1016/j.biopsycho.2018.05.015

Weightman, M. J., Air, T. M., & Baune, B. T. (2014). A review of the role of social cognition in major depressive disorder. *Frontiers in Psychiatry*, *5*. https://doi.org/10.3389/fpsyt.2014.00179

Williams, L. M., Kemp, A. H., Felmingham, K., Liddell, B. J., Palmer, D. M., & Bryant, R. A. (2007). Neural biases to covert and overt signals of fear: Dissociation by trait anxiety and depression. *Journal of Cognitive Neuroscience*, *19*(10), 1595–1608. https://doi.org/10.1162/jocn.2007.19.10.1595

Williams, L. M., Liddell, B. J., Rathjen, J., Brown, K. J., Gray, J., Phillips, M., Young, A., & Gordon, E. (2004). Mapping the time course of nonconscious and conscious perception of fear: An integration of central and peripheral measures. *Human Brain Mapping*, *21*(2), 64–74. https://doi.org/10.1002/hbm.10154

Zhang, D., He, Z., Chen, Y., & Wei, Z. (2016). Deficits of unconscious emotional processing in patients with major depression: An ERP study. *Journal of Affective Disorders*, *199*, 13–20. https://doi.org/10.1016/j.jad.2016.03.056

Zotto, M. D., & Pegna, A. J. (2015). Processing of masked and unmasked emotional faces under different attentional conditions: An electrophysiological investigation. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01691

Appendix B: Chapter 3 Supplementary Results

Supplementary materials for:

Emotional face processing correlates with depression/anxiety symptoms but not wellbeing in non-clinical adults: An event-related potential study.

Miranda R. Chilver[1,2], Haeme R.P. Park[1,2], Peter R. Schofield[1,3], C. Richard Clark[4], Leanne M. Williams[5,6], Justine M. Gatt[1,2]

[1] Neuroscience Research Australia, Randwick, New South Wales, 2031, Australia

[2] School of Psychology, University of New South Wales, Sydney, New South Wales, 2052, Australia

[3] School of Medical Sciences, University of New South Wales, Sydney, New South Wales 2052, Australia

[4] College of Education, Psychology and Social Work, Flinders University, Bedford Pakr, Australia 5042

[5]Department of Psychiatry and Behavioral Sciences, Stanford School of Medicine, Stanford University, Stanford, California 94305-5717, United States of America

[6] Mental Illness Research Education and Clinical Centers VISN21, Veterans Administration Palo Alto Health Care System, California, 94304-151-Y, United States of America

***Corresponding author:** Dr Justine Gatt; Phone (+612 93991812); Postal address: Neuroscience Research Australia, Barker St, Randwick Sydney NSW 2031 Australia. E-mail address: j.gatt@neura.edu.au

Word count:
Abstract: 221/250
Manuscript: 4640/4000
Tables: 2
Figures: 3
Supplementary Materials: 1
References: 46

Supplement 1: ERP emotion pairwise comparisons

Unmasked contrasts. Emotional faces tended to evoke smaller P1 amplitudes than neutral faces, except for sad faces which did not differ significantly from neutral faces. P1 amplitudes were larger for sad compared to other negative faces, larger for happy relative to fearful and angry faces, and larger for disgusted relative to angry faces. This pattern was reversed for the VPP and N170 where emotional faces evoked larger amplitudes compared to neutral expressions. Angry faces evoked significantly larger VPP and N170 amplitudes than all other expressions, and fearful faces evoked larger N170 amplitudes than sad, happy, and disgusted faces. Similar to the P1, P250 amplitudes were again smaller for emotional compared to neutral faces, excluding disgust which did not significantly differ from neutral. Angry faces evoked smaller P250 amplitudes relative to all other emotions, and fearful faces evoked smaller amplitudes than disgusted and happy faces.

Masked contrasts. Overall, there was less distinction between different emotions in the masked condition relative to the unmasked condition. In contrast to the unmasked condition, P1 amplitudes tended to be larger for emotional than neutral faces, with significantly larger amplitudes for sad, happy, and disgusted faces compared to neutral. The VPP also had enhanced amplitudes to emotional relative to neutral faces, except for happy faces. Happy VPP amplitudes were significantly smaller than for sad, fearful, and angry faces, and disgusted amplitudes were significantly smaller than angry faces. Angry faces evoked significantly larger amplitudes relative to disgusted faces. The N170 showed enhanced amplitudes to angry and fearful faces, which were significantly larger than neutral, happy, and disgusted faces. Angry faces also evoked larger N170 amplitude than fearful and sad faces. Finally, P250 amplitudes were attenuated to angry, fearful, and disgusted faces relative to neutral and sad faces. Fearful and angry faces also evoked significantly smaller P250

amplitudes than disgusted and happy faces and did not differ from each other.

Table S1. ERP component amplitude means and standard deviations by condition and emotion

Unmasked		**N100**	**P100**	**VPP**	**N170**	**P250**
Emotion	Neutral	-1.60 (1.42)	2.79 (2.49)	-0.47 (1.54)	0.28 (1.92)	2.93 (2.38)
	Sad	-1.59 (1.36)	2.71 (2.50)	-0.34 (1.59)	0.14 (2.00)	2.78 (2.28)
	Happy	-1.57 (1.33)	2.62 (2.42)	-0.34 (1.54)	0.16 (1.92)	2.77 (2.23)
	Disgust	-1.59 (1.33)	2.59 (2.43)	-0.32 (1.54)	0.11 (1.91)	2.84 (2.31)
	Fear	-1.58 (1.33)	2.50 (2.53)	-0.31 (1.49)	-0.08 (2.00)	2.71 (2.39)
	Angry	-1.55 (1.30)	2.46 (2.41)	-0.13 (1.47)	-0.21 (1.86)	2.40 (2.22)
Masked		**N100**	**P100**	**VPP**	**N170**	**P250**
Emotion	Neutral	-1.22 (1.18)	1.75 (2.13)	0.43 (1.47)	-1.01 (1.86)	2.10 (2.04)
	Sad	-1.20 (1.21)	1.89 (2.24)	0.58 (1.48)	-1.06 (1.94)	2.11 (2.04)
	Happy	-1.20 (1.23)	1.89 (2.22)	0.49 (1.49)	-1.03 (1.87)	2.20 (2.15)
	Disgust	-1.21 (1.17)	1.90 (2.22)	0.53 (1.45)	-0.99 (1.88)	2.25 (2.11)
	Fear	-1.22 (1.19)	1.82 (2.18)	0.60 (1.49)	-1.11 (1.80)	1.99 (1.97)
	Angry	-1.23 (1.20)	1.83 (2.18)	0.66 (1.48)	-1.17 (1.87)	1.98 (2.01)

Notes. N1 and VPP are measured from Cz, P1 is measured from the mean of O1 and O2, N170 and P250 are measured from the mean of T5 and T6. $N = 402$.

Table S2. Tukey-corrected emotion pairwise comparisons by ERP component and condition

Unmasked	**P100**		**VPP**		**N170**		**P250**	
Contrast	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Sad - Neutral	-0.08	(-0.19, 0.03)	0.13	(0.03, 0.22)*	-0.14	(-0.23, -0.04)*	-0.15	(-0.25, -0.05)*
Happy - Neutral	-0.17	(-0.28, 0.06)*	0.13	(0.04, 0.23)*	-0.12	(-0.22, -0.03)*	-0.16	(-0.26, -0.05)*
Disgust - Neutral	-0.20	(-0.31, -0.09)*	0.15	(0.05, 0.24)*	-0.17	(-0.27, -0.08)*	-0.09	(-0.19, 0.01)
Fear - Neutral	-0.29	(-0.40, -0.18)*	0.17	(0.07, 0.26)*	-0.36	(-0.45, 0.26)*	-0.22	(-0.33, -0.12)*
Angry - Neutral	-0.33	(-0.44, -0.22)*	0.34	(0.24, 0.43)*	-0.49	(-0.59, -0.39)*	-0.52	(-0.63, -0.42)*
Sad - Happy	0.09	(-0.02, 0.20)	0.00	(-0.10, 0.09)	-0.02	(-0.11, 0.08)	0.00	(-0.10, 0.11)
Sad - Disgust	0.12	(0.01, 0.23)*	-0.02	(-0.12, 0.07)	0.03	(-0.06, 0.13)	-0.06	(-0.16, 0.04)
Sad - Fear	0.21	(0.10, 0.32)*	-0.04	(-0.13, 0.06)	0.22	(0.13, 0.32)*	0.07	(-0.03, 0.18)
Sad - Angry	0.25	(0.14, 0.36)*	-0.21	(-0.30, -0.12)*	0.35	(0.26, 0.45)*	0.37	(0.27, 0.48)*
Disgust - Happy	-0.03	(-0.14, 0.08)	0.02	(-0.08, 0.11)	-0.05	(-0.14, 0.05)	0.07	(-0.04, 0.17)
Fear - Happy	-0.12	(-0.23, -0.01)*	0.03	(-0.06, 0.13)	-0.24	(-0.33, -0.14)*	-0.07	(-0.17, 0.04)
Angry - Happy	-0.16	(-0.27, -0.05)*	0.21	(0.11, 0.30)*	-0.37	(-0.46, 0.27)*	-0.37	(-0.47, -0.27)*
Disgust - Fear	0.09	(-0.02, 0.20)	-0.02	(-0.11, 0.08)	0.19	(0.09, 0.28)*	0.13	(0.03, 0.24)*
Disgust - Angry	0.13	(0.02, 0.24)*	-0.19	(-0.28, -0.09)*	0.32	(0.22, 0.41)*	0.43	(0.33, 0.54)*
Fear - Angry	0.04	(-0.07, 0.15)	-0.17	(-0.27, -0.08)*	0.13	(0.04, 0.23)*	0.30	(0.20, 0.40)*
Masked	**P100**		**VPP**		**N170**		**P250**	
Contrast	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Sad - Neutral	0.14	(0.04, 0.24)*	0.16	(0.07, 0.24)*	-0.05	(-0.14, 0.03)	-0.00	(-0.09, 0.09)
Happy - Neutral	0.14	(0.04, 0.24)*	0.07	(-0.02, 0.15)	-0.02	(-0.10, 0.07)	0.10	(0.00, 0.19)
Disgust - Neutral	0.15	(0.05, 0.25)*	0.11	(0.02, 0.19)*	0.01	(-0.07, 0.10)	0.15	(0.06, 0.24)*
Fear - Neutral	0.07	(-0.03, 0.17)	0.18	(0.09, 0.26)*	-0.10	(-0.19, -0.02)*	-0.11	(-0.20, -0.02)*

Angry - Neutral	0.08	(-0.02, 0.18)	0.24	(0.15, 0.32)*	-0.16	(-0.25, -0.08)*	-0.13	(-0.22, -0.03)*
Sad - Happy	0.00	(-0.10, 0.10)	0.09	(0.00, 0.18)*	-0.03	(-0.12, 0.05)	-0.09	(-0.19, 0.00)
Sad - Disgust	-0.01	(-0.11, 0.09)	0.05	(-0.04, 0.14)	-0.06	(-0.15, 0.02)	-0.14	(-0.24, -0.05)*
Sad - Fear	0.07	(-0.03, 0.17)	-0.02	(-0.11, 0.07)	0.05	(-0.03, 0.14)	0.12	(0.02, 0.21)*
Sad - Angry	0.06	(-0.04, 0.16)	-0.08	(-0.17, 0.01)	0.11	(0.03, 0.20)*	0.13	(0.04, 0.22)*
Disgust - Happy	0.01	(-0.09, 0.11)	0.04	(-0.05, 0.13)	0.03	(-0.05, 0.12)	0.05	(-0.04, 0.14)
Fear - Happy	-0.07	(-0.17, 0.03)	0.11	(0.02, 0.20)*	-0.08	(-0.17, 0.00)*	-0.21	(-0.30, -0.12)*
Angry - Happy	-0.07	(-0.16, 0.03)	0.17	(0.08, 0.26)*	-0.14	(-0.23, -0.06)*	-0.22	(-0.31, -0.13)*
Disgust - Fear	0.08	(-0.02, 0.18)	-0.07	(-0.16, 0.02)	0.12	(0.03, 0.20)*	0.26	(0.17, 0.35)*
Disgust - Angry	0.07	(-0.03, 0.17)	-0.13	(-0.22, -0.04)*	0.18	(0.09, 0.26)*	0.27	(0.18, 0.37)*
Fear - Angry	0.00	(-0.10, 0.10)	-0.06	(-0.15, 0.03)	0.06	(-0.02, 0.15)	0.01	(-0.08, 0.10)

Notes. * $p < 0.05$; $N = 402$.

Chapter 4:
Cognitive processing and mental health

4.1. Introduction

Mental wellbeing, defined as a state of positive psychological functioning, positive mood, and life satisfaction, has been associated with alterations in cognition, with higher wellbeing being associated with better global cognitive function, including sustained attention, working memory, inhibition, and motor coordination (Lee & Chao, 2012; Llewellyn et al., 2008; Pe et al., 2013; Routledge et al., 2017). Differences in how individuals with high wellbeing direct their attention and control it could play a role in their ability to maintain high wellbeing through more effective use of emotion regulation strategies (Schmeichel et al., 2008). In contrast, depression, anxiety, and stress symptoms (referred to here as depression/anxiety symptoms) are associated with poorer executive function in clinical and subclinical samples (Harvey et al., 2004; Lukasik et al., 2019; Moran, 2016; Snyder, 2013). These cognitive deficits have been observed in clinical groups using both behavioural and neurological measures, including event-related potentials (ERPs) which show early stages of cognitive processing by measuring electrical activity from the scalp. In clinical research, cognitive ERPs have been used as biomarkers to predict mental illness (Bernat et al., 2020; Gilmore et al., 2010). However, it remains unclear whether ERPs can be similarly applied to wellbeing, which has only been linked to changes in cognitive control through behavioural measures. Thus, the current chapter explores the association between mental wellbeing and ERPs indexing attention and inhibitory processes to determine whether variation in these cognitive processes could help explain variation in wellbeing.

While the association between mental wellbeing and attentional control and inhibition remains preliminary, there is substantial evidence that positive emotions, which form an important component of mental wellbeing (Diener, 1984; Gatt et al., 2014), alter these processes. Using experimental methods with behavioural and neurological measures, studies

have found that positive emotions broaden attentional scope (Fredrickson, 2001; Putkinen et al., 2017; Vanlessen et al., 2014), facilitate cognitive control and inhibition (Paul et al., 2021; Vanlessen et al., 2015, 2016), and improve working memory (Dreisbach & Goschke, 2004; Gray, 2001; Storbeck & Maswood, 2016). It has been suggested that the same cognitive functions aid emotion regulation processes, which might explain why these functions are also associated with wellbeing (Lee & Chao, 2012; Pe et al., 2013; Routledge et al., 2017). For example, individuals with greater working memory capacity are more likely to use emotion regulation strategies when instructed to and following negative feedback (Schmeichel et al., 2008; Schmeichel & Demaree, 2010). Meanwhile, failing to update and inhibit negative information in working memory has been associated with higher depression and anxiety symptoms (Joormann et al., 2011; Joormann & Gotlib, 2010). Thus, if positive emotions increase cognitive control, they may lead to more effective emotion regulation and maintenance of positive emotions over time, resulting in improved wellbeing.

Similar associations have been reported between cognitive control and positive emotions using experimental manipulations of positive mood. For example, similar to associations reported between inhibition and induced positive mood (Vanlessen et al., 2015), wellbeing has been positively associated with response inhibition in behavioural tasks (Lee & Chao, 2012; Routledge et al., 2017). Working memory function is also positively associated with wellbeing. One study used an affective n-back procedure to test working memory function in individuals with varying levels of wellbeing (Pe et al., 2013). They found that individuals with higher subjective wellbeing made fewer errors for positive n-back trials compared to those with poorer wellbeing. A similar positive association was found between composite wellbeing and working memory in the full TWIN-E study cohort (Routledge et al., 2017). These effects are also similar to those reported in association with positive mood

(Storbeck & Maswood, 2016). Based on these similar behavioural findings, it is possible that the alterations in ERPs indexing attention and inhibition reported in association with positive mood might also generalise to wellbeing.

Some of the key ERP components used to index attention and inhibition include the P3b, P3a, and N2 components, with the most widely investigated being the P3b. The P3b component was first recorded in response to target stimuli within an oddball paradigm where participants responded to rare target stimuli and ignored frequent standard stimuli (Polich, 2007). It is usually used to index attention allocation and cognitive load during oddball and working memory tasks (Polich, 2007; Watter et al., 2001). The P3b component has been used to investigate alterations in attentional processes associated with positive mood (Putkinen et al., 2017; Vanlessen et al., 2014), but it has not yet been applied to wellbeing research. In the context of positive emotions, which are theorised to broaden attentional scope (Fredrickson, 2001), it was expected that oddball P3b amplitudes would be reduced in the presence of a secondary task. While this effect was found in a study using auditory stimuli (Putkinen et al., 2017), an earlier study found that happy individuals actually had larger P3b amplitudes when the secondary task was spatial in nature, suggesting that both the secondary and primary tasks were easier during a positive mood state (Vanlessen et al., 2014). While these studies confirm that positive mood can alter early attentional processes in the context of dual-task paradigms, no studies to date have investigated how the P3b component might be affected by either positive mood or wellbeing in the standard oddball paradigm without a secondary task.

In contrast to the P3b, which measures attention, the N2 and P3a are used to index inhibitory processes, with current theories suggesting that the N2 is involved in inhibition of planned motor responses and the P3a in inhibition of motor activity (Huster et al., 2013; Smith et al., 2013). Just one study has used ERPs to investigate the effects of positive mood

on these inhibition related components (Vanlessen et al., 2015), and none have been conducted on wellbeing. Vanlessen et al. (2015) used mood induction to put participants into either a positive or neutral mood before testing their inhibition using a cued anti-saccade task. This task required participants to either look away from (on anti-saccade trials), or towards (on prosaccade trials) a visual probe appearing on one side of the screen. The happy mood group was found to have augmented N2 amplitude on both trial types relative to the neutral mood group despite no difference in behavioural measures. No effect was found for the P3a component. As the task was cued to let participants know whether each trial would require an anti-saccade or a prosaccade, the authors suggested that the increased N2 amplitude was a sign of increased reactive control at the cost of proactive control, meaning happy participants were less likely to prepare their inhibitory response based on the cue preceding each trial. Studies examining the relationship between inhibition and wellbeing have not used ERPs, but did report differences in behavioural performance which might indicate larger effects of wellbeing on inhibition compared to positive mood (Lee & Chao, 2012; Routledge et al., 2017).

Although ERPs have rarely been used to investigate the cognitive correlates of wellbeing and positive mood, various studies have used them to investigate the effects of clinical and subclinical depression and anxiety on cognition. Reduced attentional capture within oddball paradigms, indexed by smaller P3b amplitudes to oddball stimuli, is associated with major depression and anxiety disorders, including familial risk (Bernat et al., 2020; Bruder et al., 2011; Houston et al., 2003; Röschke & Wagner, 2003; Xu et al., 2014). More recently, the frontal ‘novelty P3’ (also called the P3a) component elicited in response to novel, non-target stimuli has also been identified as a negative predictor of psychopathology risk (Bernat et al., 2020). These effects indicate impairments in attention orienting and

processing of task-relevant stimuli in clinical groups (Bernat et al., 2020). In addition, impairments in inhibitory function have been reported in clinical depression and anxiety, indicated via both behavioural and ERP indices (Kaiser et al., 2003; Katz et al., 2010; Ruchsow et al., 2008; Xia et al., 2020). Specifically, both depression and anxiety symptoms are associated with reduced N2 amplitudes compared to non-clinical controls, and N2 amplitudes have been correlated with symptom severity (Kaiser et al., 2003; Katz et al., 2010; Xia et al., 2020). Some studies have also reported alterations to the inhibitory P3a component, with one study reporting that P3a amplitudes were smaller in depressed compared to control participants (Ruchsow et al., 2008), and another study reporting that P3a amplitudes were enhanced in anxious participants despite the same participants showing reduced N2 amplitudes (Xia et al., 2020). The association between ERPs and mental illness symptoms is of particular interest because they have been identified as candidate endophenotypes for risk due to their moderate to high heritability (Anokhin et al., 2004, 2017; Malone et al., 2014; Smit et al., 2007). The current chapter aimed to replicate the moderate heritability of these ERP components and evaluate their potential for use as endophenotypes of mental wellbeing.

The aim of this Chapter is to investigate the associations between cognitive processing, mental wellbeing, and depression/anxiety symptoms using behavioural performance and ERPs. This is done using the TWIN-E study data which included three cognitive tasks: the auditory oddball paradigm to measure attentional orienting (P3b to *targets*); the n-back paradigm to measure working memory updating and recognition (P3b to *targets* and *non-targets)*, with *distractor* trials used to index attentional orienting to novel stimuli (P3a); and the go/no-go paradigm to measure inhibition (N2 and P3a to *no-go* stimuli). To investigate the potential use of these components of interest as endophenotypes,

univariate analyses were conducted to estimate the heritability of each component; and multivariate correlated factors models were planned in the case of significant associations between mental wellbeing or depression/anxiety symptoms with ERP amplitude.

4.2. Methods

4.2.1. Participants

The participants for this study were recruited as part of the TWIN-E study of mental wellbeing and resilience, recruited through the Australian Twin Registry (now known as Twins Research Australia) between 2009 and 2012 (Gatt et al., 2012). A total of 433 same-sex monozygotic or dizygotic twins aged 18 to 61 years completed at least one of the three cognitive ERP tasks assessed. Participants with a personal or family history of mental illness or major physical illness were excluded from the study. Detailed inclusion and exclusion criteria can be found in the study protocol (Gatt et al., 2012).

This study was approved by the Human Research Ethics Committees of the University of Sydney (03-2009/11430), Flinders University (FCREC#08/09), and the University of New South Wales (HC14256).

4.2.2. Materials

Participants completed a comprehensive test battery including mental health and related questionnaires, behavioural cognitive performance, and emotional processing online before their session, as detailed elsewhere (Gatt et al., 2012). The measures relevant to the current analysis included the COMPAS-W wellbeing questionnaire which measures six subscales relating to psychological and subjective wellbeing, including composure under stress, own-worth, mastery, positivity, achievement, and satisfaction (Gatt et al., 2014). The

COMPAS-W has been validated against other mental health measures and has high internal (0.84) and test-retest reliability (0.82; Gatt et al., 2014). Depression/anxiety symptoms were measured using the Depression Anxiety Stress Scale (DASS-42; Lovibond & Lovibond, 1995). The DASS-42 has been validated within non-clinical samples against other depression and anxiety measures, and has very high internal reliability of 0.97 (Crawford & Henry, 2003).

Following the online session, participants were invited to either the Brain Dynamics Centre at the University of Sydney, NSW, Australia, or Flinders University, SA, Australia for the EEG recording. Three cognitive assessments were conducted at this session: the auditory oddball, the n-back, the go/no-go task, described below. All three tasks have been validated previously and widely applied to study healthy and clinical populations (Gordon et al., 2005; Williams et al., 2005).

4.2.2.1. Auditory oddball paradigm

Participants were presented with a total of 340 trials including 60 presentations of a high-pitched (1000 Hz) target tone and 280 presentations of a low-pitched (500 Hz) standard tone. Participants were instructed to respond to target tones but ignore standard tones. Both tones were played at 75 dB with a 50 msec duration and 1000 msec inter-stimulus interval.

4.2.2.2. N-back paradigm

Participants were presented with a total of 125 trials, each presenting either one of four white letters (B, C, D, or G) or a blue and green checkerboard on a black background for 200 msec in pseudo-random order. The inter-stimulus interval was 2500 msec. Participants were to respond with a button press when the letter onscreen matched the letter presented on

the previous trial (i.e., 1-back), and to withhold responses on all other trials. Non-repeated letter stimuli were standard trials presented on 85 trials, repeated letter target stimuli were presented on 20 trials, and the checkerboard distractor trials were presented on 20 trials.

4.2.2.3. Go/no-go paradigm

Participants were presented with 168 trials where the word “PRESS” was printed either in red or in green text on a black screen. Participants were instructed to respond with a button press when the text was green (75% of trials, n = 126) and to withhold a response when the text was red (25% of trials, n = 42). Trials were presented pseudo-randomly in blocks of six trials.

4.2.3. Procedures

4.2.3.1. EEG acquisition and processing

A 26-electrode QuickCap and NuAmps DC amplifier were used to record EEG data during the cognitive tasks at a sampling rate of 500 Hz and frequency band of 0.1-42 Hz, relative to virtual ground. Impedances were kept below 5 kΩ. The data was re-referenced offline to linked mastoids. An artifact rejection algorithm used previously (Bryant et al., 2021; Watters et al., 2018) was used that rejected epochs where three or more channels exceeded a maximum threshold of 100 µV. Horizontal and vertical eye movements were recorded from above and below the left eye, and 1.5 cm from the outer canthus of each eye to correct for blinks using the Gratton-Coles method (Gratton et al., 1983). Following artifact rejection, epochs were averaged for each experimental condition, including at least 50% of trials of each type per participant.

Grand-averaged waveforms of all conditions in each experimental task were used to select time windows for each component, based on the peak amplitude +/- 20 msec. P3b components were measured at Pz and the frontal components P3a and N2 were measured from FCz in accordance with the literature (Polich, 2007; Smith et al., 2013). Time periods used to calculate average amplitude for each component are as follows: oddball P3b from 328–368 msec, n-back P3b from 368–408 msec, n-back P3a from 344–384 msec, go/no-go N2 from 160–200 msec, and go/no-go P3a from 336–376 msec.

4.2.4. Statistical analysis

4.2.4.1. Linear mixed models

Linear mixed models were used for the statistical analysis to account for twin relatedness in all models by entering family ID as the random effect. These were fit using the *lme4* package in *R* (Bates et al., 2015; R Core Team, 2020). Pairwise comparisons to test for differences in ERP amplitude between experimental conditions were conducted using the *emmeans* package (Lenth, 2020). ERPs of interest were chosen based on the literature (Bernat et al., 2020; Vanlessen et al., 2014, 2015; Watter et al., 2001) and included the *target* P3b from the auditory oddball, *target* and *non-target* P3b from the n-back, *distractor* P3a from the n-back, and *no-go* N2 and P3a from the go/no-go. These components were tested as predictors of wellbeing and depression/anxiety symptoms in separate models, where depression/anxiety symptoms were entered as a covariate for wellbeing models and wellbeing was entered as a covariate for depression/anxiety models.

4.2.4.2. Univariate heritability

Univariate heritability for each ERP of interest was conducted using the *OpenMx* package in *R* (Scheike et al., 2014). The intra-class correlations (ICC) were used to select the starting model; where monozygotic twins had an ICC of at least double that of dizygotic twins, the ADE model was chosen as the starting model, otherwise the ACE starting model was chosen (Verweij et al., 2012). A, C, or D components were then progressively dropped from the model to identify the most parsimonious model on the basis of AIC and a chi-square test. Age, sex, and education were included as covariates in the heritability analysis. Multivariate models were planned to assess the shared heritability between ERP components of interest and wellbeing and/or depression/anxiety symptoms where significant associations were found in the linear mixed models.

4.3. Results

4.3.1. Sample characteristics

Of the 433 participants who completed at least one of the three cognitive tasks, 427 completed the n-back task, 422 completed the oddball task, and 420 completed the go/no-go task. Sample characteristics for the full sample of 433 participants are provided in Table 4.1. Subsamples for each task did not significantly differ in demographic characteristics from the full sample.

4.3.2. Behavioural performance

Individuals with high error rates, defined as errors on more than 10% of trials in the oddball task or *go* trials in the go/no-go task, or on more than 25% of trials in other

Table 4.1 Participant characteristics for participants completing at least one cognitive task

Characteristic	MZ (n = 301)	DZ (n = 132)	Total (n = 433)
Age	41.03 (12.1)	38.41 (14.4)	40.23 (12.9)
COMPAS-W (M/SD)	99.6 (10.4)	99.4 (9.8)	99.54 (10.2)
DASS-42	10.74 (10.6)	12.02 (11.2)	11.13 (10.8)
log DASS-42	0.90 (0.4)	0.97 (0.4)	0.92 (0.4)
Sex (M/F)	112/189	43/89	155/278
Handedness (R/L)	272/29	120/12	392/41

Notes. COMPAS-W = total composite measure of wellbeing (Gatt et al., 2014); *DASS-42* = Depression, Anxiety, Stress Scale (Lovibond & Lovibond, 1995); MZ = monozygotic; DZ = dizygotic; *N* = 433.

conditions were excluded from the data due to the high likelihood that they did not understand the task instructions. This removed six participants from the oddball (remaining *n* = 417), seven participants from the n-back (remaining *n* = 420), and six participants from the go/no-go task (remaining *n* = 414). Behavioural performance data for the reduced sample is provided in Table 4.2. Overall performance was high across the sample. Linear mixed models were used to assess for associations between task performance and wellbeing and depression/anxiety symptoms, described below.

Table 4.2 Behavioural performance for the auditory oddball, n-back, and go/no-go tasks

Task	Correct RT	Commission Errors	Omission Errors	Total Errors
Oddball (n = 417)	361.33 (49.89)	0.47 (1.26)	0.13 (0.49)	0.60 (1.42)
N-back (n = 420)	513.28 (100.58)	0.63 (1.05)	0.73 (1.07)	1.36 (1.64)
Go/No-Go (n = 414)	287.20 (43.01)	1.93 (1.62)	0.26 (1.06)	2.19 (2.02)

Notes. Correct RT = mean reaction time in msec for correct press response; errors indicate the mean number of errors made by type on relevant trials.

4.3.1.1. Auditory oddball paradigm

Within the oddball paradigm, mental wellbeing was associated with fewer total errors (b = -1.12, p = .002) driven by fewer commission errors (b = -1.14, p = .005), but not omission errors (b = -1.70, p = .079). There was no association between mental wellbeing and reaction time (p = .825). When covarying for depression/anxiety symptoms, the association between mental wellbeing and fewer total errors (b = -0.907, p = .006) and fewer commission errors (b = -0.90, p = .016) remained significant, and the association with fewer omission errors (b = -1.55, p = .084) remained non-significant. No new association with reaction time was found when controlling for depression/anxiety symptoms.

Depression/anxiety symptoms were not significantly associated with behavioural performance, either in terms of total errors (b = 0.02, p = .085), or commission errors (b = 0.03, p = .077) in individuals with higher compared to lower depression/anxiety symptoms. When controlling for mental wellbeing, these effects weakened further (p > .100). No associations with omission errors or reaction time were found.

4.3.1.2. N-back paradigm

Within the n-back paradigm, mental wellbeing was associated with fewer errors overall (b = -0.61, p = .039), driven by fewer commission errors (b = -0.96, p = .036) rather than omission errors (p = .293). There was no association between mental wellbeing and reaction time (p = .710). When controlling for depression/anxiety symptoms, there were no significant associations between wellbeing and behavioural performance (p > .05).

Depression/anxiety symptoms did not have a significant association with more total errors (b = 0.02, p = .072), or omission errors (p = .511), but did have a significant

association with increased commission errors (b = .04, p = .035). There was no association between depression/anxiety symptoms and reaction time (p = .315). When controlling for wellbeing, there were no significant associations between depression/anxiety symptoms and behavioural performance (p > .05).

4.3.1.3. Go/no-go paradigm

Within the go/no-go paradigm, mental wellbeing was not associated with any measure of behavioural performance, either with or without controlling for depression/anxiety symptoms (p > .100). Similarly, depression/anxiety symptoms were not associated with differences in behavioural performance, either with or without controlling for wellbeing (p > .100).

4.3.2. Event-related potentials

4.3.2.1. Auditory oddball paradigm

The auditory oddball waveform is shown in Figure 4.1. A comparison of P3b amplitude between *targets* (M = 10.30 μV, SD = 6.7) and *non-targets* (M = -0.32 μV, SD = 1.9) revealed a significant effect of condition whereby *targets* elicited significantly larger P3b amplitudes than *non-targets* (t_{416} = 34.06, p < .001). Linear mixed models revealed no significant symptoms with *target* P3b amplitude, either with or without controlling for wellbeing (both p > .100) associations between mental wellbeing and *target* P3b amplitude either with or without controlling for depression/anxiety symptoms (both p > .100), nor between depression/anxiety.

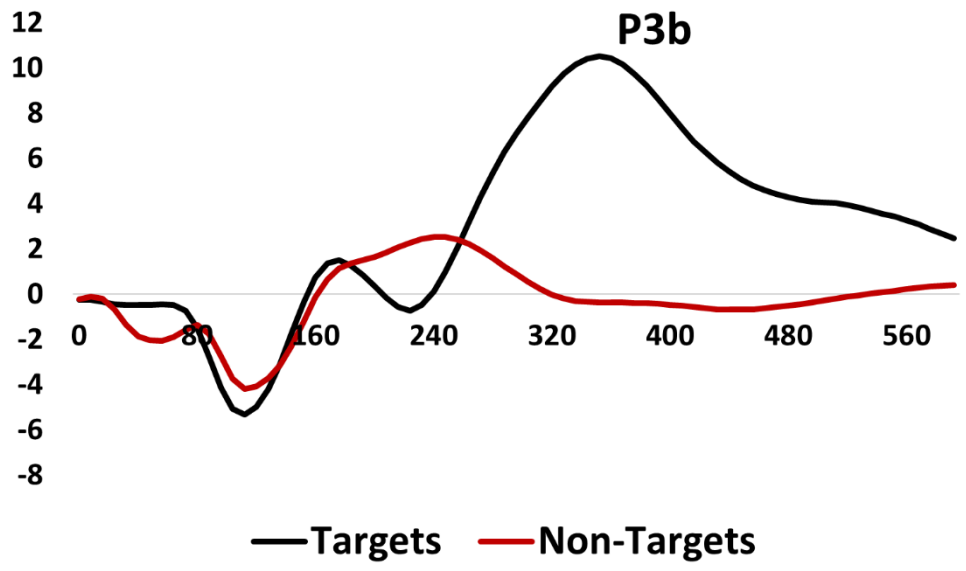


Figure 4.1 Auditory oddball waveform comparing the P3b component for *targets* and *non-targets* at Pz.

4.3.2.2. N-back task

The n-back waveform is shown in Figure 4.2. Pairwise comparisons between *targets* (M = 12.7 μV, SD = 6.2), *non-targets* (M = 10.4 μV, SD = 4.5), and *distractors* (M = 22.6 μV, SD = 7.3) found that *targets* (t_{419} = 7.24, p < .001) and *distractors* (t_{419} = 38.80, p < .001) had larger P3b amplitudes compared to *non-targets*, respectively. *Distractors* also had significantly larger P3b amplitude than *targets* (t_{419} = 31.53, p < .001). Linear mixed models revealed no significant associations between P3b amplitude for either *targets* or *non-targets* with mental wellbeing, either with or without controlling for depression/anxiety symptoms both p > .100). Furthermore, no associations were found between depression/anxiety symptoms and P3b amplitude for *targets* or *non-targets*, either with or without controlling for mental wellbeing (p > .100).

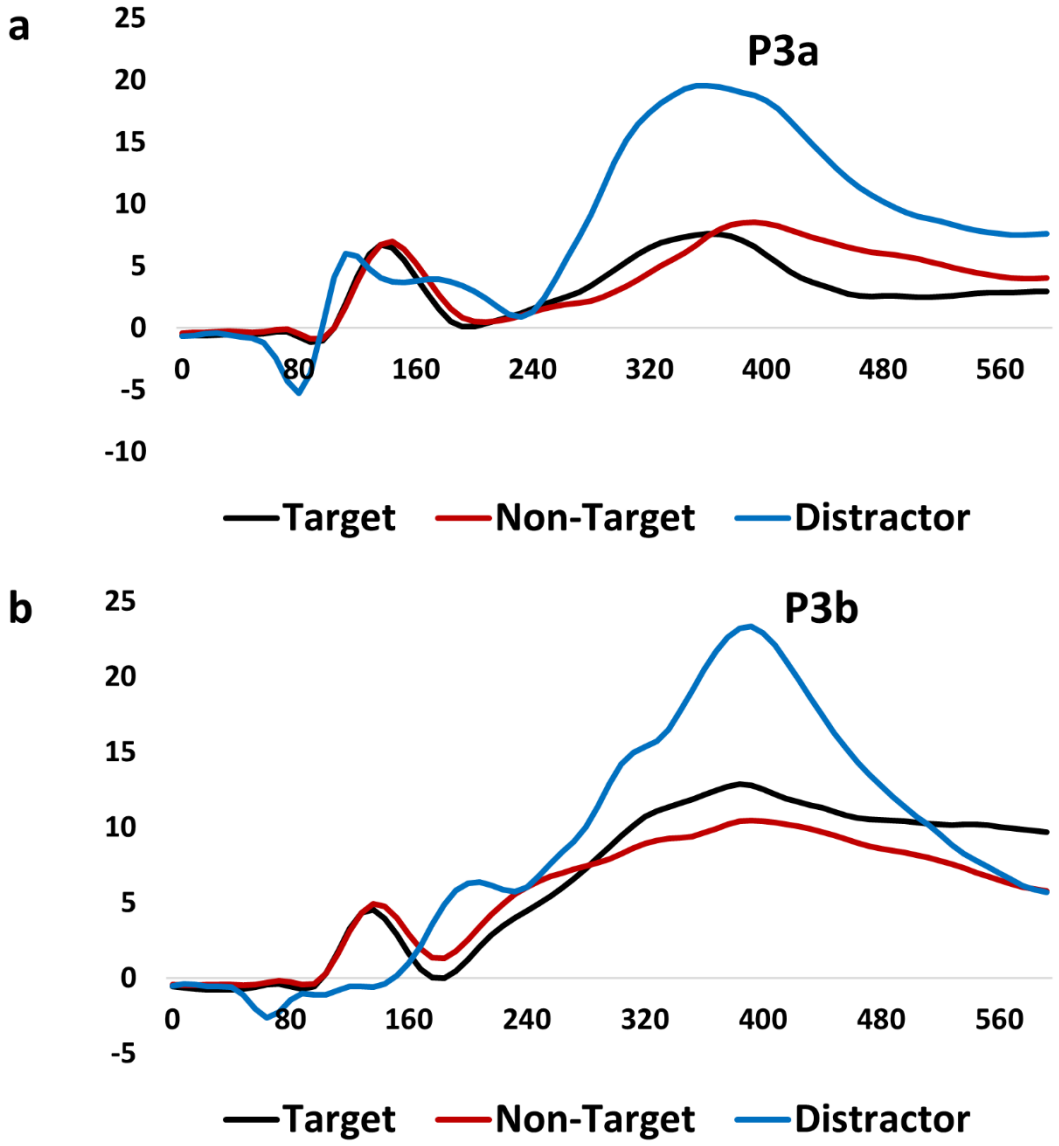


Figure 4.2 N-back waveform comparing targets, non-targets, and distractors at (a) FCz for the P3a component, and (b) Pz for the P3b component.

Frontal P3a amplitudes were also considered. Pairwise comparisons between *targets* (M = 7.43 μV, SD = 6.8), *non-targets* (M = 7.52 μV, SD = 5.3), and *distractors* (M = 19.38 μV, SD = 8.2) found that *distractors* elicited significantly larger P3a amplitude relative to *targets* (t_{419} = 35.77, p < .001) and *non-targets* (t_{419} = 35.48, p < .001), respectively. No significant difference in P3a amplitude was found between *targets* and *non-targets* (p > .100).

Linear mixed models revealed no significant association between P3a amplitude for *distractors* with mental wellbeing, regardless of whether depression/anxiety symptoms were controlled for (both $p > .100$). Similarly, no significant association was found between with depression/anxiety symptoms, regardless of whether wellbeing was controlled for (both $p > .100$).

4.3.2.3. Go/no-go paradigm

The go/no-go waveform is shown in Figure 4.3. Comparisons between *go* ($M = -0.38$ μV, $SD = 5.2$) and *no-go* ($M = -0.86$ μV, $SD = 4.9$) trials found that N2 amplitudes were significantly larger in absolute amplitude on *no-go* relative to *go* trials ($t_{413} = 3.34$, $p < .001$). Linear mixed models revealed no significant association between mental wellbeing *no-go* N2 amplitude, regardless of whether depression/anxiety symptoms were controlled for (both $p > .100$) Similarly, no significant association was found between *no-go* N2 amplitude and

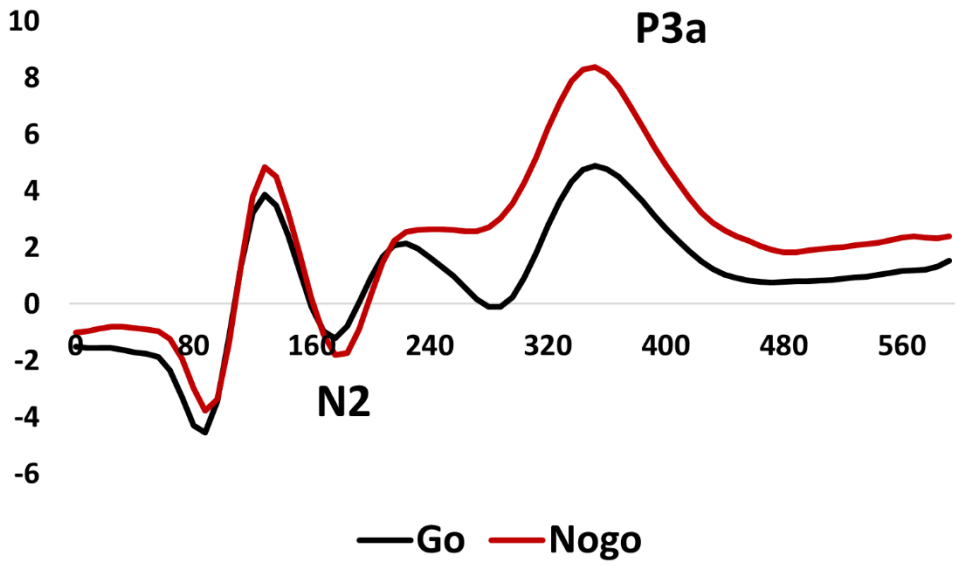


Figure 4.3 Go/no-go waveform comparing go and no-go trials at FCz for the N2 and inhibitory P3a components

depression/anxiety symptoms regardless of whether wellbeing was controlled for (both $p > .100$).

When considering P3a amplitude, comparisons between *go* ($M = 4.59\ \mu V$, $SD = 4.6$) and *no-go* ($M = 7.97\ \mu V$, $SD = 4.8$) trials found that P3a amplitude was significantly greater for *no-go* relative to *go* trials ($t_{413} = 14.91$, $p < .001$). Linear mixed models revealed no significant association between wellbeing and *no-go* P3a amplitude, regardless of whether depression/anxiety symptoms were controlled for (both $p > .100$). Similarly, no significant association was found between depression/anxiety symptoms and *no-go* P3a amplitude, regardless of whether wellbeing was controlled for (both $p > .100$).

4.3.3. Univariate heritability

Although no significant associations were found between the ERPs of interest and either mental wellbeing or depression/anxiety symptoms, the planned univariate heritability analysis was still carried out in an exploratory manner. A summary of the univariate models is provided in Table 4.3.

4.3.3.1. Auditory oddball heritability

Based on the intraclass correlations, the ACE model was chosen as the starting model for *target* P3b heritability. An AE model was found to be the best fitting model, showing significant moderate heritability of the P3b at 0.67.

4.3.3.2. N-back heritability

Based on the intraclass correlation, the ACE model was chosen as the starting model for *target* and *non-target* P3b amplitude, and for *distractor* P3a amplitude. P3b amplitude for

both *targets* and *non-targets* was found to be moderately heritable at 0.58 and 0.62, respectively, with no common environmental component. However, the CE model was the best fit for *distractor* P3a amplitude, indicating a significant effect of common environmental factors at 0.55.

4.3.3.3. Go/No-Go heritability

Based on the intraclass correlations, the ADE model was chosen as the starting model for the *no-go* N2 amplitude, but the ACE was chosen as the starting model for P3a amplitude. Both components were moderately heritable, but the N2 heritability was attributed to a dominant genetic effect at 0.62, whereas the inhibitory P3a heritability was attributed to additive genetics at 0.49.

Table 4.3 Univariate heritability by task and component for select conditions

Phenotype	ICC		Model fit					Parameter estimates		
	MZ	DZ	Model	Comparison	-2LL	AIC	p-value	A (CI)	C or D (CI)	E (CI)
Oddball	0.71	0.42	ACE	vs. saturated	2601.98	1785.98	NA	0.67	< .01	0.33
Target P3b								(0.39, 0.74)	(< .01, .26)	(0.26, 0.61)
			AE	**vs. ACE**	**2601.98**	**1783.98**	**1**	**0.67**	**-**	**0.33**
								(0.57, 0.75)		**(0.25, 0.43)**
			E	vs. AE	2692.36	1872.36	< .001	-	-	1
N-back	0.57	0.43	ACE	vs. saturated	2630.41	1810.41	NA	0.53	0.05	0.42
Target P3b								(0.11, 0.66)	(< .01, 0.42)	(0.34, 0.89)
			AE	**vs. ACE**	**2630.47**	**1808.47**	**0.812**	**0.58**	**-**	**0.42**
								(0.48, 0.67)		**(0.33, 0.52)**
			E	vs. AE	2693.61	1869.61	< .001	-	-	1
N-back	0.64	0.34	ACE	vs. saturated	2375.67	1547.67	NA	0.60	0.02	0.38
Non-Target								(0.17, 0.70)	(< .01, 0.42)	(0.30, 0.48)
P3b			**AE**	**vs. ACE**	**2375.69**	**1545.69**	**0.217**	**0.62**	**-**	**0.38**
								(0.52, 0.70)		**(0.30, 0.48)**
			E	vs. AE	2456.22	1624.22	< .001	-	-	1
N-back	0.58	0.49	ACE	vs. saturated	2899.74	2067.74	NA	0.20	0.37	0.43
Distractor								(< .01, 0.44)	(0.22, 0.65)	(0.34, 0.53)
P3a			**CE**	**vs. ACE**	**2900.76**	**2066.76**	**0.312**	**-**	**0.55**	**0.45**
									(0.44, 0.62)	**(0.38, 0.55)**
			E	vs. CE	2975.87	2139.87	< .001	-	-	1
GNG	0.63	0.02	**ADE**	**vs. saturated**	**2439.75**	**1623.75**	**NA**	**< .01**	**0.62**	**0.38**
No-Go N2								**(< .01, 0.52)**	**(0.10, 0.70)**	**(0.29, 0.90)**
			AE	vs. ADE	2444.75	1626.75	0.025	0.61	-	0.39
								(0.49. 0.70)		(0.30, 0.51)
			E	vs. AE	2508.37	1688.37	< .001	-	-	1
GNG	0.46	0.37	ACE	vs. saturated	2460.11	1644.11	NA	0.41	0.07	0.51
No-Go P3a								(0.28, 0.59)	(< .01, .31)	(0.40, 0.64)
			AE	**vs ACE**	**2460.23**	**1642.23**	**0.727**	**0.49**	**-**	**0.51**
								(0.36, 0.60)		**(0.39, 0.64)**
			E	vs. AE	2501.01	1681.01	< .001	-	-	1

Notes. ICC = Intraclass correlation; MZ = monozygotic twins; DZ = dizygotic twins; starting models were either ACE or ADE where A = additive genetic, D = dominant genetic, C = common environment, E = unique environment. Squared model components indicate their contribution as a percentage of total variance. Models in bold letters represent the best fit.

4.4. Discussion

Previous research has found that positive mood states can alter cognitive processes relating to cognitive control, attention, and inhibition (Storbeck & Maswood, 2016; Vanlessen et al., 2014, 2015). Similar alterations have been reported in the wellbeing literature, with reports of higher wellbeing being associated with better sustained attention, working memory, cognitive flexibility, inhibition, and motor coordination (Llewellyn et al., 2008; Routledge et al., 2017). Within studies investigating the effects of positive mood and mental illness on cognitive function, changes to ERP indices of attention, working memory, and inhibition have been reported (Bernat et al., 2020; Kaiser et al., 2003; Putkinen et al., 2017; Vanlessen et al., 2014, 2015; Xia et al., 2020). However, similar studies have not been conducted for ERP indices of cognitive functions with the broader construct of mental wellbeing. To address this gap, the current study explored the associations between mental wellbeing and the P3b, P3a, and N2 ERP components involved in attention, working memory, and inhibitory control within three different tasks. Although significant associations were found between mental wellbeing and behavioural performance on the auditory oddball and n-back tasks, these associations were not reflected in changes to the P3b component. Furthermore, no associations were found between behavioural performance in the go/no-go task or any other ERP components with either mental wellbeing or depression/anxiety symptoms. However, univariate heritability analyses supported past evidence indicating that the P3b, N2, and inhibitory P3a components are moderately heritable suggesting an influence of both genetics and environment in these measures.

Alterations in attention and working memory have been reported for positive relative to negative or neutral emotional states, and in individuals with elevated mental wellbeing (Pe et al., 2013; Routledge et al., 2017; Vanlessen et al., 2014). Previous work from the TWIN-E sample found that mental wellbeing was positively associated with working memory capacity

and the ability to sustain attention throughout an n-back task requiring constant working memory updating based on behavioural performance (Routledge et al., 2017). Another study found that individuals with higher wellbeing were better able to update working memory with positive stimuli compared to those with poorer wellbeing (Pe et al., 2013). Positive emotions have also been linked to better attentional control and more efficient allocation of attentional resources (Vanlessen et al., 2016) which might contribute to the observed positive effects of wellbeing on attention, as these individuals experience positive emotions more frequently. The current study replicated the positive association between attention and working memory processes found in the larger TWIN-E sample (Routledge et al., 2017), with those with higher wellbeing demonstrating fewer errors on both the n-back and oddball task. Similar to the full TWIN-E sample, the association between behavioural performance on the n-back task and mental wellbeing was no longer significant after controlling for depression/anxiety symptoms. However, more accurate responses in the oddball task, which was not tested in the larger TWIN-E cohort, was associated with higher wellbeing even after controlling for depression/anxiety symptoms in the current sub-sample. This might indicate that sustained attention, which is important for both the n-back and the oddball task, is more strongly associated with wellbeing than working memory updating, which is an additional component within the n-back task (Harvey et al., 2004; Watter et al., 2001). However, it is possible that the association between wellbeing and n-back performance (and the P3b) would be stronger in more challenging 2-back or 3-back conditions which require greater executive control relative to the 1-back condition used here (Harvey et al., 2004). This should be tested in future studies, especially since both wellbeing and positive emotions have been associated with better executive function in contexts requiring more complex management of information (Paul et al., 2021; Routledge et al., 2017; Vanlessen et al., 2016).

Although mental wellbeing was associated with better behavioural performance on the oddball and n-back tasks, this was not reflected in the P3b components used to index attention allocation and working memory, respectively. Given that previous studies that have examined the effects of positive mood on cognition have found P3b effects in the absence behavioural effects (Vanlessen et al., 2014), it was expected that the P3b component would be more sensitive to changes in cognitive processing than behavioural measures, with larger amplitudes indicating the task was performed more easily (Watter et al., 2001). Although *targets* did elicit larger P3b amplitudes relative to *non-targets* in both tasks as expected, P3b amplitudes were not significantly related to mental wellbeing, inconsistent with hypotheses. Studies associating oddball P3b amplitude with positive emotions have only done so in the context of dual-task paradigms, in which the P3b was measured in response to targets on the primary task while participants were also attending to a peripheral secondary task (Putkinen et al., 2017; Vanlessen et al., 2014). It is possible here that although behavioural performance was better in those with higher mental wellbeing, the task was not difficult enough for differences in P3b amplitude to be observed. Alternatively, as the strength of the association between wellbeing and n-back performance was relatively weak, it is also possible that the association between behavioural performance on the n-back and wellbeing was a spurious association unrelated to working memory. Instead, given the stronger association with oddball performance, wellbeing may be primarily associated with the ability to either *sustain* attention or maintain the motor control needed to avoid commission errors.

Within the context of the n-back task, *non-target* P3b amplitude is used to index working memory updating, while *target* P3b amplitude is used to index the ability identify a match with the item held in working memory (Watter et al., 2001). Wellbeing and depression/anxiety symptoms were both associated with the number of commission errors, rather than omission errors, indicating that the difference in performance is most likely

reflects differences in the ability to update working memory on each trial rather than the ability to identify a match. Thus, *non-target* P3b would be expected to correlate more strongly with wellbeing and depression/anxiety symptoms than *target* P3b amplitude. However, this was not detected in the current study. Increasing the task difficulty in future studies might increase the sensitivity of the task to associations between P3b amplitude and mental wellbeing.

In comparison to the oddball and n-back tasks where a positive association was found between wellbeing and behavioural performance, no associations were found between wellbeing and behavioural or EEG measures of inhibition using the go/no-go task. This differs from prior research, including the full TWIN-E sample, which has found positive associations between both behavioural and ERP indices of inhibition with mental wellbeing and positive mood (Lee & Chao, 2012; Routledge et al., 2017; Vanlessen et al., 2015). The lack of a behavioural association within the current sub-sample could be attributed to a loss of statistical power relative to the larger TWIN-E study cohort. Meanwhile, the use of a non-cued go/no-go task could explain the difference between the current results and those from other samples. Two other studies that have reported associations between inhibition and positive mood and wellbeing used cued, anti-saccade tasks (Lee & Chao, 2012; Vanlessen et al., 2015). The anti-saccade paradigm requires participants to inhibit the reflex of looking towards a visual probe appearing to one side of the screen, and instead requiring them to look in the opposite direction (Vanlessen et al., 2015). As this task requires the inhibition of a reflex, it might be more difficult and therefore more sensitive to differences in inhibition ability than the button press used in the current go/no-go paradigm. In addition, both studies (Lee & Chao, 2012; Vanlessen et al., 2015) used cued designs which allow participants to prepare their response before the probe appears on screen. This design was used by Vanlessen et al. (2015) to compare the use of proactive (i.e., preparing a response based on

the cue) versus reactive control (i.e., responding only based on the presentation of the probe). In line with other reports (Paul et al., 2021), Vanlessen et al. (2015) found that positive emotions were associated with increased use of reactive control, indicated by larger N2 amplitude in this group, and a reduced C1 component following the cue. It is possible that the omission of a cue in the current go/no-go paradigm reduced differences in the use of reactive control, as there was no opportunity to use proactive control. Future studies could investigate this by comparing cued and non-cued conditions within the same sample.

In addition to testing associations between cognition and wellbeing, associations with non-clinical depression/anxiety symptoms were also assessed. Within clinical and subclinical samples, depression and anxiety have been associated with deficits in attention, working memory, and inhibition (Snyder, 2013). This has been reflected in reduced P3b and novelty P3a amplitude in clinical and at-risk groups (Bernat et al., 2020; Bruder et al., 2011; Houston et al., 2003), reduced P3b amplitude in working memory tasks (Deldin et al., 2001), and reduced N2 and inhibitory P3a in go/no-go tasks (Kaiser et al., 2003; Katz et al., 2010; Ruchsow et al., 2008; Xia et al., 2020). Within the current sample, no associations were found between depression/anxiety symptoms and ERP components for any of the three tasks. This indicates that the hindering effects of depression and anxiety on cognitive processing is not evident in samples with low symptom levels without familial risk for clinical depression or anxiety. While some studies have reported effects in behavioural measures within subclinical samples (Dotson, 2014; Lukasik et al., 2019), the current sample had lower symptom levels than samples used in previous work. Furthermore, it indicates that low-level depression/anxiety symptoms have at most a small impact on cognition, based on the current behavioural performance data which was not significantly associated with depression/anxiety symptoms after controlling for wellbeing.

Finally, the current study assessed the heritability of each of the ERP components of interest. In line with previous research reporting moderate to high heritability of the P3b component (Hall et al., 2006; Smit et al., 2007; van Beijsterveldt & van Baal, 2002), the current study estimated the heritability of these components from 0.58-0.67 in the auditory oddball and n-back tasks, the remainder of the variance being attributed to unique environmental effects. In addition, the heritability of the N2 and inhibitory P3a components was estimated at 0.62 and 0.49, respectively, also consistent with past research with reported heritability estimates of 0.58-0.60 in adolescents (Anokhin et al., 2004, 2017). However, the N2 component was best explained by dominant, rather than additive, genetic effects in contrast to previous work (Anokhin et al., 2004, 2017). Notably, Anokhin et al. (2017) found that between the ages of 12 and 16, the dizygotic intra-class correlation decreased substantively while the monozygotic correlation remained relatively stable, which suggests that the dominant genetic effect might increase with age (Verweij et al., 2012). This would be consistent with the current findings from an adult sample. However, this was the first study to my knowledge to estimate the heritability of the novelty P3a component, which is a frontally-distributed component elicited in response to novel, non-target stimuli (Bernat et al., 2020; Polich, 2007). While typically studied in a three-tone variation of the auditory oddball, the current study measured the novelty P3a in response to checkerboard stimuli shown throughout the n-back task. Previous research has shown that the novelty P3a is enhanced in more difficult tasks and when the novel stimuli is more distinct from targets (Polich & Comerchero, 2003), thus the use of large checkerboard stimuli in the context of the n-back was well-suited to evoke the novelty P3a component. In the current study, common environment (referring to environmental factors that are shared within twin pairs) accounted for 0.55 of novelty P3a variance. Common environmental effects are rarely reported in EEG heritability estimates, which is likely to do most EEG/ERP studies being underpowered for

twin analysis (van Beijsterveldt & van Baal, 2002). While the current finding should be replicated in future research, it suggests that the association between novelty P3a amplitude and psychopathology risk that has recently emerged (Bernat et al., 2020) is explained by environmental, rather than heritable, factors. Further investigation of this association in clinical samples is warranted despite the lack of an association in the current non-clinical sample.

A limitation of the current study is the choice of sample, which consisted of healthy Australian adults of Caucasian descent with no personal or family history of major mental illness. This sample was chosen to focus on variation in cognition within a healthy population while reducing the confounding effects of mental illness, while also allowing for the investigation of molecular genetic effects (Gatt et al., 2012). However, this choice of sample reduces the generalisability of the results and may have made it more difficult to observe associations between ERP components and differences in mental wellbeing or depression/anxiety symptoms due to the restricted range of symptoms. In addition, the n-back task employed only a 1-back condition, which is relatively easy compared to 2-back and 3-back conditions often also included other studies (e.g., Levens & Gotlib, 2010; Pe et al., 2013). While depressive symptoms have been found to impair performance even on 1-back trials (Dotson, 2014; Harvey et al., 2004), more difficult n-back conditions might be more sensitive to potential effects of mental wellbeing.

This chapter investigated the associations between cognitive function, mental wellbeing, and depression/anxiety symptoms within a non-clinical sample. Although some behavioural indices were associated with both wellbeing and depression/anxiety symptoms, specifically within the oddball and n-back tasks, these differences were not reflected in ERP indices of attention, working memory, or inhibition. Thus, while ERPs might provide insight into the cognitive effects of clinical depression and anxiety and mood, the current

investigation suggested that these indices are not associated with differences in wellbeing or depression/anxiety symptoms within a non-clinical sample. However, the P3b, N2, and inhibitory P3a components all showed significant heritability, supporting previous literature showing that these ERP components could confer heritable risk for mental illness. In contrast, the novelty P3a component, is largely explained by environmental factors.

4.5. References

Anokhin, A. P., Golosheykin, S., Grant, J. D., & Heath, A. C. (2017). Heritability of brain activity related to response inhibition: A longitudinal genetic study in adolescent twins. *International Journal of Psychophysiology*, *115*, 112–124. https://doi.org/10.1016/j.ijpsycho.2017.03.002

Anokhin, A. P., Heath, A. C., & Myers, E. (2004). Genetics, prefrontal cortex, and cognitive control: A twin study of event-related brain potentials in a response inhibition task. *Neuroscience Letters*, *368*(3), 314–318. https://doi.org/10.1016/j.neulet.2004.07.036

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Bernat, E. M., Ellis, J. S., Bachman, M. D., & Hicks, B. M. (2020). P3 amplitude reductions are associated with shared variance between internalizing and externalizing psychopathology. *Psychophysiology*, *57*(7). https://doi.org/10.1111/psyp.13618

Bruder, G. E., Kayser, J., & Tenke, C. E. (2011). *Event-related brain potentials in depression: Clinical, cognitive, and neurophysiological implications*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195374148.013.0257

Bryant, R. A., Williamson, T., Erlinger, M., Felmingham, K. L., Malhi, G., Hinton, M., Williams, L., & Korgaonkar, M. S. (2021). Neural activity during response inhibition associated with improvement of dysphoric symptoms of PTSD after trauma-focused psychotherapy—An EEG-fMRI study. *Translational Psychiatry*, *11*(1), 218. https://doi.org/10.1038/s41398-021-01340-8

Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. *British Journal of Clinical Psychology*, *42*(2), 111–131. https://doi.org/10.1348/014466503321903544

Deldin, P. J., Keller, J., Gergen, J. A., & Miller, G. A. (2001). Cognitive bias and emotion in neuropsychological models of depression. *Cognition & Emotion*, *15*(6), 787–802. https://doi.org/10.1080/02699930143000248

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*(3), 542–575. https://doi.org/10.1037/0033-2909.95.3.542

Dotson, V. M. (2014). Unique and interactive effect of anxiety and depressive symptoms on cognitive and brain function in young and older adults. *Journal of Depression and Anxiety*, *S1*(01). https://doi.org/10.4172/2167-1044.S1-003

Dreisbach, G., & Goschke, T. (2004). How positive affect modulates cognitive control: Reduced perseveration at the cost of increased distractibility. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(2), 343–353. https://doi.org/10.1037/0278-7393.30.2.343

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology. *American Psychologist*, *56*(3), 218–226. https://doi.org/10.1O37//0OO3-O66X.56.3.218

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Gatt, J. M., Korgaonkar, M. S., Schofield, P. R., Harris, A., Clark, C. R., Oakley, K. L., Ram, K., Michaelson, H., Yap, S., Stanners, M., Wise, V., & Williams, L. M. (2012). The TWIN-E project in emotional wellbeing: Study protocol and preliminary heritability results across four MRI and DTI measures. *Twin Research and Human Genetics*, *15*(3), 419–441. https://doi.org/10.1017/thg.2012.12

Gilmore, C. S., Malone, S. M., & Iacono, W. G. (2010). Brain electrophysiological endophenotypes for externalizing psychopathology: A multivariate approach. *Behavior Genetics*, *40*(2), 186–200. https://doi.org/10.1007/s10519-010-9343-3

Gordon, E., Cooper, N., Rennie, C., Hermens, D., & Williams, L. M. (2005). Integrative Neuroscience: The role of a standardized database. *Clinical EEG and Neuroscience*, *36*(2), 64–75. https://doi.org/10.1177/155005940503600205

Gratton, G., Coles, M. G. H., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. *Electroencephalograhy and Clinical Neurophysiology*, *55*(4), 468–484. https://doi.org/10.1016/0013-4694(83)90135-9

Gray, J. R. (2001). Emotional modulation of cognitive control: Approach–withdrawal states double-dissociate spatial from verbal two-back task performance. *Journal of Experimental Psychology: General*, *130*(3), 436–452. https://doi.org/10.1037/0096-3445.130.3.436

Hall, M. H., Schulze, K., Rijsdijk, F., Picchioni, M., Ettinger, U., Bramon, E., Freedman, R., Murray, R. M., & Sham, P. (2006). Heritability and reliability of P300, P50 and duration mismatch negativity. *Behavior Genetics*, *36*(6), 845–857. https://doi.org/10.1007/s10519-006-9091-6

Harvey, P. O., Le Bastard, G., Pochon, J. B., Levy, R., Allilaire, J. F., Dubois, B., & Fossati, P. (2004). Executive functions and updating of the contents of working memory in unipolar depression. *Journal of Psychiatric Research*, *38*(6), 567–576. https://doi.org/10.1016/j.jpsychires.2004.03.003

Houston, R. J., Bauer, L. O., & Hesselbrock, V. M. (2003). Depression and familial risk for substance dependence:a P300 study of young women. *Psychiatry Research: Neuroimaging*, *124*(1), 49–62. https://doi.org/10.1016/S0925-4927(03)00074-X

Huster, R. J., Enriquez-Geppert, S., Lavallee, C. F., Falkenstein, M., & Herrmann, C. S. (2013). Electroencephalography of response inhibition tasks: Functional networks and cognitive contributions. *International Journal of Psychophysiology*, *87*(3), 217–233. https://doi.org/10.1016/j.ijpsycho.2012.08.001

Joormann, J., & Gotlib, I. H. (2010). Emotion regulation in depression: Relation to cognitive inhibition. *Cognition & Emotion*, 19.

Joormann, J., Levens, S. M., & Gotlib, I. H. (2011). Sticky thoughts: Depression and rumination are associated with difficulties manipulating emotional material in working memory. *Psychological Science*, *22*(8), 979–983. https://doi.org/10.1177/0956797611415539

Kaiser, S., Unger, J., Kiefer, M., Markela, J., Mundt, C., & Weisbrod, M. (2003). Executive control deficit in depression: Event-related potentials in a Go/Nogo task. *Psychiatry Research: Neuroimaging*, *122*(3), 169–184. https://doi.org/10.1016/S0925-4927(03)00004-0

Katz, R., De Sanctis, P., Mahoney, J. R., Sehatpour, P., Murphy, C. F., Gomez-Ramirez, M., Alexopoulos, G. S., & Foxe, J. J. (2010). Cognitive control in late-life depression: Response inhibition deficits and dysfunction of the anterior cingulate cortex. *The American Journal of Geriatric Psychiatry*, *18*(11), 1017–1025. https://doi.org/10.1097/JGP.0b013e3181d695f2

Lee, Y.-C., & Chao, H.-F. (2012). The role of active inhibitory control in psychological well-being and mindfulness. *Personality and Individual Differences*, *53*(5), 618–621. https://doi.org/10.1016/j.paid.2012.05.001

Lenth, V. R. (2020). *emmeans: Estimated marginal means, aka least-squares means* (1.5.0) [Computer software]. https://CRAN.R-project.org/package=emmeans

Levens, S. M., & Gotlib, I. H. (2010). Updating positive and negative stimuli in working memory in depression. *Journal of Experimental Psychology: General*, *139*(4), 654–664. https://doi.org/10.1037/a0020283

Llewellyn, D. J., Lang, I. A., Langa, K. M., & Huppert, F. A. (2008). Cognitive function and psychological well-being: Findings from a population-based cohort. *Age and Ageing*, *37*(6), 685–689. https://doi.org/10.1093/ageing/afn194

Lukasik, K. M., Waris, O., Soveri, A., Lehtonen, M., & Laine, M. (2019). The relationship of anxiety and stress with working memory performance in a large non-depressed sample. *Frontiers in Psychology*, *10*, 4. https://doi.org/10.3389/fpsyg.2019.00004

Malone, S. M., Vaidyanathan, U., Basu, S., Miller, M. B., Mcgue, M., & Iacono, W. G. (2014). Heritability and molecular-genetic basis of the P3 event-related brain potential: A genome-wide association study: Genome-wide association study of P3 amplitude. *Psychophysiology*, *51*(12), 1246–1258. https://doi.org/10.1111/psyp.12345

Moran, T. P. (2016). Anxiety and working memory capacity: A meta-analysis and narrative review. *Psychological Bulletin*, *142*(8), 34.

Paul, K., Pourtois, G., van Steenbergen, H., Gable, P., & Dreisbach, G. (2021). Finding a balance: Modulatory effects of positive affect on attentional and cognitive control. *Current Opinion in Behavioral Sciences*, *39*, 136–141. https://doi.org/10.1016/j.cobeha.2021.03.002

Pe, M. L., Koval, P., & Kuppens, P. (2013). Executive well-being: Updating of positive stimuli in working memory is associated with subjective well-being. *Cognition*, *126*(2), 335–340. https://doi.org/10.1016/j.cognition.2012.10.002

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019

Polich, J., & Comerchero, M. D. (2003). P3a from visual stimuli: Typicality, task, and topography. *Brain Topography*, *15*(3), 141–152.

Putkinen, V., Makkonen, T., & Eerola, T. (2017). Music-induced positive mood broadens the scope of auditory attention. *Social Cognitive and Affective Neuroscience*, *12*(7), 1159–1168. https://doi.org/10.1093/scan/nsx038

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Röschke, J., & Wagner, P. (2003). A confirmatory study on the mechanisms behind reduced P300 waves in depression. *Neuropsychopharmacology*, *28*(S1), S9–S12. https://doi.org/10.1038/sj.npp.1300139

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2017). The shared and unique genetic relationship between mental well-being, depression and anxiety symptoms and cognitive function in healthy twins. *Cognition and Emotion*, *31*(7), 1465–1479. https://doi.org/10.1080/02699931.2016.1232242

Ruchsow, M., Groen, G., Kiefer, M., Beschoner, P., Hermle, L., Ebert, D., & Falkenstein, M. (2008). Electrophysiological evidence for reduced inhibitory control in depressed patients in partial remission: A Go/Nogo study. *International Journal of Psychophysiology*, *68*(3), 209–218. https://doi.org/10.1016/j.ijpsycho.2008.01.010

Scheike, T. H., Holst, K. K., & Hjelmborg, J. B. (2014). Estimating heritability for cause specific mortality based on twin studies. *Lifetime Data Analysis*, *20*(2), 210–233. https://doi.org/10.1007/s10985-013-9244-x

Schmeichel, B. J., & Demaree, H. A. (2010). Working memory capacity and spontaneous emotion regulation: High capacity predicts self-enhancement in response to negative feedback. *Emotion*, *10*(5), 739–744. https://doi.org/10.1037/a0019355

Schmeichel, B. J., Volokhov, R. N., & Demaree, H. A. (2008). Working memory capacity and the self-regulation of emotional expression and experience. *Journal of Personality and Social Psychology*, *95*(6), 1526–1540. https://doi.org/10.1037/a0013345

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & de Geus, E. J. C. (2007). Genetic contribution to the P3 in young and middle-aged adults. *Twin Research and Human Genetics*, *10*(2), 335–347. https://doi.org/10.1375/twin.10.2.335

Smith, J. L., Jamadar, S., Provost, A. L., & Michie, P. T. (2013). Motor and non-motor inhibition in the Go/NoGo task: An ERP and fMRI study. *International Journal of Psychophysiology*, *87*(3), 244–253. https://doi.org/10.1016/j.ijpsycho.2012.07.185

Snyder, H. R. (2013). Major depressive disorder is associated with broad impairments on neuropsychological measures of executive function: A meta-analysis and review. *Psychological Bulletin*, *139*(1), 81–132. https://doi.org/10.1037/a0028727

Storbeck, J., & Maswood, R. (2016). Happiness increases verbal and spatial working memory capacity where sadness does not: Emotion, working memory and executive control. *Cognition and Emotion*, *30*(5), 925–938. https://doi.org/10.1080/02699931.2015.1034091

van Beijsterveldt, C. E. M., & van Baal, G. C. M. (2002). Twin and family studies of the human electroencephalogram: A review and a meta-analysis. *Biological Psychology*, *61*(1–2), 111–138. https://doi.org/10.1016/S0301-0511(02)00055-8

Vanlessen, N., De Raedt, R., Koster, E. H. W., & Pourtois, G. (2016). Happy heart, smiling eyes: A systematic review of positive mood effects on broadening of visuospatial attention. *Neuroscience & Biobehavioral Reviews*, *68*, 816–837. https://doi.org/10.1016/j.neubiorev.2016.07.001

Vanlessen, N., De Raedt, R., Mueller, S. C., Rossi, V., & Pourtois, G. (2015). Happy and less inhibited? Effects of positive mood on inhibitory control during an antisaccade task revealed using topographic evoked potential mapping. *Biological Psychology*, *110*, 190–200. https://doi.org/10.1016/j.biopsycho.2015.07.004

Vanlessen, N., Rossi, V., De Raedt, R., & Pourtois, G. (2014). Feeling happy enhances early spatial encoding of peripheral information automatically: Electrophysiological time-course and neural sources. *Cognitive, Affective, & Behavioral Neuroscience*. https://doi.org/10.3758/s13415-014-0262-2

Verweij, K. J. H., Mosing, M. A., Zietsch, B. P., & Medland, S. E. (2012). Estimating Heritability from Twin Studies. In R. C. Elston, J. M. Satagopan, & S. Sun (Eds.), *Statistical Human Genetics: Methods and Protocols* (pp. 151–170). Humana Press. https://doi.org/10.1007/978-1-61779-555-8_9

Watter, S., Geffen, G. M., & Geffen, L. B. (2001). The n-back as a dual-task: P300 morphology under divided attention. *Psychophysiology*, *38*(6), 998–1003. https://doi.org/10.1111/1469-8986.3860998

Watters, A. J., Harris, A. W. F., & Williams, L. M. (2018). Electrocortical reactivity to negative and positive facial expressions in individuals with a family history of major depression. *Biological Psychology*, *136*, 127–135. https://doi.org/10.1016/j.biopsycho.2018.05.015

Williams, L. M., Simms, E., Clark, C. R., Paul, R. H., Rowe, D., & Gordon, E. (2005). The test-retest reliability of a standardized neurocognitive and neurophysiological test battery: 'NeuroMarker'. *International Journal of Neuroscience*, *115*(12), 1605–1630. https://doi.org/10.1080/00207450590958475

Xia, L., Mo, L., Wang, J., Zhang, W., & Zhang, D. (2020). Trait anxiety attenuates response inhibition: Evidence from an ERP study using the Go/NoGo task. *Frontiers in Behavioral Neuroscience*, *14*, 28. https://doi.org/10.3389/fnbeh.2020.00028

Xu, S., Chai, H., Hu, J., Xu, Y., Chen, W., & Wang, W. (2014). Passive event-related potentials to a single tone in treatment-resistant depression, generalized anxiety disorder, and borderline personality disorder patients. *Journal of Clinical Neurophysiology*, *31*(5), 488–492. https://doi.org/10.1097/WNP.0000000000000091

Chapter 5: Improving wellbeing with positive psychology interventions

Published as:

Chilver, M. R., & Gatt, J. M. (2021). Six-week online multi-component positive psychology intervention improves subjective wellbeing in young adults. *Journal of Happiness Studies.* https://doi.org/10.1007/s10902-021-00449-3

Author contributions:

MRC conceptualised the study, created the materials, carried out recruitment & data collection, analysis, and wrote the first draft of the paper. JMG helped guide study design, research questions for analysis and interpretation, and edited drafts.

5.1 Preamble

Chapters 2 to 5 of this thesis focused on identifying EEG correlates of mental wellbeing that might be used to indicate predisposition towards wellbeing within a healthy sample. The results showed that only resting EEG power, not emotional or cognitive ERPs, was associated with mental wellbeing. Because these results were based on a cross-sectional sample, it is unclear whether resting EEG power is associated with a changeable or stable aspect of wellbeing. That is, does resting EEG change as wellbeing changes, or does it indicate a stable marker of one's predisposition towards a certain level of wellbeing? It is also possible that resting EEG would help predict an individual's treatment response to behavioural interventions. As positive psychology interventions (PPIs) have been widely used to improve mental wellbeing in general populations, it seemed fitting to use PPIs to assess whether resting EEG changes with wellbeing levels, and whether resting EEG at baseline can predict early reactivity to PPIs. For this, a short and effective PPI program was needed. The development and assessment of this PPI is presented in the current chapter. Due to the commencement of the ongoing COVID-19 pandemic during this trial, the EEG component could not be carried out. Nonetheless, this study serves to demonstrate that even a relatively short, online PPI can outperform an active control in improving mental wellbeing. This design may be used in future trials in conjunction with EEG measures to clarify the link between resting EEG profile and treatment response.

5.2. Abstract

Improving mental wellbeing has a range of benefits for society, including increased productivity, longevity, and resiliency. However, interventions designed to improve mental wellbeing are often only compared to waitlist controls, leaving uncertainty regarding the mechanisms of their effectiveness. The current study in 326 participants assessed a six-week positive psychology intervention against an active control (n = 163) in an online randomized control trial. Outcome measures included life satisfaction, wellbeing (subjective and psychological wellbeing), stress, depression and anxiety symptoms, and self-compassion. The potential moderating effect of participating during the ongoing COVID-19 pandemic was also explored. The intervention group showed greater improvements in life satisfaction by week six ($\beta = 0.18$, $p = .014$) and were maintained through to seven weeks post-baseline ($\beta = 0.23$, $t = 3.07$, $p = .002$) and remained significant when accounting for COVID-19 restrictions. An improvement in composite wellbeing from baseline to seven weeks post-baseline was detected when accounting for COVID-19 restrictions. Composite wellbeing and total depression and anxiety symptoms improved significantly more in the intervention group for participants with low baseline resiliency resources. These findings support the efficacy of using online multi-component positive psychology interventions in boosting wellbeing and reducing distress symptoms particularly in individuals with fewer resiliency resources who may need added support.

Keywords: COVID-19; randomized control trial; resilience; COMPAS-W; stress

5.3. Introduction

Mental wellbeing can be defined as a state of optimal positive functioning that is related but independent from mental illness (World Health Organization, 2004). States of mental wellbeing are not only desirable in the general population (Parks et al., 2012; Sanders et al., 2019), but also associated with increased longevity (Martín-María et al., 2017) and health (Kushlev et al., 2020), improved work productivity (Gandy et al., 2016; Hamar et al., 2015), and resilience against mental illness (Grant et al., 2013; Iasiello et al., 2019; Lamers et al., 2015). Many people actively seek out methods to improve their mental wellbeing (Parks et al., 2012; Sanders et al., 2019). Developing evidence-based interventions that are accessible to the general population is important to help individuals promote their own wellbeing and improve life satisfaction, health, and productivity of the general population.

A range of interventions including acts of kindness, gratitude, positive reminiscence, and self-compassion have been proposed to improve mental wellbeing (for review see Sin & Lyubomirsky, 2009). Collectively, these interventions have been referred to as positive psychology interventions (PPIs). Some activities have a stronger evidence base than others. Acts of kindness interventions, for instance, have been found to have a moderate effect size (Cohen's d = .28) on subjective wellbeing in a meta-analysis of 27 studies with over 4000 participants (Curry et al., 2018). Another popular PPI, gratitude, has been found to have a similar effect size (d = .31) when compared against a measurement-only control condition, but a much smaller effect size (d = .14) when compared against a matched control activity (Davis et al., 2016). Some other interventions have a smaller research base but show promising outcomes. Positive reminiscence is a psychological intervention commonly used in elderly samples, often applied in nursing homes (Meléndez Moral et al., 2015; Pinquart & Forstmeier, 2012). In these samples, the effect size has also been moderate (Hedge's g = .33) for measures of positive wellbeing based on a meta-analysis of 128 studies (Pinquart &

Forstmeier, 2012). The benefits found in older adults appear to generalise to younger samples based on a study of young adults (Hallford & Mellor, 2016). Relative to these other interventions, self-compassion interventions are reported to have a moderate effect size (Pearson's r = .47) on overall wellbeing in a meta-analysis including 79 samples and over 16,000 participants (Zessin et al., 2015). It is noted that while the observed effect of self-compassion was strong across studies, studies included in the meta-analysis were not required to have a control condition. Nonetheless, each of these interventions show great promise in their effectiveness.

While the aforementioned interventions showed significant positive effects on mental wellbeing on their own, it has been suggested that providing a variety of activities, rather than just one, improves their overall effectiveness (Schueller & Parks, 2012). Variety may make PPIs more appealing to users, resulting in higher engagement and efficacy (Schueller & Parks, 2012). Furthermore, the application of multi-component PPIs (MPPIs) is theorised to reduce hedonic adaptation, improving their effectiveness over time (Bao & Lyubomirsky, 2014; Lyubomirsky, 2010). A meta-analysis of 50 randomised control trials on multi-component PPIs found them to be effective in improving both subjective (g = .34) and psychological (g = .39) wellbeing (Hendriks et al., 2020), with a particular advantage in improving psychological wellbeing over single-component PPIs with effect sizes of d = .34 and d = .20 reported for subjective and psychological wellbeing, respectively (Bolier et al., 2013).

Although these meta-analyses all provide evidence for the efficacy of PPIs, it is unclear whether online interventions can achieve the same results as face-to-face interventions, and whether PPIs are more effective than other non-evidence-based activities due to a placebo effect. For instance, one of the largest studies of online PPIs failed to find a significant difference in wellbeing between the intervention condition, an exercise

intervention, or simply reading a book on positive psychology (Joutsenniemi et al., 2014). However, multiple online studies using wait-list control groups have found significant improvements from PPIs (Drozd et al., 2014; Feicht et al., 2013; Schotanus-Dijkstra et al., 2017). Online interventions that have been effective relative to active control conditions tend to be lower-powered (e.g., n < 50) and focused on older adults, limiting their generalisability (e.g., Hausmann et al., 2017). Thus, larger studies with active control conditions are needed to determine whether MPPIs are more effective than non-MPPI activities.

The current study aimed to address this gap by delivering a six-week online MPPI in a university sample with an active control condition. Three components were chosen for delivery based on past evidence suggesting that between two and four interventions is more effective than one or six interventions (Parks et al., 2012). Given their evidence base and ease of adaptation to an online format, self-compassion, acts of kindness, and positive reminiscence were chosen as interventions for the current study. In comparison, the control group received self-esteem, acts of novelty, and neutral reminiscence modules. The control condition tasks were designed to be as similar as possible to the intervention tasks while omitting the key mechanism believed to account for the positive effects of the interventions. It was hypothesised that there would be a significant interaction between time and condition such that improvements in wellbeing over time would be larger in the treatment group relative to the control group. Changes in self-compassion and depression and anxiety symptoms were also evaluated and expected to improve more in the intervention group relative to controls over the course of the study. A secondary aim of this study was to assess whether baseline levels of resiliency, referring to the level of support systems available to participants, would moderate the effects of the intervention. This was measured using a social-ecological measure developed for adults by the Resilience Research Centre (Liebenberg & Moore, 2018). It was expected that those with lower levels of resiliency

resources at baseline would have more to gain from the intervention and therefore show greater improvements in mental wellbeing than those with higher levels of resiliency resources at baseline.

5.4. Materials and Methods

5.4.1. Design

The study was carried out as a randomised control trial over a six-week period. The intervention and control groups both included three modules, closely matched on activity type. Participants were randomly assigned to a treatment group upon completing the baseline questionnaire using a random number generator in Qualtrics. The order of activities within each condition was also chosen using random number generation with six possibilities. All participants completed the baseline questionnaire prior to gaining access to the modules, which they were instructed to complete once a week over a period of six weeks. This was followed by a questionnaire seven weeks post-baseline. Participants were not informed which condition they were assigned to until the end of the study.

5.4.2. Participants & Procedures

Participants were first year psychology students from the University of New South Wales who volunteered to participate in the study in exchange for course credit. There were three rounds of data collection over the study period, from June 10th 2019 to April 30th 2020. Round 1 occurred from June 10th to August 11th 2019, Round 2 occurred from September 13th to November 30th 2019, and Round 3 occurred from February 14th to April 30th 2020. For context, Australia's first case of COVID-19 community transmission was reported on March 2nd 2020, and COVID-19 restrictions were gradually introduced from mid-March 2020. The University of New South Wales cancelled all in-person classes from March 20th 2020.

Four-hundred twenty-nine participants enrolled in the study, 260 of whom enrolled in Round 3 data collection (i.e., partly during COVID-19). Twenty participants were excluded for not completing the baseline questionnaire. Of the remaining 409 participants, 290 (71%) were female. The mean age of the sample was 19.61 (*SD* = 3.05). All consenting participants were eligible to participate. The study was approved by the Human Research Ethics Behavioural Sciences Committee at UNSW (HC3216).

Upon completing the baseline questionnaire, participants were emailed a link to the first weekly activity which was hosted by Qualtrics (Provo, UT). Reminders were emailed five and seven days after the initial email if the task was not yet completed. The link to the weekly tasks was always sent on the same day of the week as the first task. Participants who did not access any of the weekly task links were considered to have withdrawn consent to participate and excluded from data analysis. Of the 409 participants who completed the baseline questionnaires, 326 participants were included in the final analyses once drop-outs and non-completers were accounted for.

5.4.2.1. Intervention exercises

The intervention condition was made up of three modules, each consisting of two weeks of activities (six weeks in total). Participants were randomly assigned the order of modules, given in the format of ABCABC, such that they would complete part one of each module before completing part two of each module in the same order. Full task instructions can be found in the supplementary materials (S1).

Self-compassion. The instructions for the self-compassion module were based on descriptions of self-compassion activities described in previous research (Breines & Chen, 2012). Participants were instructed to consider events that have made them feel negatively about themselves, then imagine how they might respond to a friend going through a similar

experience. Compassionate responses were defined based on (Neff, 2003a) as those which focus on kindness rather than judgement, shared rather than isolating experiences, and balanced rather than polarised responses (not suppressing or exaggerating the consequences). After considering this definition, participants were instructed to write a self-compassionate letter to themselves about those events. Three unique prompts were given in each week for participants to consider.

Acts of kindness. The acts of kindness instructions were based on those provided in Curry et al. (2018). Participants were asked to brainstorm acts of kindness they would feel comfortable doing for others within the next week. They were specifically instructed to come up with kind acts that they do not usually practice, with either new kind acts for someone they are regularly kind to, or familiar kind acts towards someone they are not usually kind to. After identifying acts of kindness they could complete, participants were instructed to complete the acts before returning to record what they completed. A minimum of 24 hours was required to pass before participants could submit the questionnaire to reduce false responses. In the second part, participants were told they could repeat the same tasks, or different ones.

Positive reminiscence. Positive reminiscence task instructions drew upon research carried out in an online study including young adults (Hallford & Mellor, 2016). The study reported that positive reminiscence responses that focused on problem solving and identity-forming events (i.e., positive events that had a lasting impact on their life) were found to significantly improve self-esteem and meaning, and identity-forming events also improved positive affect. Based on this, three prompts were given in part one and part two that targeted ways in which participants had overcome difficulties in the past or recalled events that had a significant impact on their life. The instructions asked participants to imagine they were telling the story to a friend as they wrote their responses.

5.4.2.2. Control exercises

The control group exercises were chosen based on those used in past research. Self-esteem was used as a control condition for self-compassion (Breines & Chen, 2012), acts of novelty was used as a control for acts of kindness (Buchanan & Bardi, 2010), and neutral reminiscence was used as a control for positive reminiscence (Hallford & Mellor, 2016). The *self-esteem module* differed from the self-compassion module in that participants were asked to focus on the positive aspects of negative situations in their responses rather than being compassionate to themselves. In the *acts of novelty module*, participants were asked to come up with ways to change their routine, either by doing activities they do not usually do, or by changing how they go about their usual activities. In the *control reminiscence module*, participants were given prompts about things they were good at or emotional moments instead of those related to overcoming challenging or defining events.

5.4.3. Measures

Mental wellbeing was measured using a composite measure called the COMPAS-W, designed to capture both subjective and psychological aspects of mental wellbeing (Gatt et al., 2014). This questionnaire consists of an overall Wellbeing score in addition to six subcomponents: *Composure*, relating to one's ability to cope with stressful situations; *Own-worth*, including self-esteem and autonomy; *Mastery*, relating to self-confidence and perceived control of one's environment; *Positivity*, having a positive outlook; *Achievement*, relating to goal orientation and striving; and *Satisfaction*, including satisfaction with life, work, health, and relationships. Items are scored on a scale of one to five, from strongly disagree to strongly agree. The measure has been validated in adult and adolescent samples with demonstrated high internal reliability (r = .84), test-retest reliability (r = .82) and construct validity (Gatt et al., 2014). This measure was administered at baseline, week three,

week six, and at seven weeks post-baseline to balance the ability to track progress over the study duration and reducing load on participants.

The five-item Satisfaction with Life Scale (Diener et al., 1985) was used to measure life satisfaction. This was chosen in addition to the COMPAS-W for its brevity and wide usage as a measure of subjective wellbeing. Items are rated on a 7-point Likert scale. It has high estimated internal reliability in the range of .79-.89, and high test-retest reliability over periods under four months (Pavot & Diener, 2008). This scale was measured weekly.

Stress was measured using the 10-item Perceived Stress Scale (Cohen, 1988; Cohen et al., 1983). It is a well-established stress measure with high internal consistency (Cronbach's alpha = .89) and established convergent and divergent validity (Roberti et al., 2006). Items are rated on a 5-point scale from 0 indicating *Never* to 4 indicating *Very Often.* This scale was administered weekly to monitor ongoing stress levels throughout the intervention, particularly because stress was expected to increase during the university semester.

Depression and anxiety symptoms were measured using the 21-item version of Depression Anxiety Stress Scale (Crawford & Henry, 2003; Lovibond & Lovibond, 1995). It is widely used in non-clinical populations to measure negative symptoms. It has been validated in large samples and has demonstrated high test-retest reliability (Crawford & Henry, 2003). Items are scored on a 4-point scale, with 0 indicating *Did not apply to me at all*, to 3 indicating *Applied to me very much or most of the time.* Participants completed this questionnaire at baseline and at seven weeks post-baseline.

Self-compassion was measured using the Self-Compassion Scale (Neff, 2003b) to determine corresponding changes in self-compassion during the intervention. This questionnaire is the most widely used measure of self-compassion in psychological research. The questionnaire consists of 26 items ranked on a 5-point scale. It includes six subscales:

self-kindness, self-judgement, common humanity, isolation, mindfulness, and over-identification. Participants completed this questionnaire at baseline and at seven weeks post-baseline.

The Resilience Research Centre Adult Resilience Measure (Liebenberg & Moore, 2018) was measured at baseline as an indicator of resiliency resources. It includes 28 items with a 5-point response scale ranging from *Describes me extremely well* to *Does not describe me*. The scale is designed to measure the contextual resources that support resilience processes. These include aspects of social and community inclusion, family support, spirituality, identity, and personal skills and competencies.

5.4.4. Data Analysis

5.4.4.1. Power analysis

An *a priori* power analysis was conducted based on a repeated measures, within by between interaction model using G*power3 (Faul et al., 2007). The power analysis was conducted on the basis of a small effect size ($f = .10$), with $\alpha = .05$ and only two time points to ensure power for measures taken only at baseline and seven weeks post-baseline. The results indicated a sample of 200 participants (n = 100) would be required for 80% power, and a sample of 266 (n = 133) participants would be required for 90% power. Due to higher than expected attrition, the final analysis was instead conducted using a linear mixed model which is better able to handle missing data (Krueger & Tian, 2004).

5.4.4.2. Missing data

Multiple imputation was conducted using the *mice* package in *R* (R Core Team, 2020; van Buuren & Groothuis-Oudshoorn, 2011). This was done separately for each condition using the same method involving classification and regression trees (*cart* method). Twenty-

five imputations were run based on the overall percentage of data missing, which was approximately 25% of all data.

5.4.4.3. Modelling

Linear mixed models were conducted in *R* with the *lme4* package (Bates et al., 2015) using all 25 data imputations and the original, non-imputed dataset. Results from each imputation were pooled using *mice* (van Buuren & Groothuis-Oudshoorn, 2011). Participant ID was added as the random effect and mental health outcomes as fixed effects. We then tested whether the effects were dependent on baseline resiliency resources or gender by adding interaction terms with each variable to each model. Significant resiliency moderation effects were explored *post hoc* by dividing the sample into three equal groups and testing the time by group interaction within each level of resiliency resources. This method was also used to plot the three-way interactions. To evaluate effect size, while Cohen's *d* is not generally reported as an effect size for linear mixed models due to its inability to capture the covariance structure of the random effects, it was estimated here for the significant intervention effects to provide a more direct comparison to past findings. Cohen's *d* was estimated from the standardised beta coefficients and standard error using the following formula: $\beta / \sqrt{(n)} * SE$. Cohen's *d* cannot be estimated for interactions including continuous measures as it is designed for group-based comparisons only. As a rule of thumb, Cohen's *d* effects sizes of 0.20 are considered 'small', 0.5 are considered 'medium', and 0.8 are considered 'large' effects.

As the study was partly conducted during 2020 when Australia began to introduce social distancing restrictions to reduce the spread of COVID-19, we also tested whether participating during these restrictions had an impact on the efficacy of the intervention. To account for this, additional models were run with a continuous variable representing the

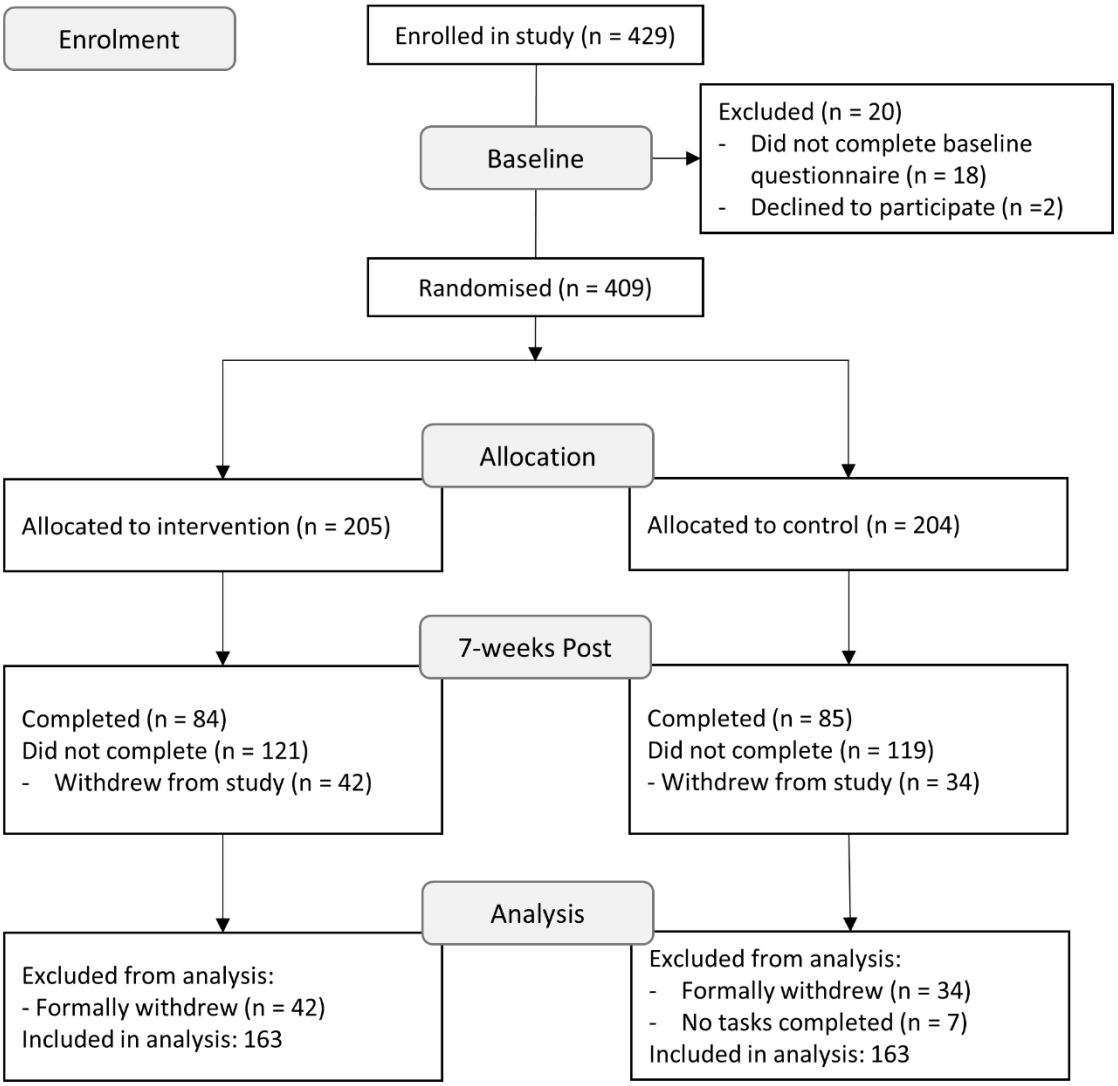
number of weeks that participants were enrolled in the study since the first introduction of COVID-19 restrictions in Australia (entered as March 13, 2020). Thus, participants who enrolled on March 13 would have a score of seven indicating they would have experienced seven weeks of total COVID-19 restrictions by the end of their study participation, whereas participants who were enrolled on February 14, 2020 (the first day of Round 3) would have a score of three and those who enrolled in Round 1 and 2 were given a score of zero.

5.5. Results

5.5.1. Participant characteristics

Of the 429 participants who enrolled in the study, 20 were excluded because they failed to complete the baseline questionnaire, and a further 83 were excluded because they withdrew from the study or did not access any of the weekly tasks. The remaining sample (N = 326, n = 163) had a mean age of 19.7 (SD = 3.2) and included 229 females (70%). One hundred and twenty-five participants completed all six of the weekly activities. A CONSORT diagram depicting participant flow is shown in Figure 5.1.

As shown in Table 5.1, no significant differences were found at baseline for any of the outcome variables of interest including wellbeing, life satisfaction, stress, depression and anxiety symptoms, self-compassion, nor resiliency resources between the control group and the intervention group. T-tests comparing participants who completed at least five of the weekly activities to those who completed less than five suggested that completers had significantly higher Satisfaction with Life Scale scores (M = 24.97, SD = 6.57 vs M = 22.93, SD = 6.57), lower Perceived Stress Scale scores (M = 16.47, SD = 6.48 vs M = 18.78, SD = 6.36), and lower DASS-21 total scores (M = 25.57, SD = 20.50 vs M = 30.93, SD = 23.01) than non-completers.



Weekly participation breakdown

Condition		Week 1	Week 2	Week 3	Week 4	Week 5	Week 6
Intervention	Task and survey	131	109	95	87	89	84
	Survey only	32	28	24	13	4	11
	Not completed	42	68	86	105	112	110
Control	Task and survey	132	125	128	93	89	89
	Survey only	31	20	14	15	18	5
	Not completed	41	59	62	96	97	110

Notes. Task and survey indicates full completion for that week; Survey only indicates that the outcome measures were completed, but the intervention/control task was not completed.

Figure 5.1 CONSORT diagram of study participants

Table 5.1 Descriptive statistics and t-tests comparing the intervention with the control group at baseline

Variable	Intervention *n = 163*		Control *n = 163*		*t* (324)	*p value*
	M	*SD*	*M*	*SD*		
SWLS	23.55	6.89	23.88	6.38	0.45	0.65
PSS	18.56	6.52	17.23	6.42	1.84	0.07
COMPAS-W	94.29	12.77	94.97	12.46	0.49	0.63
DASS-21^{+}	3.10	0.94	2.99	1.02	1.00	0.32
SCS	2.99	0.63	2.94	0.56	0.68	0.50
RRC-ARM	107.66	16.53	106.16	17.51	0.79	0.43

Notes. SWLS = Satisfaction with Life Scale; PSS = Perceived Stress Scale; COMPAS-W = COMPAS-W Wellbeing Score; DASS-21 = Depression Anxiety Stress Scale; SCS = Self-Compassion Scale; RRC-ARM = Resilience Research Centre Adult Resilience Measure. $^{+}$DASS-21 scores were log-transformed.

Bivariate Pearson correlation coefficients between key measures at baseline are shown in Table 5.2. All correlations were significant. As expected, mental wellbeing, life satisfaction, self-compassion, and resiliency resources were all positively correlated with one another, including COMPAS-W subscales, and each was negatively correlated with perceived stress and depression and anxiety symptoms.

5.5.2. Intervention effects

5.5.2.1. COMPAS-W Wellbeing

There was a significant main effect of time for mental wellbeing, indicating that when averaged across both conditions, there was a reduction in wellbeing from baseline to week three ($\beta = -0.15$, $t = -2.52$, $p = .012$) and week six ($\beta = -0.14$, $t = -2.37$, $p = .018$) that was not maintained through to seven weeks post-baseline ($p = .465$). There was no significant interaction between condition and time. However, the moderation analyses showed that the treatment effect on wellbeing was dependent on whether students participated during COVID-19 restrictions and their baseline resiliency resources. While there was no observed

Table 5.2 Bivariate Pearson correlations between the survey measures at baseline

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. COMPAS-W														
2. Composure	0.74													
3. Own-worth	0.79	0.46												
4. Mastery	0.57	0.19	0.46											
5. Positivity	0.75	0.51	0.57	0.25										
6. Achievement	0.60	0.22	0.39	0.44	0.30									
7. Satisfaction	0.86	0.76	0.66	0.23	0.66	0.33								
8. SWLS	0.69	0.57	0.48	0.20	0.63	0.38	0.68							
9. PSS	-0.60	-0.55	-0.50	-0.15	-0.45	-0.24	-0.67	-0.54						
10. DASS-21^{+}	-0.61	-0.55	-0.44	-0.15	-0.50	-0.25	-0.68	-0.50	0.67					
11. Depression^{+}	-0.64	-0.52	-0.47	-0.20	-0.54	-0.34	-0.67	-0.57	0.64	0.84				
12. Anxiety^{+}	-0.50	-0.48	-0.38	-0.12	-0.35	-0.18	-0.59	-0.40	0.55	0.82	0.63			
13. Stress^{+}	-0.51	-0.49	-0.38	-0.11	-0.44	-0.15	-0.59	-0.41	0.63	0.90	0.65	0.67		
14. SCS	0.64	0.66	0.52	0.18	0.47	0.22	0.63	0.51	-0.58	-0.54	-0.50	-0.42	-0.53	
15. RRC-ARM	0.68	0.45	0.51	0.29	0.66	0.45	0.59	0.61	-0.40	-0.46	-0.50	-0.34	-0.40	0.44

Notes. SWLS = Satisfaction with Life Scale; PSS = Perceived Stress Scale; COMPAS-W = COMPAS-W Wellbeing Score; DASS-21 = Depression Anxiety Stress Scale; SCS = Self-Compassion Scale; RRC-ARM = Resilience Research Centre Adult Resilience Measure. $^{+}$DASS-21 and subscales were log-transformed. All correlations are significant at $p < 0.05$.

effect of COVID-19 restrictions on wellbeing, accounting for this in the model revealed a significant condition by time interaction at seven weeks post-baseline (β = 0.33, *t* = 2.21, *estimated Cohen's d* = 0.17, *p* = .028), indicating greater improvements in wellbeing in the intervention group relative to the active control group from baseline to seven weeks post-baseline (Figure 5.2a, Table S1). There was also a significant three-way interaction between resiliency resources, time, and condition at week three (β = -0.15, *t* = -1.36, *p* = .054) and week six (β = -0.19, *t* = -2.32, *p* = .021), indicating greater improvements in wellbeing for those with lower levels of baseline resiliency resources. To examine this effect further, the time by condition interaction was tested in participants with high, medium, and low resiliency resources based on tertile cut-offs. We found the low baseline resiliency group showed greater improvement in the intervention relative to the control condition at week six (β = 0.34, *t* = 2.24, *estimated d* = 0.18, *p* = .026) and seven weeks post-baseline (β = 0.35, *t* = 2.31, *estimated d* = 0.18, *p* = .022) (Figure 5.3a, Table S1). There was a strong overall relationship between resiliency and wellbeing, indicating that higher resiliency was associated with higher wellbeing throughout the intervention.

5.5.2.2. COMPAS-W Composure

Composure significantly increased from baseline to week six (β = 0.14, *t* = 2.00, *p* = .046) and seven weeks post-baseline (β = 0.16, *t* = 2.29, *p* = .023) when averaging across both conditions (Table S2). Neither of these effects remained when accounting for COVID-19 restrictions. There were no effects of condition, and effectiveness of the intervention was not moderated by baseline resiliency resources or gender.

5.5.2.3. COMPAS-W Own-worth

Own-worth significantly reduced from baseline to week three (β = -0.26, *t* = -2.85, *p* = .004) and week six (β = -0.44, *t* = -4.64, *p* < .001), but this was not maintained at post (*p* =

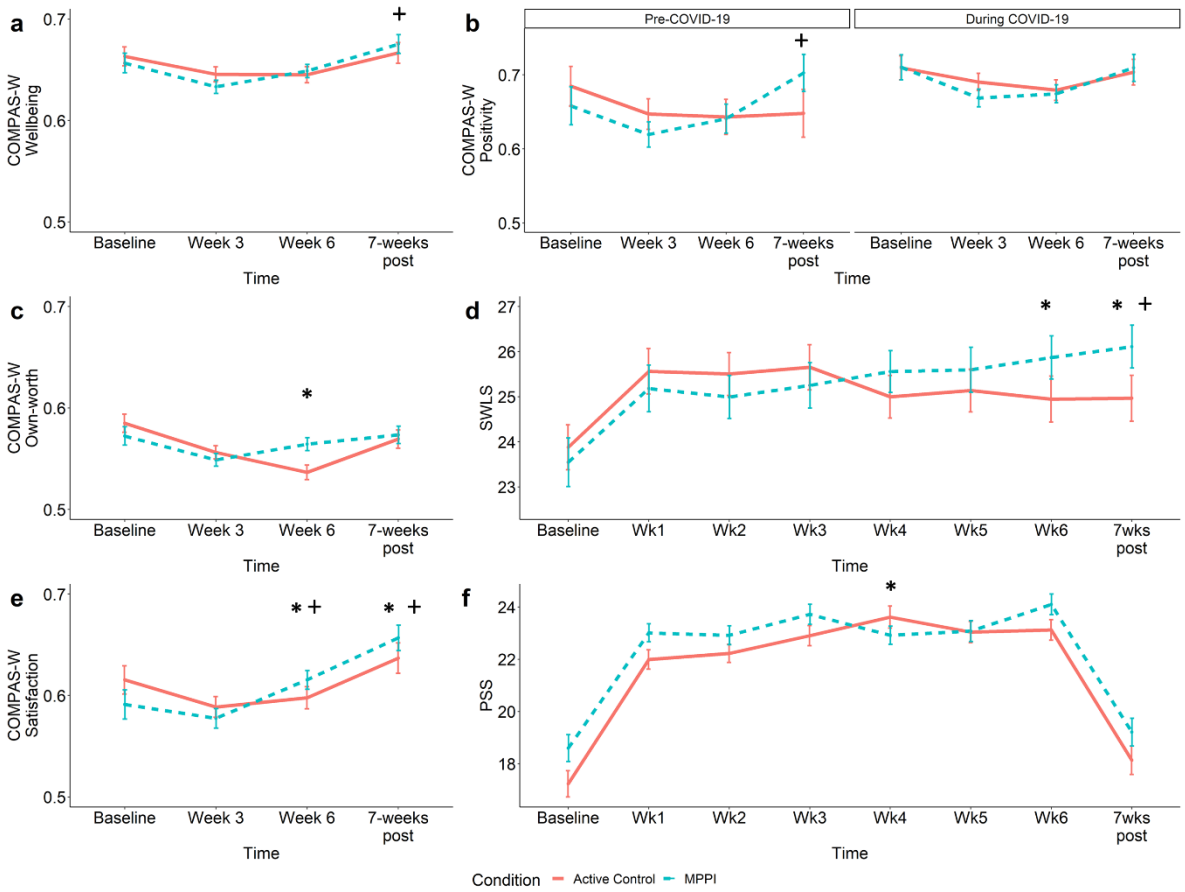


Figure 5.2 Significant overall effects of the intervention relative to the active control group for (a) COMPAS-W Wellbeing, (b) COMPAS-W Positivity (moderated by COVID-19 restrictions), (c) COMPAS-W Own-worth, (d) Satisfaction with Life Scale (SWLS), (e) COMPAS-W Satisfaction, and (f) Perceived Stress Scale (PSS) scores. * indicates significantly larger improvements in the intervention group compared to the control group relative to baseline without accounting for COVID-19 restrictions. + indicates significantly larger improvements in the intervention group compared to the control group relative to baseline when accounting for COVID-19 restrictions. COMPAS-W scores have been normalised to a scale of 0 – 1 for comparative purposes.

.197). A significant condition by time interaction was found for Own-worth at week six (β = 0.38, *t* = 2.80, *estimated d* = 0.22, *p* = .005), with the control condition showing a reduction in own-worth over time as compared to the intervention group who instead showed little change over time (Figure 5.2c, Table S3). When accounting for COVID-19 restrictions, the main effect of time on Own-worth at week three (*p* = .211) and the interaction effect at week six was no longer significant (*p* = .069), but there was still a significant main effect from baseline to week six showing a reduction in Own-worth averaged across both groups (*p* =

.004). The effect of the intervention was not moderated by baseline resiliency resources or gender.

5.5.2.4. COMPAS-W Mastery

There was a significant reduction in Mastery from baseline to week three (β = -0.25, *t* = -3.00, *p* = .003) and week six (β = -0.26, *t* = -3.05, *p* = .002) when averaging across treatment and control conditions that was not maintained through to seven weeks post-baseline (*p* = .205, Table S4). These effects remained when accounting for COVID-19 restrictions. There was no significant time by condition interaction, but there was a three way-interaction between time, condition, and resiliency resources such that the intervention was more effective relative to the control condition for individuals with lower baseline resiliency resources. However, when participants were split into high, medium, and low resiliency groups, no group showed significantly greater improvements in the intervention condition relative to controls over time. The effect of the intervention was not moderated by gender.

5.5.2.5. COMPAS-W Positivity

There was a significant decrease in Positivity from baseline to week three (β = -0.14, *t* = -2.09, *p* = .037) and week six (β = -0.19, *t* = -2.73, *p* = .007) that were not maintained through to seven weeks post-baseline (*p* = .286). However, when accounting for COVID-19 restrictions, the reductions in Positivity at week three (*p* = .144) and week six (*p* = .062) were not significant. Accounting for COVID-19 lockdown revealed a significant time by condition interaction at seven weeks post-baseline demonstrating greater improvements in Positivity for the intervention group relative to the control group (β = 0.49, *t* = 2.79, *estimated d* = 0.21, *p* = .006). There was also a three-way interaction between time, condition, and COVID-19 at seven weeks post-baseline (β = -0.12, *t* = -2.40, *p* = .017) showing that improvements in

Positivity for the intervention group relative to the control group were smaller for individuals participating during COVID-19 restrictions compared to those who participated before the restrictions were introduced (Figure 5.2b, Table S5). Inspection of the graphs suggested the reduced efficacy of the intervention during COVID-19 could be due to the participants in Round 3 having higher baseline Positivity than participants in Rounds 1 and 2. A t-test revealed that this effect was marginally significant ($t(169) = 1.52$, $p = .085$). The effect of the intervention was not moderated by baseline resiliency resources or gender.

5.5.2.6. COMPAS-W Achievement

There was no evidence for any effect of the intervention or time on Achievement in either the control or intervention conditions over the study period, and no moderating effect of COVID-19, baseline resiliency, or gender (Table S6).

5.5.2.7. COMPAS-W Satisfaction

There was a significant decrease in Satisfaction from baseline to week three when averaging across both groups ($\beta = -0.16$, $t = -2.39$, $p = .017$). However, this effect was not maintained at week six ($p = .151$) and reversed with a significant positive effect of time by seven weeks post-baseline ($\beta = 0.14$, $t = 2.05$, $p = .041$). There was a significant time by condition interaction indicating greater improvements in Satisfaction for the intervention compared to controls at week six ($\beta = 0.25$, $t = 2.53$, *estimated* $d = 0.19$, $p = .012$) and seven weeks post-baseline ($\beta = 0.29$, $t = 2.90$, *estimated* $d = 0.23$, $p = .004$) relative to baseline (Figure 5.2e, Table S7). Participating during COVID-19 restrictions was found to have a somewhat positive effect on Satisfaction ($\beta = 0.07$, $t = 2.02$, $p = .043$), and the intervention effect found at week six ($\beta = 0.41$, $t = 2.59$, *estimated* $d = 0.20$, $p = .010$) and seven weeks post-baseline remained significant ($\beta = 0.48$, $t = 2.83$, *estimated* $d = 0.22$, $p = .005$) (Figure 5.2e, Table S7). Furthermore, the main effects of time on Satisfaction at week three ($p =$

.116) and seven weeks post-baseline (p = .766) were not significant when accounting for COVID-19 restrictions in the model. The impact of the intervention on Satisfaction was not moderated by baseline resiliency resources or gender.

5.5.2.8. Satisfaction with Life Scale (SWLS)

There was a significant increase in life satisfaction each week of the program relative to baseline, averaging across both conditions (β = 0.18, t = 3.41, p = .001 at seven weeks post-baseline). There was a significant time by condition interaction indicating greater improvement in life satisfaction for the intervention group relative to the control group from baseline to week six (β = 0.18, t = 2.47, *estimated d* = 0.20, p = .014) and seven weeks post-baseline (β = 0.23, t = 3.07, *estimated d* = 0.26, p = .002) (Figure 5.2d, Table S8). When accounting for COVID-19 restrictions, the main and interaction effects at seven weeks post-baseline remained significant (β = 0.29, t = 2.48, *estimated d* = 0.19, p = .014), but the interaction effect at week six did not (p = .096) (Figure 5.2d, Table S8). There was also a significant positive main effect of participating during COVID-19 restrictions on life satisfaction (β = 0.09, t = 2.35, p = .019). The effect of the intervention was not moderated by baseline resiliency resources or gender.

5.5.2.9. Perceived Stress Scale (PSS)

There was a significant main effect of time on perceived stress such that when averaged across both groups, stress was higher during weeks one to six relative to baseline. There was a significant time by condition interaction at week four indicating lower perceived stress for the intervention condition relative to the control condition (β = -0.31, t = -2.97, *estimated d* = -0.24, p = .003) (Figure 5.2f, Table S9). A similar trend was evident at week five but did not reach significance (β = -0.19, t = -1.79, p = .073). These interactions were not significant when accounting for COVID-19 restrictions (p < .279).

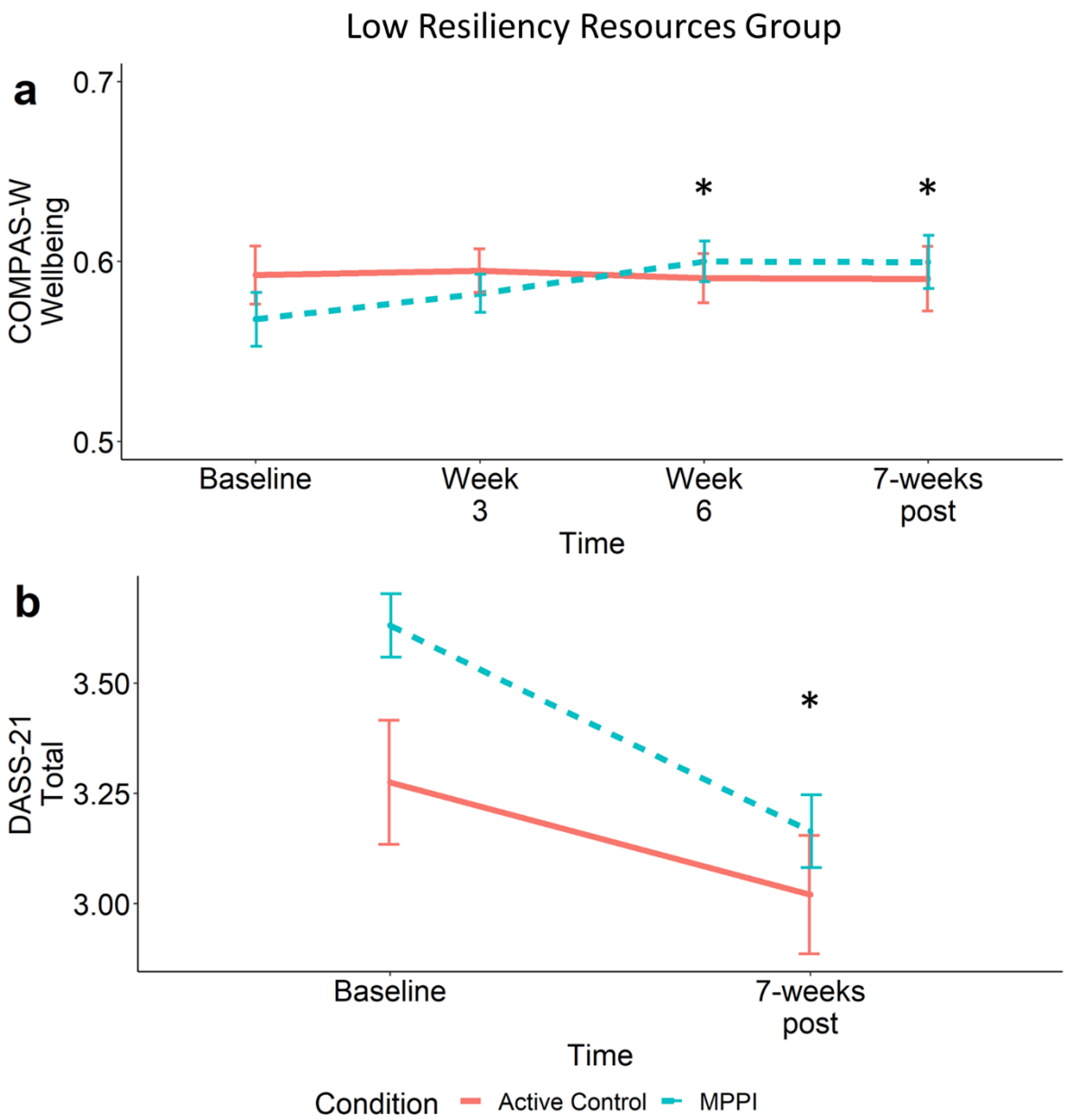


Figure 5.3 Significant moderation effects of intervention effects at low baseline resiliency resources for (a) COMPAS-W Wellbeing and (b) log-transformed DASS-21 depression and anxiety total scores. Low resiliency was defined as a score less than 101 (N = 104, n = 54 in Intervention group) using the Resilience Resource Centre Adult Resilience Measure (RRC-ARM). * indicates significantly greater improvements in the intervention group compared to the control group relative to baseline. COMPAS-W scores were normalised to a scale of 0 – 1 for comparative purposes.

The main effect of time on perceived stress was moderated by baseline resiliency, indicating that those with more resiliency resources at baseline had larger increases in stress during the program, averaged across conditions up to week five ($\beta = 0.14$, $t = 2.63$, $p = .009$). There was also a main effect of gender such that male participants had lower stress than

females at week one (β = -0.50, t = -3.33, p = .001), and there was a significant time by gender interaction indicating that males had larger increases in stress at week three compared to females (β = -0.30, t = -2.03, p = .042).

5.5.2.10. Depression, Anxiety, Stress Scale (DASS-21)

A significant main effect of time was found for the DASS-21 scores, indicating a reduction in symptoms over time when averaged across both groups (β = -0.23, t = -3.20, p = .001). There was no interaction between condition and time, showing no difference between the intervention and control condition at the end of the program. When accounting for COVID-19 restrictions, the main effect of time on DASS-21 scores was no longer significant (p = .248), and there was a main effect of condition showing that the intervention group had lower DASS-21 scores overall relative to the control group, but no interaction suggests the change over time was similar between the two groups. The effect of the intervention was moderated by baseline resiliency (β = 0.21, t = 2.10, p = .036), indicating that the intervention group showed greater symptom reductions relative to the control group for participants with low baseline resiliency resources. This effect is shown in Figure 3.3b (Table S10). The effect of the intervention was not moderated by gender. An analysis of the DASS-21 subscales revealed that the main effect on total DASS-21 scores was driven by reductions in anxiety (β = -0.41, t = -5.29, p < .001) and stress (β = -0.25, t = -3.53, p = .001) seven weeks post-baseline, but not by change in depressive symptoms (Table S11-S13). However, none of the subscales were significantly moderated by resiliency as was observed for the total scale (Table S11-S13).

5.5.2.11. Self-Compassion Scale

No change in self-compassion was noted throughout the experiment, and no interactions were found with COVID-19 restrictions, gender, or baseline resiliency (Table S14).

5.6. Discussion

The aim of this study was to test the effectiveness of a six-week positive psychology intervention program against an active control group. The results indicate that an intervention made up of self-compassion, acts of kindness, and positive reminiscence can improve life satisfaction to a greater degree than comparable control tasks. This was found with both the COMPAS-W Satisfaction subscale ($\beta = 0.29$, estimated $d = 0.22$) and the Satisfaction with Life Scale ($\beta = 0.23$, estimated $d = 0.25$), with both effects emerging regardless of COVID-19 restrictions. COMPAS-W Own-worth (measuring autonomy and self-esteem) also improved in the intervention relative to the control group at week six compared to baseline but was not significant when accounting for COVID-19 restrictions. In contrast, greater improvements in composite wellbeing and COMPAS-W Positivity were found for the intervention group relative to the control group only when accounting for COVID-19 restrictions. The effect of the intervention on composite wellbeing and DASS-21 scores was moderated by baseline resiliency such that those with poor resiliency resources at the start of the trial benefitted more from the intervention condition than those with more resources. Thus, the current trial demonstrates that MPPIs delivered online can be effective in improving life satisfaction regardless of resiliency resources and may improve composite wellbeing and reduce depression, anxiety, and stress symptoms in individuals with poor perceived support.

The positive effect of the intervention on *subjective wellbeing* indicated by improvements in life satisfaction (measured here using both the COMPAS-W Satisfaction subscale and the SWLS) and positivity (COMPAS-W Positivity) is consistent with past studies which have found online MPPIs to improve subjective wellbeing relative to waitlist control groups (Drozd et al., 2014; Feicht et al., 2013; Schotanus-Dijkstra et al., 2017). This improvement has been found across a range of subjective wellbeing measures, including the WHO five-factor wellbeing index after a seven-week intervention (Feicht et al., 2013), affect balance

after a four-week intervention (Drozd et al., 2014), and all components of the Keyes' Mental Health Continuum (Short Form) in those who completed a supported self-help program over eight to twelve weeks (Schotanus-Dijkstra et al., 2017). The effect sizes reported in the current study for measures of subjective wellbeing were small, ranging from d = .22 to d = 0.25 overall (or 0.19 – 0.22 when accounting for COVID). While lower than the overall effect size reported for MPPIs in a recent meta-analysis (g = .34 for subjective wellbeing), our effect sizes are similar to the effect size reported when low-quality studies, defined as meeting less than three of six criteria outlined by the Cochrane Collaboration assessment tool (Higgins et al., 2011), were excluded from the analysis (g = 0.26) (Hendriks et al., 2020). The current study therefore provides evidence that online MPPI programs of only six weeks are a viable approach to improving subjective wellbeing over and above any placebo effect.

In contrast to the effects found for subjective wellbeing, the current intervention was not as effective in improving measures of psychological wellbeing (e.g., COMPAS-W Own-worth, Mastery and Achievement). Other than the study by Schotanus-Dijkstra et al. (2017), very few studies have examined *composite* or *psychological measures of wellbeing* in relation to online MPPIs. The current findings suggest that while composite or psychological wellbeing can be improved (e.g., for both composite wellbeing and Own-worth), an online intervention of six weeks is not sufficient to produce robust effects. Most interventions that have shown improvements in psychological wellbeing in particular used longer trial duration of nine to twelve weeks and are most often delivered in person (Hendriks et al., 2020), which could explain why the improvements in composite wellbeing and Own-worth reported here were only weak effects (d = .17 and .23, respectively) in comparison to past studies (g = .31). Furthermore, while improvements in psychological wellbeing have been reported previously for online interventions, this was in the context of participants having email support from a personal counsellor in addition to the assigned activities, which likely improved the

effectiveness of the intervention compared the current study where all activities were completely self-administered (Schotanus-Dijkstra et al., 2017). Nonetheless, the current study found evidence for temporary benefits in Own-worth (d = .23), capturing psychological wellbeing domains relating to self-esteem and autonomy, and improvements in composite wellbeing were apparent for individuals with poor baseline resiliency. A longer intervention period may improve the effectiveness of the interventions used here. It is also possible that the specific intervention tasks applied here are better suited to improving subjective aspects of wellbeing. Future research should explore whether including activities more targeted to psychological wellbeing outcomes would translate to expanded effects. Such strategies may include activities that focus on promoting elements of Own-worth, Mastery and Achievement (e.g., activities focusing on building self-confidence, strengths, and goal striving).

In addition to effects on wellbeing, there is some evidence that the intervention impacted depression and anxiety symptoms using the DASS-21. Specifically, only intervention participants with poor baseline resiliency showed greater reductions in overall scores compared to control participants. This effect was significant only for the total DASS-21 score and not the specific subscales. By comparison, the perceived stress scale (PSS) was not moderated by resiliency, and the significant reduction in perceived stress for the intervention relative to the control group at week four did not remain significant when accounting for COVID-19 restrictions. It is notable however that the DASS-21 and PSS are two different measures of distress. While the DASS-21 measures *symptoms* of depression, anxiety and stress including for example an inability to relax or a feeling of tension (Lovibond & Lovibond, 1995), the Perceived Stress Scale measures the *appraisal* of events as more or less stressful (Cohen, 1988). Thus, the intervention appears to have been more useful in improving how some symptoms of depression and anxiety are dealt with despite life events (like COVID-19) still being appraised as stressful. Future trials could implement

activities that also focus on the cognitive appraisal of stressful life events, such as cognitive behavioural therapy.

It is important to consider the co-occurrence of the COVID-19 pandemic during the final data collection phase of this study. More than half of the participants were undergoing the study while COVID-19 restrictions were introduced in Australia in March and April 2020. Accounting for COVID-19 restrictions had an impact on some of the study outcomes, particularly in relation to the COMPAS-W total Wellbeing score, where a significant effect of the intervention relative to the control condition was only significant when COVID-19 restrictions were accounted for. Participating during COVID-19 restrictions may have impacted the effectiveness of the Acts of Kindness intervention in particular as participants were more limited in the types of social interactions they could partake in during this time. We also found a three-way interaction between time, condition, and COVID-19 restrictions for COMPAS-W Positivity indicating that while the intervention group showed significant improvements in Positivity relative to the control group (d = .21), these improvements were smaller for those who participated during COVID-19 restrictions. While this could be interpreted as a negative effect of the pandemic, observation of Figure 5.2b suggests that it might be explained by the higher baseline Positivity observed in Round 3 compared to earlier rounds of data collection. This was supported by a t-test that showed a marginally significant trend in this direction (p = .085). This difference could be explained by the timing of Round 3 data collection relative to the academic year. That is, these participants were first year students participating at the beginning of their university training after their summer and Christmas break. In comparison, participants who did not participate during COVID-19 restrictions were in the middle or end of their academic year, which is when mental health problems are known to increase (Duffy et al., 2020). Thus, the reduced effectiveness of the intervention in improving Positivity during COVID-19 restrictions might actually be

explained by these participants having higher Positivity from the beginning of the intervention, resulting in a ceiling effect. Due to this potential confound, COVID-19 effects should be interpreted with caution.

The current study was designed to examine whether a combination of PPIs can improve mental wellbeing rather than to test whether specific interventions were effective, therefore we cannot conclude whether some activities or certain prompts contributed more to the overall effects than others. For instance, while the intervention overall showed significant improvements in wellbeing, there was no significant improvement in self-compassion scores despite the expectation that improved self-compassion would mediate improvements in mental wellbeing (Zessin et al., 2015). It is therefore unclear whether this null result reflects an ineffective self-compassion exercise or a measurement of self-compassion not sensitive to intervention changes. Also, because self-compassion was only measured at the beginning and end of the program, it is possible that the intervention produced temporary improvements in self-compassion scores that were not measured at intermediary time-points and not maintained through to the final assessment. Furthermore, the salience of the event that participants recalled for the self-compassion activity may have varied between participants, potentially affecting its impact. Yet, the salience of events reported was not examined here so we cannot determine their impact. In future studies, alternative and more frequent measures of self-compassion and the salience of chosen events would be needed to clarify these effects.

The use of an active control group instead of a waitlist control is a key strength of the current study. This experimental design helped keep attrition rates similar in both groups as the amount of time spent on tasks was comparable. It also provided evidence that MPPI activities are indeed more effective than non-MPPI activities and helps rule out a placebo effect as participants were blinded to their assigned condition until the conclusion of the study. These results are in contrast to a number of past online MPPIs that did not find

significant improvements in mental wellbeing relative to active controls. For instance, in a large community sample of Finnish adults, an intervention consisting of good deeds, gratitude, optimism, and reducing rumination produced no significant improvement in happiness as measured by the Happiness-Flourishing Scale, or depressive symptoms in the intervention group relative to controls who either exercised or read a book about happiness (Joutsenniemi et al., 2014). However, they did find that the good deeds intervention resulted in the greatest improvements in happiness relative to the other activities, indicating some evidence in support of this specific PPI. Another study conducted in HIV-positive patients failed to find significant improvements in positive affect after a five-session intervention when compared with facilitator interviews (Moskowitz et al., 2017). In contrast, one small study of older adults with osteoarthritis found a significant improvement in life satisfaction and reduction in negative affect following a six-week phone program compared to an active control group (Hausmann et al., 2017). While the current study was based on a very specific age group and socio-educational demographic of university students, it was a relatively larger sample than many previous studies and showed further evidence that online MPPIs can effectively improve subjective wellbeing relative to active controls in a different age group. While current and past findings suggests that MPPIs can be effective across the lifespan, further work should assess whether the findings generalise to different socio-economic backgrounds and vulnerable groups.

Apart from the specific socio-demographic targeted in the current sample, another limitation of the current study is the significant amount of attrition that occurred over the intervention period. This was handled using multiple imputation to account for uncertainty in the missing the data, using an intention to treat analysis, and a larger sample was recruited over three rounds to obtain more study completers. However, it is impossible to know whether individuals who did not complete the study would have responded differently from

those who remained, especially given that those who continued with the study had higher life satisfaction, lower stress and DASS-21 scores at baseline relative to non-completers. Given that we found greater improvements in those with lower resiliency at baseline, it is possible that the intervention effects may have been even more apparent if the non-completers remained in the program. However, it is also possible that those who withdrew from the study did so due to finding the intervention ineffective in meeting their needs. Moreover, while our study was conducted completely online, other approaches using in-person assessments showed a much lower attrition rate (16%) and have suggested that taking this approach could help lower attrition rates in future research (Kushlev et al., 2020). Another limitation is the potential homogeneity within the three training activities that might arise from differences in the salience of events selected (e.g., for the self-compassion or reminiscence exercises), and differences in existing social networks (e.g., for the acts of kindness). In the current study, we did not collate measures of salience or personal networks, but instead analysed the impact of all three training modules as a whole. Future studies could consider such variations and how they may potentially modify the outcomes. Finally, our last time-point was seven weeks post-baseline and so we were unable to examine the long-term maintenance of any significant effects found. Studies using similar intervention tasks have found effects lasting up to six months (Hausmann et al., 2017) suggesting that long-term effects may be present. This remains to be confirmed in future studies.

In conclusion, this study provides new evidence of the effectiveness of MPPIs relative to active control activities in primarily improving subjective wellbeing. The intervention remained effective even when delivered under COVID-19 restrictions in Australia, and there is evidence that composite wellbeing improved more in the intervention group when the impact of COVID-19 restrictions was accounted for in the model. The intervention was found to be more effective in improving composite wellbeing, and depression and anxiety

symptoms within individuals with low baseline resiliency resources, suggesting that MPPIs may be particularly useful for those with fewer resources to cope with stressful situations. Future studies are needed to determine whether different MPPI activities could be used to promote improvements in other aspects of wellbeing such as the COMPAS-W subscales of Composure, Mastery and Achievement. In summary, the current study indicates that online MPPIs including acts of kindness, positive reminiscence, and self-compassion outperform active control tasks and show promise as a means to improve mental wellbeing and symptoms of distress.

5.7. References

Bao, K. J., & Lyubomirsky, S. (2014). Making happiness last: Using the Hedonic Adaptation Prevention Model to extend the success of positive interventions. In *The Wiley Blackwell Handbook of Positive Psychological Interventions* (pp. 371–384). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118315927.ch21

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). https://doi.org/10.18637/jss.v067.i01

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: A meta-analysis of randomized controlled studies. *BMC Public Health*, *13*(1), 119. https://doi.org/10.1186/1471-2458-13-119

Breines, J. G., & Chen, S. (2012). Self-compassion increases self-improvement motivation. *Personality and Social Psychology Bulletin*, *38*(9), 1133–1143. https://doi.org/10.1177/0146167212445599

Buchanan, K. E., & Bardi, A. (2010). Acts of kindness and acts of novelty affect life satisfaction. *The Journal of Social Psychology*, *150*(3), 235–237. https://doi.org/10.1080/00224540903365554

Cohen, S. (1988). Perceived stress in a probability sample of the United States. In *The social psychology of health* (pp. 31–67). Sage Publications, Inc.

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, *24*(4), 385. https://doi.org/10.2307/2136404

Crawford, J. R., & Henry, J. D. (2003). The Depression Anxiety Stress Scales (DASS): Normative data and latent structure in a large non-clinical sample. *British Journal of Clinical Psychology*, *42*(2), 111–131. https://doi.org/10.1348/014466503321903544

Curry, O. S., Rowland, L. A., Van Lissa, C. J., Zlotowitz, S., McAlaney, J., & Whitehouse, H. (2018). Happy to help? A systematic review and meta-analysis of the effects of performing acts of kindness on the well-being of the actor. *Journal of Experimental Social Psychology*, *76*, 320–329. https://doi.org/10.1016/j.jesp.2018.02.014

Davis, D. E., Choe, E., Meyers, J., Wade, N., Varjas, K., Gifford, A., Quinn, A., Hook, J. N., Van Tongeren, D. R., Griffin, B. J., & Worthington, E. L. (2016). Thankful for the little things: A meta-analysis of gratitude interventions. *Journal of Counseling Psychology*, *63*(1), 20–31. https://doi.org/10.1037/cou0000107

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Drozd, F., Mork, L., Nielsen, B., Raeder, S., & Bjørkli, C. A. (2014). Better Days – A randomized controlled trial of an internet-based positive psychology intervention. *The Journal of Positive Psychology*, *9*(5), 377–388. https://doi.org/10.1080/17439760.2014.910822

Duffy, A., Keown-Stoneman, C., Goodday, S., Horrocks, J., Lowe, M., King, N., Pickett, W., McNevin, S. H., Cunningham, S., Rivera, D., Bisdounis, L., Bowie, C. R., Harkness, K., & Saunders, K. E. A. (2020). Predictors of mental health and academic outcomes in first-year university students: Identifying prevention and early-intervention targets. *BJPsych Open*, *6*(3), e46. https://doi.org/10.1192/bjo.2020.24

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Feicht, T., Wittmann, M., Jose, G., Mock, A., von Hirschhausen, E., & Esch, T. (2013). Evaluation of a seven-week web-based happiness training to improve psychological

well-being, reduce stress, and enhance mindfulness and flourishing: A randomized controlled occupational health study. *Evidence-Based Complementary and Alternative Medicine*, *2013*, 1–14. https://doi.org/10.1155/2013/676953

Gandy, W. M., Coberley, C., Pope, J. E., & Rula, E. Y. (2016). Comparison of the utility of two assessments for explaining and predicting productivity change: Well-being versus an HRA. *Journal of Occupational & Environmental Medicine*, *58*(1), 69–75. https://doi.org/10.1097/JOM.0000000000000598

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Grant, F., Guille, C., & Sen, S. (2013). Well-being and the risk of depression under stress. *PLoS ONE*, *8*(7), e67395. https://doi.org/10.1371/journal.pone.0067395

Hallford, D. J., & Mellor, D. (2016). Brief reminiscence activities improve state well-being and self-concept in young adults: A randomised controlled experiment. *Memory*, *24*(10), 1311–1320. https://doi.org/10.1080/09658211.2015.1103875

Hamar, B., Coberley, C., Pope, J. E., & Rula, E. Y. (2015). Well-being improvement in a midsize employer: Changes in well-being, productivity, health risk, and perceived employer support after implementation of a well-being improvement strategy. *Journal of Occupational & Environmental Medicine*, *57*(4), 367–373. https://doi.org/10.1097/JOM.0000000000000433

Hausmann, L. R. M., Youk, A., Kwoh, C. K., Ibrahim, S. A., Hannon, M. J., Weiner, D. K., Gallagher, R. M., & Parks, A. (2017). Testing a positive psychological intervention for osteoarthritis. *Pain Medicine*, *18*(10), 1908–1920. https://doi.org/10.1093/pm/pnx141

Hendriks, T., Schotanus-Dijkstra, M., Hassankhan, A., de Jong, J., & Bohlmeijer, E. (2020). The efficacy of multi-component positive psychology interventions: A systematic review and meta-analysis of randomized controlled trials. *Journal of Happiness Studies*, *21*(1), 357–390. https://doi.org/10.1007/s10902-019-00082-1

Higgins, J. P. T., Altman, D. G., Gotzsche, P. C., Juni, P., Moher, D., Oxman, A. D., Savovic, J., Schulz, K. F., Weeks, L., Sterne, J. A. C., Cochrane Bias Methods Group, & Cochrane Statistical Methods Group. (2011). The Cochrane Collaboration's tool for assessing risk of bias in randomised trials. *BMJ*, *343*(oct18 2), d5928–d5928. https://doi.org/10.1136/bmj.d5928

Iasiello, M., van Agteren, J., Keyes, C. L. M., & Cochrane, E. M. (2019). Positive mental health as a predictor of recovery from mental illness. *Journal of Affective Disorders*, *251*, 227–230. https://doi.org/10.1016/j.jad.2019.03.065

Joutsenniemi, K., Kaattari, C., Härkänen, T., Pankakoski, M., Langinvainio, H., Lönnqvist, J., Mattila, A. S., & Mustonen, P. (2014). E-mail based exercises in happiness, physical activity and readings: A randomized trial on 3274 Finns. *Journal of Psychiatry*, *17*(5).

Krueger, C., & Tian, L. (2004). A comparison of the general linear mixed model and repeated measures ANOVA Using a dataset with multiple missing data points. *Biological Research For Nursing*, *6*(2), 151–157. https://doi.org/10.1177/1099800404267682

Kushlev, K., Heintzelman, S. J., Lutes, L. D., Wirtz, D., Kanippayoor, J. M., Leitner, D., & Diener, E. (2020). Does happiness improve health? Evidence from a randomized controlled trial. *Psychological Science*, *31*(7), 807–821. https://doi.org/10.1177/0956797620919673

Lamers, S. M. A., Westerhof, G. J., Glas, C. A. W., & Bohlmeijer, E. T. (2015). The bidirectional relation between positive mental health and psychopathology in a

longitudinal representative panel study. *The Journal of Positive Psychology*, *10*(6), 553–560. https://doi.org/10.1080/17439760.2015.1015156

Liebenberg, L., & Moore, J. C. (2018). A social ecological measure of resilience for adults: The RRC-ARM. *Social Indicators Research*, *136*(1), 1–19. https://doi.org/10.1007/s11205-016-1523-y

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Lyubomirsky, S. (2010). *Hedonic adaptation to positive and negative experiences*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195375343.013.0011

Martín-María, N., Miret, M., Caballero, F. F., Rico-Uribe, L. A., Steptoe, A., Chatterji, S., & Ayuso-Mateos, J. L. (2017). The impact of subjective well-being on mortality: A meta-analysis of longitudinal studies in the general population. *Psychosomatic Medicine*, *79*(5), 565–575. https://doi.org/10.1097/PSY.0000000000000444

Meléndez Moral, J. C., Fortuna Terrero, F. B., Sales Galán, A., & Mayordomo Rodríguez, T. (2015). Effect of integrative reminiscence therapy on depression, well-being, integrity, self-esteem, and life satisfaction in older adults. *The Journal of Positive Psychology*, *10*(3), 240–247. https://doi.org/10.1080/17439760.2014.936968

Moskowitz, J. T., Carrico, A. W., Duncan, L. G., Cohn, M. A., Cheung, E. O., Batchelder, A., Martinez, L., Segawa, E., Acree, M., & Folkman, S. (2017). Randomized controlled trial of a positive affect intervention for people newly diagnosed with HIV. *Journal of Consulting and Clinical Psychology*, *85*(5), 409–423. https://doi.org/10.1037/ccp0000188

Neff, K. D. (2003a). Self-compassion: An alternative conceptualization of a healthy attitude toward oneself. *Self and Identity*, *2*(2), 85–101. https://doi.org/10.1080/15298860309032

Neff, K. D. (2003b). The development and validation of a scale to measure self-compassion. *Self and Identity*, *2*(3), 223–250. https://doi.org/10.1080/15298860309027

Parks, A. C., Della Porta, M. D., Pierce, R. S., Zilca, R., & Lyubomirsky, S. (2012). Pursuing happiness in everyday life: The characteristics and behaviors of online happiness seekers. *Emotion*, *12*(6), 1222–1234. https://doi.org/10.1037/a0028587

Pavot, W., & Diener, E. (2008). The Satisfaction With Life Scale and the emerging construct of life satisfaction. *The Journal of Positive Psychology*, *3*(2), 137–152. https://doi.org/10.1080/17439760701756946

Pinquart, M., & Forstmeier, S. (2012). Effects of reminiscence interventions on psychosocial outcomes: A meta-analysis. *Aging & Mental Health*, *16*(5), 541–558. https://doi.org/10.1080/13607863.2011.651434

R Core Team. (2020). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Roberti, J. W., Harrington, L. N., & Storch, E. A. (2006). Further psychometric support for the 10-item version of the Perceived Stress Scale. *Journal of College Counseling*, *9*(2), 135–147. https://doi.org/10.1002/j.2161-1882.2006.tb00100.x

Sanders, C. A., Schueller, S. M., Parks, A. C., & Howell, R. T. (2019). Understanding long-term trajectories in web-based happiness interventions: Secondary analysis from two web-based randomized trials. *Journal of Medical Internet Research*, *21*(6), e13253. https://doi.org/10.2196/13253

Schotanus-Dijkstra, M., Drossaert, C. H. C., Pieterse, M. E., Boon, B., Walburg, J. A., & Bohlmeijer, E. T. (2017). An early intervention to promote well-being and flourishing

and reduce anxiety and depression: A randomized controlled trial. *Internet Interventions*, *9*, 15–24. https://doi.org/10.1016/j.invent.2017.04.002

Schueller, S. M., & Parks, A. C. (2012). Disseminating self-help: Positive psychology exercises in an online trial. *Journal of Medical Internet Research*, *14*(3), e63. https://doi.org/10.2196/jmir.1850

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology*, *65*(5), 467–487. https://doi.org/10.1002/jclp.20593

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*(3). https://doi.org/10.18637/jss.v045.i03

World Health Organization. (2004). *Promoting mental health*. World Health Organization. https://public.ebookcentral.proquest.com/choice/publicfullrecord.aspx?p=4978588

Zessin, U., Dickhäuser, O., & Garbade, S. (2015). The relationship between self-compassion and well-being: A meta-analysis. *Applied Psychology: Health and Well-Being*, *7*(3), 340–364. https://doi.org/10.1111/aphw.12051

Appendix C: Chapter 5 Supplementary Results

Six-week online multi-component positive psychology intervention improves subjective wellbeing in young adults

Miranda R. Chilver[a,b] & Justine M. Gatt[a,b*]

[a]*Neuroscience Research Australia, Sydney, Australia;* [b]*School of Psychology, University of New South Wales, Sydney, New South Wales, 2052, Australia*

***Corresponding author:** Justine Gatt, Neuroscience Research Australia, Barker St, Randwick, Sydney, NSW, 2031, Australia, e-mail address: j.gatt@neura.edu.au

Contents

S1. Task instructions 222

Intervention Activities 222

Acts of kindness. 222

Self-compassion. 227

Positive Reminiscence. 230

Control Activities 233

Acts of Novelty. 233

Self-esteem. 236

Reminiscence Control. 239

Table S1. COMPAS-W Wellbeing linear mixed model results 242

Table S2. COMPAS-W Satisfaction linear mixed model results 243

Table S3. COMPAS-W Composure linear mixed model results 244

Table S4. COMPAS-W Own-worth linear mixed model results 245

Table S5. COMPAS-W Mastery linear mixed model results 246

Table S6. COMPAS-W Positivity linear mixed model results 247

Table S7. COMPAS-W Achievement linear mixed model results 248

Table S8. Satisfaction with Life Scale linear mixed model results 249

Table S9. Perceived Stress Scale linear mixed model results 251

Table S10. Depression Anxiety Stress Scale (DASS-21) linear mixed model results 254

Table S11. DASS-21 Depression linear mixed model results 255

Table S12. DASS-21 Anxiety linear mixed model results 256

Table S13. DASS-21 Stress linear mixed model results 257

Table S14. Self-Compassion Scale linear mixed model results. 258

S1. Task instructions

Intervention Activities

Acts of kindness

Part 1. The purpose of this week's exercise is to learn to appreciate the positive impact that we can have on others through our actions. Everyone has experienced the impact of an unexpected act of kindness, and everyone has the ability to do kind things for others. This week you are challenged to complete at least 5 acts of kindness that are new for you.

To do this, first consider the kind acts that you do for others on a regular basis. Perhaps you regularly compliment your friends, help them study, or do chores at home that benefit other people in your household. Take a moment to list some acts of kindness that you already do on a regular basis.

Now that you've considered some of the things you already do, take a moment to consider how you could expand your acts of kindness either for different people or different acts. For instance, if you already feel comfortable buying a coffee for a friend, you might consider buying a coffee for someone else – a stranger or a newer acquaintance. Alternatively, if you feel less comfortable reaching out to someone new, consider new acts of kindness you could do for someone you're already close to. Write a kind message to someone who is important to you, or invite a friend to a social event. Acts of kindness do not have to directed towards a specific person, but could be more general such as taking time to clean up litter in your neighbourhood, making a donation to a charity (clothes, money, or time), or giving a blood donation.

Here are some examples of acts of kindness you could do:

- Leave an encouraging comment on a media post
- Pick up litter
- Give away an unwanted item for free instead of selling
- Make a charity donation
- Do a favour for someone else
- Invite someone to an event
- Buy a coffee for the person behind you in line
- Call a parent or grandparent
- Buy an unexpected gift
- Offer to help a friend study

With these ideas in mind, brainstorm 5 acts of kindness you could realistically do within the next week. Remember it is completely up to you which acts of kindness you choose. There is no obligation to spend money, talk to strangers, or spend a large amount of time. Pick things that you think will be meaningful to the recipients but also achievable within your budget and timeframe.

Now consider what days of the week you could do these activities. Some people might choose to do all 5 acts in a single day, whereas others might prefer to spread them out throughout the week.

Consider the days that would be most suitable for your acts of kindness. Next to each day, fill in the number of acts you think you could do on that day. The total should add up to

5.

At the end of the week, you will be given an opportunity to report back on the acts you actually completed. There is no obligation to stick to the tasks or days identified here. You may find throughout the week that opportunities arise for acts of kindness that you did not consider here. To keep track of these acts, you might find it useful to note down your acts of kindness as you complete them.

Now that you've brainstormed the acts of kindness for the week, please rate how confident you are that you will be able to complete at least 5 acts of kindness within the next 7 days.

Please exit and return using the same link in your email link once you have completed your tasks. All previous responses will be saved.

Following minimum 24-hour break:

The task for this week was to complete new acts of kindness for others that you wouldn't normally do to draw attention to the positive impact that your actions can have on other people.

Please provide a short description of each of the acts of kindness you completed for this task.

Which act of kindness do you think had the greatest positive impact on other people?

Thinking about the act of kindness that you think had the greatest impact on other people, please describe below how you think you made them feel, and why.

Imagine you were a bystander to the act of kindness you described above. How would

you feel as a witness to that act of kindness?

Part 2. Earlier in this study, you were asked to complete 5 acts of kindness that were new for you. The task for this week is to complete an additional 5 acts of kindness. This time you can feel free to repeat the same acts you did last time, or try new things. Take a moment to list some acts of kindness that you already did, or considered doing for this task the first time:

As a reminder, here is a list of ideas that was presented to you before:

- Leave an encouraging comment on a media post
- Pick up litter
- Give away an unwanted item for free instead of selling
- Make a charity donation
- Do a favour for someone else
- Invite someone to an event
- Buy a coffee for the person behind you in line
- Call a parent or grandparent
- Buy an unexpected gift
- Offer to help a friend study

With these ideas in mind, brainstorm 5 acts of kindness you could realistically do within the next week. Remember it is completely up to you which acts of kindness you choose. There is no obligation to spend money, talk to strangers, or spend a large amount of time. Pick things that you think will be meaningful to the recipients but also achievable

within your budget and timeframe.

Now consider what days of the week you could do these activities. Some people might choose to do all 5 acts in a single day, whereas others might prefer to spread them out throughout the week. Consider the days that would be most suitable for your acts of kindness. Next to each day, fill in the number of acts you think you could do on that day. The total should add up to 5.

At the end of the week, you will be given an opportunity to report back on the acts you actually completed. There is no obligation to stick to the tasks or days identified here. You may find throughout the week that opportunities arise for acts of kindness that you did not consider here. To keep track of these acts, you might find it useful to note down your acts of kindness as you complete them.

Please exit and return using your email link once you have completed your tasks. All previous responses will be saved.

Following minimum 24-hour break:

Please provide a short description of each of the acts of kindness you completed for this task.

Which act of kindness do you think had the greatest positive impact on other people?

Thinking about the act of kindness that you think had the greatest impact on other people, please describe below how you think you made them feel, and why.

Imagine you were a bystander to the act of kindness you described above. How would you feel as a witness to that act of kindness?

Self-compassion.

The task for this week is focused on understanding how you view yourself in difficult times. There are 3 separate activities. You should allow at least 5 minutes for each activity. You can do all of them at once, or use your link to return at any time in the next 7 days to complete it. Many people find that they treat themselves differently from how they treat others when going through a difficult time.

To provide an example of this, think about a time when you failed to achieve a goal. This could include getting a lower mark on an exam than you wanted, not being hired for a job you wanted, or disappointing a friend. Please share below some of the things you thought about yourself immediately following this event.

Now consider when someone you admire experienced something similar. They set a goal for themselves that they failed to achieve and were feeling very upset about it. As a friend to this person, what are some things you would consider saying to them following this event?

Now, re-read both responses. Both responses are displayed on-screen.

You might find similar responses in both cases, or you might find that the thoughts you had about yourself were much less compassionate than what you would say to a friend going through a similar experience.

A compassionate response can be characterised by three things:

- A focus on kindness rather than judgement
- A focus on universal rather than isolating experiences

- A balanced approach that doesn't rely on suppressing or exaggerating the consequences

Please re-write a compassionate response to the same experience as above. In writing this response, avoid statements of judgement ("just because you didn't pass that exam doesn't mean you are stupid"), focus on universal experiences ("everyone makes mistakes"), and take a balanced view of the situation ("it will make things harder for next time, but you can still succeed"). You can write in the first person (e.g. "I can...") if you want to.

Briefly outline an experience that made you feel inadequate, that still makes you feel negative emotions when you think about it. With this event in mind, write a self-compassionate response to yourself. It might help to consider how you might comfort a friend in the same situation. It should be 1-2 paragraphs long. In writing this response, avoid statements of judgement ("just because you didn't pass that exam doesn't mean you are stupid"), focus on universal experiences ("everyone makes mistakes"), and take a balanced view of the situation ("it will make things harder for next time, but you can still succeed").

Briefly outline something you did that still makes you feel guilty when you think about it.

With this event in mind, write a self-compassionate response to yourself. It might help to consider how you might comfort a friend in the same situation. It should be 1-2 paragraphs long. In writing this response, avoid statements of judgement ("just because you didn't pass that exam doesn't mean you are stupid"), focus on universal experiences ("everyone makes mistakes"), and take a balanced view of the situation ("it will make things harder for next time, but you can still succeed").

Part 2. The task for this week is focused on understanding how you view yourself when you

make mistakes. This task is similar to one you did a few weeks ago. There are 3 separate activities. You should allow at least 5 minutes for each activity. You can do all of them at once, or use your link to return at any time in the next 7 days to complete it.

Many people find that they treat themselves differently from how they treat others when things don't go as well as expected. To provide an example of this, think about a time when you felt embarrassed for something that you did. This could be related to an assessment, a social interaction, or a mistake you made. Please share below some of the things you thought about yourself immediately following this event. Now think about a time when someone you know was embarrassed about something, but you didn't think it was a big deal.

As a friend to this person, what are some things you would consider saying to them following this event? You might find similar responses in both cases, or you might find that the thoughts you had about yourself were much less compassionate than what you would say to a friend going through a similar experience.

A compassionate response can be characterised by three things:

- A focus on kindness rather than judgement
- A focus on universal rather than isolating experiences
- A balanced approach that doesn’t rely on suppressing or exaggerating the consequences

Please re-write a compassionate response to the same experience as above. In writing this response, avoid statements of judgement (“just because you didn’t pass that exam doesn’t mean you are stupid”), focus on universal experiences (“everyone makes mistakes”), and take

a balanced view of the situation ("it will make things harder for next time, but you can still succeed"). You can write in the first person (e.g. "I can...") if you want to.

Briefly outline something that recently made you feel self-critical. This could be related to an assessment, a social interaction, or a mistake you made. With this event in mind, write a self-compassionate response to yourself. It might help to consider how you might comfort a friend in the same situation. It should be 1-2 paragraphs long. In writing this response, avoid statements of judgement ("just because you didn't pass that exam doesn't mean you are stupid"), focus on universal experiences ("everyone makes mistakes"), and take a balanced view of the situation ("it will make things harder for next time, but you can still succeed").

Briefly outline something that recently made you feel disappointed with yourself. This could be related to an assessment, a social interaction, or a mistake you made.

With this event in mind, write a self-compassionate response to yourself. It might help to consider how you might comfort a friend in the same situation. It should be 1-2 paragraphs long. In writing this response, avoid statements of judgement ("just because you didn't pass that exam doesn't mean you are stupid"), focus on universal experiences ("everyone makes mistakes"), and take a balanced view of the situation ("it will make things harder for next time, but you can still succeed").

Positive Reminiscence.

The task for this week is focused on remembering positive past experiences and considering the impact of those experiences on who you are today.

For this task to be effective, it is important that you choose examples that are particularly meaningful to yourself. There will be three activities, all of which will ask you to

write about a personal experience. You can choose to complete all the activities at once, or spread them throughout the week. Please aim to spend at least 5 minutes on each task.

Take a moment to think about a time when you were faced with a difficult problem, something that was very stressful at the time that you eventually overcame. This event might be something you experienced recently, or it could be from many years ago. It could be relevant to your relationships, your education, your job, or a hobby.

Now that you have an example in mind, try to tell the whole story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe what the problem was, why it was significant for you, why it was difficult to overcome, how you eventually solved it, and how it feels to have overcome it. This task should take around 5 minutes.

Take a moment to think about some of the things you are good at. When thinking of examples, consider things you do regularly or that you enjoy. It could be something you're very good at, or just something you've improved a lot at. It could be relevant to your relationships, your education, your job, or a hobby. Pick one of those skills and write about how you got from where you started – the first time you tried that activity that you can remember, to where you are now. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how you felt about it when you first started, how you started to get better, how your feelings changed as you started to improve, and how it feels now that you consider how far you've come. This task should take around 5 minutes.

Take a moment to think about a time when you were very anxious about something, but you did it anyway. This could be something that happened recently, or a long time ago. It could be relevant to your relationships, your education, your job, or a hobby. With this event

in mind, try to tell it as a story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, how you gained the courage to do it anyway, how it felt as you did it, and what happened afterwards. This task should take around 5 minutes.

Part 2. The task for this week is focused on remembering positive past experiences and considering the impact of those experiences on who you are today. For this task to be effective, it is important that you choose examples that are particularly meaningful to yourself. There will be three activities, all of which will ask you to write about a personal experience. You can choose to complete all the activities at once, or spread them throughout the week. Please aim to spend at least 5 minutes on each task.

Take a moment to think about an event from your childhood that you think has had a lasting impact on who you are today. This event could be relevant to your family life, your school, your friendships, or a one-off life event. Now that you have an example in mind, try to tell the whole story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe the context of the event, what happened, why it was significant for you, and how it has impacted your self-identity. This task should take around 5 minutes.

Take a moment to think about a relationship that you have or had in the past that greatly influenced you. It could be a relationship with a family member, a friend, a romantic partner, colleague, or other relationship. Now that you have an example in mind, try to tell a story about this relationship. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how you met, what your relationship was like, how it influenced you, and how you think you would be different without this person in your life. This task should take around 5 minutes.

Take a moment to think about a major change that happened in your life that has influenced who you are today. This could be something that happened recently, or a long time ago. It could be relevant to your relationships, your education, your job, a hobby, or where you live. With this event in mind, try to tell the whole story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe the context before the change, what the change was, how it happened, how it impacted you at the time, and how it impacts you now. This task should take around 5 minutes.

Control Activities

Acts of Novelty.

Part 1. The purpose of this week's exercise is to learn to appreciate the positive impact that variation can have in our lives. Everyone has experienced the impact of trying new things, and everyone has the ability to add variety in their own lives. This week you are challenged to complete at least 5 activities that add variation to your usual routine.

To do this, first consider the kinds of activities you do on a regular basis. Think about things in your daily routine that stay very similar from week to week. For instance, you might cook similar meals each week, leave for university at the same time of day, or talk to the same people. Take a moment to list some of the things you currently do on a regular basis.

Now that you've considered some of the things you do very regularly, take a moment to consider how you could adapt these activities to add more variation to your life. This does not mean you have to change everything completely, but it could mean changing the content of your activities slightly, or changing the time that you do them. For instance, if you always eat out on a particular day, you could order a different meal or try a new restaurant. Alternatively, if you usually leave university as soon as your classes end, you could try

staying later. You could also add a completely new activity, like playing a new game.

Here are some examples of things you could change:

- Eat somewhere different
- Try a new recipe
- Try a new type of exercise
- Talk to someone you don't regularly talk to
- Play a new game
- Take a different route home
- Wake up at a different time
- Do a regular activity in a different location
- Wear your hair differently

With these ideas in mind, brainstorm 5 ways you could realistically add variation to your life in the next week. Remember it is completely up to you how you do this. Pick things that are different from what you normally do, but also achievable within your budget and timeframe. Now consider what days of the week you could do these activities. Some people might choose to do all 5 variations in a single day, whereas others might prefer to spread them out throughout the week. Consider the days that would be most suitable for your routine variations. Next to each day, fill in the number of acts you think you could do on that day. The total should add up to 5.

At the end of the week, you will be given an opportunity to report back on the

variations you actually completed. There is no obligation to stick to the tasks or days identified here. You may find throughout the week that opportunities arise for variations that you did not consider here. To keep track of the new things that you do, it might be useful to write them down as you complete them. Please exit and return using your email link after you have completed your tasks. All previous responses will be saved.

Following minimum 24-hour break:

The task for this week was to add new variation to your routine to draw attention to the positive impact of trying new things. Please start by indicating how many routine variations you completed as a result of this task (changes that you wouldn't normally do).

Please provide a short description of each of the routine variations you completed for this task.

Which routine variation do you think had the greatest positive impact on yourself?

Thinking about the routine variation that had the greatest positive impact on yourself, please describe below how it made you feel, and why it impacted you.

Part 2. Earlier in this study, you were asked to complete 5 activities that add variation to your usual routine that were new for you. The task for this week is to complete an additional 5 routine variations. This time you can feel free to repeat the same acts you did last time, or try new things. Take a moment to list some acts of novelty that you already did, or considered doing for this task the first time.

As a reminder, here is a list of ideas that was presented to you before:

- Eat somewhere different

- Try a new recipe
- Try a new type of exercise
- Talk to someone you don't regularly talk to
- Play a new game
- Take a different route home
- Wake up at a different time
- Do a regular activity in a different location
- Wear your hair differently

Based on your experience of this task last time, brainstorm 5 ways you could realistically add variation to your life in the next week. Remember it is completely up to you how you do this. Pick things that are different from what you normally do, but also achievable within your budget and timeframe.

Following minimum 24-hour break:

Please provide a short description of each of the routine variations you completed for this task.

Which routine variation do you think had the greatest positive impact on yourself?

Thinking about the routine variation that had the greatest positive impact on yourself, please describe below how it made you feel, and why it impacted you.

Self-esteem.

Part 1. The task for this week is focused on understanding how you view yourself in difficult times. There are 3 separate activities. You should allow at least 5 minutes for each activity. You can do all of them at once, or use your link to return at any time in the next 7 days to complete it.

Many people find that they treat themselves differently from how they treat others when going through a difficult time. To provide an example of this, think about a time when you failed to achieve a goal. This could include getting a lower mark on an exam than you wanted, not being hired for a job you wanted, or disappointing a friend.

Please share below some of the things you thought about yourself immediately following this event. Now consider when someone you admire experienced something similar. They set a goal for themselves that they failed to achieve and were feeling very upset about it. As a friend to this person, what are some things you would consider saying to them following this event?

Now, re-read both responses. Both responses are displayed on-screen.

You might find similar responses in both cases, or you might find that the thoughts you had about yourself were more focused on negative traits than the comments you might make to a friend. Focusing on negative aspects of a situation can make it much harder to move afterwards compared to when you stay focused on your positive traits. Please re-write response to the same experience as above that focuses on your positive traits rather than on your failures.

In writing this response, focus on only the positive aspects surrounding the event you described above. Do your best to avoid acknowledging any negative traits in your response. For anything that comes up that is negative, try to find a positive viewpoint on the same trait.

Please write your response below.

Briefly outline an experience that made you feel inadequate, that still makes you feel negative emotions when you think about it. With this event in mind, write a positive letter to yourself about the situation. It should be 1-2 paragraphs long. In writing this response, focus only on the positive outcomes from this event, and positive traits about yourself that make up for the negative aspects of the experience.

Briefly outline something you did that still makes you feel guilty when you think about it. With this event in mind, write a positive letter to yourself about the situation. It should be 1-2 paragraphs long. In writing this response, focus only on the positive outcomes from this event, and positive traits about yourself that make up for the negative aspects of the experience.

Part 2. The task for this week is focused on understanding how you view yourself when you make mistakes. This task is similar to one you did a few weeks ago. There are 3 separate activities. You should allow at least 5 minutes for each activity. You can do all of them at once, or use your link to return at any time in the next 7 days to complete it. Many people find that they treat themselves differently from how they treat others when things don't go as well as expected.

To provide an example of this, think about a time when you felt embarrassed for something that you did. This could include getting a lower mark on an exam than you wanted, not being hired for a job you wanted, or disappointing a friend. Please share below some of the things you thought about yourself immediately following this event.

Now consider when someone you know was embarrassed about something, but you didn't think it was a big deal. As a friend to this person, what are some things you would

consider saying to them following this event? Both responses are displayed on-screen.

You might find similar responses in both cases, or you might find that the thoughts you had about yourself were more focused on negative traits than the comments you might make to a friend. Focusing on negative aspects of a situation can make it much harder to move afterwards compared to when you stay focused on your positive traits. Please re-write response to the same experience as above that focuses on your positive traits rather than on your failures. In writing this response, focus on only the positive aspects surrounding the event you described above. Do your best to avoid acknowledging any negative traits in your response. For anything that comes up that is negative, try to find a positive viewpoint on the same trait.

Briefly outline an experience that recently made you feel self-critical. This could be related to an assessment, a social interaction, or a mistake you made. With this event in mind, write a positive letter to yourself about the situation. It should be 1-2 paragraphs long. In writing this response, focus only on the positive outcomes from this event, and positive traits about yourself that make up for the negative aspects of the experience.

Briefly outline something that recently made you feel disappointed with yourself. This could be related to an assessment, a social interaction, or a mistake you made.

With this event in mind, write a positive letter to yourself about the situation. It should be 1-2 paragraphs long. In writing this response, focus only on the positive outcomes from this event, and positive traits about yourself that make up for the negative aspects of the experience.

Reminiscence Control.

Part 1. The task for this week is focused on remembering past experiences. For this task to be

effective, it is important that you choose examples that you can remember well. There will be three tasks, all of which will ask you to write about an event in your life. You can choose to complete all the activities at once, or spread them throughout the week. Please aim to spend at least 5 minutes on each task.

Take a moment to think about a time from your past that you can remember well. This event might be something you experienced recently, or it could be from many years ago. It could be relevant to your relationships, your education, your job, or a hobby.

Now that you have an example in mind, try to tell the whole story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, what happened, and how it ended. This task should take around 5 minutes.

Take a moment to think about some of the things you are good at. It could be relevant to your relationships, your education, your job, or a hobby. With that activity in mind, write about the last time you did that activity that you can remember well. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, what happened, and how it ended.

This task should take around 5 minutes.

Take a moment to think about a time when you were emotional about something. This could be something that happened recently, or a long time ago. It could be relevant to your relationships, your education, your job, or a hobby. With this event in mind, try to tell it as a story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, what happened, and how it ended. This task should take around 5 minutes.

Part 2. The task for this week is focused on remembering past experiences. For this task to be effective, it is important that you choose examples that you can remember well. There will be three tasks, all of which will ask you to write about an event in your life. You can choose to complete all the activities at once, or spread them throughout the week. Please aim to spend at least 5 minutes on each task.

Take a moment to think about an event from your childhood that you can remember well. This event could be relevant to your family life, your school, your friendships, or a one-off life event. Now that you have an example in mind, try to tell the whole story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, what happened, and how it ended. This task should take around 5 minutes.

Take a moment to think about a relationship that you have or had in the past. It could be a relationship with a family member, a friend, a romantic partner, colleague, or other relationship. Now that you have an example in mind, try to tell a story about this relationship. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the relationship started, what the relationship was like, and something memorable that happened in this relationship. This task should take around 5 minutes.

Take a moment to think about a major change that has happened in your life. This could be something that happened recently, or a long time ago. It could be relevant to your relationships, your education, your job, a hobby, or where you live. With this event in mind, try to tell it as a story. You can include as much detail as you want, but please do not include names in your response. Imagine you are telling a story to a friend. Describe how the event started, what happened, and how it ended. This task should take around 5 minutes.

Table S1. COMPAS-W Wellbeing linear mixed model results

COMPAS-W Wellbeing		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		0.04	0.07	-0.11	0.18	0.05	0.06	-0.07	0.16	-0.13	0.12	-0.36	0.11
Time	Wk3	***-0.15**	**0.06**	**-0.26**	**-0.03**	***-0.15**	**0.06**	**-0.26**	**-0.04**	-0.18	0.09	-0.36	0.01
	Wk6	***-0.14**	**0.06**	**-0.26**	**-0.03**	***-0.15**	**0.06**	**-0.26**	**-0.03**	***-0.20**	**0.10**	**-0.39**	**0.00**
	7wk post	0.04	0.06	-0.07	0.16	0.04	0.06	-0.07	0.16	-0.02	0.10	-0.22	0.17
Intervention		-0.05	0.11	-0.26	0.15	-0.06	0.08	-0.21	0.10	0.05	0.17	-0.29	0.38
Time x Intervention	Wk3	-0.06	0.08	-0.22	0.10	-0.06	0.08	-0.22	0.10	-0.04	0.14	-0.30	0.23
	Wk6	0.08	0.09	-0.09	0.25	0.08	0.08	-0.08	0.24	0.13	0.14	-0.14	0.40
	7wk post	0.15	0.09	-0.02	0.32	0.15	0.09	-0.02	0.32	*** 0.33**	**0.15**	**0.04**	**0.62**
RRC-ARM						0.67	0.06	0.56	0.79				
Time x RRC-ARM	Wk3					***-0.18**	**0.06**	**-0.29**	**-0.07**				
	Wk6					***-0.12**	**0.06**	**-0.24**	**-0.01**				
	7wk post					0.03	0.06	-0.08	0.14				
Intervention x RRC-ARM						0.08	0.08	-0.08	0.23				
Time x Intervention x RRC-ARM	Wk3					-0.15	0.08	-0.30	0.00				
	Wk6					***-0.19**	**0.08**	**-0.35**	**-0.03**				
	7wk post					-0.11	0.08	-0.27	0.05				
COVID-19 Weeks										0.06	0.04	-0.01	0.14
Time x COVID-19 Weeks	Wk3									0.01	0.03	-0.04	0.07
	Wk6									0.02	0.03	-0.04	0.08
	7wk post									0.03	0.03	-0.03	0.09
Intervention x COVID-19 Weeks										-0.04	0.05	-0.14	0.06
Time x Condition x COVID-19 Weeks	Wk3									-0.01	0.04	-0.09	0.07
	Wk6									-0.02	0.04	-0.10	0.06
	7wk post									-0.07	0.04	-0.16	0.02

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S2. COMPAS-W Composure linear mixed model results

COMPAS-W Composure		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		-0.10	0.08	-0.25	0.05	-0.10	0.07	-0.23	0.04	-0.21	0.12	-0.45	0.03
Time	Wk3	0.06	0.07	-0.07	0.19	0.06	0.07	-0.07	0.19	0.03	0.11	-0.18	0.25
	Wk6	*** 0.14**	**0.07**	**0.00**	**0.27**	*** 0.14**	**0.07**	**0.00**	**0.27**	0.12	0.11	-0.09	0.34
	7wk post	*** 0.16**	**0.07**	**0.02**	**0.30**	*** 0.16**	**0.07**	**0.02**	**0.30**	0.12	0.12	-0.11	0.35
Intervention		-0.03	0.11	-0.24	0.18	-0.03	0.10	-0.22	0.16	0.11	0.18	-0.24	0.45
Time x Intervention	Wk3	0.01	0.10	-0.18	0.20	0.01	0.10	-0.18	0.20	0.02	0.16	-0.31	0.34
	Wk6	-0.02	0.10	-0.21	0.17	-0.02	0.10	-0.21	0.17	0.03	0.16	-0.28	0.33
	7wk post	0.12	0.09	-0.06	0.30	0.12	0.09	-0.06	0.30	0.21	0.17	-0.12	0.55
RRC-ARM						*** 0.39**	**0.07**	**0.25**	**0.52**				
Time x RRC-RM	Wk3					0.04	0.07	-0.09	0.17				
	Wk6					0.09	0.07	-0.04	0.23				
	7wk post					0.06	0.07	-0.07	0.19				
Intervention x RRC-ARM						0.06	0.10	-0.13	0.25				
Time x Intervention x RRC-ARM	Wk3					-0.13	0.09	-0.31	0.05				
	Wk6					-0.17	0.10	-0.37	0.02				
	7wk post					-0.14	0.10	-0.33	0.06				
COVID-19 Weeks										0.04	0.04	-0.03	0.12
Time x COVID-19 Weeks	Wk3									0.01	0.03	-0.05	0.08
	Wk6									0.00	0.03	-0.06	0.07
	7wk post									-0.06	0.09	-0.06	0.09
Intervention x COVID-19 Weeks										-0.05	0.05	-0.16	0.05
Time x Condition x COVID-19 Weeks	Wk3									0.00	0.05	-0.10	0.09
	Wk6									-0.02	0.05	-0.11	0.07
	7wk post									-0.04	0.05	-0.14	0.07

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S3 COMPAS-W Own-worth linear mixed model results

COMPAS-W Own-worth		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		*** 0.18**	**0.08**	**0.03**	**0.32**	*** 0.18**	**0.07**	**0.05**	**0.32**	0.05	0.12	-0.19	0.29
Time	Wk3	***-0.26**	**0.09**	**-0.44**	**-0.08**	***-0.27**	**0.09**	**-0.44**	**-0.09**	-0.19	0.15	-0.49	0.11
	Wk6	***-0.44**	**0.10**	**-0.63**	**-0.26**	***-0.45**	**0.09**	**-0.63**	**-0.27**	***-0.47**	**0.16**	**-0.79**	**-0.15**
	7wk post	-0.13	0.10	-0.32	0.07	-0.13	0.10	-0.32	0.06	-0.20	0.16	-0.51	0.11
Intervention		-0.13	0.11	-0.34	0.08	-0.13	0.10	-0.32	0.06	-0.13	0.17	-0.48	0.21
Time x Intervention	Wk3	0.04	0.13	-0.22	0.30	0.04	0.13	-0.22	0.29	0.04	0.22	-0.39	0.47
	Wk6	*** 0.38**	**0.13**	**0.11**	**0.64**	*** 0.38**	**0.13**	**0.12**	**0.63**	0.41	0.22	-0.03	0.85
	7wk post	0.15	0.14	-0.12	0.43	0.15	0.14	-0.12	0.42	0.40	0.23	-0.05	0.84
RRC-ARM						*** 0.57**	**0.07**	**0.44**	**0.70**				
Time x RRC-ARM	Wk3					***-0.34**	**0.09**	**-0.52**	**-0.16**				
	Wk6					***-0.30**	**0.09**	**-0.48**	**-0.11**				
	7wk post					-0.01	0.09	-0.19	0.17				
Intervention x RRC-ARM						0.00	0.10	-0.19	0.19				
Time x Intervention x RRC-ARM	Wk3					-0.08	0.13	-0.33	0.16				
	Wk6					-0.06	0.13	-0.32	0.19				
	7wk post					-0.05	0.13	-0.31	0.20				
COVID-19 Weeks										0.05	0.04	-0.02	0.12
Time x COVID-19 Weeks	Wk3									0.04	0.22	-0.39	0.47
	Wk6									0.41	0.22	-0.03	0.85
	7wk post									0.03	0.05	-0.07	0.12
Intervention x COVID-19 Weeks										0.00	0.05	-0.10	0.10
Time x Condition x COVID-19 Weeks	Wk3									0.00	0.07	-0.13	0.13
	Wk6									-0.01	0.07	-0.14	0.12
	7wk post									-0.09	0.07	-0.23	0.04

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S4. COMPAS-W Mastery linear mixed model results

COMPAS-W Mastery		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		0.13	0.08	-0.02	0.27	0.13	0.07	-0.01	0.27	0.17	0.12	-0.08	0.41
Time	Wk3	***-0.25**	**0.08**	**-0.42**	**-0.09**	***-0.25**	**0.08**	**-0.41**	**-0.09**	***-0.32**	**0.14**	**-0.59**	**-0.05**
	Wk6	***-0.26**	**0.08**	**-0.42**	**-0.09**	***-0.26**	**0.08**	**-0.42**	**-0.09**	***-0.44**	**0.14**	**-0.72**	**-0.17**
	7wk post	-0.12	0.09	-0.30	0.06	-0.12	0.09	-0.29	0.06	-0.14	0.15	-0.43	0.15
Intervention		0.00	0.11	-0.21	0.21	0.00	0.10	-0.20	0.20	-0.09	0.18	-0.43	0.26
Time x Intervention	Wk3	-0.12	0.12	-0.35	0.12	-0.12	0.12	-0.36	0.11	-0.01	0.20	-0.40	0.38
	Wk6	-0.03	0.12	-0.27	0.21	-0.03	0.12	-0.27	0.21	0.06	0.20	-0.33	0.44
	7wk post	0.04	0.13	-0.21	0.29	0.04	0.13	-0.20	0.29	0.08	0.20	-0.32	0.48
RRC-ARM						*** 0.22**	**0.07**	**0.08**	**0.36**				
Time x RRC-ARM	Wk3					0.03	0.08	-0.13	0.19				
	Wk6					0.05	0.09	-0.12	0.23				
	7wk post					0.02	0.09	-0.15	0.19				
Intervention x RRC-ARM						*** 0.22**	**0.10**	**0.02**	**0.42**				
Time x Intervention x RRC-ARM	Wk3					***-0.25**	**0.12**	**-0.48**	**-0.03**				
	Wk6					-0.21	0.12	-0.44	0.03				
	7wk post					-0.04	0.12	-0.28	0.19				
COVID-19 Weeks										-0.02	0.04	-0.09	0.06
Time x COVID-19 Weeks	Wk3									0.03	0.04	-0.05	0.11
	Wk6									0.07	0.04	-0.01	0.16
	7wk post									0.01	0.04	-0.08	0.09
Intervention x COVID-19 Weeks										0.03	0.05	-0.07	0.14
Time x Condition x COVID-19 Weeks	Wk3									-0.04	0.06	-0.16	0.07
	Wk6									-0.03	0.06	-0.15	0.08
	7wk post									-0.02	0.06	-0.13	0.10

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S5. COMPAS-W Positivity linear mixed model results

COMPAS-W Positivity		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		0.09	0.08	-0.06	0.24	0.10	0.06	-0.02	0.22	-0.06	0.12	-0.30	0.18
Time	Wk3	***-0.14**	**0.07**	**-0.28**	**-0.01**	***-0.15**	**0.07**	**-0.27**	**-0.02**	-0.16	0.11	-0.39	0.06
	Wk6	***-0.19**	**0.07**	**-0.33**	**-0.05**	***-0.19**	**0.07**	**-0.33**	**-0.06**	-0.22	0.12	-0.44	0.01
	7wk post	-0.08	0.08	-0.23	0.07	-0.08	0.07	-0.23	0.06	-0.18	0.13	-0.43	0.08
Intervention		-0.01	0.11	-0.22	0.20	-0.01	0.09	-0.18	0.16	-0.04	0.18	-0.39	0.30
Time x Intervention	Wk3	-0.10	0.10	-0.29	0.09	-0.10	0.09	-0.29	0.08	-0.04	0.17	-0.38	0.29
	Wk6	0.01	0.10	-0.18	0.20	0.01	0.09	-0.17	0.19	0.14	0.16	-0.18	0.47
	7wk post	0.17	0.12	-0.06	0.39	0.17	0.11	-0.05	0.39	*** 0.49**	**0.18**	**0.15**	**0.84**
RRC-ARM						*** 0.66**	**0.06**	**0.54**	**0.78**				
Time x RRC-ARM	Wk3					***-0.25**	**0.07**	**-0.38**	**-0.12**				
	Wk6					***-0.21**	**0.07**	**-0.35**	**-0.07**				
	7wk post					0.04	0.07	-0.10	0.18				
Intervention x RRC-ARM						0.10	0.09	-0.07	0.27				
Time x Intervention x RRC-ARM	Wk3					-0.15	0.10	-0.35	0.05				
	Wk6					-0.13	0.09	-0.31	0.05				
	7wk post					-0.19	0.10	-0.38	0.00				
COVID-19 Weeks										0.06	0.04	-0.02	0.13
Time x COVID-19 Weeks	Wk3									0.01	0.03	-0.06	0.08
	Wk6									0.01	0.04	-0.06	0.08
	7wk post									0.04	0.04	-0.04	0.11
Intervention x COVID-19 Weeks										0.01	0.05	-0.09	0.12
Time x Condition x COVID-19 Weeks	Wk3									-0.02	0.05	-0.12	0.08
	Wk6									-0.05	0.05	-0.15	0.05
	7wk post									***-0.12**	**0.05**	**-0.22**	**-0.02**

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S6. COMPAS-W Achievement linear mixed model results

COMPAS-W Achievement		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		-0.06	0.08	-0.21	0.09	-0.05	0.07	-0.18	0.08	-0.22	0.12	-0.46	0.03
Time	Wk3	0.04	0.06	-0.08	0.16	0.04	0.06	-0.08	0.16	-0.03	0.10	-0.22	0.17
	Wk6	0.04	0.06	-0.08	0.17	0.04	0.06	-0.08	0.17	0.04	0.11	-0.17	0.25
	7wk post	0.05	0.06	-0.08	0.17	0.05	0.06	-0.08	0.17	0.02	0.11	-0.19	0.24
Intervention		0.04	0.11	-0.17	0.25	0.04	0.10	-0.15	0.23	0.22	0.18	-0.13	0.57
Time x Intervention	Wk3	-0.14	0.09	-0.32	0.03	-0.14	0.09	-0.32	0.03	-0.11	0.15	-0.40	0.18
	Wk6	-0.07	0.10	-0.26	0.13	-0.07	0.10	-0.26	0.13	-0.07	0.16	-0.38	0.24
	7wk post	-0.02	0.10	-0.21	0.16	-0.02	0.10	-0.21	0.16	-0.02	0.15	-0.32	0.27
RRC-ARM						*** 0.53**	**0.07**	**0.40**	**0.66**				
Time x RRC-ARM	Wk3					-0.07	0.06	-0.19	0.05				
	Wk6					0.01	0.07	-0.13	0.14				
	7wk post					0.00	0.07	-0.13	0.14				
Intervention x RRC-ARM						-0.18	0.10	-0.37	0.01				
Time x Intervention x	Wk3					0.10	0.09	-0.07	0.28				
RRC-ARM	Wk6					0.00	0.09	-0.18	0.19				
	7wk post					-0.05	0.10	-0.24	0.14				
COVID-19 Weeks										0.06	0.04	-0.01	0.14
Time x COVID-19 Weeks	Wk3									0.03	0.03	-0.03	0.09
	Wk6									0.00	0.03	-0.07	0.07
	7wk post									0.01	0.03	-0.06	0.07
Intervention x COVID-19 Weeks										-0.07	0.05	-0.18	0.04
Time x Condition x COVID-19 Weeks	Wk3									-0.01	0.05	-0.10	0.08
	Wk6									0.00	0.05	-0.09	0.10
	7wk post									0.00	0.05	-0.09	0.09

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S7. COMPAS-W Satisfaction linear mixed model results

COMPAS-W Satisfaction		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		0.02	0.07	-0.13	0.16	0.02	0.06	-0.10	0.15	-0.18	0.12	-0.41	0.06
Time	Wk3	***-0.16**	**0.07**	**-0.29**	**-0.03**	***-0.16**	**0.06**	**-0.28**	**-0.04**	-0.17	0.11	-0.38	0.04
	Wk6	-0.10	0.07	-0.23	0.04	-0.10	0.07	-0.23	0.03	-0.15	0.12	-0.38	0.07
	7wk post	*** 0.14**	**0.07**	**0.01**	**0.27**	*** 0.14**	**0.06**	**0.01**	**0.26**	0.03	0.11	-0.19	0.26
Intervention		-0.14	0.11	-0.35	0.07	-0.14	0.09	-0.32	0.03	-0.05	0.17	-0.38	0.29
Time x Intervention	Wk3	0.07	0.10	-0.12	0.25	0.07	0.09	-0.11	0.25	0.14	0.15	-0.16	0.44
	Wk6	*** 0.25**	**0.10**	**0.06**	**0.44**	*** 0.25**	**0.10**	**0.06**	**0.43**	*** 0.41**	**0.16**	**0.10**	**0.72**
	7wk post	*** 0.29**	**0.10**	**0.09**	**0.48**	*** 0.29**	**0.10**	**0.10**	**0.48**	*** 0.48**	**0.17**	**0.15**	**0.81**
RRC-ARM						*** 0.62**	**0.06**	**0.50**	**0.74**				
Time x RRC-ARM	Wk3					***-0.25**	**0.06**	**-0.38**	**-0.13**				
	Wk6					***-0.22**	**0.07**	**-0.36**	**-0.09**				
	7wk post					-0.01	0.07	-0.14	0.12				
Intervention x RRC-ARM						0.05	0.09	-0.12	0.23				
Time x Intervention x RRC-ARM	Wk3					-0.09	0.09	-0.27	0.08				
	Wk6					-0.11	0.09	-0.30	0.07				
	7wk post					-0.10	0.09	-0.28	0.08				
COVID-19 Weeks										*** 0.07**	**0.04**	**0.00**	**0.15**
Time x COVID-19 Weeks	Wk3									0.01	0.03	-0.06	0.07
	Wk6									0.02	0.03	-0.05	0.09
	7wk post									0.04	0.04	-0.03	0.11
Intervention x COVID-19 Weeks										-0.04	0.05	-0.14	0.07
Time x Condition x COVID-19 Weeks	Wk3									-0.03	0.05	-0.12	0.07
	Wk6									-0.06	0.05	-0.16	0.03
	7wk post									-0.07	0.05	-0.18	0.03

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S8. Satisfaction With Life Scale linear mixed model results

SWLS		Model 1				Model 2				Model 3			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper
Intercept		***-0.20**	**0.08**	**-0.36**	**-0.04**	***-0.20**	**0.06**	**-0.32**	**-0.08**	***-0.43**	**0.12**	**-0.67**	**-0.19**
Time	Wk1	*** 0.26**	**0.05**	**0.17**	**0.35**	*** 0.26**	**0.05**	**0.18**	**0.35**	*** 0.19**	**0.07**	**0.04**	**0.33**
	Wk2	*** 0.26**	**0.05**	**0.16**	**0.35**	*** 0.26**	**0.05**	**0.16**	**0.35**	*** 0.27**	**0.08**	**0.12**	**0.42**
	Wk3	*** 0.28**	**0.05**	**0.19**	**0.37**	*** 0.28**	**0.05**	**0.19**	**0.37**	*** 0.26**	**0.08**	**0.10**	**0.41**
	Wk4	*** 0.18**	**0.05**	**0.08**	**0.28**	*** 0.18**	**0.05**	**0.08**	**0.28**	*** 0.23**	**0.08**	**0.07**	**0.39**
	Wk5	*** 0.20**	**0.05**	**0.10**	**0.30**	*** 0.20**	**0.05**	**0.10**	**0.30**	*** 0.29**	**0.08**	**0.13**	**0.46**
	Wk6	*** 0.17**	**0.05**	**0.07**	**0.27**	*** 0.17**	**0.05**	**0.07**	**0.27**	*** 0.22**	**0.08**	**0.06**	**0.38**
	7wk post	*** 0.18**	**0.05**	**0.08**	**0.28**	*** 0.18**	**0.05**	**0.08**	**0.28**	*** 0.16**	**0.08**	**0.00**	**0.32**
Intervention		-0.08	0.11	-0.29	0.13	-0.08	0.09	-0.25	0.09	0.01	0.18	-0.34	0.35
Time x Intervention	Wk1	-0.02	0.06	-0.14	0.11	-0.02	0.06	-0.14	0.11	0.05	0.11	-0.16	0.25
	Wk2	-0.03	0.07	-0.17	0.10	-0.03	0.07	-0.17	0.10	-0.01	0.11	-0.23	0.21
	Wk3	-0.02	0.07	-0.15	0.12	-0.02	0.07	-0.15	0.12	0.03	0.12	-0.20	0.26
	Wk4	0.13	0.07	-0.01	0.27	0.13	0.07	-0.01	0.26	0.16	0.11	-0.06	0.39
	Wk5	0.11	0.08	-0.03	0.26	0.11	0.07	-0.03	0.26	0.09	0.13	-0.16	0.34
	Wk6	*** 0.18**	**0.07**	**0.04**	**0.33**	*** 0.18**	**0.07**	**0.04**	**0.33**	0.21	0.12	-0.04	0.45
	7wk post	*** 0.23**	**0.07**	**0.08**	**0.37**	*** 0.22**	**0.07**	**0.08**	**0.37**	*** 0.29**	**0.12**	**0.06**	**0.52**
RRC-ARM						*** 0.62**	**0.06**	**0.50**	**0.74**				
Time x RRC-ARM	Wk1					0.06	0.04	-0.03	0.15				
	Wk2					-0.02	0.05	-0.11	0.07				
	Wk3					0.03	0.05	-0.06	0.13				
	Wk4					-0.05	0.05	-0.14	0.05				
	Wk5					-0.05	0.05	-0.15	0.05				
	Wk6					-0.02	0.05	-0.12	0.08				
	7wk post					-0.02	0.06	-0.13	0.10				
Intervention x RRC-ARM						-0.03	0.09	-0.19	0.14				
Time x Intervention x RRC-ARM	Wk1					-0.03	0.06	-0.16	0.09				

	Wk2	-0.06	0.07	-0.19	0.07				
	Wk3	-0.13	0.07	-0.26	0.00				
	Wk4	-0.05	0.07	-0.18	0.09				
	Wk5	-0.07	0.07	-0.21	0.08				
	Wk6	-0.09	0.07	-0.23	0.05				
	7wk post	-0.11	0.08	-0.26	0.04				
COVID-19 Weeks						***0.09**	**0.04**	**0.01**	**0.16**
Time x COVID-19 Weeks	Wk1					0.05	0.11	-0.16	0.25
	Wk2					-0.01	0.11	-0.23	0.21
	Wk3					0.03	0.12	-0.20	0.26
	Wk4					0.16	0.11	-0.06	0.39
	Wk5					0.09	0.13	-0.16	0.34
	Wk6					0.21	0.12	-0.04	0.45
	7wk post					0.29	0.12	0.06	0.52
Intervention x COVID-19 Weeks						-0.03	0.05	-0.14	0.07
Time x Condition x COVID-19 Weeks	Wk1					-0.02	0.03	-0.09	0.04
	Wk2					-0.01	0.03	-0.07	0.06
	Wk3					-0.02	0.03	-0.09	0.05
	Wk4					-0.01	0.03	-0.08	0.06
	Wk5					0.01	0.04	-0.06	0.08
	Wk6					-0.01	0.04	-0.08	0.06
	7wk post					-0.03	0.03	-0.09	0.04

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S9. Perceived Stress Scale linear mixed model results

PSS		Model 1				Model 2				Model 3				Model 4			
		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
				Lower	Upper			Lower	Upper			Lower	Upper			Lower	Upper
Intercept		***-0.66**	**0.07**	**-0.80**	**-0.52**	***-0.66**	**0.07**	**-0.80**	**-0.53**	***-0.56**	**0.12**	**-0.79**	**-0.33**	***-0.49**	**0.09**	**-0.66**	**-0.32**
Time	Wk1	*** 0.79**	**0.07**	**0.66**	**0.92**	*** 0.79**	**0.07**	**0.66**	**0.92**	***0.73**	**0.11**	**0.52**	**0.95**	*** 0.73**	**0.08**	**0.57**	**0.89**
	Wk2	*** 0.83**	**0.07**	**0.69**	**0.96**	*** 0.83**	**0.07**	**0.69**	**0.96**	***0.85**	**0.11**	**0.63**	**1.07**	*** 0.74**	**0.08**	**0.58**	**0.91**
	Wk3	*** 0.93**	**0.07**	**0.80**	**1.07**	*** 0.94**	**0.07**	**0.80**	**1.07**	***0.85**	**0.12**	**0.62**	**1.07**	*** 0.83**	**0.09**	**0.66**	**1.00**
	Wk4	*** 1.05**	**0.07**	**0.90**	**1.19**	*** 1.05**	**0.07**	**0.91**	**1.19**	***0.98**	**0.12**	**0.75**	**1.22**	*** 0.97**	**0.09**	**0.80**	**1.15**
	Wk5	*** 0.95**	**0.07**	**0.81**	**1.09**	*** 0.95**	**0.07**	**0.82**	**1.09**	***0.94**	**0.12**	**0.71**	**1.17**	*** 0.88**	**0.09**	**0.71**	**1.05**
	Wk6	*** 0.96**	**0.07**	**0.82**	**1.10**	*** 0.96**	**0.07**	**0.82**	**1.10**	***1.00**	**0.12**	**0.77**	**1.23**	*** 0.93**	**0.09**	**0.75**	**1.10**
	7wk post	0.12	0.08	-0.03	0.27	0.12	0.08	-0.03	0.27	***0.32**	**0.12**	**0.07**	**0.56**	0.14	0.10	-0.05	0.33
Intervention		0.08	0.10	-0.12	0.28	0.08	0.10	-0.11	0.27	-0.15	0.17	-0.47	0.17	-0.02	0.12	-0.26	0.21
Time x Intervention	Wk1	-0.02	0.10	-0.21	0.17	-0.02	0.09	-0.20	0.17	0.14	0.16	-0.17	0.44	0.05	0.11	-0.17	0.27
	Wk2	-0.08	0.10	-0.27	0.11	-0.08	0.10	-0.26	0.11	0.02	0.16	-0.29	0.33	0.01	0.12	-0.21	0.24
	Wk3	-0.05	0.10	-0.24	0.15	-0.05	0.10	-0.24	0.14	0.10	0.17	-0.22	0.42	0.03	0.12	-0.20	0.26
	Wk4	***-0.31**	**0.10**	**-0.51**	**-0.11**	***-0.31**	**0.10**	**-0.51**	**-0.11**	-0.18	0.17	-0.51	0.15	***-0.22**	**0.13**	**-0.47**	**0.02**
	Wk5	-0.19	0.10	-0.39	0.02	-0.19	0.10	-0.39	0.01	-0.16	0.18	-0.51	0.18	-0.11	0.12	-0.35	0.13
	Wk6	-0.01	0.10	-0.21	0.19	-0.01	0.10	-0.21	0.19	-0.02	0.17	-0.36	0.32	0.04	0.13	-0.21	0.28
	7wk post	-0.04	0.11	-0.26	0.17	-0.04	0.11	-0.25	0.17	-0.24	0.18	-0.61	0.12	0.00	0.13	-0.26	0.26
RRC-ARM						***-0.39**	**0.07**	**-0.52**	**-0.26**								
Time x RRC-ARM	Wk1					*** 0.14**	**0.07**	**0.01**	**0.27**								
	Wk2					*** 0.15**	**0.07**	**0.02**	**0.28**								
	Wk3					*** 0.25**	**0.07**	**0.11**	**0.40**								
	Wk4					*** 0.25**	**0.07**	**0.11**	**0.39**								
	Wk5					*** 0.19**	**0.07**	**0.05**	**0.33**								
	Wk6					*** 0.14**	**0.07**	**0.00**	**0.28**								
	7wk post					-0.02	0.08	-0.18	0.14								

Intervention x RRC-ARM		-0.03	0.10	-0.22	0.15								
Time x Intervention x RRC-ARM	Wk1	0.04	0.09	-0.14	0.23								
	Wk2	0.09	0.10	-0.10	0.27								
	Wk3	-0.03	0.10	-0.23	0.17								
	Wk4	0.02	0.10	-0.18	0.22								
	Wk5	0.03	0.10	-0.17	0.23								
	Wk6	0.07	0.11	-0.14	0.29								
	7wk post	0.07	0.11	-0.15	0.28								
COVID-19 Weeks						-0.04	0.04	-0.11	0.03				
Time x COVID-19 Weeks	Wk1					0.02	0.03	-0.04	0.09				
	Wk2					-0.01	0.03	-0.08	0.06				
	Wk3					0.03	0.04	-0.04	0.10				
	Wk4					0.02	0.04	-0.04	0.09				
	Wk5					0.00	0.04	-0.07	0.08				
	Wk6					-0.02	0.04	-0.09	0.05				
	7wk post					***-0.08**	**0.04**	**-0.15**	**0.00**				
Intervention x COVID-19 Weeks						0.09	0.05	-0.01	0.19				
Time x Condition x COVID-19 Weeks	Wk1					-0.06	0.05	-0.15	0.03				
	Wk2					-0.04	0.05	-0.13	0.06				
	Wk3					-0.06	0.05	-0.16	0.04				
	Wk4					-0.05	0.05	-0.15	0.05				
	Wk5					-0.01	0.05	-0.12	0.10				
	Wk6					0.00	0.05	-0.10	0.11				
	7wk post					0.08	0.06	-0.04	0.20				
Gender										***-0.50**	**0.15**	**-0.79**	**-0.20**
Time x Gender	Wk1									0.18	0.14	-0.10	0.46
	Wk2									0.24	0.14	-0.04	0.52
	Wk3									*** 0.30**	**0.15**	**0.01**	**0.59**

	Wk4	0.23	0.16	-0.08	0.53
	Wk5	0.20	0.15	-0.10	0.50
	Wk6	0.09	0.15	-0.21	0.39
	7wk post	-0.05	0.17	-0.39	0.28
Intervention x Gender		0.25	0.22	-0.18	0.68
Time x Condition x Gender	Wk1	-0.21	0.21	-0.62	0.20
	Wk2	-0.28	0.21	-0.70	0.14
	Wk3	-0.21	0.22	-0.64	0.22
	Wk4	-0.27	0.23	-0.72	0.18
	Wk5	-0.23	0.23	-0.68	0.22
	Wk6	-0.17	0.25	-0.64	0.31
	7wk post	-0.19	0.25	-0.67	0.29

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time x intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. Model 4 tests the moderation effect of gender. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; reference level for Time is baseline; reference level for Intervention is Control; reference level for Gender is Female. *$p < 0.05$, n = 136.

Table S10. Depression Anxiety Stress Scale (total DASS-21) linear mixed model results

DASS-21 Total	Model 1				Model 2				Model 3			
	β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
			Lower	Upper			Lower	Upper			Lower	Upper
Intercept	0.06	0.07	-0.08	0.21	0.06	0.07	-0.07	0.19	0.21	0.12	-0.02	0.44
Time	***-0.23**	**0.07**	**-0.36**	**-0.09**	***-0.23**	**0.07**	**-0.36**	**-0.09**	-0.13	0.12	-0.36	0.09
Intervention	-0.05	0.10	-0.25	0.15	-0.05	0.09	-0.23	0.13	***-0.35**	**0.17**	**-0.68**	**-0.02**
Time x Intervention	0.02	0.10	-0.17	0.22	0.02	0.10	-0.17	0.22	0.09	0.17	-0.24	0.41
RRC-ARM					***-0.34**	**0.07**	**-0.47**	**-0.22**				
Time x RRC-ARM					0.01	0.07	-0.13	0.15				
Intervention x RRC-ARM					-0.18	0.09	-0.36	0.00				
Time x Intervention x RRC-ARM					*** 0.21**	**0.10**	**0.01**	**0.41**				
COVID-19 Weeks									-0.06	0.04	-0.13	0.01
Time x COVID-19 Weeks									-0.04	0.03	-0.10	0.03
Intervention x COVID-19 Weeks									*** 0.11**	**0.05**	**0.01**	**0.21**
Time x Condition x COVID-19 Weeks									-0.02	0.05	-0.12	0.07

Notes. All model output based on standardised outcomes and DASS-21 scores have been log transformed. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; Time indicates change from baseline to 7-weeks post; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S11. DASS-21 Depression linear mixed model results

DASS-21 Depression	Model 1				Model 2				Model 3			
	β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
			Lower	Upper			Lower	Upper			Lower	Upper
Intercept	-0.03	0.07	-0.18	0.11	-0.04	0.07	-0.16	0.09	0.14	0.12	-0.09	0.38
Time	0.03	0.07	-0.11	0.18	0.03	0.07	-0.11	0.18	0.08	0.12	-0.16	0.32
Intervention	-0.01	0.10	-0.22	0.19	-0.01	0.09	-0.19	0.17	-0.27	0.17	-0.60	0.07
Time x Intervention	-0.08	0.10	-0.28	0.12	-0.08	0.10	-0.27	0.12	-0.06	0.17	-0.40	0.27
RRC-ARM					-0.44	0.07	-0.57	-0.32				
Time x RRC-ARM					0.08	0.07	-0.06	0.22				
Intervention x RRC-ARM					-0.12	0.09	-0.30	0.06				
Time x Intervention x RRC-ARM					0.17	0.10	-0.03	0.37				
COVID-19 Weeks									-0.07	0.04	-0.14	0.00
Time x COVID-19 Weeks									-0.02	0.04	-0.09	0.05
Intervention x COVID-19 Weeks									0.10	0.05	0.00	0.20
Time x Condition x COVID-19 Weeks									0.00	0.05	-0.11	0.10

Notes. All model output based on standardised outcomes and DASS-21 scores have been log transformed. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; Time indicates change from baseline to 7-weeks post; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S12. DASS-21 Anxiety linear mixed model results

DASS-21 Anxiety	Model 1				Model 2				Model 3			
	β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
			Lower	Upper			Lower	Upper			Lower	Upper
Intercept	*** 0.15**	**0.07**	**0.01**	**0.29**	*** 0.15**	**0.07**	**0.01**	**0.28**	0.21	0.12	-0.02	0.45
Time	***-0.41**	**0.08**	**-0.56**	**-0.26**	***-0.41**	**0.08**	**-0.55**	**-0.26**	***-0.30**	**0.13**	**-0.55**	**-0.05**
Intervention	-0.06	0.10	-0.26	0.14	-0.06	0.10	-0.25	0.13	***-0.35**	**0.17**	**-0.68**	**-0.02**
Time x Intervention	0.10	0.11	-0.11	0.31	0.10	0.11	-0.11	0.31	0.09	0.18	-0.28	0.45
RRC-ARM					***-0.25**	**0.07**	**-0.39**	**-0.12**				
Time x RRC-RM					0.02	0.08	-0.13	0.17				
Intervention x RRC-ARM					-0.10	0.10	-0.29	0.09				
Time x Intervention x RRC-ARM					0.19	0.11	-0.03	0.40				
COVID-19 Weeks									-0.03	0.04	-0.10	0.04
Time x COVID-19 Weeks									-0.04	0.04	-0.12	0.04
Intervention x COVID-19 Weeks									*** 0.11**	**0.05**	**0.01**	**0.21**
Time x Condition x COVID-19 Weeks									0.01	0.06	-0.10	0.11

Notes. All model output based on standardised outcomes and DASS-21 scores have been log transformed. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; Time indicates change from baseline to 7-weeks post; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S13. DASS-21 Stress linear mixed model results

DASS-21 Stress	Model 1				Model 2				Model 3			
	β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
			Lower	Upper			Lower	Upper			Lower	Upper
Intercept	0.06	0.07	-0.08	0.20	0.05	0.07	-0.08	0.19	0.15	0.12	-0.08	0.39
Time	***-0.25**	**0.07**	**-0.40**	**-0.11**	***-0.25**	**0.07**	**-0.39**	**-0.11**	-0.13	0.12	-0.36	0.11
Intervention	-0.06	0.10	-0.26	0.14	-0.06	0.10	-0.25	0.13	-0.28	0.17	-0.61	0.05
Time x Intervention	0.07	0.10	-0.14	0.27	0.07	0.10	-0.13	0.27	0.08	0.17	-0.26	0.42
RRC-ARM					***-0.29**	**0.07**	**-0.42**	**-0.16**				
Time x RRC-RM					-0.01	0.08	-0.16	0.14				
Intervention x RRC-ARM					-0.17	0.10	-0.36	0.01				
Time x Intervention x RRC-ARM					0.20	0.11	-0.01	0.41				
COVID-19 Weeks									-0.04	0.04	-0.11	0.03
Time x COVID-19 Weeks									-0.05	0.04	-0.12	0.02
Intervention x COVID-19 Weeks									0.08	0.05	-0.02	0.18
Time x Condition x COVID-19 Weeks									0.00	0.05	-0.11	0.10

Notes. All model output based on standardised outcomes and DASS-21 scores have been log transformed. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; Time indicates change from baseline to 7-weeks post; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Table S14. Self-Compassion Scale linear mixed model results

SCS	Model 1				Model 2				Model 3			
	β	SE	95% CI		β	SE	95% CI		β	SE	95% CI	
			Lower	Upper			Lower	Upper			Lower	Upper
Intercept	-0.04	0.07	-0.18	0.11	-0.03	0.07	-0.16	0.10	-0.12	0.12	-0.36	0.11
Time	0.02	0.06	-0.09	0.13	0.02	0.06	-0.09	0.13	-0.09	0.10	-0.28	0.10
Intervention	0.05	0.11	-0.15	0.26	0.05	0.10	-0.14	0.24	0.20	0.17	-0.14	0.54
Time x Intervention	-0.12	0.08	-0.28	0.04	-0.12	0.08	-0.28	0.04	0.03	0.14	-0.23	0.30
RRC-ARM					*** 0.42**	**0.07**	**0.29**	**0.55**				
Time x RRC-ARM					-0.03	0.06	-0.15	0.08				
Intervention x RRC-ARM					0.01	0.10	-0.18	0.19				
Time x Intervention x RRC-ARM					-0.06	0.08	-0.22	0.11				
COVID-19 Weeks									0.03	0.04	-0.04	0.11
Time x COVID-19 Weeks									0.04	0.03	-0.02	0.10
Intervention x COVID-19 Weeks									-0.06	0.05	-0.16	0.05
Time x Condition x COVID-19 Weeks									-0.06	0.04	-0.14	0.03

Notes. All model output based on standardised outcomes. Model 1 includes the primary main effects and time by intervention interaction. Model 2 tests the moderation effect of resiliency resources. Model 3 tests the moderation effect of time relative to the start of COVID-19 restrictions in Australia. SE = standardised standard error; 95% CI = 95% confidence interval; RRC-ARM = Resilience Resource Centre Adult Resilience Measure as measured at baseline; Time indicates change from baseline to 7-weeks post; reference level for Intervention is Control. *$p < 0.05$, n = 136.

Chapter 6:
General Discussion

Until recently, mental wellbeing was largely understood only as far as its relationship to mental illness. This has left significant gaps in the current understanding of mental wellbeing, including its underlying neural mechanisms, how it is best promoted, and identifying what makes individuals predisposed to high or low levels of wellbeing. This thesis aimed to explore potential electrophysiological endophenotypes for mental wellbeing, namely resting EEG, emotional event-related potentials (ERPs), and cognitive ERPs, that might be used to indicate genetic predisposition towards wellbeing and predict responsiveness to treatments such as positive psychology interventions (PPIs). Chapters 2, 3, and 4 focused on exploring potential electrophysiological correlates of mental wellbeing and depression/anxiety symptoms that could be used as candidate endophenotypes. Chapter 5 presented the results of a randomised controlled trial that aimed to test the effectiveness of a short online PPI in improving mental wellbeing relative to an active control group. This intervention may be used in future trials in conjunction with EEG measures to investigate whether electrophysiological measures can predict early responsivity to PPIs. This discussion provides an overview of the conclusions from each study, followed by a discussion of implications of the results, limitations, and future research directions.

6.1. Resting EEG as a marker of mental wellbeing

The aim of Chapter 2 was to investigate the previously unexplored relationship between absolute resting EEG power and mental wellbeing. Resting EEG power captures spontaneous brain activity independent from task demands, similar to the default mode network examined in fMRI research (Knyazev et al., 2011; Neuner et al., 2014). Although the default mode network has been previously associated with mental wellbeing (Luo et al., 2016), links between resting EEG power and mental wellbeing have been limited to alpha asymmetry studies (Alessandri et al., 2015; Urry et al., 2004; Xu et al., 2018). In clinical research, absolute resting EEG power, especially increased alpha and beta power, has been

associated with depression, anxiety, and stress (Grin-Yatsenko et al., 2009; Knyazev et al., 2006; Schutter & van Honk, 2005; van Peer, 2008), suggesting potential for a relationship between absolute power and wellbeing. Therefore, the first aim of Chapter 2 was to explore the association between mental wellbeing and EEG, including both alpha asymmetry and absolute resting EEG power.

Previous studies have estimated the heritability of absolute resting EEG power to be very high (h^2 = 0.80-0.90) (McLoughlin et al., 2014; Smit et al., 2005), while the heritability of alpha asymmetry is very low (h^2 = 0.0-0.27) (Anokhin et al., 2006). This means that while alpha asymmetry might be useful as a state biomarker of mental wellbeing (Urry et al., 2004; Xu et al., 2018), it is not regarded as a candidate endophenotype (Anokhin et al., 2006; McLoughlin et al., 2014). Should absolute resting EEG power be associated with wellbeing, its high heritability would make it a more promising candidate endophenotype for mental wellbeing. Thus, the second aim of Chapter 2 was to estimate the heritability of resting EEG power and to assess whether a genetic correlation between wellbeing and resting EEG power accounts for any observed associations between them.

In contrast to previous studies which have found associations between wellbeing and alpha asymmetry (Alessandri et al., 2015; Urry et al., 2004), the current investigation found no such relationship. This could be due to the sensitivity of alpha asymmetry to daily fluctuations in mood and other situational factors that were not controlled for in the current study (Harmon-Jones & Gable, 2018). A novel association, however, was identified between a specific profile of alpha, beta, and delta power (ABD) with mental wellbeing, where high alpha and delta power combined with low beta power was associated with greater wellbeing, independent from depression/anxiety symptoms. Most past research has focused on the relationship between individual frequency bands and mental illnesses such as depression or anxiety (Fingelkurts & Fingelkurts, 2015; Grin-Yatsenko et al., 2009). However, some

findings have indicated that coupling between different frequency bands, suggesting that the pattern of both frequencies increasing and decreasing in unison, may be more relevant to mental states including stress and anxiety than individual frequencies (Knyazev et al., 2006; Schutter & van Honk, 2005; van Peer, 2008). The current results extend these findings to mental wellbeing, showing that the interactions between different frequencies are a better predictor of wellbeing than individual frequencies. Past studies have associated increased alpha power with more severe depressive symptoms (Fingelkurts & Fingelkurts, 2015), but this is usually reported in the presence of higher beta power also (Grin-Yatsenko et al., 2009). Here, higher alpha power was found to indicate higher wellbeing when beta power was also low and delta power was high. Given that alpha power is associated with greater internal attention including mind wandering (Arnau et al., 2020; Benedek et al., 2014; Ceh et al., 2020), whereas beta power has been associated with depressive rumination (Ferdek et al., 2016), and delta power is associated with reward processing (Knyazev, 2012), the ABD profile may be indicative of more positive mind wandering in individuals with high wellbeing. Further research into how these frequencies interact to indicate higher wellbeing is warranted.

The univariate heritability analysis confirmed that both this ABD profile and mental wellbeing were moderately heritable (h^2 = 0.37 and 0.39, respectively). Thus, a multivariate correlated factors model was conducted to estimate the degree to which environmental and genetic factors accounted for the observed association. This analysis found that 93.7% of the phenotypic correlation between mental wellbeing and the ABD profile was attributed to a genetic correlation, suggesting that common genes explain variance in ABD power and mental wellbeing. This finding suggests that resting EEG power can serve as a candidate endophenotype for mental wellbeing. Endophenotypes are relatively stable, heritable physiological traits that can be used to indicate one’s predisposition towards certain

phenotypes (Gottesman & Gould, 2003; McLoughlin et al., 2014). While the ABD profile identified here appears to meet this criteria, further work is needed to assess the stability of this profile over time and evaluate its use in predicting long-term wellbeing outcomes. While individual frequency bands are relatively stable over time (Smit et al., 2005), the lower heritability of the ABD profile relative to individual frequencies in the current study suggest that this ABD profile might be less stable than individual frequencies. Thus, it is worth investigating whether this resting EEG profile changes with one's current state of wellbeing or if it is a more stable indicator of one's predisposition towards experiencing higher wellbeing.

6.2. Emotional face processing and mental health

Following evidence that resting EEG power is associated with mental wellbeing, the next aim, explored in Chapters 3 and 4, was to investigate whether task-related processes measured using ERPs are associated with mental wellbeing. Chapter 3 specifically focused on exploring the relationship between mental wellbeing and emotional face processing. Alterations to emotional face processing have been found in clinical and subclinical samples with depression and anxiety, usually supporting a mood-congruency bias indicated by faster and more accurate behavioural responses and enhanced ERP amplitudes to negative stimuli (Chen et al., 2014; Dai & Feng, 2012; Weightman et al., 2014; Williams et al., 2007; Zhang et al., 2016). Although ERP components including the VPP and N170 are typically sensitive to different emotional expressions in healthy samples (Hinojosa et al., 2015; Smith et al., 2013), some studies have found these emotion-sensitive effects to be diminished in clinical, subclinical, and at-risk groups (Chen et al., 2014; Watters et al., 2018; Zhang et al., 2016). While no prior studies have examined the association between mental wellbeing and emotion processing using ERPs, behavioural and fMRI results from the TWIN-E study found that wellbeing was associated with faster processing of happy expressions indicated through

behavioural performance (Routledge et al., 2018), and greater activation of the inferior frontal gyrus for happy relative to neutral expressions using fMRI (Park et al., 2021). Chapter 3 aimed to extend upon these findings using ERP methods. Given that past research has found differential associations between subclinical symptoms of depression and anxiety with conscious compared to subconscious processing (Williams et al., 2007), both masked (subconscious) and unmasked (conscious) viewing conditions were examined.

The second aim of Chapter 2 was to assess the heritability of emotion-sensitive ERPs. Although past research has estimated the heritability of emotion-related ERP to be moderately heritable (h^2 = 0.42–0.64) (Anokhin et al., 2010), these estimates were based on ERP amplitude for each emotion condition, without necessarily capturing emotion-specific effects by either subtracting or regressing out variance associated with neutral face processing. As variation in emotion-specific processing is of interest to clinical research, a previous study aimed to address this gap by estimating the heritability of the N170 and P200 for fearful faces after regressing out variance shared with neutral faces (Shannon et al., 2013). The authors found no evidence that fear-specific processing was significantly heritable. However, as only fearful expressions were assessed, the study did not assess whether the processing of other emotional expressions, including sad and happy expressions, were heritable. Here, it was important to test whether the processing of other emotional expressions is heritable to clarify their potential use as candidate endophenotypes, as has been suggested previously (Anokhin et al., 2010). Therefore, the second aim of Chapter 3 was to investigate the heritability of emotion-specific processing for each ERP component of interest, and test whether any associations found between emotional processing and mental wellbeing could be explained by a genetic correlation, similar to Chapter 2.

In contrast to previous findings from the TWIN-E sample (Park et al., 2021; Routledge et al., 2018), no association was found between emotion-specific processing and

mental wellbeing after correcting the false discovery rate. However, a significant association was found between depression/anxiety symptoms and N170 amplitude for Fearful relative to Happy expressions within the masked condition, whereby high depression/anxiety symptoms were associated with a lack of N170 differentiation between fearful and happy facial expressions. This effect remained significant when covarying for wellbeing, indicating that depression/anxiety symptoms are associated with reduced differentiation between these emotions regardless of levels of wellbeing. The finding that early emotional processing was associated with depression/anxiety symptoms aligns with previous research showing a lack of neural differentiation between different emotional expressions in clinical and at-risk groups (Chen et al., 2014; Watters et al., 2018; Zhang et al., 2016) and shows that these alterations can extend to even low symptom levels. However, the lack of an association with mental wellbeing is at odds with past findings from the larger TWIN-E study which associated higher mental wellbeing with faster reaction times (Routledge et al., 2018) and greater activation of the right inferior frontal gyrus (Park et al., 2021). These past findings would suggest that wellbeing is associated with changes to the neural processing of happy faces, however, the current results did not support this. Yet, as only early ERPs were examined here (i.e., ERPs within 300 msec of stimulus onset), it is possible that associations between wellbeing and emotional processing emerge in later stages of processing, which would be better captured by fMRI or later ERPs. For instance, the late positive potential (LPP) is a an ERP emerging around 300 msec that lasts for the duration of stimulus presentation and captures emotional arousal and elaborative processing of emotional stimuli (Cuthbert et al., 2000; Myruski et al., 2019). LPP activity has also been linked to activation in the right inferior frontal gyrus (Matsuda & Nittono, 2015), which has shown increased activation in response to happy relative to neutral faces in individuals with high wellbeing (Park et al.,

2021). Future research using longer stimulus presentation and inter-stimulus intervals could be used to assess whether the LPP is altered in association with wellbeing.

While the univariate heritability analysis found evidence that some components of disgusted, sad, and angry face processing was somewhat heritable (h^2 = 0.19-0.26), these components were not significantly associated with either mental wellbeing or depression/anxiety symptoms in the current sample. However, alterations to the processing of sad and disgusted faces have been reported in individuals who are either clinically depressed (Chen et al., 2014; Zhang et al., 2016) or have familial risk for depression (Watters et al., 2018). Thus, while these ERP indices are unlikely to prove useful as markers of wellbeing, they might yet show potential use as markers capturing heritable risk for depression within clinical populations.

6.3. Cognitive processing and mental health

Where Chapter 3 aimed to investigate the associations between mental health and emotion processing, Chapter 4 aimed to investigate the associations with cognition. Past evidence has indicated that both wellbeing and the experience of positive emotions are associated with similar improvements in cognitive processing. These alterations have been more extensively researched in the context of positive emotions, where they have been found to broaden attentional scope (Fredrickson, 2001; Putkinen et al., 2017; Vanlessen et al., 2014), improve attentional control and inhibition (Dreisbach & Goschke, 2004; Paul et al., 2021; Vanlessen et al., 2015, 2016), and improve working memory (Gray, 2001; Storbeck & Maswood, 2016). Similar effects have been reported to be associated with wellbeing, where higher subjective wellbeing has been linked with improvements in working memory, inhibition, sustained attention, and general cognitive ability (Lee & Chao, 2012; Llewellyn et al., 2008; Pe et al., 2013; Routledge et al., 2017). Given these similarities, it could be

expected that mental wellbeing would also be associated with alterations in ERPs, which have previously been associated with positive emotions (Putkinen et al., 2017; Vanlessen et al., 2014, 2015) and mental illness (Bernat et al., 2020; Kaiser et al., 2003; Xia et al., 2020), but not tested for wellbeing in a healthy population.

The first aim of Chapter 4 was to investigate the associations between mental wellbeing, depression/anxiety symptoms, and cognitive ERPs. Namely, the P3b, novelty P3a, and inhibitory N2 and P3a components were investigated on the basis of prior research. The P3b component has been used to investigate attention and working memory in positive emotions (Putkinen et al., 2017; Vanlessen et al., 2014) and in clinical depression and anxiety (Bernat et al., 2020; Bruder et al., 2009; Deldin et al., 2001). Meanwhile, the N2 has been reportedly enhanced in positive emotional states relative to neutral states (Vanlessen et al., 2014), and both the N2 and inhibitory P3a are reportedly reduced in depressed and anxious samples (Kaiser et al., 2003; Katz et al., 2010; Ruchsow et al., 2008; Xia et al., 2020). The novelty P3a component has also been recently identified as a marker of psychopathology risk (Bernat et al., 2020), but has not previously been investigated in the context of positive emotions. Thus, these components were the ERPs of interest for Chapter 4, assessed using an auditory oddball paradigm (P3b), an n-back paradigm with novel distractors (P3b and novelty P3a), and a go/no-go paradigm (N2 and inhibitory P3a). In addition, to assess the potential use of these components as candidate endophenotypes for wellbeing and to replicate past findings (Anokhin et al., 2017; Smit et al., 2007; van Beijsterveldt & van Baal, 2002), the heritability of all components was also assessed in Chapter 4.

The results of Chapter 4 showed that despite behavioural associations between cognitive function and both wellbeing and depression/anxiety symptoms emerging within the auditory oddball and n-back task, none of the ERPs of interest were associated with either mental wellbeing or depression/anxiety symptoms within the TWIN-E sample. Furthermore,

unlike behavioural results reported in past studies, including the larger TWIN-E study (Lee & Chao, 2012; Routledge et al., 2017), no association was found between wellbeing or depression/anxiety symptoms with inhibition in the current subsample. Given past indications that ERP indices are more sensitive to detecting differences in cognitive function than behavioural indices (Vanlessen et al., 2014), it was surprising that none of the ERPs of interest were associated with mental health outcomes. This could be an indication that the effects of wellbeing on cognition are small and might only be detectable in larger samples (Routledge et al., 2017) or when using more challenging tasks, such as the inhibition of reflexes (Lee & Chao, 2012; Vanlessen et al., 2015), higher working memory load (Pe et al., 2013; Storbeck & Maswood, 2016), or dual-task paradigms (Putkinen et al., 2017; Vanlessen et al., 2014). It is also possible that later cognitive processes, such as error-monitoring captured in the error-related negativity (ERN) component, play a stronger role in performance differences between individuals with higher relative to lower wellbeing. The ERN is a negative-going component that is elicited within 100 msec of making a commission error, with larger amplitudes correlated with better behavioural performance (Weinberg et al., 2015). Although the ERN has not yet been associated with mental wellbeing, previous work has indicated that positive moods increase ERN amplitude (Bakic et al., 2014), which could indicate better performance monitoring and explain why positive moods and wellbeing are associated with better behavioural performance. While the ERN could not be examined in the current cognitive tasks because more commission errors are needed for the ERN to be reliable (Meyer et al., 2013), including slightly more difficult tasks in future research would allow for the investigation of this component.

The univariate heritability analysis revealed that all the ERPs of interest apart from the novelty P3a were moderately heritable, in line with past research (Anokhin et al., 2017; Smit et al., 2007; van Beijsterveldt & van Baal, 2002). In contrast, the novelty P3a was

explained best by common and unique environmental factors. As no previous studies have estimated the heritability of the novelty P3a component, the finding that P3a amplitude is explained primarily by common and unique environmental effects should be confirmed in future research. In conclusion, Chapter 4 found that while cognitive ERPs may serve as candidate endophenotypes for mental disorders, there is currently no evidence that they are associated with wellbeing.

6.4. Effectiveness of positive psychology interventions

Following the investigation of potential endophenotype markers of mental wellbeing in Chapters 2 to 4, the aim of Chapter 5 was to test the efficacy of a short, online PPI. Such an intervention, if effective, could be used in future research to investigate whether EEG measures can predict early reactivity, and whether changes in wellbeing from participating in the intervention can alter EEG activity. Due to the introduction of COVID-19 restrictions during the pilot trial, the EEG component was not feasible. Therefore, Chapter 5 focused on assessing the efficacy of the intervention during the early stages of the ongoing pandemic. Although previous studies, including meta-analyses, have supported the effectiveness of PPIs in improving subjective and psychological wellbeing, the same meta-analyses reported significant heterogeneity between individual intervention programs (Bolier et al., 2013; Hendriks et al., 2020). A short but effective online intervention was desired to improve the feasibility of repeating the intervention with EEG measures. However, as different intervention durations and delivery modes (face to face vs. online) have been suggested to be sources of heterogeneity among PPIs (Bolier et al., 2013), it was possible that a short, online intervention might not be effective. Therefore, the intervention program developed and assessed in Chapter 5 was designed to assess whether such an intervention would remain effective in improving mental wellbeing against an active control group.

Based on previous research indicating that the added variety of multi-component PPIs may increase their efficacy (Proyer et al., 2015; Sheldon et al., 2013), but that two to four interventions was more effective than up to six (Parks et al., 2012), a program of three modules was chosen. These modules included acts of kindness, positive reminiscence, and self-compassion, based on prior evidence of their effectiveness (Curry et al., 2018; Hallford & Mellor, 2016; Pinquart & Forstmeier, 2012; Zessin et al., 2015). To evaluate whether these activities were more effective than active control tasks, acts of novelty, neutral reminiscence, and self-esteem conditions were used in the control group. These control activities used similar elements to each of the intervention tasks, but omitted key aspects believed to contribute to their positive effects on wellbeing. The efficacy of the interventions was assessed in the current study using the COMPAS-W wellbeing scale (Gatt et al., 2012), the Satisfaction With Life Scale (Diener et al., 1985), the Self-Compassion Scale (Neff, 2003), and the Depression, Anxiety, Stress Scale (Lovibond & Lovibond, 1995). Furthermore, to test whether the efficacy of treatment was related to pre-existing resiliency resources such as social support, the Resilience Research Centre – Adult Resilience Measure (RRC-ARM) was also included and investigated as a moderator in the analyses (Liebenberg & Moore, 2018).

The results showed significantly greater improvement in life satisfaction, measured using both the COMPAS-W Satisfaction subscale (Gatt et al., 2014), and the Satisfaction With Life Scale (Diener et al., 1985). This effect remained significant when covarying for ongoing COVID-19 restrictions, indicating that the intervention was effective in improving subjective wellbeing even during an ongoing stressful event. Additionally, the intervention group showed improvement in COMPAS-W Own-worth, but this effect was lost when accounting for COVID-19 restrictions. In contrast, a positive effect of the intervention on COMPAS-W Positivity emerged only after accounting for COVID-19 restrictions. The moderation analysis revealed that the positive effects of the program on both mental

wellbeing and on depression/anxiety symptoms were larger in individuals with lower resiliency resources at the start of the program; these individuals also tended to have lower mental wellbeing scores at baseline. It is noted that the while the intervention did improve composite wellbeing when controlling for COVID-19 restrictions, this was driven by improvements in subjective components of wellbeing rather than improvements in psychological components. This could be due to the short duration of the program as previous programs targeting psychological wellbeing outcomes have tended to be of longer duration, around 12 weeks on average (Bolier et al., 2013; Hendriks et al., 2020). This has implications for using the intervention program to investigate how markers of composite wellbeing, such as resting EEG, change over time.

The positive effect of the intervention on subjective and composite wellbeing is in line with past online PPI studies that have used waitlist control groups (Drozd et al., 2014; Feicht et al., 2013; Schotanus-Dijkstra et al., 2017). However, some previous studies using active control groups similar to the present study have failed to find significant improvements in wellbeing (Joutsenniemi et al., 2014; Moskowitz et al., 2017), although a phone-based program in older adults did find a positive effect of a PPI program over an active control (Hausmann et al., 2017). The finding that online interventions are significantly more effective than control tasks over a short period has positive implications for public health programs. Because online interventions are cost-effective, they can be used to reach large populations including individuals who might otherwise be difficult to reach (Bolier et al., 2013). Furthermore, even small effect sizes can have large public health benefits when applied to a large population (Huppert, 2009). Finally, as intervention effectiveness was mediated by baseline resiliency resources whereby individuals with fewer support resources available to them at the start of the intervention benefitted more than those with more available support

resources, this suggests that these programs could be targeted towards more vulnerable groups who need the support.

6.5. Results summary and implications

Taken together, this thesis provides a thorough investigation into the electrophysiological correlates of mental wellbeing. The key finding was that resting EEG measures, specifically the profile of alpha, beta, and delta power, are significantly associated with mental wellbeing within a healthy sample, regardless of concurrent depression/anxiety symptoms. Meanwhile, emotional and cognitive ERPs were not significantly associated with mental wellbeing when accounting for depression/anxiety symptoms. While resting EEG and ERPs are both heritable, the current findings can only suggest that resting EEG serves as a viable candidate endophenotype for wellbeing, as only resting EEG power was significantly associated with wellbeing. This was supported by a multivariate correlated factors model which confirmed that the association between resting EEG and mental wellbeing was primarily explained by a genetic correlation. Finally, the efficacy of a short online PPI was assessed to facilitate the investigation into whether resting EEG predicts early responsivity to PPIs and whether changes in wellbeing are reflected in EEG measures. Although the ongoing COVID-19 pandemic made it unfeasible to carry out the planned follow-up study, the intervention was found to significantly improve subjective wellbeing relative to an active control group within six weeks. Thus, this thesis has substantially progressed current understanding of the electrophysiological correlates of mental wellbeing and ways to promote it.

These findings have implications for understanding the neural basis of mental wellbeing and the search for more effective interventions. First, the finding that resting EEG, but not task-based ERP measures, were associated with mental wellbeing suggests that what

the mind is doing at rest may be more important for mental wellbeing than how specific stimuli is processed. This would be consistent with the previous work showing that activation in the default mode network is associated with wellbeing (Luo et al., 2016), and that the contents of a person's thoughts is a better predictor of happiness than how they spend their time (Killingsworth & Gilbert, 2010). For instance, participants who spent more time thinking about their current activities or in engaging in pleasant mind wandering were happier than those who spent more time engaged in neutral or unpleasant forms of mind wandering (Killingsworth & Gilbert, 2010). Resting EEG power, specifically alpha power, has previously been shown to increase during mind wandering (Arnau et al., 2020; Ceh et al., 2020). Meanwhile, increases in beta power have been associated with rumination (Ferdek et al., 2016), and delta power has been associated with both reward processes and inattention. It would be worth investigating in future research whether the ABD profile is indicative of certain thought processes like pleasant mind wandering to determine if this would explain the observed association with wellbeing.

Second, the finding that mental wellbeing was not significantly associated with early emotional and cognitive ERPs but was associated with behavioural performance on these tasks (Routledge et al., 2017, 2018), suggests that the behavioural effects are possibly driven by alterations in later stages of processing not evaluated here. Later ERPs that could be examined in future research include the LPP and ERN components. The LPP reflects more elaborative emotion-related processes and has been associated with activation in the right IFG (Matsuda & Nittono, 2015; Myruski et al., 2019). The same region was found to show greater activation for happy relative to neutral faces in individuals with high wellbeing using fMRI (Park et al., 2021). Thus, alterations to the LPP component could help explain why individuals with higher wellbeing were faster at identifying happy faces (Routledge et al., 2018). For the cognitive tasks, investigating the ERN component would be useful to

potentially explain why behavioural performance was improved in individuals with higher wellbeing as this component is involved in performance monitoring and larger ERN components are associated with better task performance (Weinberg et al., 2015).

The results from the PPI trial provide evidence that online interventions can outperform active control tasks in improving wellbeing within a period as short as six weeks. Most previous online PPI studies have instead used waitlist control groups (e.g., Drozd et al., 2014; Feicht et al., 2013; Schotanus-Dijkstra et al., 2017), leaving it unclear whether the positive effects of PPIs were due to placebo effects or more general positive effects from trying new activities (Buchanan & Bardi, 2010). Furthermore, some previous studies using short, online interventions with active control groups have reported no significant improvements in wellbeing for the intervention group relative to controls (e.g., Joutsenniemi et al., 2014; Moskowitz et al., 2017). Thus, the current results show that even short, online interventions can improve mental wellbeing, albeit with a small effect size (estimated Cohen's *d* of 0.18-0.23). The type of intervention activities chosen might contribute to heterogeneity between studies (Bolier et al., 2013). The present intervention activities (i.e., acts of kindness, positive reminiscence, and self-compassion) were chosen based on previous meta-analytic evidence of their effectiveness (Curry et al., 2018; Pinquart & Forstmeier, 2012; Zessin et al., 2015). Each of these interventions is designed to promote a positive view of oneself (Hallford & Mellor, 2016; Neff, 2003). Similarly, the acts of kindness activity can help interrupt negative thought patterns such as rumination by engendering positive thoughts about oneself and others (Layous et al., 2014).

Finally, this thesis supports the dual-factor theory of mental health, whereby mental illness and mental wellbeing represent two distinct components of mental health (Greenspoon & Saklofske, 2001; Keyes, 2005; Suldo & Shaffer, 2008). For instance, the association between a resting ABD profile and wellbeing was independent from mental illness

symptoms, and alterations to emotion processing were associated with depression/anxiety symptoms, but not with mental wellbeing. This supports the idea that markers of wellbeing are not necessarily the same as markers of depression/anxiety symptoms, and that markers of wellbeing should be studied in addition to markers of mental illness and related symptoms. Further implications for mental wellbeing come from the intervention trial, which was found to mostly improve subjective components of wellbeing rather than psychological components within the COMPAS-W wellbeing scale. Given that there was been ongoing debate regarding whether subjective and psychological wellbeing are distinct forms of wellbeing (Disabato et al., 2016; Goodman et al., 2018), it is theoretically important to know that subjective and psychological wellbeing components are not equally improved though the PPIs selected here, suggesting different underlying mechanisms for each. It is possible that the same activities could influence psychological wellbeing if practised for a longer time period such as twelve weeks (Hendriks et al., 2020). Alternatively, psychological components might be more responsive to interventions that have more focus on autonomy, mastery or life purpose, such as goal setting (Thorsteinsen & Vittersø, 2018).

6.6. Limitations

The studies discussed in the current thesis should be interpreted in light of their limitations relating to sample characteristics, study design, and statistical models used.

6.6.1. Sample characteristics

6.6.1.1. TWIN-E sample

The TWIN-E study sample was used in Chapters 2, 3, and 4. This sample was selected for the primary purpose of investigating variation within a healthy sample without a history of mental illness (Gatt et al., 2012). This meant that certain exclusion criteria had to be applied which may limit the generalisability of the results. More specifically, individuals

were excluded if they reported a history of previous mental disorder, or current mental illness, if they were under 18 or over 65 years of age to avoid potential confounding with mental illness or developmental differences. Furthermore, to facilitate genomic analyses (reported elsewhere) and heritability analyses, the sample was limited to Australians of European descent and same-sex twin pairs. While these choices were made in line with the study aims, it is possible that the findings might not generalise to more diverse populations with varying levels of wellbeing and mental health status (past or present). Furthermore, the current sample was highly educated with 73% of participants completing training beyond high school compared to 51% of the general Australian population at the time the TWIN-E data was collected (Australian Bureau of Statistics, 2016). Higher education could also be associated with higher household income and other environmental factors known to influence mental wellbeing but not accounted for here (Diener & Biswas-Diener, 2009; Kristoffersen, 2018). These participants' characteristics might therefore reduce the generalisability of the current findings to individuals with lower education or socio-economic status. The results should therefore be replicated in more diverse samples, including individuals with current or past history of mental illness. This would help clarify whether markers of wellbeing, such as resting EEG power, remain independent from mental illness symptoms when including a broader range of symptom levels.

6.6.1.2. Intervention sample

Although the intervention trial described in Chapter 5 was based on an independent sample without exclusion criteria as used in the twin study, it was based on a convenience sample of first-year psychology students. University students make up a significant proportion of participants in psychological studies globally due to the ease of recruitment (Peterson, 2001; Peterson & Merunka, 2014). However, it has been previously shown that

university samples are homogenous (Peterson, 2001), and are not representative of the general population (Hanel & Vione, 2016), which could limit the generalisability of the results. However, similar PPI trials have been conducted in diverse samples including young to older adults (Hallford & Mellor, 2016; Pinquart & Forstmeier, 2012), clinical groups (e.g., Hausmann et al., 2017), and different cultures (Hendriks et al., 2018). Thus, the reported intervention effects are expected to generalise beyond the student population included in the present study.

A potentially more concerning aspect of the intervention sample was the high rate of attrition. Of the 326 participants who completed at least one week of the intervention, only 173 completed week six, indicating an attrition rate of 47%. Although this high attrition rate is similar to other online interventions (e.g., Schueller & Parks, 2012), it does raise concerns about the generalisability of the results. It is possible that individuals who did not complete the study were predominantly individuals with poor early reactivity to the intervention, who have been shown previously to engage less with PPIs than those who initially respond well to the intervention (Cohn & Fredrickson, 2010; Proyer et al., 2015). The results also showed that drop-outs had lower life satisfaction, and higher depression, anxiety, and stress symptoms than continuers, which could contribute to an apparent increase in mean wellbeing over the course of the intervention. Multiple imputation and an intention-to-treat analysis were used to reduce the potential bias in the results (Kenward & Carpenter, 2007; White et al., 2012); however, replicating the study with lower attrition rates would be ideal. It is possible that including in-person assessments at the beginning and end of an online interventions program could help to reduce attrition (e.g., Kushlev et al., 2020), which might bring the attrition rate of otherwise online studies closer to that of in-person studies (Balakrishnan et al., 2014). However, it is noted that such an approach would not have been feasible within the context of the COVID-19 pandemic because of restrictions limiting in-

person testing. Furthermore, COVID-19 might have played a direct role in increasing the attrition rate in the current study as participant retention was lower during the third data collection wave in 2020 relative to the initial waves of data collection that took place in 2019. Regardless, efforts should be made in future work to increase participant retention by including in-person assessments or providing a monetary incentive for completing all components (Balakrishnan et al., 2014).

6.6.2. Study design

6.6.2.1. Self-report measures

All the primary outcome measures of this thesis were based on self-report measures. These included measures of wellbeing (Diener et al., 1985; Gatt et al., 2014), depression, anxiety and stress symptoms (Cohen et al., 1983; Lovibond & Lovibond, 1995), resiliency resources (Liebenberg & Moore, 2018), and self-compassion (Neff, 2003). Each of the selected measures have been previously applied and validated within a range of different samples. Although self-report measures can be potentially limited by social desirability bias (Heintzelman et al., 2015; Perinelli & Gremigni, 2016) and demand characteristics (Nichols & Maner, 2008), they are arguably the best available measure for capturing participants' psychological states for the constructs examined here due to the personal insight that participants have about their own mental states (Haeffel & Howard, 2010). Regardless, including social desirability measures in future studies to control for potential positive response bias may still be useful to ensure that the associations reported here are truly reflective of wellbeing and not response biases.

Another consideration regarding the chosen measures is that the conclusions of this research were based primarily on two self-report measures: the COMPAS-W for wellbeing and the DASS-42 for depression/anxiety symptoms. This raises the question of whether the

results will generalise when other measures of wellbeing or depression/anxiety symptoms are used. Both of these measures have been validated against other measures of similar constructs. For instance, the COMPAS-W was moderately correlated with the Satisfaction with Life Scale and with other constructs well-recognised to be related to mental wellbeing such as extraversion and neuroticism (Gatt et al., 2014). The DASS-42 has also been validated against other measures of depression and anxiety, showing strong correlations with other measures of depression and anxiety, including the Hospital Depression and Anxiety Scale (Crawford & Henry, 2003). Therefore, while a limited set of measures were used in the current project, these measures have been shown to be associated with other related constructs, indicating that the results would generalise to other related measures.

6.6.2.2. Online data collection

Both the TWIN-E sample and the intervention samples' questionnaire data were collected online. Concerns have been raised about the quality of data collected online due to inattentiveness or intentional misrepresentation (Johnson, 2005). Participants in online studies might have more distractions present, they might multi-task, or complete measures more quickly. However, more recent studies of online samples have found similar data quality and experimental results for online compared to lab-based samples, suggesting they are equivalent measures (Crump et al., 2013; Germine et al., 2012). Larger samples can also be recruited online, which can help reduce measurement error resulting from the slightly poorer data quality of online samples (Brown et al., 2014; Stewart et al., 2017). Finally, the COMPAS-W questionnaire, which was the primary outcome measure of this thesis, was validated online and includes reverse-scored items to reduce the impact of inaccurate responding (Gatt et al., 2014).

Within the TWIN-E study, it is noted that the online questionnaires took place at a different point in time to the EEG measures, with the median time difference between the online data collection and in-person data collection being three months. However, wellbeing, which was the primary outcome measure, was found to be relatively stable over a 12-month period with an intra-class correlation of 0.82 (Jamshidi et al., 2020). Thus, the delay in testing was not expected to have significant implications for the associations between wellbeing and the electrophysiological measures included here. However, the delay may have impacted associations with less stable constructs such as positive mood or depression/anxiety symptoms. This might explain why no association was found between alpha asymmetry and wellbeing, in contrast with previous reports (Alessandri et al., 2015; Urry et al., 2004), as alpha asymmetry is more sensitive to one's current mood than resting EEG measures (Harmon-Jones & Gable, 2018) and less heritable (Anokhin et al., 2006). It might have also reduced the strength of the association between wellbeing and cognitive ERPs because cognitive ERPs are known to vary with one's current mood (Vanlessen et al., 2014, 2015), which is likely to vary between the online and in-person session. However, the ERPs tested have shown high test-retest reliability (0.74-0.86) (Williams et al., 2005) and the behavioural data collected within the ERP session for the cognitive tasks was still significantly associated with mental wellbeing and depression/anxiety symptoms despite the measurement gap. As such, it is expected that the gap in testing would have a relatively minor impact on the results.

6.6.2.3. Emotion and cognitive paradigms

Chapters 3 and 4 assessed the association between electrophysiological correlates of emotional and cognitive processing with mental wellbeing and non-clinical depression/anxiety symptoms. The tasks used to measure these functions have been previously validated in clinical and non-clinical groups (Gordon et al., 2005; Williams et al.,

2004, 2005). However, these tasks have primarily been used to investigate alterations in emotional and cognitive processing within *clinical groups* including depression and anxiety (Williams et al., 2011), attention deficit/hyper-activity disorder (Williams, Hermens, et al., 2010) and schizophrenia (Williams, Nagy, et al., 2010). The goal of including these tasks in the TWIN-E study was to assess how these hallmark markers of mental illness vary within a non-clinical population (Gatt et al., 2012). It is possible that these tasks were not associated with wellbeing because they were not challenging enough to detect small differences in cognitive function within a non-clinical sample. Past research associating wellbeing and positive emotions with cognition have tended to use more challenging working memory tasks. For instance, while the current study only used a 1-back condition within the n-back task, many other studies in non-clinical groups use the more challenging 2-back and 3-back conditions (Dreisbach & Goschke, 2004; Pe et al., 2013). Similarly, inhibition tasks used in positive psychology have focused on the inhibition of reflexive eye movements (Lee & Chao, 2012; Vanlessen et al., 2015), which are more difficult to inhibit relative to the button press response used here. Although behavioural performance within the n-back and auditory oddball were still associated with wellbeing in the current design, using more challenging cognitive tasks might be required to detect differences in ERP amplitude associated with wellbeing. In terms of the emotion task, including varying levels of emotional intensity, rather than a single intensity level, could be used to investigate whether associations with wellbeing emerge when more mild emotional expressions are used (Jaworska et al., 2010). Differences might be more pronounced for more mild expressions because interpreting more neutral expressions as either more positive or negative is an indication of mood congruency bias (Cavanagh & Geisler, 2006).

6.6.2.4. Intervention assessment

Within the intervention study reported in Chapter 5, the focus was to assess the effectiveness of a multi-component PPI against active control groups. However, it might also be useful to understand whether specific intervention tasks (i.e., acts of kindness, positive reminiscence, and self-compassion) or prompts were more effective than others. Due to the study design, this could not be assessed. Because all of the intervention activities were chosen based on past meta-analytic evidence of their effectiveness (Curry et al., 2018; Pinquart & Forstmeier, 2012; Zessin et al., 2015), it was expected that all of the interventions would contribute to the overall effect on wellbeing. Nonetheless, the lack of an observable effect of the intervention on self-compassion scores raises the concern that the self-compassion module was ineffective, despite being based on a previously validated protocol (Breines & Chen, 2012). Thus, more detailed research into the effects of each individual intervention should be conducted in future work.

Finally, although the control conditions were selected to be highly similar to the active intervention conditions, it is noted that some aspects of the intervention were more social than the control activities. This consideration is particularly relevant for the acts of kindness intervention which involved reflecting on the impact that each act of kindness had on other people, an aspect that was not included in the acts of novelty comparison condition. Including measures of social connectedness and further examining the social nature of both acts of kindness and acts of novelty would help clarify whether differences in the level of social interaction contributed to the larger effect size in the intervention relative to the control group.

6.6.3. Statistical limitations

6.6.3.1. Twin model limitations

One of the key aims of this thesis was to assess whether electrophysiological measures share genetic variance with mental wellbeing, as this would indicate their relevance as candidate endophenotypes. Twin models were used to assess this. One of the assumptions of the twin model is the equal environments assumption, where monozygotic and dizygotic twins are assumed to have equally similar environments (Verweij et al., 2012). Some evidence has suggested that monozygotic twins have more similar environments than dizygotic twins (Horwitz et al., 2003), however, it has also been noted that some of this increased similarity could be due to genetic factors (Derks et al., 2006). Although violations of the equal environments assumptions tend to have only a small impact on twin model estimates (Felson, 2014), it can lead to inflation of heritability estimates and underestimation of common environmental effects. Another assumption of the twin model is that monozygotic twins share all of their genes, while dizygotic twins share 50% of their genes on average (Verweij et al., 2012). However, assortative mating, which is the tendency for individuals to choose partners who are more similar to themselves, can increase the percentage of shared genes in dizygotic twin pairs. This would lead to an over-estimation of the common environmental component of the twin model. Although these assumptions were not tested for in the current analysis, the impact of a violation is expected to be small, especially as the heritability estimates obtained for wellbeing (Bartels, 2015), resting EEG (Smit et al., 2005), and ERPs (Smit et al., 2007; van Beijsterveldt & van Baal, 2002) provided here aligned with previous research using independent twin samples.

The limitations of the twin model also have implications for the correlated factors model used to assess the genetic correlation between resting EEG and wellbeing in Chapter 2. Similar to how assortative mating could impact the univariate heritability estimates, assortative mating could also lead to a ‘spurious’ genetic correlation between traits, whereby certain features are inherited together based on mating preferences or chromosomal proximity

of genes. The genetic correlation could also be caused by different types of pleiotropy, which is where a single gene impacts multiple traits (Hackinger & Zeggini, 2017). This can be due to a direct effect of the same gene on more than one trait, or it can be a mediated effect whereby the gene impacts Trait A, which then influences Trait B. Further research into the association between resting EEG and wellbeing would help clarify whether a causal relationship exists between the two traits, or if they are simply correlated. In addition, genomic methods could be used to assess whether the same genes influence both traits directly, however, this would require much larger sample sizes than are currently available for EEG and wellbeing (Visscher et al., 2008).

6.7. Future research directions

This thesis extended the current understanding of the electrophysiological correlates of mental wellbeing. EEG power was identified as a promising candidate endophenotype for wellbeing, however, no robust associations were found between mental wellbeing and ERP indices of emotion or cognitive processing. Based on this, future research should focus on further exploring the association between resting EEG and wellbeing, including whether it could be used to predict early reactivity to PPIs and other mental health interventions, and whether there is a causal relationship between resting EEG power and wellbeing. Associations between emotional and cognitive processing with wellbeing could also be further investigated to clarify whether more challenging or emotionally valanced cognitive tasks have stronger associations with wellbeing.

The finding that resting EEG power was associated with wellbeing appears to align with past research indicating an association between activation in the default mode network measured using fMRI and mental wellbeing (Knyazev et al., 2011; Luo et al., 2016; Neuner et al., 2014). However, future research using both resting EEG and functional connectivity

analyses should further clarify whether the resting EEG profile is associated specifically with the default mode network, or whether other networks are also involved. Furthermore, as the current research used a cross-sectional sample, longitudinal designs could also be considered to clarify whether resting EEG profiles are predictive of changes in wellbeing over time. Using experimental methods could also help clarify whether the relationship between resting EEG and mental wellbeing is causal or simply correlational. One of the aims of developing the PPI program described in Chapter 5 was to test whether resting EEG at baseline would be predictive of early reactivity to the intervention, and whether changes in wellbeing due to the intervention would be reflected in changes in resting EEG patterns. One study has used a similar method to investigate the association between alpha asymmetry and mental wellbeing, finding that a larger shift from left to right frontal alpha asymmetry was associated with greater improvements in wellbeing (Xu et al., 2018). Alternatively, neurofeedback protocols, which have been used previously to train individuals to change their resting EEG activity (e.g., Kluetsch et al., 2014), could be used to explore whether changing resting EEG patterns results in changes in wellbeing.

6.8. Conclusion

This thesis provided the first investigation into the associations between mental wellbeing with electrophysiological correlates of resting brain function, emotion processing and cognitive processing. Resting EEG power was found to be associated with mental wellbeing such that greater alpha and delta power combined with low beta power predicted higher wellbeing. Twin models showed that this association was best explained by a genetic correlation, suggesting that resting EEG poses as a candidate endophenotype for mental wellbeing. In contrast, no significant associations between wellbeing and electrophysiological correlates of either emotional or cognitive processing were identified. Chapter 5 reported on the results of a short, online PPI which found that practicing acts of kindness, positive

reminiscence, and self-compassion can improve wellbeing over and above similar control tasks. This intervention may be used in future research to further investigate the association between resting EEG power and wellbeing, including the prediction of early reactivity using resting EEG power as a predictive endophenotype.

6.9. References

Alessandri, G., Caprara, G. V., & De Pascalis, V. (2015). Relations among EEG-alpha asymmetry and positivity personality trait. *Brain and Cognition*, *97*, 10–21. https://doi.org/10.1016/j.bandc.2015.04.003

Anokhin, A. P., Golosheykin, S., Grant, J. D., & Heath, A. C. (2017). Heritability of brain activity related to response inhibition: A longitudinal genetic study in adolescent twins. *International Journal of Psychophysiology*, *115*, 112–124. https://doi.org/10.1016/j.ijpsycho.2017.03.002

Anokhin, A. P., Golosheykin, S., & Heath, A. C. (2010). Heritability of individual differences in cortical processing of facial affect. *Behavior Genetics*, *40*(2), 178–185. https://doi.org/10.1007/s10519-010-9337-1

Anokhin, A. P., Heath, A. C., & Myers, E. (2006). Genetic and environmental influences on frontal EEG asymmetry: A twin study. *Biological Psychology*, *71*(3), 289–295. https://doi.org/10.1016/j.biopsycho.2005.06.004

Arnau, S., Löffler, C., Rummel, J., Hagemann, D., Wascher, E., & Schubert, A. (2020). Inter-trial alpha power indicates mind wandering. *Psychophysiology*, *57*(6). https://doi.org/10.1111/psyp.13581

Australian Bureau of Statistics. (2016). *Educational qualifications in Australia* (2016 Census Data Summary, pp. 1–2).

Bakic, J., Jepma, M., De Raedt, R., & Pourtois, G. (2014). Effects of positive mood on probabilistic learning: Behavioral and electrophysiological correlates. *Biological Psychology*, *103*, 223–232. https://doi.org/10.1016/j.biopsycho.2014.09.012

Balakrishnan, N., Colton, T., Everitt, B., Piegorsch, W., Ruggeri, F., & Teugels, J. L. (Eds.). (2014). *Wiley StatsRef: Statistics Reference Online* (1st ed.). Wiley. https://doi.org/10.1002/9781118445112

Bartels, M. (2015). Genetics of wellbeing and its components satisfaction with life, happiness, and quality of life: A review and meta-analysis of heritability studies. *Behavior Genetics*, *45*(2), 137–156. https://doi.org/10.1007/s10519-015-9713-y

Benedek, M., Schickel, R. J., Jauk, E., Fink, A., & Neubauer, A. C. (2014). Alpha power increases in right parietal cortex reflects focused internal attention. *Neuropsychologia*, *56*, 393–400. https://doi.org/10.1016/j.neuropsychologia.2014.02.010

Bernat, E. M., Ellis, J. S., Bachman, M. D., & Hicks, B. M. (2020). P3 amplitude reductions are associated with shared variance between internalizing and externalizing psychopathology. *Psychophysiology*, *57*(7). https://doi.org/10.1111/psyp.13618

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: A meta-analysis of randomized controlled studies. *BMC Public Health*, *13*(1), 119. https://doi.org/10.1186/1471-2458-13-119

Breines, J. G., & Chen, S. (2012). Self-compassion increases self-improvement motivation. *Personality and Social Psychology Bulletin*, *38*(9), 1133–1143. https://doi.org/10.1177/0146167212445599

Brown, H. R., Zeidman, P., Smittenaar, P., Adams, R. A., McNab, F., Rutledge, R. B., & Dolan, R. J. (2014). Crowdsourcing for cognitive science – the utility of smartphones. *PLoS ONE*, *9*(7), e100662. https://doi.org/10.1371/journal.pone.0100662

Bruder, G. E., Kroppmann, C. J., Kayser, J., Stewart, J. W., McGrath, P. J., & Tenke, C. E. (2009). Reduced brain responses to novel sounds in depression: P3 findings in a novelty oddball task. *Psychiatry Research*, *170*(2–3), 218–223. https://doi.org/10.1016/j.psychres.2008.10.023

Buchanan, K. E., & Bardi, A. (2010). Acts of kindness and acts of novelty affect life satisfaction. *The Journal of Social Psychology*, *150*(3), 235–237. https://doi.org/10.1080/00224540903365554

Cavanagh, J. F., & Geisler, M. W. (2006). Mood effects on the ERP processing of emotional intensity in faces: A P3 investigation with depressed students. *International Journal of Psychophysiology*, *60*(1), 27–33. https://doi.org/10.1016/j.ijpsycho.2005.04.005

Ceh, S. M., Annerer-Walcher, S., Körner, C., Rominger, C., Kober, S. E., Fink, A., & Benedek, M. (2020). Neurophysiological indicators of internal attention: An electroencephalography–eye-tracking coregistration study. *Brain and Behavior*, *10*(10). https://doi.org/10.1002/brb3.1790

Chen, J., Ma, W., Zhang, Y., Wu, X., Wei, D., Liu, G., Deng, Z., Zhang, Z., & Yang, L. (2014). Distinct facial processing related negative cognitive bias in first-episode and recurrent major depression: Evidence from the N170 ERP component. *PLoS ONE*, *9*(10), e109176. https://doi.org/10.1371/journal.pone.0109176

Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. *Journal of Health and Social Behavior*, *24*(4), 385. https://doi.org/10.2307/2136404

Cohn, M. A., & Fredrickson, B. L. (2010). In search of durable positive psychology interventions: Predictors and consequences of long-term positive behavior change. *The Journal of Positive Psychology*, *5*(5), 355–366. https://doi.org/10.1080/17439760.2010.508883

Crump, M. J. C., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PLoS ONE*, *8*(3), e57410. https://doi.org/10.1371/journal.pone.0057410

Curry, O. S., Rowland, L. A., Van Lissa, C. J., Zlotowitz, S., McAlaney, J., & Whitehouse, H. (2018). Happy to help? A systematic review and meta-analysis of the effects of performing acts of kindness on the well-being of the actor. *Journal of Experimental Social Psychology*, *76*, 320–329. https://doi.org/10.1016/j.jesp.2018.02.014

Cuthbert, B. N., Schupp, H. T., Bradley, M. M., Birbaumer, N., & Lang, P. J. (2000). Brain potentials in affective picture processing: Covariation with autonomic arousal and affective report. *Biological Psychology*, *52*(2), 95–111. https://doi.org/10.1016/S0301-0511(99)00044-7

Dai, Q., & Feng, Z. (2012). More excited for negative facial expressions in depression: Evidence from an event-related potential study. *Clinical Neurophysiology*, *123*(11), 2172–2179. https://doi.org/10.1016/j.clinph.2012.04.018

Deldin, P. J., Keller, J., Gergen, J. A., & Miller, G. A. (2001). Cognitive bias and emotion in neuropsychological models of depression. *Cognition & Emotion*, *15*(6), 787–802. https://doi.org/10.1080/02699930143000248

Derks, E. M., Dolan, C. V., & Boomsma, D. I. (2006). A test of the equal environment assumption (EEA) in multivariate twin studies. *Twin Research and Human Genetics*, *9*(3), 403–411. https://doi.org/10.1375/twin.9.3.403

Diener, E., & Biswas-Diener, R. (2009). Will Money Increase Subjective Well-Being?: A Literature Review and Guide to Needed Research. In E. Diener (Ed.), *The Science of Well-Being* (Vol. 37, pp. 119–154). Springer Netherlands. https://doi.org/10.1007/978-90-481-2350-6_6

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Disabato, D. J., Goodman, F. R., Kashdan, T. B., Short, J. L., & Jarden, A. (2016). Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-being. *Psychological Assessment*, *28*(5), 471–482. https://doi.org/10.1037/pas0000209

Dreisbach, G., & Goschke, T. (2004). How positive affect modulates cognitive control: Reduced perseveration at the cost of increased distractibility. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*(2), 343–353. https://doi.org/10.1037/0278-7393.30.2.343

Drozd, F., Mork, L., Nielsen, B., Raeder, S., & Bjørkli, C. A. (2014). Better Days – A randomized controlled trial of an internet-based positive psychology intervention. *The Journal of Positive Psychology*, *9*(5), 377–388. https://doi.org/10.1080/17439760.2014.910822

Feicht, T., Wittmann, M., Jose, G., Mock, A., von Hirschhausen, E., & Esch, T. (2013). Evaluation of a seven-week web-based happiness training to improve psychological well-being, reduce stress, and enhance mindfulness and flourishing: A randomized controlled occupational health study. *Evidence-Based Complementary and Alternative Medicine*, *2013*, 1–14. https://doi.org/10.1155/2013/676953

Ferdek, M. A., van Rijn, C. M., & Wyczesany, M. (2016). Depressive rumination and the emotional control circuit: An EEG localization and effective connectivity study. *Cognitive, Affective, & Behavioral Neuroscience*, *16*(6), 1099–1113. https://doi.org/10.3758/s13415-016-0456-x

Fingelkurts, A. A., & Fingelkurts, A. A. (2015). Altered structure of dynamic electroencephalogram oscillatory pattern in major depression. *Biological Psychiatry*, *77*(12), 1050–1060. https://doi.org/10.1016/j.biopsych.2014.12.011

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology. *American Psychologist*, *56*(3), 218–226. https://doi.org/10.1O37//0OO3-O66X.56.3.218

Gatt, J. M., Burton, K. L. O., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new

composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213. https://doi.org/10.1016/j.psychres.2014.04.033

Gatt, J. M., Korgaonkar, M. S., Schofield, P. R., Harris, A., Clark, C. R., Oakley, K. L., Ram, K., Michaelson, H., Yap, S., Stanners, M., Wise, V., & Williams, L. M. (2012). The TWIN-E Project in Emotional Wellbeing: Study protocol and preliminary heritability results across four MRI and DTI measures. *Twin Research and Human Genetics*, *15*(3), 419–441. https://doi.org/10.1017/thg.2012.12

Germine, L., Nakayama, K., Duchaine, B. C., Chabris, C. F., Chatterjee, G., & Wilmer, J. B. (2012). Is the Web as good as the lab? Comparable performance from Web and lab in cognitive/perceptual experiments. *Psychonomic Bulletin & Review*, *19*(5), 847–857. https://doi.org/10.3758/s13423-012-0296-9

Goodman, F. R., Disabato, D. J., Kashdan, T. B., & Kauffman, S. B. (2018). Measuring well-being: A comparison of subjective well-being and PERMA. *The Journal of Positive Psychology*, *13*(4), 321–332. https://doi.org/10.1080/17439760.2017.1388434

Gordon, E., Cooper, N., Rennie, C., Hermens, D., & Williams, L. M. (2005). Integrative Neuroscience: The role of a standardized database. *Clinical EEG and Neuroscience*, *36*(2), 64–75. https://doi.org/10.1177/155005940503600205

Gottesman, I. I., & Gould, T. D. (2003). The endophenotype concept in psychiatry: Etymology and strategic intentions. *American Journal of Psychiatry*, *160*(4), 636–645. https://doi.org/10.1176/appi.ajp.160.4.636

Gray, J. R. (2001). Emotional modulation of cognitive control: Approach–withdrawal states double-dissociate spatial from verbal two-back task performance. *Journal of Experimental Psychology: General*, *130*(3), 436–452. https://doi.org/10.1037/0096-3445.130.3.436

Greenspoon, P. J., & Saklofske, D. H. (2001). Toward an integration of subjective well-being and psychopathology. *Social Indicators Research*, *54*, 81–108. https://doi.org/10.1023/A:1007219227883

Grin-Yatsenko, V. A., Baas, I., Ponomarev, V. A., & Kropotov, J. D. (2009). EEG power spectra at early stages of depressive disorders. *Journal of Clinical Neurophysiology*, *26*(6), 401–406. https://doi.org/10.1097/WNP.0b013e3181c298fe

Hackinger, S., & Zeggini, E. (2017). Statistical methods to detect pleiotropy in human complex traits. *Open Biology*, *7*(11), 170125. https://doi.org/10.1098/rsob.170125

Haeffel, G. J., & Howard, G. S. (2010). Self-report: Psychology's four-letter word. *The American Journal of Psychology*, *123*(2), 181. https://doi.org/10.5406/amerjpsyc.123.2.0181

Hallford, D. J., & Mellor, D. (2016). Brief reminiscence activities improve state well-being and self-concept in young adults: A randomised controlled experiment. *Memory*, *24*(10), 1311–1320. https://doi.org/10.1080/09658211.2015.1103875

Hanel, P. H. P., & Vione, K. C. (2016). Do student samples provide an accurate estimate of the general public? *PLOS ONE*, *11*(12), e0168354. https://doi.org/10.1371/journal.pone.0168354

Harmon-Jones, E., & Gable, P. A. (2018). On the role of asymmetric frontal cortical activity in approach and withdrawal motivation: An updated review of the evidence. *Psychophysiology*, *55*(1). https://doi.org/10.1111/psyp.12879

Hausmann, L. R. M., Youk, A., Kwoh, C. K., Ibrahim, S. A., Hannon, M. J., Weiner, D. K., Gallagher, R. M., & Parks, A. (2017). Testing a positive psychological intervention for osteoarthritis. *Pain Medicine*, *18*(10), 1908–1920. https://doi.org/10.1093/pm/pnx141

Heintzelman, S. J., Trent, J., & King, L. A. (2015). Revisiting desirable response bias in well-being reports. *The Journal of Positive Psychology*, *10*(2), 167–178. https://doi.org/10.1080/17439760.2014.927903

Hendriks, T., Schotanus-Dijkstra, M., Hassankhan, A., de Jong, J., & Bohlmeijer, E. (2020). The efficacy of multi-component positive psychology interventions: A systematic review and meta-analysis of randomized controlled trials. *Journal of Happiness Studies*, *21*(1), 357–390. https://doi.org/10.1007/s10902-019-00082-1

Hendriks, T., Schotanus-Dijkstra, M., Hassankhan, A., Graafsma, T., Bohlmeijer, E., & de Jong, J. (2018). The efficacy of positive psychology interventions from non-Western countries: A systematic review and metaanalysis. *International Journal of Wellbeing*, *8*(1), 71–98. https://doi.org/10.5502/ijw.v8i1.711

Hinojosa, J. A., Mercado, F., & Carretié, L. (2015). N170 sensitivity to facial expression: A meta-analysis. *Neuroscience & Biobehavioral Reviews*, *55*, 498–509. https://doi.org/10.1016/j.neubiorev.2015.06.002

Horwitz, A. V., Videon, T. M., Schmitz, M. F., & Davis, D. (2003). Rethinking twins and environments: Possible social sources for assumed genetic influences in twin research. *Journal of Health and Social Behavior*, *44*(2), 111. https://doi.org/10.2307/1519802

Huppert, F. A. (2009). A new approach to reducing disorder and improving well-being. *Perspectives on Psychological Science*, *4*(1), 108–111. https://doi.org/10.1111/j.1745-6924.2009.01100.x

Jamshidi, J., Williams, L. M., Schofield, P. R., Park, H. R. P., Montalto, A., Chilver, M. R., Bryant, R. A., Toma, C., Fullerton, J. M., & Gatt, J. M. (2020). Diverse phenotypic measurements of wellbeing: Heritability, temporal stability and the variance explained

by polygenic scores. *Genes, Brain and Behavior*, *19*(8). https://doi.org/10.1111/gbb.12694

Jaworska, N., Thompson, A., Shah, D., Fisher, D., Ilivitsky, V., & Knott, V. (2010). Electrocortical effects of acute tryptophan depletion on emotive facial processing in depression-prone individuals. *European Neuropsychopharmacology*, *20*(7), 473–486. https://doi.org/10.1016/j.euroneuro.2010.03.002

Johnson, J. A. (2005). Ascertaining the validity of individual protocols from Web-based personality inventories. *Journal of Research in Personality*, *39*(1), 103–129. https://doi.org/10.1016/j.jrp.2004.09.009

Joutsenniemi, K., Kaattari, C., Härkänen, T., Pankakoski, M., Langinvainio, H., Lönnqvist, J., Mattila, A. S., & Mustonen, P. (2014). E-mail based exercises in happiness, physical activity and readings: A randomized trial on 3274 Finns. *Journal of Psychiatry*, *17*(5).

Kaiser, S., Unger, J., Kiefer, M., Markela, J., Mundt, C., & Weisbrod, M. (2003). Executive control deficit in depression: Event-related potentials in a Go/Nogo task. *Psychiatry Research: Neuroimaging*, *122*(3), 169–184. https://doi.org/10.1016/S0925-4927(03)00004-0

Katz, R., De Sanctis, P., Mahoney, J. R., Sehatpour, P., Murphy, C. F., Gomez-Ramirez, M., Alexopoulos, G. S., & Foxe, J. J. (2010). Cognitive control in late-life depression: Response inhibition deficits and dysfunction of the anterior cingulate cortex. *The American Journal of Geriatric Psychiatry*, *18*(11), 1017–1025. https://doi.org/10.1097/JGP.0b013e3181d695f2

Kenward, M. G., & Carpenter, J. (2007). Multiple imputation: Current perspectives. *Statistical Methods in Medical Research*, *16*(3), 199–218. https://doi.org/10.1177/0962280206075304

Keyes, C. L. M. (2005). Mental illness and/or mental health? Investigating axioms of the Complete State Model of Health. *Journal of Consulting and Clinical Psychology*, *73*(3), 539–548. https://doi.org/10.1037/0022-006X.73.3.539

Killingsworth, M. A., & Gilbert, D. T. (2010). A wandering mind is an unhappy mind. *Science*, *330*(6006), 932–932. https://doi.org/10.1126/science.1192439

Kluetsch, R. C., Ros, T., Théberge, J., Frewen, P. A., Calhoun, V. D., Schmahl, C., Jetly, R., & Lanius, R. A. (2014). Plastic modulation of PTSD resting-state networks and subjective wellbeing by EEG neurofeedback. *Acta Psychiatrica Scandinavica*, *130*(2), 123–136. https://doi.org/10.1111/acps.12229

Knyazev, G. G. (2012). EEG delta oscillations as a correlate of basic homeostatic and motivational processes. *Neuroscience & Biobehavioral Reviews*, *36*(1), 677–695. https://doi.org/10.1016/j.neubiorev.2011.10.002

Knyazev, G. G., Schutter, D. J. L. G., & van Honk, J. (2006). Anxious apprehension increases coupling of delta and beta oscillations. *International Journal of Psychophysiology*, *61*(2), 283–287. https://doi.org/10.1016/j.ijpsycho.2005.12.003

Knyazev, G. G., Slobodskoj-Plusnin, J. Y., Bocharov, A. V., & Pylkova, L. V. (2011). The default mode network and EEG alpha oscillations: An independent component analysis. *Brain Research*, *1402*, 67–79. https://doi.org/10.1016/j.brainres.2011.05.052

Kristoffersen, I. (2018). Great expectations: Education and subjective wellbeing. *Journal of Economic Psychology*, *66*, 64–78. https://doi.org/10.1016/j.joep.2018.04.005

Kushlev, K., Heintzelman, S. J., Lutes, L. D., Wirtz, D., Kanippayoor, J. M., Leitner, D., & Diener, E. (2020). Does happiness improve health? Evidence from a randomized controlled trial. *Psychological Science*, *31*(7), 807–821. https://doi.org/10.1177/0956797620919673

Layous, K., Chancellor, J., & Lyubomirsky, S. (2014). Positive activities as protective factors against mental health conditions. *Journal of Abnormal Psychology*, *123*(1), 3–12. https://doi.org/10.1037/a0034709

Lee, Y.-C., & Chao, H.-F. (2012). The role of active inhibitory control in psychological well-being and mindfulness. *Personality and Individual Differences*, *53*(5), 618–621. https://doi.org/10.1016/j.paid.2012.05.001

Liebenberg, L., & Moore, J. C. (2018). A social ecological measure of resilience for adults: The RRC-ARM. *Social Indicators Research*, *136*(1), 1–19. https://doi.org/10.1007/s11205-016-1523-y

Llewellyn, D. J., Lang, I. A., Langa, K. M., & Huppert, F. A. (2008). Cognitive function and psychological well-being: Findings from a population-based cohort. *Age and Ageing*, *37*(6), 685–689. https://doi.org/10.1093/ageing/afn194

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Luo, Y., Kong, F., Qi, S., You, X., & Huang, X. (2016). Resting-state functional connectivity of the default mode network associated with happiness. *Social Cognitive and Affective Neuroscience*, *11*(3), 516–524. https://doi.org/10.1093/scan/nsv132

Matsuda, I., & Nittono, H. (2015). The intention to conceal activates the right prefrontal cortex: An event-related potential study. *NeuroReport*, *26*(4), 223–227. https://doi.org/10.1097/WNR.0000000000000332

McLoughlin, G., Makeig, S., & Tsuang, M. T. (2014). In search of biomarkers in psychiatry: EEG-based measures of brain function. *American Journal of Medical Genetics Part B: Neuropsychiatric Genetics*, *165*(2), 111–121. https://doi.org/10.1002/ajmg.b.32208

Meyer, A., Riesel, A., & Proudfit, G. H. (2013). Reliability of the ERN across multiple tasks as a function of increasing errors. *Psychophysiology*, *50*(12), 1220–1225. https://doi.org/10.1111/psyp.12132

Moskowitz, J. T., Carrico, A. W., Duncan, L. G., Cohn, M. A., Cheung, E. O., Batchelder, A., Martinez, L., Segawa, E., Acree, M., & Folkman, S. (2017). Randomized controlled trial of a positive affect intervention for people newly diagnosed with HIV. *Journal of Consulting and Clinical Psychology*, *85*(5), 409–423. https://doi.org/10.1037/ccp0000188

Myruski, S., Bonanno, G. A., Cho, H., Fan, B., & Dennis-Tiwary, T. A. (2019). The late positive potential as a neurocognitive index of emotion regulatory flexibility. *Biological Psychology*, *148*, 107768. https://doi.org/10.1016/j.biopsycho.2019.107768

Neff, K. D. (2003). The development and validation of a scale to measure self-compassion. *Self and Identity*, *2*(3), 223–250. https://doi.org/10.1080/15298860309027

Neuner, I., Arrubla, J., Werner, C. J., Hitz, K., Boers, F., Kawohl, W., & Shah, N. J. (2014). The default mode network and EEG regional spectral power: A simultaneous fMRI-EEG study. *PLoS ONE*, *9*(2), e88214. https://doi.org/10.1371/journal.pone.0088214

Nichols, A. L., & Maner, J. K. (2008). The Good-Subject Effect: Investigating participant demand characteristics. *The Journal of General Psychology*, *135*(2), 151–166. https://doi.org/10.3200/GENP.135.2.151-166

Park, H. R. P., Chilver, M. R., Montalto, A., Jamshidi, J., Schofield, P. R., Williams, L. M., & Gatt, J. M. (2021). Associations between mental wellbeing and fMRI neural bases underlying responses to positive emotion in a twin sample. *Psychological Medicine*, 1–9. https://doi.org/10.1017/S0033291721002695

Parks, A. C., Della Porta, M. D., Pierce, R. S., Zilca, R., & Lyubomirsky, S. (2012). Pursuing happiness in everyday life: The characteristics and behaviors of online happiness seekers. *Emotion*, *12*(6), 1222–1234. https://doi.org/10.1037/a0028587

Paul, K., Pourtois, G., van Steenbergen, H., Gable, P., & Dreisbach, G. (2021). Finding a balance: Modulatory effects of positive affect on attentional and cognitive control. *Current Opinion in Behavioral Sciences*, *39*, 136–141. https://doi.org/10.1016/j.cobeha.2021.03.002

Pe, M. L., Koval, P., & Kuppens, P. (2013). Executive well-being: Updating of positive stimuli in working memory is associated with subjective well-being. *Cognition*, *126*(2), 335–340. https://doi.org/10.1016/j.cognition.2012.10.002

Perinelli, E., & Gremigni, P. (2016). Use of social desirability scales in clinical psychology: A systematic review. *Journal of Clinical Psychology*, *72*, 534–551. https://doi.org/10.1002/jclp.22284

Peterson, R. A. (2001). On the use of college students in social science research: Insights from a second-order meta-analysis. *Journal of Consumer Research*, *28*(3), 450–461. https://doi.org/10.1086/323732

Peterson, R. A., & Merunka, D. R. (2014). Convenience samples of college students and research reproducibility. *Journal of Business Research*, *67*(5), 1035–1041. https://doi.org/10.1016/j.jbusres.2013.08.010

Pinquart, M., & Forstmeier, S. (2012). Effects of reminiscence interventions on psychosocial outcomes: A meta-analysis. *Aging & Mental Health*, *16*(5), 541–558. https://doi.org/10.1080/13607863.2011.651434

Proyer, R. T., Wellenzohn, S., Gander, F., & Ruch, W. (2015). Toward a better understanding of what makes positive psychology interventions work: Predicting happiness and depression from the person × intervention fit in a follow-up after 3.5 years. *Applied*

Psychology: Health and Well-Being, *7*(1), 108–128. https://doi.org/10.1111/aphw.12039

Putkinen, V., Makkonen, T., & Eerola, T. (2017). Music-induced positive mood broadens the scope of auditory attention. *Social Cognitive and Affective Neuroscience*, *12*(7), 1159–1168. https://doi.org/10.1093/scan/nsx038

Routledge, K. M., Burton, K. L. O., Williams, L. M., Harris, A., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2017). The shared and unique genetic relationship between mental well-being, depression and anxiety symptoms and cognitive function in healthy twins. *Cognition and Emotion*, *31*(7), 1465–1479. https://doi.org/10.1080/02699931.2016.1232242

Routledge, K. M., Williams, L. M., Harris, A. W. F., Schofield, P. R., Clark, C. R., & Gatt, J. M. (2018). Genetic correlations between wellbeing, depression and anxiety symptoms and behavioral responses to the emotional faces task in healthy twins. *Psychiatry Research*, *264*, 385–393. https://doi.org/10.1016/j.psychres.2018.03.042

Ruchsow, M., Groen, G., Kiefer, M., Beschoner, P., Hermle, L., Ebert, D., & Falkenstein, M. (2008). Electrophysiological evidence for reduced inhibitory control in depressed patients in partial remission: A Go/Nogo study. *International Journal of Psychophysiology*, *68*(3), 209–218. https://doi.org/10.1016/j.ijpsycho.2008.01.010

Schotanus-Dijkstra, M., Drossaert, C. H. C., Pieterse, M. E., Boon, B., Walburg, J. A., & Bohlmeijer, E. T. (2017). An early intervention to promote well-being and flourishing and reduce anxiety and depression: A randomized controlled trial. *Internet Interventions*, *9*, 15–24. https://doi.org/10.1016/j.invent.2017.04.002

Schueller, S. M., & Parks, A. C. (2012). Disseminating self-help: Positive psychology exercises in an online trial. *Journal of Medical Internet Research*, *14*(3), e63. https://doi.org/10.2196/jmir.1850

Schutter, D. J. L. G., & van Honk, J. (2005). Salivary cortisol levels and the coupling of midfrontal delta–beta oscillations. *International Journal of Psychophysiology*, *55*(1), 127–129. https://doi.org/10.1016/j.ijpsycho.2004.07.003

Shannon, R. W., Patrick, C. J., Venables, N. C., & He, S. (2013). 'Faceness' and affectivity: Evidence for genetic contributions to distinct components of electrocortical response to human faces. *NeuroImage*, *83*, 609–615. https://doi.org/10.1016/j.neuroimage.2013.06.014

Sheldon, K. M., Boehm, J., & Lyubomirsky, S. (2013). *Variety is the spice of happiness: The Hedonic Adaptation Prevention Model*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199557257.013.0067

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & de Geus, E. J. C. (2007). Genetic contribution to the P3 in young and middle-aged adults. *Twin Research and Human Genetics*, *10*(2), 335–347. https://doi.org/10.1375/twin.10.2.335

Smit, D. J. A., Posthuma, D., Boomsma, D. I., & Geus, E. J. C. (2005). Heritability of background EEG across the power spectrum. *Psychophysiology*, *42*(6), 691–697. https://doi.org/10.1111/j.1469-8986.2005.00352.x

Smith, E., Weinberg, A., Moran, T., & Hajcak, G. (2013). Electrocortical responses to NIMSTIM facial expressions of emotion. *International Journal of Psychophysiology*, *88*(1), 17–25. https://doi.org/10.1016/j.ijpsycho.2012.12.004

Stewart, N., Chandler, J., & Paolacci, G. (2017). Crowdsourcing samples in cognitive science. *Trends in Cognitive Sciences*, *21*(10), 736–748. https://doi.org/10.1016/j.tics.2017.06.007

Storbeck, J., & Maswood, R. (2016). Happiness increases verbal and spatial working memory capacity where sadness does not: Emotion, working memory and executive control.

Cognition and Emotion, *30*(5), 925–938. https://doi.org/10.1080/02699931.2015.1034091

Suldo, S. M., & Shaffer, E. J. (2008). Looking beyond psychopathology: The dual-factor model of mental health in youth. *School Psychology Review*, *37*(1), 52–68. https://doi.org/10.1080/02796015.2008.12087908

Thorsteinsen, K., & Vittersø, J. (2018). Striving for wellbeing: The different roles of hedonia and eudaimonia in goal pursuit and goal achievement. *International Journal of Wellbeing*, *8*(2), 89–109. https://doi.org/10.5502/ijw.v8i2.733

Urry, H. L., Nitschke, J. B., Dolski, I., Jackson, D. C., Dalton, K. M., Mueller, C. J., Rosenkranz, M. A., Ryff, C. D., Singer, B. H., & Davidson, R. J. (2004). Making a life worth living: Neural correlates of well-being. *Psychological Science*, *15*(6), 367–372. https://doi.org/10.1111/j.0956-7976.2004.00686.x

van Beijsterveldt, C. E. M., & van Baal, G. C. M. (2002). Twin and family studies of the human electroencephalogram: A review and a meta-analysis. *Biological Psychology*, *61*(1–2), 111–138. https://doi.org/10.1016/S0301-0511(02)00055-8

van Peer, J. (2008). Cortisol administration enhances the coupling of midfrontal delta and beta oscillations. *International Journal of Psychophysiology*, *67*(2), 144–150. https://doi.org/10.1016/j.ijpsycho.2007.11.001

Vanlessen, N., De Raedt, R., Koster, E. H. W., & Pourtois, G. (2016). Happy heart, smiling eyes: A systematic review of positive mood effects on broadening of visuospatial attention. *Neuroscience & Biobehavioral Reviews*, *68*, 816–837. https://doi.org/10.1016/j.neubiorev.2016.07.001

Vanlessen, N., De Raedt, R., Mueller, S. C., Rossi, V., & Pourtois, G. (2015). Happy and less inhibited? Effects of positive mood on inhibitory control during an antisaccade task

revealed using topographic evoked potential mapping. *Biological Psychology*, *110*, 190–200. https://doi.org/10.1016/j.biopsycho.2015.07.004

Vanlessen, N., Rossi, V., De Raedt, R., & Pourtois, G. (2014). Feeling happy enhances early spatial encoding of peripheral information automatically: Electrophysiological time-course and neural sources. *Cognitive, Affective, & Behavioral Neuroscience*. https://doi.org/10.3758/s13415-014-0262-2

Verweij, K. J. H., Mosing, M. A., Zietsch, B. P., & Medland, S. E. (2012). Estimating Heritability from Twin Studies. In R. C. Elston, J. M. Satagopan, & S. Sun (Eds.), *Statistical Human Genetics: Methods and Protocols* (pp. 151–170). Humana Press. https://doi.org/10.1007/978-1-61779-555-8_9

Visscher, P. M., Hill, W. G., & Wray, N. R. (2008). Heritability in the genomics era—Concepts and misconceptions. *Nature Reviews Genetics*, *9*(4), 255–266. https://doi.org/10.1038/nrg2322

Watters, A. J., Harris, A. W. F., & Williams, L. M. (2018). Electrocortical reactivity to negative and positive facial expressions in individuals with a family history of major depression. *Biological Psychology*, *136*, 127–135. https://doi.org/10.1016/j.biopsycho.2018.05.015

Weightman, M. J., Air, T. M., & Baune, B. T. (2014). A review of the role of social cognition in major depressive disorder. *Frontiers in Psychiatry*, *5*. https://doi.org/10.3389/fpsyt.2014.00179

Weinberg, A., Dieterich, R., & Riesel, A. (2015). Error-related brain activity in the age of RDoC: A review of the literature. *International Journal of Psychophysiology*, *98*(2), 276–299. https://doi.org/10.1016/j.ijpsycho.2015.02.029

White, I. R., Carpenter, J., & Horton, N. J. (2012). Including all individuals is not enough: Lessons for intention-to-treat analysis. *Clinical Trials*, *9*(4), 396–407. https://doi.org/10.1177/1740774512450098

Williams, L. M., Hermens, D. F., Thein, T., Clark, C. R., Cooper, N. J., Clarke, S. D., Lamb, C., Gordon, E., & Kohn, M. R. (2010). Using brain-based cognitive measures to support clinical decisions in ADHD. *Pediatric Neurology*, *42*(2), 118–126. https://doi.org/10.1016/j.pediatrneurol.2009.08.010

Williams, L. M., Kemp, A. H., Felmingham, K., Liddell, B. J., Palmer, D. M., & Bryant, R. A. (2007). Neural biases to covert and overt signals of fear: Dissociation by trait anxiety and depression. *Journal of Cognitive Neuroscience*, *19*(10), 1595–1608. https://doi.org/10.1162/jocn.2007.19.10.1595

Williams, L. M., Liddell, B. J., Rathjen, J., Brown, K. J., Gray, J., Phillips, M., Young, A., & Gordon, E. (2004). Mapping the time course of nonconscious and conscious perception of fear: An integration of central and peripheral measures. *Human Brain Mapping*, *21*(2), 64–74. https://doi.org/10.1002/hbm.10154

Williams, L. M., Nagy, M. T., Docherty, J., & Gordon, E. (2010). Emotion, thinking, and brain synchrony in schizophrenia: An integrative model. *Mind & Brain, The Journal of Psychiatry*, *1*(1), 14.

Williams, L. M., Rush, A. J., Koslow, S. H., Wisniewski, S. R., Cooper, N. J., Nemeroff, C. B., Schatzberg, A. F., & Gordon, E. (2011). International Study to Predict Optimized Treatment for Depression (iSPOT-D), a randomized clinical trial: Rationale and protocol. *Trials*, *12*(1), 4. https://doi.org/10.1186/1745-6215-12-4

Williams, L. M., Simms, E., Clark, C. R., Paul, R. H., Rowe, D., & Gordon, E. (2005). The test-retest reliability of a standardized neurocognitive and neurophysiological test

battery: ‘NeuroMarker’. *International Journal of Neuroscience*, *115*(12), 1605–1630. https://doi.org/10.1080/00207450590958475

Xia, L., Mo, L., Wang, J., Zhang, W., & Zhang, D. (2020). Trait anxiety attenuates response inhibition: Evidence from an ERP study using the Go/NoGo task. *Frontiers in Behavioral Neuroscience*, *14*, 28. https://doi.org/10.3389/fnbeh.2020.00028

Xu, Y.-Y., Feng, Z.-Q., Xie, Y.-J., Zhang, J., Peng, S.-H., Yu, Y.-J., & Li, M. (2018). Frontal alpha EEG asymmetry before and after positive psychological interventions for medical students. *Frontiers in Psychiatry*, *9*, 432. https://doi.org/10.3389/fpsyt.2018.00432

Zessin, U., Dickhäuser, O., & Garbade, S. (2015). The relationship between self-compassion and well-being: A meta-analysis. *Applied Psychology: Health and Well-Being*, *7*(3), 340–364. https://doi.org/10.1111/aphw.12051

Zhang, D., He, Z., Chen, Y., & Wei, Z. (2016). Deficits of unconscious emotional processing in patients with major depression: An ERP study. *Journal of Affective Disorders*, *199*, 13–20. https://doi.org/10.1016/j.jad.2016.03.056