An Examination of the Role of Trait Emotional Intelligence in Psychotherapy

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"I, Pablo Alejandro Ignacio Perez Diaz, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis".
Abstract

There is little doubt that the trait EI (Trait emotional intelligence) theory and measures have been found valid and reliable in several settings. This thesis aims to examine the role of trait EI on psychotherapeutic outcomes. This dissertation provides psychometric evidence of the TEIQe-SF (Trait Emotional Intelligence Questionnaire-Short form) in Chilean general and clinical population \( (n_1 = 335, n_2 = 120) \) in studies one and two. The results supported a bi-factor multidimensional structure, besides informing full measurement invariance (through MGCFA, i.e., Multigroup Confirmatory Factor Analysis) between the original and the Chilean adaptation of the TEIQe-SF questionnaire. Since cultural peculiarities may influence trait EI, in study three, the author examined the relationship between trait EI and key sociodemographic variables through analyses of variance (ANOVA) and MGCFA in four countries \( (n = 2,228) \). The findings indicated significant trait EI differences across countries for age, gender, educational attainment, civil status, and occupation. Measurement invariance was acceptable, especially for age, gender, and education, supporting the cross-cultural consistency of the TEIQe-SF. The fourth study explored the adequacy of trait EI as a predictor explaining the variance in psychotherapeutic outcome longitudinally through a multilevel, quasi-experimental design across psychotherapist-patient dyads \( (n_1 = 67, n_2 = 39) \). Outcome variability was found for most dependent variables from start to the end of treatment. Patient trait EI significantly predicted variations in the overall outcome and symptom distress, whilst therapist trait EI significantly predicted variations in the overall outcome and interpersonal relationships. The alliance interacted with the treatment at a significant degree, although these effects explained less outcome variance than those of trait EI. The interaction between patient trait EI and therapist trait EI was a stronger predictor of symptom distress and the overall outcome than the alliance. Overall, the findings point to the importance of trait EI in psychotherapy.
Impact Statement

The contributions of the present dissertation are manifold. First, the advances within academia are theoretical, methodological, and practical. From the theory, the re-examination of the internal structure of the TEIQue-SF, the robust evidence of measurement invariance in general and clinical populations in Chile, and the evidence of cross-cultural measurement invariance across several sociodemographic strata, significantly expanded the former coverage of the trait EI construct and the TEIQue-SF. Moreover, the examination of the role of trait EI in psychotherapy advances a line of research scarcely explored, through the recognition of trait EI as a fundamental predictor of psychotherapy outcome variance. Here, the future developments are expected to be numerous, as the investigated role has been found highly substantial.

The reviewers and editors of the peer review journals where the respective doctoral manuscripts were published, acknowledged the abovementioned theoretical, methodological, and practical contributions. An additional academic contribution from the doctoral studies is the direct impact over further university teaching and research elsewhere. Although, it is expected this influence may be more extensive in Latin-America given the populations studied. An example of this repercussion may be found in the co-authored trait EI related research in Brazil, which was partially influenced by the two firstly published studies of the doctoral thesis. Likewise, ongoing researchers have benefited from sophisticated R and Mplus coding and other related supplementary material, which have been openly shared in scholarly repositories whenever possible.

Second, the contributions outside academia may be better depicted as related to professional psychological practice. In this regard, the advantage of having a validated and invariant (i.e., equivalent across measurements) brief trait EI measure in Chilean Spanish represents an opportunity from the practitioner perspective for more precise psychological
assessment in numerous settings, including clinical, educational, and organisational. In addition, from the public policy angle, the pieces of research render altogether substantial evidence in favour of considering the trait EI theory and the related measures as important for interpreting several psychological concomitants beyond what scholars had posed. For instance, through the mostly uncharted role of the trait EI construct on the psychotherapeutic outcome, as the fourth piece of research proved, or the formerly unconfirmed invariance of the construct across populations and sociodemographic correlates, as the third piece of research demonstrated.

Proper recognition of these effects from psychologists, related mental health practitioners, and the extended health community could influence mental health policymakers to incorporate trait emotional intelligence as a mental health predictor in prevention, diagnosis, and intervention across settings. From the psychotherapist perspective, the demonstrated predictive role of trait EI on psychotherapeutic outcomes, as well as the trait EI interactions between patient and psychotherapist inform for more careful consideration of these ramifications across the psychotherapeutic treatment. All of which may advise on the potential course of the trait EI effects for psychotherapy and overall psychological wellbeing across clinical populations.
# Table of Contents

**Chapter 1: Introduction to the Dissertation** .................................................. 11

1.1–Background to the Research ............................................................................. 12

1.2–Research Problem, Research Issues and Contributions ................................. 16

1.3–Overview of Method ....................................................................................... 17

1.4–Outline of the Dissertation .............................................................................. 18

**Chapter 2: Literature Review** ........................................................................... 20

2.1–Introduction .................................................................................................... 20

2.2–Trait Emotional Intelligence Theory and the Trait EI Questionnaires ............... 20

2.3–Gender Differences in Trait EI ....................................................................... 30

2.4–Other Sociodemographic Differences Supported by Trait EI ....................... 32

2.5–Generalisability of Psychological and Personality Findings Across Human Populations ...... 33

2.6–The Study of Emotional Intelligence (EI) in Chile and Latin-America ................ 42

2.7–The Relevance of Trait EI for Clinical Psychology ........................................ 45

2.8–Impact of the Therapeutic Relationship on the Psychotherapeutic Outcome ........ 49

2.9–Therapist Effects on the Psychotherapeutic Outcome ................................... 56

2.10–Patient Effects on the Psychotherapeutic Outcome ..................................... 59

2.11–Data Analysis for Assessing the Structure and Reliability of a Questionnaire .......... 61

2.12–The Role of Multiple Imputation ........................................................................ 64

**Chapter 3: Validation and Adaptation of the TEIQue-SF in Chilean General and Clinical Population (Studies 1 and 2)** ................................................. 66

3.1–Introduction .................................................................................................... 66

3.2–Method ........................................................................................................... 67

3.3–Results ............................................................................................................ 76
Chapter 4: Trait EI Construct Invariance Across Populations and Sociodemographic Characteristics (Study 3) ................................................................. 101
4.1–Introduction .................................................................................. 101
4.2–Method ......................................................................................... 102
4.3–Results ........................................................................................ 106
4.4–Discussion .................................................................................. 116

Chapter 5: Testing the Role of Trait EI in the Psychotherapeutic Setting (Study 4) ........ 120
5.1–Introduction .................................................................................. 120
5.2–Method ......................................................................................... 121
5.3–Results ........................................................................................ 131
5.4–Discussion .................................................................................. 166

Chapter 6: Summary of the Research ..................................................................... 176
6.1–Introduction .................................................................................. 176
6.2–Conclusions on the research propositions .............................................. 178
6.3–Implications for Theory .................................................................. 184
6.4–Implications for Policy and Practice ..................................................... 190
6.5–Limitations and Strengths of the Research ............................................. 195
6.6–Implications for Methodology .............................................................. 197
6.7–Implications for Future Research ......................................................... 198

References ........................................................................................... 204
Appendices ............................................................................................. 269
Table of Appendices ............................................................................... 270
List of Tables

Table 1. Descriptive Statistics for the TEI Measures in the Pilot General Sample ........................................77
Table 2. Descriptive Statistics for the Trait EI Factors in the Chilean Samples ........................................78
Table 3. Standardised Factor Loadings for the Spanish-Chilean-TEIQue-SF Items in General Population .........................................................................................................................87
Table 4. Standardised Factor Loadings for the Spanish-Chilean-TEIQue-SF Items in Clinical Population .................................................................................................................................91
Table 5. Multiple Group Measurement Invariance Model Comparisons ......................................................94
Table 6. Descriptive Statistics for the TEIQue-SF Datasets ........................................................................109
Table 7. Independent Samples t-Tests With Global Trait EI as the DV ......................................................111
Table 8. Global Trait EI Analyses of Variance (ANOVAs) by Education, Civil Status, and Occupation ..........112
Table 9. Multiple Group Measurement Invariance Comparisons by Sociodemographic Characteristics ....115
Table 10. Descriptive Statistics for the Independent, Dependent, and Moderator Variables ...........134
Table 11. Variability of Outcome Measures Across Patients (Null Model) ..............................................141
Table 12. Psychotherapeutic Change Through Time by the Dependent Variables (Model Time) ........142
Table 13. Patients’ Trait EI Slope Variations .................................................................................................144
Table 14. Slope Variations of Alliance Measures Across Outcomes .........................................................149
Table 15. Slope Variations between Trait EI and Alliance Measures on Outcomes .........................................155
Table 16. Patient’s and Therapist’s Trait EI and Alliance Interactions on the Overall Outcome and Symptom Distress ........................................................................................................158
Table 17. Patient’s and Therapist’s Factor-Level Trait EI Interactions on the Overall Outcome and Symptom Distress ........................................................................................................163
Table 18. Summary Listing of the Contributions by Chapter ....................................................................184
Table 19. Summary Listing of Implications for Policy and Practice by Chapter ...........................................193
List of Figures

Figure 1. Illustration of Higher-order and Bi-factor Models Obtained Through CFA in R ...................... 84
Figure 2. Bi-factor ESEM With ML Estimator, Target Rotation and M.I. in General Population .............. 85
Figure 3. Bi-factor ESEM With ML Estimator, Target Rotation and M.I. in Clinical Population .......... 90
Figure 4. Illustration of the Base ESEM Bi-factor Model Tested Through Measurement Invariance Analyses Across Sociodemographic Variables .................................................................................................................. 108
Figure 5. Illustration of the General Model and Variables Tested Throughout the Study ..................... 128
Figure 6. Correlation Matrix of the Variables Included in Study Four .................................................. 132
Figure 7. Pre and Post Dependent Variables Changes Across Patients: Model Time ............................ 139
Figure 8. Patient’s trait EI Slope Variations Across Dependent Variables and Time ............................ 145
Figure 9. Alliance Measures Slope Variations Across Dependent Variables and Time ....................... 156
Figure 10. Patient’s and Therapist’s Global Trait EI Interactions Plot on the Overall Outcome and Symptom Distress ................................................................................................................................................................................. 159
Figure 11. Patient’s and Therapist’s Factor-Level Trait EI Interactions Plots on the Overall Outcome and Symptom Distress ................................................................................................................................................................................. 164
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Chapter 1: Introduction to the Dissertation

The overall objective of the present dissertation is to explore the adequacy of the trait emotional intelligence theory (trait EI) as a latent model explaining the variance in psychotherapeutic outcome over time. Currently, the literature regarding psychotherapeutic outcome mostly relies on the relationship between patient and psychotherapist. However, not much has been said in terms of the personality interchange in this relationship, despite endogenous and exogenous variables potentially affecting outcomes, such as neurological differences, treatment adherence, medication, psychotherapeutic approach, type of centre in which the psychotherapy is provided, and so forth. Therefore, trait EI theory and related questionnaires provide a psychometrically robust basis from which to ascertain the role that personality plays in psychotherapeutic outcomes, including clinical symptoms, wellbeing, and social and work functionality; whilst testing the potential incremental predictive role of several factors.

In line with these aims, four studies were conducted. The first and second studies aimed to adapt and validate a short form of trait EI questionnaire (TEIQue-SF) in Chile. Consequently, these studies provide researchers and practitioners with a valid and reliable local questionnaire for assessing trait EI in general and clinical population, whilst communicating evidence of internal structure equivalence between the locally adapted questionnaire in Chile (Spanish-Chilean-TEIQue-SF), and the original measure in the United Kingdom. Subsequently, the third study explored in further detail the trait EI construct equivalence cross-culturally and across the sociodemographic variables of gender, age, education, civil status, and occupation. Measurement invariance allows testing for the psychometric equivalence of a construct across different cultures and populations (Greiff & Iliescu, 2017). Four datasets, comprising more than 2200 subjects were contrasted through MGCFA (Multigroup Confirmatory Factor Analysis), a technique that allows assessing measurement invariance,
taking as a basis the proposed bi-factor internal structure implemented in the first and second studies. Two of these countries were from Latin-America (Brazil and Chile) and two from Europe (England and Italy). After testing measurement invariability of the trait EI construct and ANOVAs (Analyses of Variance) comparing trait EI across different sociodemographic strata, trait EI effects in psychotherapy were explored. Accordingly, 67 psychotherapeutic dyads were examined longitudinally after the course of a short psychological intervention across four mental health centres, in which participating psychotherapists diverged in their therapeutic approach.

1.1–Background to the Research

This section will introduce the fields of study, which will be later expanded in the literature review.

1.1.1–EI, TEI theory, and Future Developments for Clinical Research.

As Petrides, Pita et al. (2007) declared, emotional intelligence (EI) has received steady attention in the psychological and health-related literature, being a useful construct for understanding behaviours and outcomes across numerous settings, such as educational, organisational and clinical. John Dewey (1909) firstly coined the term social intelligence, who defined it as “the power of observing and comprehending social situations” (p. 22). The Deweyan conceptualisation of social intelligence emphasizes that the individual is inseparable from the social surrounding (Kauppi et al., 2019). According to Kauppi et al., Dewey envisioned intelligence as a social phenomenon acquired through experiences framed in social relationships, practices, and reciprocities that are only meaningful within the individual’s social network. Therefore, the Deweyan conceptualisation of social intelligence was more related to the interaction between the individual and others, than to an personal attribute, as proposed decades later in the emotional intelligence literature.
Petrides (2011b) posited that the term *social intelligence* as an individual attribute, can be traced to Thorndike (1920). According to Thorndike, social intelligence denotes the ability of understanding and managing people wisely. The term *emotional intelligence* first appeared in Van Ghent’s (1953) analysis of the English novel on Jane Austen’s characters depicted in *Pride and Prejudice*. The first academic attempt in English to define *emotional intelligence* is traceable to Payne (1985), who firstly investigated the concept, focusing on the societal suppressing effects on emotionality. However, it was not until the 1990s that EI emerged as a defined psychological construct in the peer review literature, as it was conceptualised as a set of abilities largely comparable to cognitive intelligence (O’Connor et al., 2019) by Salovey and Mayer (1990), who defined EI as: “the ability to monitor one’s own and others’ feelings and emotions, to discriminate among them and to use this information to guide one’s thinking and actions” (p. 189), framing EI within the broad field of social intelligence, as previously defined.

Two main paradigms have been proposed for comprehending and assessing EI. The first concerns emotion-related dispositions, as measured through self-report questionnaires, namely trait EI, whereas the second refers to emotion-related cognitive abilities measured through performance-based tests. This conceptual distinction is reflected in empirical findings showing a very low correlation between trait EI and ability EI (e.g., O’Connor & Little, 2003; Warwick & Nettelbeck, 2004). Trait EI corresponds to the typical performance approach, which accounts for the actual emotional management capacity, whereas ability EI matches a maximal performance type of measurement, which evaluates the emotionality according to objective knowledge of emotions (Freudenthaler & Neubauer, 2007).

Petrides and Furnham (2000a, 2001) noted that the lack of agreement in the operationalisation of EI was problematic for the study of the construct, as different approaches would likely yield non-comparable results. Similarly, Roberts et al. (2001)
highlighted that ability trait EI suffered from measurement error, as different scoring procedures in it (i.e., expert and consensus) yielded contradictory results. Since these early studies to the EI field, more than twenty years of research have consolidated these two approaches to emotionality in the psychological literature, each with its characteristic measurement approach and theoretical development backing it. Scholars currently agree that the distinction between trait EI and ability EI is clear and that both perspectives have merit (e.g., Sarrionandia & Mikolajczak, 2020). The difference in the measurement approach between the two supports unique theoretical interpretations on emotional intelligence, which has been claimed as sufficient for most EI instruments (O’Connor et al., 2019), and especially for self-report measures as they tend to correlate with each other (Pérez et al., 2005).

The present dissertation examines all the research propositions and hypotheses in each of the included studies under the umbrella of the trait EI paradigm, as the dissertation intends to provide a personality-based comprehension of psychotherapeutic outcomes in clinical Psychology. The trait EI theory is especially appropriate for this aim, as the taxonomy is embedded within the personality framework (Petrides & Furnham, 2000a). The main advantages of trait EI theory and the related questionnaires, in comparison to other trait personality taxonomies and questionnaires, are their conceptual and explanatory power, as trait EI allows researchers to predict behaviour, attitudes and achievement effectively (Petrides, Pita, et al., 2007). These authors have declared that the pathways for future developments in trait EI should progress from basic to applied research. Thus, prospective and cross-cultural studies emerge as two of the most attractive research designs for enriching the theory and its implications for psychometrics and personality.

Petrides et al. (2016) have recently stressed the relevance of these types of studies: “compared to mental and subjective health, the relationships of trait EI with objective indicators of health status remain underresearched” (p. 337). For instance, Mikolajczak et al.
(2007) discovered that trait EI was associated with lower reactivity to stress, both psychologically and biologically. The first, measured through the Positive and Negative Affect Schedule (PANAS, Watson et al., 1988), and the second via cortisol secretion. This piece of research also reported trait EI incremental validity regarding stress reactivity vis-à-vis social desirability, alexithymia, and the big five-factor model of personality.

Moreover, Sarrionandia and Mikolajczak (2020), conducted a meta-analysis with over 100 studies, which were selected after stringent criteria was applied, concluding that trait EI affects physical health through numerous behaviours. Among these, social support \((r = .33)\) and sleep \((r = .36)\) are the two most largely affected by trait EI, whilst physical health \((r = .17)\) and substance use \((r = –.10)\) are behaviours moderately driven by trait EI. Regarding biological indicators, the results of the study suggested that HPA axis (i.e., Hypothalamic-pituitary-adrenal axis, mainly involved in stress response, among other processes), and possible blood glucose are mediators of trait EI on health outcomes. Likewise, Arora et al. (2011) have provided evidence with medical students, where higher trait EI students experienced more stress during unfamiliar surgical scenarios, although they were able to recover more easily than their lower trait EI classmates. This finding poses the question of how trait EI may influence practitioner’s performance.

1.1.2—Predictors for the Psychotherapeutic Outcome.

Norcross (2001) has suggested that there is converging evidence linking the personality of the psychotherapist to the outcome of psychotherapy. Moreover, Norcross and Hill (2004) have stated that some key relationship elements or behaviours emanating from both the psychotherapist and the client have a considerable effect on the clinical outcome of the patient; among the most relevant: therapeutic alliance, empathy, goal consensus and collaboration. Horvath and Greenberg (1986, 1989) developed the most salient relationship questionnaire in
the literature (WAI, i.e., Working Alliance Inventory), which assesses the working therapeutic alliance. The inventory has been shown reliable ($\alpha = .91$) and valid, providing a stable three-factor structure, congruent with the formerly developed theoretical framework by Bordin (1979).

In the psychotherapeutic literature, these effects have been described as patient and therapist effects impacting psychotherapy outcomes. Here, the therapeutic alliance plays a role that has been highlighted by scholars, which is mostly unaltered across therapeutic approaches. Accordingly, these effects will be review in further detail in the literature review.

1.2–Research Problem, Research Issues and Contributions

There is no evidence yet for or against the hypothesis that psychotherapists with high trait EI may perform better in terms of their psychotherapeutic outcome with their patients, or if this effect is somehow mediated by patient’s trait EI. Consequently, a whole range of studies considering trait EI measurements for both patient and psychotherapist may improve prediction of prospective outcomes in psychological treatment. For instance, psychotherapists low in trait EI may perform worse in terms of patient’s psychotherapeutic outcomes, and patients low in trait EI could benefit less from the intervention at the end of treatment. The studies in this dissertation expand the scope regarding trait EI implications for the clinical field. For instance, besides studying the effect of the Global Trait EI score vis-à-vis the psychological intervention, it would be highly relevant to ascertain whether trait EI at the factor-level accounts for substantial psychotherapeutic outcome variance in comparison to the alliance.

The two first investigations examine the Chilean validation and psychometric structure supporting the Spanish-Chilean-TEIQue in general and clinical populations. Additionally, these studies inspect measurement invariance for the questionnaire, compared to the original TEIQue-SF. The third study examines trait EI construct equivalence across different
populations and sociodemographic variables by comparing four-country datasets using the respective locally adapted trait EI questionnaires. With this evidence providing a basis for accurately studying trait EI effects in psychotherapy, the author scrutinises patient’s and therapist’s trait EI implications on psychotherapeutic outcomes through a multicentre, longitudinal, multilevel, quasi-experimental design in study four. Therefore, different centres are approached through a prospective research design for the development of this last inquiry, in which patients are nested on their respective therapist, and the expected predicted effect from trait EI is tested across them.

1.3–Overview of Method

During the development of the dissertation, multivariate statistical procedures were applied to fulfil the objectives established for the studies. Exploratory Structural Equation Modelling (ESEM) was performed when testing the underlying latent variables of trait EI questionnaires. In addition to ESEM and other factorial analyses, other multivariate statistical modelling methods were implemented when comparing groups across the studies, such as multigroup measurement invariance, linear multivariate regression analyses, multivariate analysis of variance, multivariate analyses of co-variance among others. Most of these procedures relied on the General Linear Model (GLM), whereas other multivariate techniques explored non-linear relationships among data. As a wide range of analytic tools is utilised, some studies implemented between-subject designs, whereas others used within-subject designs (i.e., approaches useful for the longitudinal assessment of patient outcomes). Likewise, during the development of the chapters, univariate procedures were applied when necessary. As for reliability, Omega and Cronbach’s Alpha indexes were informed where appropriate, as the report of these two reliability indexes is a recommended practice (Sjitsma, 2009).
1.4–Outline of the Dissertation

The layout of the dissertation resembles the overall aim of the dissertation, as conducted through different populations and research designs. Hence, the chapters are presented as follows:

- **Chapter two: Literature review.** This chapter covers a literature review on the trait EI theory, related salient measures, most relevant findings, local studies with Latin-American populations, and their applicability to the aims of the dissertation. The generalisability of the construct is examined as linked to the cross-cultural personality literature. The role of the alliance in psychotherapy and the expected outcomes from psychological treatment are presented. Moreover, the specific effects associated with the patient and the therapist regarding psychotherapeutic outcomes are examined. The chapter also introduces the theoretical psychometric basis supporting the data analytic approaches implemented across the dissertation.

- **Chapter three: Validation and Adaptation of the TEIQue-SF in Chilean General and Clinical Population.** This section explores the psychometric evidence of the TEIQue-SF in Chilean general and clinical participants. Cognitive interviews and focus groups meetings were performed to adapt the questionnaire from the TEIQue-SF original English form to Chilean Spanish. A pilot sample \(n = 70\), a general population validation sample \(n =335\), and a clinical population validation sample \(n =120\) were assessed with the adapted questionnaire. The findings from the studies included in this chapter form the basis of the dissertation. This chapter accounts for study one and two.

- **Chapter four: Trait EI Construct Invariance Across Populations and Sociodemographic Characteristics.** This chapter portrays cross-cultural evidence through four independently collected TEIQue-SF datasets from general population (i.e., Brazil, Chile, Italy and the U.K.). The trait EI construct is cross-culturally contrasted
across several sociodemographic variables through ANOVAs and MGCFA. A special focus is placed on gender, age, education, marital and occupational status, as the evidence of trait EI mean differences is inconclusive across these sociodemographic correlates (e.g., Tsaousis & Kazi, 2013). Moreover, the cross-cultural invariability of the trait EI construct is not well-established. This research clarifies these gaps in the literature by contrasting these four datasets, comprising over 2200 subjects. This chapter accounts for study three.

- **Chapter five: Testing the Role of Trait EI in the Psychotherapeutic Setting.** This chapter examines the role of Trait EI in the psychotherapeutic context through longitudinal, quasi-experimental research. Psychotherapy dyads were assessed with the adapted and validated Spanish-Chilean-TEIQue-SF. The overall aim of the chapter is to test whether patient’s trait EI and psychotherapist’s trait EI (I.Vs.) explain the variance of psychotherapeutic outcomes (D.V.), after a short psychological intervention. This study was implemented in Chilean university mental health clinics, with clinical patients as participants at the first level (n = 67), and psychotherapists at the second level (n = 39). Multilevel linear models with level one centred predictors were conducted through the progressive introduction of random effects via growth curves analyses, in accordance with the literature. This research accounts for study four.

- **Chapter six: Summary of the Research.** The last part of the thesis provides a review and evaluation of the complete dissertation. In a nutshell, it discusses the main conclusions, implications and recommendations for future research.
Chapter 2: Literature Review

2.1–Introduction

This chapter will summarise the relevant literature regarding emotional intelligence and their study in the sociodemographic context where the studies were conducted. The section describes the trait EI theory and the measures developed from it, which comprises the base for understanding the studies theoretically. A contrast to findings derived from trait EI studies and other taxonomies will be placed throughout this chapter, and more generally, throughout the dissertation. The different forms of analysing the internal structure of a questionnaire and the role of measurement invariance as fundamental strategies supporting the generalisability of cross-cultural findings will be clarified. Likewise, the contribution of key sociodemographic correlates interacting with trait EI variables on relevant criteria will be addressed, as this is fundamental for understanding the findings of studies one to three. Later, the chapter will focus on the importance of trait EI for clinical psychology and psychotherapeutic outcomes, and the role of therapeutic alliance and other contextual variables possibly affecting outcome variance. The former, not without introducing the theoretical background and suitability of the data-analytic procedures implemented for assessing the structure and reliability of questionnaires, and the role of multiple imputation for dealing with missing data.

2.2–Trait Emotional Intelligence Theory and the Trait EI Questionnaires

Trait EI is formally defined as a constellation of emotional perceptions, which are assessed through questionnaires and rating scales (Petrides, Pita, et al., 2007). In the literature, trait EI has also been referred to as trait emotional self-efficacy (Petrides, Furnham, et al., 2007). The construct essentially concerns people’s perceptions of their emotional and social effectiveness (Van der Linden et al., 2017), providing a framework for the integration
of the affective aspects of personality, which were formerly overlooked and partly scattered across multiple, allegedly orthogonal, dimensions (Petrides et al., 2016). As mentioned in section 1.1.1., trait EI is a personality-based conceptualisation of emotional intelligence, mostly unrelated to cognitive intelligence (unlike ability EI), consistent with models of differential Psychology, which has shown discriminant, concurrent, incremental, and predictive validity compared to well-regarded personality frameworks (Petrides, Furnham, et al., 2007). Therefore, as these authors posited, trait EI relates to emotion-related individual differences, which lies at lower levels of trait taxonomies (Petrides & Furnham, 2001; Petrides, Pita, et al., 2007).

In pioneer research on the coverage of trait EI, De Raad (2005) discovered that 42% of trait EI items are strongly associated with Big Five’s factor IV (i.e., Neuroticism), whereas 52% of the items were equally distributed across Big Five’s factor I (Extraversion), II (Agreeableness), and III (Conscientiousness); whilst the remaining 7% of items was associated with Big Five’s factor V (Openness to experience). The direction of the correlation between trait EI items and Big Five’s factors was mostly negatively in the case of factor IV, and mostly positively as to factors I, II, III, and V. In other words, trait EI is positively associated with Extraversion, Agreeableness, Conscientiousness, and Openness to experience, whilst being inversely correlated to Neuroticism. In this study, 437 items from six well-regarded trait EI emotional intelligence measures were included, and the Abridged Big Five Circumplex (AB5C) was utilised as a representation of the Big Five model.

In a second study included in the same manuscript, the author pooled Big Five items regarding its relevance to emotional intelligence, from which De Raad (2005) arrived at a four-factor structure through PCA (Principal Component Analysis). This second inquiry concluded that the four extracted emotional intelligence factors (i.e., Respect, Social competence, Emotional control, and Sagacity and intelligence) resemble the first study’s
findings, as Respect correlates strongly and positively with Agreeableness, Social competence correlates positively and substantially with Extraversion, Emotional control correlates inversely and significantly with Neuroticism, and Sagacity and Intelligence correlates positively and significantly with Openness to experience. According to De Raad, Respect refers to taking into account others’ opinions, interests, strengths and weaknesses, Social competence is about finding yourself in the company of others, Emotional control is the ability to leave emotions aside, Sagacity and intelligence refers to being perceptive, understanding circumstances quickly, and being critical. The author concluded from these studies that the Big Five’s Conscientiousness domain is not used as an emotional intelligence resource. Moreover, trait EI would represent a stripped Big Five, especially regarding rational information processing, supporting Van der Zee et al.’s (2002) results on a weak association between the variables. The latter diverges with Petrides and Furnham (2001) and Saklofske et al. ’(2003) findings, researchers that reported a substantial correlation between trait EI and Conscientiousness, as will be reviewed in the present section.

According to Petrides and Furnham (2001), trait EI theory encompasses various dispositions from the personality domain, such as empathy and assertiveness (Goleman, 1983), social intelligence (Thorndike, 1920), personal intelligence, and ability EI (Mayer and Salovey, 1997) in the form of self-perceived abilities. Petrides and Furnham declared that the construct emerged from a content analysis of the salient literature of EI, being this the basis on which all TEI questionnaires are constructed. This ground comprises fifteen facets, which are the simplest psychometric description of trait EI, as developed by Petrides and Furnham. According to these authors, it is expectable to obtain a fair amount of cross-loadings between these facets, being this the reason why oblique structures (i.e., where factors are allowed to correlate to some degree, see McDonald, 2014) are better suited for the study of the internal factor structure of trait EI questionnaires.
The fifteen trait EI facets are: Adaptability, Assertiveness, Emotion perception, Emotion control, Emotion expression, Emotion management, Impulse control, Relationships, Self-esteem, Self-motivation, Social awareness, Stress management, Trait empathy, Trait happiness and Trait optimism. Adaptability refers to being flexible and willing to adapt to new conditions, Assertiveness is to being straightforward, frank, and willing to stand up for their rights, Emotion expression implies being capable of communicating feelings to others, Emotion management relates to influencing other people’s feelings, Emotion perception is about clearly identifying own and other people’s feelings, Emotion regulation is being capable of controlling own emotions, Impulse control refers to being reflective and less likely to give in, Relationships is the capability of maintaining fulfilling personal relationships, Self-esteem relates to being successful and self-confident, Self-motivation is described as being determined and unlikely to give up against adversity, Social competence relates to being accomplished in networking and social settings, Stress management is to withstand pressure and stress, Trait Empathy refers to being capable of taking someone else’s perspective, Trait Happiness is about being cheerful and find satisfaction in life, whilst Trait optimism implies being confident and likely to look on the bright side of life (Petrides, Furnham et al., 2007).

In the abovementioned publication, Petrides and Furnham (2001) conducted a principal axis (PA) exploratory factor analysis (EFA), taking as a starting point the EQ-i (i.e., the emotional intelligence inventory, Bar-On, 1997). EFA accounted for a four-factor structure, unlabelled at the time of the publication, which later derived into the four-factor basis of the TEI questionnaires (i.e., Well-being, Self-control, Emotionality and Sociability, see Petrides, 2009). Moreover, the authors proposed the incipient idea that a single factor was deemed to account better for the variability of the fifteen tested variables, introducing the notion of a general trait EI factor accounting for global emotion-related variability, which
later evolved into the Global trait EI factor (see Petrides, 2009). Individuals who are generally better adapted, feel positive, happy, and fulfilled, will score high on Well-being. Those with strong determination and a healthy degree of control over their urges and desires will score high on Self-control. Those who see themselves as emotionally capable and are in touch with their own and other’s people feelings will score high on Emotionality. Persons who believe they are socially competent, good listeners, and can communicate assertively with people from heterogeneous backgrounds will score high on Sociability (Petrides, 2009).

Moreover, in Petrides and Furnham’s (2001), the nature of trait EI (as measured by the EQ-i) against Eysenck’s gigantic three framework was tested, since factor patterns were investigated between the two. Eysenck’s gigantic three personality taxonomy is characterised by three super-factors, namely, Psychoticism (P), Extraversion (E), and Neuroticism (N). The first has been considered as a combination of low Agreeableness and low Conscientiousness when contrasted with the Big five-factor model (Goldberg, 1991; McCrae & Costa, 1985), whilst the two latter mostly represent the factors equally labelled within the Big Five framework (Zuckerman et al., 1993). The factor patterns reported by Petrides and Furnham revealed that trait EI facets were mostly independent of Eysenckian super-factors, providing early discriminant validity for the trait EI construct vis-à-vis Eysenck Gigantic Three. However, there was still some overlap between the two paradigms, which was accounted mainly by low correlations between the factors N \((r = -.31)\) and E \((r = .29)\) with trait EI facets, and by a less noticeable negative correlation between P and trait EI \((r = -.14)\).

In a second study in Petrides and Furnham (2001), the factor pattern between trait EI (as measured by the EQ-i) and Big Five’s factors and facets were contrasted. Here, there was a higher overlap between the taxonomies. Although the correlation between trait EI and the factors N \((r = -.29)\) and E \((r = .30)\) remained virtually unchanged, trait EI positively correlated to a similar degree with Big Five’s factor C (i.e., Conscientiousness, \(r = .35\),
which is not depicted in the Eysenckian framework, and to a lesser extent to factor O (i.e., Openness to experience, $r = .13$). Here, nine of the fifteen trait EI facets remained statistically distinct from Big Five, and consequently, trait EI discriminant validity was less distinguishable than Eysenck gigantic three. These results are consistent with those of Saklofske et al. (2003), who reported substantially positive correlations between trait EI and the Big Five’s factors E ($r = .51$), C ($r = .38$), O ($r = .27$) and A ($r = .18$), and a robust negative correlation between trait EI and the factor N ($r = -.37$). Petrides and Furnham concluded from the findings of these studies that new trait EI measures should be developed to account better for the construct, which was the starting point for the trait EI measures designed by Petrides and colleagues.

In contrast to other emotional intelligence (EI) measures, the trait EI questionnaires have a detailed and fully developed theoretical basis and nomological network, including associations with several health outcomes (Batselé et al., 2019; Martins et al., 2010, and Sarrionandia & Mikolajczak, 2020; for reviews, Schinckus et al., 2018), academic performance (MacCann et al., 2020), job satisfaction (Li et al., 2018), life satisfaction and subjective happiness (Stamatopoulou et al., 2016), stress management (Martínez-Monteagudo et al., 2019; Saddki et al., 2017), and other fundamental psychological variables (see Andrei et al., 2016, for a review; see also Di Fabio & Kenny, 2019; Farnia et al., 2018).

Petrides, Furnham et al. (2007) explained the main advantages of trait EI theory and the trait EI instruments compared to related personality taxonomies, are the conceptual development and explanatory power, which according to the authors, exceed the gains on predictive and incremental validity. More recently, trait EI questionnaires have shown consistent cumulative effects beyond the Big Five and coping strategies in the prediction of critical clinical criteria (Siegling, Vesely, et al., 2015). The pathways for future developments in trait EI range from basic to applied research, where prospective clinical studies are one of
the most attractive designs for enriching the trait EI literature and its implications for the field of personality and individual differences (Petrides, Furnham, et al., 2007, Petrides et al., 2016).

Trait EI theory provides a comprehensive framework for investigating the role of personality (both the therapist’s and the patient’s) in the psychotherapeutic relationship and outcome. In addition, Petrides et al. (2017) have demonstrated the protective role of trait EI on psychopathology in a transdiagnostic sample (i.e., comprised of patients carrying different diagnoses), as trait EI was positively associated with the effect of self-reported mindfulness and negatively associated to patient’s self-reported irrational beliefs. This research determined that nearly half of the variance in psychopathology scores was explained by patient trait EI.

Parker et al. (2020) studied the longitudinal effect of trait EI on relationship satisfaction in a sample of Canadian undergraduate students who were followed up until middle adulthood for over 15 years. The researchers reported relatively high within-person stability regarding trait EI, as assessed by test-retest Pearson correlation ($r = .49$ for men and $.50$ for women), although trait EI scores increased significantly from time 1 to time 2. Additionally, trait EI acted as moderator of relationship satisfaction at time 2, supporting the stance that trait EI contributes to the development of satisfying and nurturing interpersonal relationships across the first half of lifespan, an association previously reported in meta-analytic (see Malouff et al., 2014) and quasi-experimental research (see Nelis et al., 2011).

Trait EI is not exempt from criticism. For instance, Roberts et al. (2001) posed that several problems and omissions are embedded in EI research using self-report measures, as trait EI does. The main argument here is that these measures rely on people’s self-understanding of emotions, which might lead to inaccurate representations, social desirability, deception, and impression management. However, as Roberts et al.
acknowledged, these weaknesses are common to all self-report scales and do not apply to trait EI exclusively. A second critic, briefly mentioned in the development of the current section, refers to trait EI being a proxy measure of the Big Five framework (De Raad, 2005; Roberts et al., 2001). This critic especially applies to early measures of trait EI (e.g., Bar-On’s EQ-i, 1997), prior to current developments of trait EI on which the dissertation relies, as developed by Petrides and colleagues since the early 2000s.

2.2.1. The Trait Emotional Intelligence Questionnaire (TEIQue)

The Trait Emotional Intelligence Questionnaire (TEIQue) was explicitly developed as the operationalisation vehicle for trait emotional intelligence theory, and it is the only instrument that comprehensively covers the sampling domain of the construct. According to Petrides, Furnham et al. (2007), the Trait Emotional Intelligence Questionnaire (TEIQue): “aims to capture comprehensively the affective aspects of personality through a particular factor structure, but mostly through a unique distribution of variance” (p. 160). In contrast to other emotional intelligence (EI) measures, the TEIQue has a detailed and fully developed theoretical basis and nomological network.

The factor structure of the questionnaire comprises Global trait EI at its apex, four interrelated factors in the middle (Well-being, Self-control, Emotionality and Sociability), and fifteen narrow facets at the bottom characterising the general attribute (Petrides, 2009), as introduced in the previous section. Short forms, like the TEIQue-SF, allow accessing only to the four-factor structure, whereas full trait EI forms allow for facets descriptions as the last unit of psychometric description for the scales (Cooper & Petrides, 2010). However, the unidimensionality of the construct (as measured by the TEIQue-SF) has been claimed in Cooper and Petrides (2010), since reliability scores tend to be lower when the construct is recovered at the four-factor level (i.e., multidimensionally). Moreover, there are other trait EI
questionnaires tailored for children, adolescents, and other purposes, all of which have been
developed with explicit and full reference to the trait EI theory, as conceived by Petrides and
colleagues (see Petrides, 2009).

2.2.2—The Trait Emotional Intelligence-Short Form (TEIQue-SF)

The TEIQue-SF was intended as a valid measure of the Global trait EI factor, thus
yielding a global trait EI score. However, it is possible to obtain scores on the four factors
from the questionnaire, although they tend to be somewhat less reliable than those obtained
from the complete adult form of the instrument. Additionally, full forms allow for facets
descriptions, which the TEIQue-SF does not (Cooper & Petrides, 2010). According to
Petrides (2009), high scorers for Well-being indicate a generalised sense of fulfilment and
happiness, whilst high scorers for Self-control display a healthy degree of control over their
impulses and external circumstances. Similarly, high scorers for Emotionality are more
connected with their own and other people’s emotional states, whereas high scorers for
Sociability are known for having a great social influence (see Petrides, 2009).

2.2.2.1—Factor-dimensionality of the TEIQue-Short Form. Cooper and Petrides
(2010) studied a large sample of university students and laypeople in the United Kingdom
with the TEIQue-SF. The researchers presented evidence for the unidimensionality of the
construct following an Item Response Theory (IRT) model with Exploratory Factor Analysis
in two consecutive studies, in which they found a good model fit. In Spain, Laborde et al.
(2016) provided contrasting results. The researchers supported a hierarchical four-factor
structure with a second-order factor (Global trait EI) instead of a unidimensional, for both the
full and short TEI questionnaires in a large sample of students. CFA (Confirmatory Factor
Analysis) showed that the TEIQue-SF four-factor structure replicated with an excellent fit: $\chi^2$
(2) = 6.29, $p < 0.001$, $CFI$ (Comparative Fit Index) = 0.99, $RMSEA$ (Root Mean Square Error
of Approximation) = 0.05, 90% CI (Confidence Interval) [0.03, 0.08], and SRMR (Standardized Root Mean Squared Residual) = 0.02. In Germany, Jacobs et al. (2015) examined a large sample of occupational therapists, providing evidence for a multidimensional higher-order structure of the TEIQue-SF (Morin et al., 2015; Rindskopf & Rose, 1988). The researchers reported a good model fit after allowing for correlations between factor errors $\chi^2 (84) = 143.45$, $p < 0.001$, $CFI = 0.95$, $RMSEA = 0.04$, and $SRMR = 0.04$. Both the German and the Spanish studies modelled the internal structure of the questionnaire through item parceling (i.e., aggregating items and using these aggregates as indicators of latent constructs, see Matsunaga, 2008), which differs from directly performing factor analysis at the item level. Item parceling has disadvantages, such as obscuring true relationships between items (Marsh, Lüdtke, et al., 2013).

2.2.2.2–Reliability of the TEIQue-Short form. Cooper and Petrides (2010) reported that the original questionnaire was reliable at the Global trait EI factor in two consecutive studies conducted in the United Kingdom, where the researchers reported Cronbach’s Alpha for women and men in each piece of research (i.e., $\alpha$; study one, $\alpha_{Women} = .88$, $\alpha_{Men} = .89$ and study two, $\alpha_{Women} = .87$, $\alpha_{Men} = .88$). In Germany, Jacobs et al. (2015) reported a similar reliability score for the Global trait EI factor ($\alpha = .88$), although the researchers found only adequate reliability indices at the factor-level, being them all below .7 except Well-being ($\alpha = .85$). In Greece, Stamatopoulou et al. (2016) analysed the reliability of the questionnaire. The researchers reported similar reliability scores at the general and factor-level to the study by Jacobs et al., with Self-control being the lowest ($\alpha = .60$) and Well-being the highest ($\alpha = .78$), excluding the Global trait EI factor ($\alpha = .89$). Similarly, Laborde et al. (2016) reported in their Spanish sample that Global trait EI ($\alpha = .88$) and Well-being ($\alpha = .83$) were highly reliable. However, the reliability scores for Self-control, Emotionality and Sociability were all around .7, which is considered acceptable (Taber, 2018). In China, Feher
et al. (2019) reported very similar figures for the Global trait EI ($\alpha = .88$) and for the trait EI factor-level, which ranged from .47 (Sociability) to .82 (Well-being) using Cronbach’s Alpha. Neri-Uribe and Juárez-García (2016) reported mostly adequate reliability scores at the factor-level ($\omega = .61, .83$) in their Mexican sample, although they did not consider a general factor explaining the variance for the full scale, which was the aim of the original TEIQue-SF (Petrides, 2009). In summary, there is substantial evidence for asserting that Global trait EI, as measured by the TEIQue-SF, is highly reliable and that the factor-level reliability scores show some dispersion, ranging from satisfactory to high-reliability scores.

2.3–Gender Differences in Trait EI

Cooper and Petrides (2010) reported a significant gender difference regarding Global trait EI, although of small effect size ($d = 0.16$), favouring women to men in the original validation sample. Similarly, Tsaousis and Kazi (2013) reported gender differences in trait EI mainly favouring women over men, as women had higher scores on caring and empathy ($CR = 4.09$), expression and recognition of emotions ($CR = 3.76$), albeit having lower scores in the use of emotions ($CR = 4.09$), and no difference in control of emotions ($CR = 1.67$). In this publication, the effect size measure implemented was the critical ratio index ($CR$), which represents the parameter estimate divided by the standard error, and it should be interpreted as a $Z$ score (i.e., $\pm 1.96$ to be significant).

Fernández-Berrocal et al. (2001) provided cross-cultural evidence in favour of cultural differences (individualistic vs collectivist) influencing trait EI discrepancies between women and men ($r^2 = .34, \beta = .20$). Petrides and Furnham (2000b, 2006) mostly reported non-significant gender differences on trait EI in the U.K, with the exception of higher scores on social skills for women over men ($d = 0.40$) in the former and stress in the latter ($d = 0.42$). Similarly, Ugarriza (2001) did not find notable differences between women and men on total EQ scores in Peru using the EQ-I (Emotional Quotient Inventory), nor Saklofske et
al. (2003) when using a Global trait EI measure \(d = 0.04\), and \(d = 0.19\), respectively). Conversely, Shahzad and Bagum (2012) found a significant difference favouring men \(d = 0.56\). Other scholars have also reported non-significant results on gender comparisons (see Atta et al., 2013; Lyusin, 2006; Saklofske et al., 2007; Siegling et al., 2014). Therefore, the findings regarding trait EI and gender are inconclusive.

Early trait EI research has typically relied on t-tests or ANOVAs, which are subject to measurement error (Vandenberg & Lance, 2000) and can be considered statistically suboptimal. Without conducting measurement invariance analyses, the constancy of a construct across genders is unwarranted (e.g., Petrides et al., 2003). Additionally, studies comprising small or unbalanced samples usually lack the statistical power necessary for generalising gender interpretations. Lastly, cross-cultural research addressing gender invariance with heterogeneous populations is scarce, as most studies have exclusively relied on samples comprising university students (see Siegling, Furnham, et al., 2015). Moreover, due to the variety of trait EI measures used in the literature and variations on whether analyses are performed on a Global trait EI composite or subscales scores, it is sometimes difficult to accumulate sufficient reliable evidence, which is why TEIQue-specific meta-analyses have been reported. For instance, Andrei et al. (2016) conducted a metanalysis with 24 articles covering a wide range of criteria. The authors concluded that trait EI is a statistically and substantial incremental predictor of multiple psychological variables.

With these limitations in mind, the following studies have presented trait EI measurement invariance for gender with large samples. Tsaousis and Kazi (2013) provided robust evidence in favour of measurement invariance for the construct when assessed by the Greek Scale of Emotional Intelligence (GEIS). These authors evaluated trait EI through subscale-scores, instead of providing an overall composite, in a Greek sample of over 2000 individuals. Similarly, Siegling, Furnham, et al. (2015) tested gender invariance for trait EI in
a cross-cultural study with over 2700 university students, concluding that the construct is invariant for gender when taking the Global trait EI composite as the criterion, regardless of whether participants were assessed by a long trait EI form (i.e., TEIQue) or a short form (i.e., TEIQue-SF). The general conclusion seems to be that any gender differences in Global trait EI are usually accompanied by small effect sizes (see also MacCann et al., 2020). However, more noticeable, albeit less reliable gender differences, have been reported at the factor and facet levels of trait EI (e.g., Petrides & Furnham, 2000b).

2.4–Other Sociodemographic Differences Supported by Trait EI

Many researchers have reported positive and significant correlations between trait EI and age (Bar-On, 1997; Chapman & Hayslip, 2006; Derksen et al., 2002; Petrides & Furnham, 2006; Tsaousis & Kazi, 2013; Ugarriza, 2001), although a few others have not (Fernández-Berrocal et al., 2004; Shipley et al., 2010). The findings here are not settled, even though the literature provides more substantial support for a positive and significant association between trait EI and age.

Other sociodemographic variables, such as educational attainment and civil and occupational status, have not been extensively investigated in the literature since participants are typically described in terms of gender and age only. Regarding occupation, individual differences—such as personality and EI traits—exert a strong influence on career choice (Chaudhary & Rangnekar, 2017; Farnia et al., 2018; Sanchez-Ruiz et al., 2013). For instance, Siegling et al. (2014) reported higher Global trait EI scores in a sample of managers compared to the normative general population. The dissertation will furnish further evidence on the relationship between trait EI and these sociodemographic characteristics.
2.5–Generalisability of Psychological and Personality Findings Across Human Populations

2.5.1– The Problem of Generalising Conclusions Drawn From WEIRD Samples

Henrich et al. (2010) noticed in an extensive review that many psychological phenomena have assumed to be universal by scholars, and thus would generalise irrespective of the populations studied. In reality, this idea is largely unsupported by empirical data across several domains. These authors coined the term WEIRD (western, educated, industrialised, rich and democratic) to refer to those participants usually included in most of the extant literature. More specifically, North American undergraduates whose data form the majority of experimental research in psychology, cognitive science, economics and affiliated fields. These populations are considered highly peculiar by the researchers of the study, and therefore, no claim on the generalisability of results drawn from these samples can be established. The researchers compared industrialised societies with small-scale societies, western societies with non-industrialised societies, North Americans with other western societies, besides contrasting university-educated North Americans with non-university-educated nationals. The scholars also contrasted university students with non-student adults, depending on the available data.

In the first contrast, the authors concluded that although several domains appear comparable, others like visual illusions, social motivations (fairness), folk-biological cognition (i.e., the study about how people classify and relate with the biological world, see Atran, 1999), and spatial cognition were significantly higher in industrialised populations compared to non-industrialised societies. In the second contrast, western societies emerged as outliers on several fundamental psychological dimensions, such as anti-social punishment, cooperation, independent self-concept, analytic and moral reasoning. The third contrast
determined that North American participants are far more individualistic than any other population. Moreover, North American undergraduates tended to depart even more from non-western people on individualism, moral reasoning, worldview regarding death thoughts, and perceptions of choice when contrasted with North American nationals without similar educational credentials. Henrich et al. (2010) concluded as an overall takeaway message for scholars in psychological research that it is preferable to have comparative data across diverse population rather than claiming generalisation of findings without having cross-cultural supporting empirical data.

In the studies included in the dissertation, and especially in study three, this notion is embraced. Muthukrishna et al. (2020) have proved the stance by Henrich et al. (2010) that North American have a cultural distance regarding various psychological outcomes in comparison with 79 nations comprising 85% of the world’s population sites, through a dataset comprising two waves of the World Values Survey (i.e., 2005-2009 and 2010-2014, Inglehart et al., 2014). The authors contrasted these countries (comprising over 170,000 participants overall) with Hofstede’s (2001) cultural dimensions (i.e., collectivism-individualism, power distance, feminity-masculinity, and uncertainty avoidance), Gelfand et al.’ (2011) Tightness-Looseness construct (i.e. society strongly normed versus societies with weak social norms), Schwartz’s (2006) values (i.e., community values that help regulate human behaviour across societies), the five-factor model of personality (see McCrae et al. 2005 and section 2.5.3), several cultural distance measures (see Mayer & Zignago, 2012), and other psychological and behavioural measures (e.g., blood donations, diplomat parking tickets, corruption).

Muthukrishna et al. (2020) emphasized the posture that cultural distances do not unidimensionally range from WEIRD to non-WEIRD populations. Thus, these authors included China, the second-largest economy globally, as a common cultural point of
reference in this type of analysis. The authors concluded that the distance between North American culture and the remaining 79 countries’ culture is substantial, as it is the cultural distance between Chinese culture and the culture of the other included countries. Therefore, proving the point anticipated by Henrich et al. that North American and Chinese participants (as demonstrated in the research) are the WEIRDest populations regarding psychological research. Hence, strictly speaking, the remaining 78 countries statistically depart on cultural values from North American and Chinese inhabitants, being possible to classify these remaining countries as non-WEIRD countries, or at the very least significantly WEIRDless than the two referenced countries above, following the multidimensional posture argued by the authors.

The research conducted by Muthukrishna et al. (2020) is paramount to understand the contributions and theoretical pertinency of study three (chapter four of the dissertation). In study three, four country-level datasets are compared through analyses of variance and measurement invariance on the premise that cultural and sociodemographic differences between nations may affect the interpretation and cross-cultural validity of trait EI. In other words, with the certainty that North American and Chinese populations are indeed the truly WEIRD countries in the world, the research contrasted two developed countries (i.e., Italy and the United Kingdom) and two developing nations (i.e., Brazil and Chile), as labelled by the United Nations (2021); with the belief that cultural distances under the multidimensional WEIRD framework (as presented by Muthukrishna et al., 2020), support the suitability of contrasting WEIRDer (i.e., developed, as represented by Italy and the United Kingdom) and WEIRDless countries (i.e., developing, as represented by Brazil and Chile).

The conceptualisation is not only theoretically but empirically appropriate, as the cultural distance between North American population and those of Great Britain, albeit large, is one of the shortest from the 78 countries studied by Muthukrishna et al., making Great
Britain the 5th *WEIRDest* country in the world with a point value of .046, 95% *C.I.* [.043, .051], and Italy the 8th, with a point value of .061, 95% *C.I.* [.059, .065]. In contrast, Brazil is the 12th *WEIRDest* country in the world, with a point value of .072, 95% *CI* [.069, .075], and Chile is the 19th, with a point value of .078, 95% *C.I.* [.075, .081], when taking the United States as the reference (i.e., 0). In conclusion, in terms of the WEIRD framework, the comparison between these four country-datasets was in practice an investigation between *WEIRD*er and *WEIRD* less countries, as a proxy of what would ideally be including a sample from North America (i.e., WEIRD), given the greater similarity between Great Britain/Italy to North America, as westernised, educated, industrialised, rich and democratic countries, vis-à-vis the less advantaged developing countries included in the study (i.e., Brazil and Chile). Moreover, it is important to highlight that in Henrich et al.’ (2010) publication, both Brazilian and Chilean populations are exemplified as non-WEIRD populations. In the case of Brazil regarding psychological essentialism and personal choice, whereas Chilean populations are claimed as distinct to North American (i.e., non-WEIRD for simplicity) regarding positive self-views, psychological essentialism, and holistic reasoning.

### 2.5.2–The Importance of Measurement Invariance

Measurement invariance is a statistical property that pursues the psychometric equivalence of a construct across different target cultures (Greiff & Iliescu, 2017). In quantitative Psychology, cross-cultural comparability is usually evaluated through multigroup confirmatory factor analysis (MGCFA). This technique is capable of testing cross-national equivalence over several countries (Jöreskog, 1971; Meitinger, 2017).

In the following studies, measurement invariance was tested through progressive nested models, ranging from configural to scalar invariance (Vandenberg & Lance, 2000). Configural invariance represents the baseline. It assumes that groups share the same conceptual framework without equality constraints on any parameter. Metric invariance
requires equivalence of factor loadings, meaning that each item contributes to the latent construct similarly across different groups. Scalar invariance allows for the comparison of latent means across groups (Putnick & Bornstein, 2016). This type of invariance analysis derives from constraining intercepts to be equal among groups. If there is enough evidence for scalar invariance, then scores are considered invariant, i.e., equivalent (Chen, 2007; Tóth-Király et al., 2017). Likewise, there is the possibility of examining the fourth level of invariance, namely, strict measurement invariance, which is also referred to as residual invariance. Attaining invariance at this level is often unrealistic in cross-cultural research, and as Vanderberg and Lance (2000) stressed, testing for this type of invariance is not a precondition for assessing mean equivalence, as the residuals are not part of the latent factor model.

Changes of the fit statistics across the nested models from configural to scalar invariance should fall within a specific range. For instance, changes in CFI and RMSEA up to -.010 and .015, respectively support the invariance of the more restricted (nested) model when compared to the less restricted model. Similarly, changes in SRMR of .015 and .030 support metric and scalar invariance, respectively (Chen, 2007). All these specific types of invariance are necessary to claim that a construct is fully invariant.

Meade et al. (2008) proposed applying differential criteria regarding sample size, type of invariance tested, and statistic of fit used for comparison, standards which were adhered to interpret the invariance results in the dissertation. The interpretation of the findings from the studies of the current dissertation that included measurement invariance analyses, weighted these criteria following these authors suggestions.

2.5.3–The Cross-cultural Universality of Personality Traits

McCrae et al. (2005) provided robust evidence of the universality of personality traits through cross-cultural research in fifty countries under the umbrella of the Big Five-factor
model (i.e., neuroticism, extraversion, openness, agreeableness, conscientiousness, see Costa & McCrae, 1992). The researchers studied the internal consistency, factor congruence, as well as age and sex differences across culturally diverse countries, determining that the universality of the trait psychology was supported. Trait personality was measured by the NEO-PI-R, an instrument based on observed ratings, which has been shown to be reliable and valid in its original form (McCrae & Costa, 1985), and was linguistically locally adapted from the previously adapted self-report versions in each country and language. The original factor structure replicated in all the cultures included in the study, except for one factor in one country. Internal consistency coefficients across factors were very high, with only a handful of countries displaying reliability scores below what is considered adequate according to the authors (i.e., < .70, see also Taber, 2018). Moreover, almost identical congruence coefficients were reported across countries, supporting the equivalence of the originally proposed five-factor structure. The researchers concluded that the quality of country data was substantially linked to cross-cultural equivalence, as samples varied in size and composition, and in some countries, demographic data were not registered. Moreover, the fit between the instrument, the cultural background, and participants’ experience with the type of implemented measure may explain variations of internal consistency and factor scores across countries.

McCrae (2013) argues that the universality of personality traits is biologically ingrained, as these traits are fundamentally the same everywhere. However, the author highlights at least three different levels in which the personality profile of a culture can be analysed: ethos, national character stereotypes, and aggregate personality traits. First, the ethos refers to the anthropological perspective in which personality is affected by the customs and institutions of culture. In this regard, some cultures would be more prone to some personality-based conventions than others. For instance, McCrae (2009) exemplified this by comparing Japanese and United States culture, as the former emphasizes shame and self-
abasement as methods of social control, whereas North Americans are culturally driven to adventure and philanthropy.

Second, the national character stereotype refers to a believed typical national personality profile. For instance, British are deemed to be mostly reserved by others, whereas Chinese are perceived as inscrutable. This level of cultural comparability is largely unsupported in the literature (e.g., Hrebickova & Graf, 2014; Terracciano et al., 2005). Third, the study of aggregate personality traits refers to the idea of examining trait mean levels across cultures, which according to McCrae (2009), is the most meaningful and straightforward methodological investigation on the relationship between personality traits and culture. The obstacles in studying aggregate personality traits cross-culturally, mainly narrow down to locally suitable and accurate inventories to assess the studied trait, and the attainment of scalar equivalence, which in practice implies that the means of the personality attributes are mostly the same across cultures. Scalar invariance is a central methodological feature in cross-cultural psychology, which is usually difficult to achieve (e.g., Byrne & Campbell, 2000), as explained in the previous section. McCrae concludes in his review of cross-cultural trait assessment that aggregate personality scores are still very limited in the extant literature. Other prominent scholars previously raised this claim (e.g., Schmitt et al., 2007), even though the implications are crucial for personality psychology and related disciplines, such as behaviour genetics, psychobiography, and cross-cultural psychology.

Schmitt et al. (2007) studied samples from 56 nations with the Big Five Inventory (BFI; Benet-Martínez & John, 1998), a self-report measure based on the Big Five-factor model previously described, comprising nearly 18,000 individuals. The researchers replicated the five-dimensional structure (i.e., neuroticism, extraversion, openness, agreeableness, conscientiousness) across major world regions. The Big Five means predicted common outcomes, such as self-esteem, sociosexuality (i.e., the willingness to engage in uncommitted
sexual relations, Simpson & Gangestad, 1991), and national five-factor personality profiles. Moreover, the researchers informed of a distinctive high mean in South America regarding openness to experience and a typical low mean in East Asia for this variable compared to the other regions, among other less prominent regional disparities. However, the researchers did not conduct measurement invariance for testing the equivalence of the construct across countries. Instead, they relied on the similarity of the theoretically proposed factor structure across regions.

Allik and McCrae (2004) informed of neighbouring countries having similar personality means, whereas regions either geographically or historically apart differentiated more on personality trait scale scores. McCrae (2002) has reported smaller variability within Asian and African cultures regarding personality traits, whilst European and American cultures showed a higher dispersion. As Schmitt et al. (2007) posed, comparing mean levels of personality traits across cultures is a legitimate endeavour. Therefore, personality traits’ means are informative in the comprehension of salient relationships between culture and psychological features (see LeVine, 2001; Saucier & Goldberg, 2001).

Ion et al. (2017) studied the cross-cultural pertinency of the HEXACO model, which goes a step further than the previously described five-factor model as it comprises a six-factor model framework of trait personality. According to the authors, this personality paradigm includes components highly related to the Big Five-factor model, such as Emotionality (E), Extraversion (X), Agreeableness (A), Conscientiousness (C) and Openness to Experience (O). However, it incorporates an original dimension named Honesty-Humility (H). The six-factor model is not a mere extension of the five-factor model, although some overlap between these taxonomies is expected (Ashton & Lee, 2007). Ion et al. conducted the study with the HEXACO-PI-R (Ashton & Lee, 2001), a questionnaire comprising 200 items, 24 facets and six dimensions, based on the HEXACO model.
The researchers studied the universality of the six-factor model across five non-WEIRD countries: India, Indonesia, Oman, Romania, and Thailand, and more than 1600 participants overall. Each of these countries with a distinctive language and mainstream religion. The researchers concluded from their findings that although there was an acceptable construct equivalence across the countries, this only held at the facet and factor structure of the implemented questionnaire (i.e., configural invariance), and across factor loadings (i.e., metric invariance) between countries. However, intercepts were not equivalent, which indicates no latent mean comparability can be reliably drawn from the use of the HEXACO model across the studied countries, at least when assessed through the HEXACO-PI-R.

Thielmann et al. (2020) studied the universality of the six-factor model (i.e., HEXACO) across sixteen countries through the HEXACO-100 (Lee & Ashton, 2018), a half-length version of the previously described HEXACO-PI-R. The countries included in the study had each a distinctive language. Therefore, local adaptations of the measure were implemented. Similar to what Ion et al. (2017) reported in their study, Thielmann et al. informed of configural and metric invariance when comparing the samples through multigroup measurement invariance. However, as in Ion et al., scalar invariance was not supported, meaning that latent means equivalence between the countries, as studied through the HEXACO model, was not supported.

Regarding trait EI, most studies in the field have relied on WEIRD student samples, with the inherent bias that generalisations taken from these samples entail, especially regarding emotions, cognitions, and motivations, as highlighted by Henrich et al. (2010). Exceptions are rare; for instance, Ugarriza (2001) approached a heterogenous general population sample in Peru, who validated and adapted Bar-On’s emotional quotient inventory (EQ-I; Bar-On, 1997) in a sample of nearly 2000 individuals. The author of the study confirmed a second-order internal structure of the questionnaire as originally proposed by
Bar-On. Moreover, Ugarriza concluded that trait EI increased with age and that there were non-significant gender differences in global trait EI (as discussed in section 2.3). However, generally small effect size differences were discovered amongst several facets of the measure (i.e., in the range 0.08-0.50), similarly to what Petrides and Furnham (2000b) reported. Trait EI examinations in non-WEBIRD clinical samples are scarcer, with studies two and four presented in the dissertation as some of the few examples outside European, North American and Asian populations.

2.6--The Study of Emotional Intelligence (EI) in Chile and Latin-America

Although some studies have examined EI in Chile, either their nature does not fit with the taxonomies already in place, or they suffer from methodological flaws. Therefore, addressing EI scientifically, with well-defined construct operationalisations, is one of the most desirable pathways for assessing the subjectivity of emotional experience (Petrides, 2009). Current research on emotional intelligence in Chile and Latin-America has usually not responded to psychometrically founded constructs. At most, local research has relied on trait EI scales of which no prior supporting psychometric evidence has been reported in the country. This comes as a severe limitation for assessing trait EI accurately in Chile and the region. For instance, some studies in the country have relied on the Spanish adaptation of the TMMS-48 (Trait Meta-Mood Scale-Spanish translation), performed in the late nineties in Spain (Fernández-Berrocal et al., 1998). Fernández-Berrocal et al. (2001) conducted a study based on this questionnaire using four measures of emotional stability, where participants of the U.S.A., Spain and Chile were compared cross-culturally regarding their trait EI and emotional stability. The authors concluded that the Spanish sample had a significantly lower mean for trait EI compared to the U.S.A. and Chilean populations. They also obtained the highest score for emotional balance. Although these authors did not inform measurement invariance between the samples, it can be deducted from the significant differences in means,
that the trait EI construct, as measured by the TMMS-48, is likely to be non-invariant across applications, which raises uncertainty regarding latent means equivalence. Consequently, as Putnick and Bornstein (2016) stated, performing measuring invariance is essential to assess the invariance of any construct. The former justifies the necessity of introducing a non-invariant measure for assessing trait EI in the region, which can be equivalent across countries and applications.

The TMMS-48 was later replaced by the Spanish validation of its modified version—the TMMS-24—, a task performed by the same research team (Fernández-Berrocal et al., 2004). This shorter measure, with only 24 items, was claimed to be better than the prior by eliminating items with loadings below .40 through PCA. In northern Chile, the TMMS-24 was used for assessing 117 special-education officers (Veloso-Besio et al., 2013). These researchers found a high and significant correlation between trait EI and life satisfaction, subjective happiness, and resilience. Likewise, a multiple regression model confirmed the role of trait EI as predictor explaining life satisfaction. A third study took place in southern Chile, where trait EI and psychological wellbeing (i.e., unrelated to trait EI, but to wellbeing as a state construct) were studied in a sample of 97 nurses (Veliz-Burgos et al., 2018). In this study, the authors reported high levels of trait EI with the TMMS-24. This study revealed a high and positive correlation between trait EI scores and psychological well-being (i.e., state).

Omar et al. (2014) cross-culturally validated the self-report emotional intelligence test (Schutte et al., 1998) in Latin-America. The researchers could not replicate the original unidimensional solution claimed by Schutte et al., informing a satisfactory fit for a model with two latent variables. These researchers employed principal component analysis (PCA), although PCA is regarded as a linear combination of correlated variables, in contrast to factor analysis, in which factors represent latent variables that cannot be measured directly (Revelle, 2012; Surh, 2005). Additionally, the authors did not inform a proper measurement invariance
procedure. In Peru, Ugarriza (2001) examined the factor structure of Bar-On’s (1997) Emotional Quotient Inventory (EQ-I) in a large sample, providing evidence for construct validity. However, beyond $\chi^2$, fit indices were not informed in the study, nor any measurement invariance procedure. Unsuccessful efforts for validating trait EI measures, such as the TEIQue-SF, have taken place in Mexico. In this country, Neri-Uribe and Juárez-García (2016), did not find enough support for the questionnaire’s original factor structure, nor for the fit of the overall model through CFA.

Moreover, Laborde et al. (2014) studied one sample of sport science students training for sports competitions with the Spanish adaptation of the TEIQue-SF (Pérez-González, 2010), which is a very specific population, with very skewed age ($N=128$, $M=22.40$), and a rather relatively small sample size for the purposes of comparing the internal structure of a questionnaire. For instance, this sample is not comparable to the general population sample included in study one of the dissertation, not only because of the sample size, the very skewed mean age of participants, but because most likely it comes from a high very socioeconomic strata. Sports competitors in Latin-America come almost exclusively from highly privilege socioeconomic layers, as centralised state funding for supporting a career in sports is scarce (in the best case) to non-existent. It is also not comparable to the sample included in study 2 of the dissertation, which was mainly collected from low and middle socioeconomic strata (e.g., De la Parra et al., 2019). More importantly, Laborde et al. did not study the internal structure of TEI questionnaires in Ecuador. Instead, these authors conducted a path analysis on hypothesis testing specifically directed towards sport competitors, without any previous adaptation or examination of the internal structure of the Spanish questionnaire in the country. For these reasons, Laborde et al.’ study is not a comparable reference in Latin-America to the aims and scope of the dissertation.
In Brazil, Perazzo et al. (2020) studied the internal structure of the Brazilian adaptation of the TEIQue-SF in a sample of over 500 university students. In this examination, the authors reported satisfactory fit statistics for the measure after testing the internal structure of the questionnaire through bi-factor ESEM (Exploratory Structural Equation Modelling) modelling. Likewise, they proved the incremental validity of trait EI over Big Five variables and measurement invariance between the Chilean and U.K. versions of the measure. The incremental validity in this study was investigated through two-step hierarchical linear regressions, where life satisfaction and happiness (criteria) were regressed onto the big-five dimensions in the first step, followed by trait EI in a second step. The incremental effects of trait EI over the big-five framework reported in the study are consistent with previous meta-analytic research (e.g., Andrei et al., 2016).

2.7–The Relevance of Trait EI for Clinical Psychology

Until now, studies conducted with trait EI measures in general population samples have been reviewed, of which most were composed of undergraduate students and people from the community. However, the relevance of the construct for populations suffering from mental health conditions is well documented. For example, Martins et al. (2010), investigated the role of trait EI on health status after contrasting nearly 20.000 participants over 100 studies in a meta-analytic study, concluding that trait EI is strongly associated with overall health status \((r = .34, Z = 41.45)\), mental health status \((r = .36, Z = 33.31)\), psychosomatic health status \((r = .33, Z = 23.45)\) and physical health status \((r = .27, Z = 12.40)\). The researchers highlighted the unique predictive role of trait EI on mental health outcomes, when measured by the TEIQue \((r = .51, Z = 27.82)\) compared to other well-regarded emotional intelligence measures, such as the EQ-I (Emotional Quotient Inventory, Bar-On, 1997), the SEIS (Schutte Emotional Intelligence Scale, Schutte et al., 1998) and the TMMS (Trait Meta Mood Scale, Salovey et al., 1995). Furthermore, the researchers posed that the line of
research studying the effects of trait EI on health outcomes has reached sturdiness and abundance in the literature.

Moreover, different researchers have reported a negative correlation between trait EI and depressive, anxious, phobic, and obsessive symptoms. For instance, Mikolajczak et al. (2009) informed that trait EI moderated the impact of laboratory-induced stress on mood change, meaning that higher trait EI scores were significantly associated with less mood deterioration. The authors suggest that screening clinical populations with trait EI measures is more efficient than assessing them through other well-regarded personality constructs, such as the Big Five personality factors, as trait EI provides a more comprehensive retrieval of emotion-related characteristics. This last feature is crucial in psychotherapeutic settings.

In addition, psychopathy and personality disorders have been found inversely associated with trait EI (see Malterer et al., 2008; Petrides, Pérez-González et al., 2007; Sinclair & Feigenbaum, 2012). The dark triad of personality (i.e., narcissism, Machiavellianism, and psychopathy) has also been strongly correlated with trait EI in a genetic behavioural investigation (Petrides, Vernon, et al., 2011). These researchers concluded that Global trait EI was positively linked to narcissism, and negatively related to Machiavellianism and psychopathy. Moreover, Petrides et al. (2017) conducted a study in Spain on a sample of 121 transdiagnostic (i.e., with various diagnoses) psychiatric outpatients (65% males, mean age= 39 years) to investigate potential predictive pathways to psychopathology. The researchers fitted a model in SEM, in which they included three predictors: trait EI (as measured by the Spanish adaptation of the TEIQue-SF, Pérez-González, 2010), a mindfulness questionnaire (i.e., Five Factors Mindfulness Questionnaire, Baer et al., 2006), and a measure of irrational beliefs (i.e., the Spanish adaptation of the Irrational Beliefs Test, Calvete & Cardeñoso, 1999), reporting that these predictors accounted for 44% of the variance in psychopathology (as measured by the Spanish version of the
Millon Clinical Multi-Axial Inventory II, Ávila-Espada et al., 2002). There were substantial predictive and protective effects coming from trait EI and mindfulness on irrational beliefs and psychopathology. In a subsequent analysis, the researchers discovered an accumulative effect of trait EI over the remaining predictors, which was mainly attributable to the Well-being factor.

Aside from mood and general psychopathology, trait EI has been found to moderate psychological symptoms in cancer patients. For instance, Smith, Petrides, et al. (2012) reported that trait EI was inversely associated with worries during the early onset of urological cancer, meaning that lower levels of trait EI were associated with increased concern. Similarly, Smith, Turner, et al. (2012) provided evidence from prostate and bladder cancer patients, who also suffered from state anxiety. After conducting a multiple regression analysis, the researchers concluded that trait EI was a significant predictor against state anxiety, worry about appointments with doctors, the outcome of the consultation, and was also positively and significantly associated with patient’s perceived social support.

Several other syndromes and disorders have been related to trait EI. For instance, Petrides, Hudry, et al. (2011) compared a sample of clinically diagnosed Asperger patients in the United Kingdom with a control sample taken from normative data, using the full form of the trait emotional intelligence questionnaire (TEIQue). The researchers reported a significantly higher Global trait EI for the controls than for the clinical sample ($p < .001$, $\eta^2 = 0.40$, i.e., partial eta-squared). This trend was fully supported when including the factor-level as predictors (i.e., Well-being, Self-control, Emotionality and Sociability), and partially replicated—with the exceptions of three facets—when testing the same effect after including the fifteen facets that the TEIQue allows.
Moreover, Andrei and Petrides (2013) reported that trait EI correlates directly to positive affect, and negatively to negative affect and somatic complaints. These researchers concluded that trait EI predicts somatic complaints over and above positive and negative affect, supporting the incremental validity of the construct in this respect, and yielding strong evidence of its protective role on mental health. Similar to the previous research are the findings of Costa et al. (2014) with patients suffering from inflammatory diseases. These researchers discovered substantial mean differences in well-being scores between controls and patients diagnosed with rheumatoid arthritis, as well as significant mean differences in sociability scores between controls and patients diagnosed with both rheumatoid arthritis and rheumatoid arthritis plus another comorbidity (i.e., clinical diagnosis). In both comparisons, healthy control groups scored higher than clinical patients for the abovementioned trait EI factors. Similarly, Baughman et al. (2011) have provided genetic and environmental evidence supporting a strong and inverse association between alexithymia (i.e., a personality trait characterised by a deficit in identifying, describing, and externalising effectively emotions) and trait EI.

Furthermore, Aslanidou et al. (2018) reported significantly lower Global trait EI as well as factor-level scores (except the Emotionality factor) for individuals suffering from drug addiction when compared to controls. In the aforementioned study, the difference in trait EI means between addicted individuals and controls were of medium effect size for Global trait EI, Well-being and Sociability, whereas the mean difference regarding Self-control presented a small effect size. In this study, trait EI, and mostly the Well-being factor, was negatively and significantly correlated with depression, anxiety, and somatic symptoms ($p < .01$, with $R^2$– i.e., R-Squared– of 0.45, 0.16, and 0.18, respectively).
2.8–Impact of the Therapeutic Relationship on the Psychotherapeutic Outcome

2.8.1–Emergence of the Therapeutic Relationship as a concept

In the literature, the therapeutic alliance may be referred to under various designations, such as working alliance, helping alliance, and therapeutic alliance. The first and the oldest conceptualisation depicting the quality of the therapeutic relationship dates back to Freud (1913), whose concept of transference has been paramount in the development of clinical psychology as a field. Freud argued that the transference is rooted in past relationships with parents and unresolved childhood conflicts, which are later unconsciously projected onto and recreated with the therapist (Horvath, 2018a).

A second approach was later developed by Rogers (1951), who was inspired by humanistic-existential perspectives in clinical Psychology. Rogers posed that the offer from the therapist of a positive, honest, accepting, and empathetic interpersonal relationship would provide the patient with a sense of safety, acceptance, and feeling of being valued. As Picchioni (1981) highlighted, in Carl Rogers’ milestone, Counseling and Psychotherapy (Rogers & Carmichael, 1942), Rogers had a pioneer comprehension of personality and its relationship to psychotherapy, as personality was for him a realistic, tangible source of continued growth and conscious choice, as the therapist should respond to the whole person of the patient.

Rogers (1957) further elucubrated on this stance by proposing six conditions that were necessary to occur to constructive personality change:

1) Two persons are in psychological contact, 2) The first, whom we shall term the client, is in a state of incongruence, being vulnerable or anxious, 3) The second person, whom we shall term the therapist, is congruent or integrated in the relationship, 4) The therapist experiences unconditional positive regard for the client, 5) The therapist experiences an empathic understanding of the client's internal frame of reference and endeavors to
communicate this experience to the client, 6) The communication to the client of the therapist’s empathic understanding and unconditional positive regard is to a minimal degree achieved (p. 96).

More modern developments based on the Rogerian approach have emphasized the conscious aspects of the alliance and defined it as the holistic collaborative aspects of the therapist-patient relationship (Flückiger et al., 2018). A third major allusion in the literature to the therapeutic relationship came later with the work of Goldfried (1980), who argued that a positive relationship between patient and therapist generates confidence in the therapist and consequently on the quality of the therapeutic process. A fourth taxonomy expands on the idea that the relationship within therapy provides patients with the opportunity to experiment and try out new and healthier relational patterns (Castonguay, 2000).

Horvath (2018a) proposes that these four frameworks for comprehending the therapeutic relationship have been utilised and emphasized to different degrees in the traditional currents of therapy (i.e., psychodynamic, behavioural-cognitive, familiar-systems, Rogerian/person-centred). Psychodynamic and person-centred models, according to Horvath, consider the relationship between patient and therapist as the core of treatment, whereas in behavioural-cognitive and systems models, the relationship is part of the overall setting on which the elements of treatment are displayed (DeRubeis & Feeley, 1991).

2.8.2–The Dodo Effect

It was not until Wampold arisen to the conclusion that all therapies are beneficial (see Wampold & Imel, 2015) that the link between specific theories and therapy outcome was generally disproven. This inference became known as the Dodo Bird verdict, referencing Lewis Carroll’s (1865) Alice’s Adventures in Wonderland famous quote, in which after a race, each one of the participants deserved a prize. From this interpretation of psychotherapeutic
outcomes, the concept of common factors or ingredients across different treatments became the standard, although the idea of commonality across therapies was not novel (e.g., Frank, 1961; Rosenzweig, 1936).

The early promoters of the therapeutic relationship who accounted for trans-theoretical gains in psychological treatment were Bordin (1979) and Luborsky et al. (1983). These scholars shared the notion of the alliance between patient and therapist as universal, conscious, and related to the collaborative aspects of the affiliation established in psychotherapeutic settings (see Horvath & Luborsky, 1993, for a review). From them, it was Bordin who probably was the most influential, as he formulated a trans-theoretical model of the alliance, suggesting this model was a pre-requisite for positive outcomes in all forms of psychotherapy. According to Bordin, distinct therapies focus on different tasks and goals, and thus, patient and therapist establish characteristic bonds. The tasks refer to the specific activities conducted by the patient as part of the treatment. The goals represent the general objectives of the treatment, whilst the bond represents the affective quality of the relationship between patient and therapist. The strength of the alliance is a function of the degree of agreement between patient and therapist on tasks and goals. In this exchange, the emotional bond mediates the level of understanding on goals and tasks.

Muran and Safran (1998) posed that Bordin’s seminal contribution led the path for the proliferation of alliance measures and related research. The best example of this can be found in the development of the Working Alliance Inventory (WAI) and related forms, as first developed by Horvath and Greenberg (1986). Other measures for capturing the complexity of the alliance in family therapy, as well as for assessing empathy, immediacy, and positive regard in therapeutic dyads, have recently received attention in the field literature (Tishby & Wiseman, 2018).
2.8.3–Models Accounting for the Therapeutic Relationship

Norcross and Hill (2004) suggested that certain key relationship elements or behaviours emanating from both therapists and patients have a considerable effect on patient’s clinical outcomes. Norcross and Lambert (2019) proposed two models to account for the impact on psychotherapeutic outcomes. The first model, namely: the improvement in psychotherapy patients as a function of therapeutic factors, estimates the percentage of outcome variance as a function of therapeutic elements, such as common factors (i.e., relationship-driven factors: empathy, goal consensus/collaboration, the therapeutic alliance, and positive regard, see Laska et al., 2014, for a review), expectancy (the placebo effect), the techniques implemented, and extra-therapeutic factors (i.e., self-change, spontaneous remission, social support, and fortuitous events). The authors emphasised this first model has not been derived from meta-analyses but rather on non-systematic research and accounts only for the explained variance, according to what is known to work. The model allocates 40% to the extra-therapeutic change, 30% to common factors, 15% to the placebo effect, and up to 15% to the implemented therapeutic techniques.

The second model, namely: the psychotherapy outcomes attributable to therapeutic factors, considers the unexplained variance (i.e., unknown factors affecting psychotherapeutic outcomes), and is directly derived from meta-analytic research. In this model, 35% of the total variance is deemed to be unexplained, the patient’s contribution is 30%, the therapeutic relationship accounts for 15%, and the treatment method up to 10%. In comparison, the contribution of the therapist accounts for 7%. Other remaining factors are considered to account for 3% of the outcome.

Messer and Fishman (2018) proposed two models capturing distinct theoretical orientations in psychotherapy. These are the relationship-focused interventions (RFIs) and
non-relationship-focused interventions (N-RFIs). According to these authors, RFIs are directed towards establishing, maintaining, and encouraging the therapeutic relationship. In contrast, N-RFIs are directed towards other features of the treatment, such as modifying patient’s irrational thinking, helping them to regulate better their emotions, or promoting the capacity of introspection regarding patient’s dynamics. Messer and Fishman claimed that relationship-building should be considered more a common theme across therapies than a true common underlying factor. For instance, most scholars agree that psychodynamic therapy is designed to address the therapeutic relationship (i.e., RFIs) and that the treatment is based on the relationship. In contrast, cognitive behavioural treatment leans more to N-RFIs, where the relationship is necessary, although not sufficient. Moreover, family therapy would be an RFIs where the relationship is essential but not enough.

Zilcha-Mano (2017) proposes that the alliance could be separated into trait and state alliance, in which the trait element refers to the general level and more stable characteristics, as evaluated through a single or aggregated assessment of the alliance. This trait alliance would emerge from the patient’s pre-treatment characteristics (i.e., interpersonal patterns) that would determine the creation of this special type of alliance. In contrast, the state level relates to the changes that take place over the treatment, which are usually reflected in rupture and repair processes of the therapeutic bond. According to Zilcha-Mano and Barber (2018), trait and state aspects would also be in constant interaction with the patient’s interpersonal relational patterns outside the therapeutic setting, and the actual response from the therapist to patient’s trait alliance offer would greatly determine psychotherapeutic outcomes. These authors state that the same trait alliance trend could be addressed noticeably differently at the state alliance level when rupture, i.e., “episodes of tension or breakdown in the collaborative relationship between patient and therapist” (Safran & Muran, 2011, p. 80), and repair processes (i.e., the processes reinstating this relationship, see Safran & Muran, 2011) are promptly addressed, which will be
reflected in positive outcomes. For instance, a patient’s trait-like tendency to not feel understood would have different results depending on whether actions are taken or not in the state alliance with the therapist.

2.8.4—Evidence Supporting the Effectiveness of the Therapeutic Relationship

Meta-analytic research has shown that the alliance has a positive effect on the therapeutic outcome, although of moderate effect size (Flückiger et al., 2018; Martin et al., 2000). Similarly, Horvath et al. (2011) reported that the quality of the alliance explains between 6% and 9% of the outcome variance, which according to the authors is a modest but reliable and statistically significant effect. Norcross and Lambert (2019) concluded after contrasting several meta-analytic studies, that small-to-medium size effects on psychotherapeutic outcomes derived from the therapeutic relationship, and that moderation analyses consistently showed that the patient’s perspective on the therapeutic relationship is a better predictor of outcome than the therapist’s perspective. Nevertheless, the authors highlighted that establishing causal connections between relationship correlates and outcome treatment is methodologically challenging. For instance, Elliot et al. (2019) advocated for a general strategy to assess the type of evidence claiming generalisable causal inference, which includes: precedence of the condition (i.e., outcome measured before and after treatment), plausibility with a well-regarded theoretical background explaining effects, the statistical validity of the findings, the internal validity of the research design, construct validity, and external validity.

Further meta-analytic studies have demonstrated the effectiveness of alliance in individual, child and adolescence, couple and family therapy, with medium-size effects ranging from .40 to .62 (Norcross & Lambert, 2019). These elements of the relationship have shown to contribute significantly to psychotherapeutic outcomes with small-to-medium effect sizes as well. Among them, collaboration (.61), goal consensus (.49), cohesion in group
therapy (.56), empathy (.58), positive regard/affirmation (.28), and collecting and delivering patient feedback (.49). However, Constantino et al. (2017) cast doubt on the alliance as a consistent indicator for measuring therapeutic effectiveness, as therapist’s contribution to alliance quality varies across studies (Baldwin & Imel, 2013). Similarly, Eubanks-Carter et al. (2010) have proposed that the progressive strengthening of the alliance during treatment does not necessarily predict beneficial psychotherapeutic outcomes.

Moreover, Horvath (2018a) poses that the alliance, although broadly accepted, cannot account for all the elements embedded in the relationship between patient and therapist, which requires full scrutiny on the context supporting these factors and their relation to the communality of psychotherapeutic treatment, regardless of the therapeutic approach. The author recognises that currently, the concrete, external objects to define or limit the scope of outcomes in psychotherapy are missing. In this regard, Schattner and Tishby (2018) declared that further research depicting patient-therapist dyads is needed to examine how relational patterns affect the choice and impact of specific interventions. Additionally, Horvath (2018b) posed that the lack of clarity regarding the link between the alliance and other relational constructs could obscure the distinctive role of the alliance and the remaining elements affecting the therapeutic relationship.

2.8.5– Short-term Psychotherapies and Implications to the Therapeutic Relationship

Safran and Muran (1998) suggested that the surge of brief psychological treatments can be attributed to modern changes in the social, political, and economic environment, being an essential component of the current psychological provision in clinical practice (Messer & Warren, 1995). Garfield (1994) posed that several decades of research on the length of psychotherapy conducted in the United States have shown that most of the clinical treatments corresponded to a type of brief psychotherapy, usually of 15 to 25 sessions (Garfield, 1997).
Scholars agree that due to time restrictions, a greater focus on the therapeutic goal, a more active role from the therapist, as well as separation and termination emerging more frequently in session, are all crucial features characterising time-bounded treatments which affect the therapeutic relationship (e.g., Garfield, 1997; Safran & Muran, 1998).

On the one hand, brief therapy has generally reached positive outcomes for patients, even though the aims and shape are different to prolonged therapy (e.g., Koss & Shiang, 1994; Nieuwsma et al., 2012). Meta-analytic research has reported non-significant statistical differences between psychotherapies delivered in 6 sessions compared to those implemented in a range of 7 to 16 sessions (Cuijpers et al., 2009). On the other hand, a follow-up of patients enrolled in a short-term depression research programme showed that only 30% of patients treated with cognitive therapy and 26% of patients treated with interpersonal therapy met stringent criteria for psychological recovery after 18 months (Elkin, 1994).

Moreover, the evidence supporting the effectiveness of the alliance in short psychotherapeutic interventions is well documented. For instance, Horvath & Bedi (2002) proposed that the link between alliance and outcome becomes evident by the third session onwards and cannot be accounted for previous therapeutic improvements. Similarly, Klein et al. (2003) provided evidence of early alliance significantly predicting improvement in chronically depressed patients when treated with cognitive-behavioural analysis system of psychotherapy (CBASP), a type of cognitive behavioural approach explicitly tailored for patients suffering from chronic depression (e.g., McCullough, 2003).

2.9–Therapist Effects on the Psychotherapeutic Outcome

In the psychotherapeutic literature, therapist effects depict the predictable variability among therapist on patient outcomes, regardless of patient effects and other secondary features affecting the output (Barkham et al., 2017). Norcross and Lambert (2019) have emphasised
that the most significant psychotherapeutic outcome variance not attributable to pre-existent patient characteristics comprises individual therapist differences and the developing therapeutic relationship between the dyad, with these therapist’s effects mostly stable over time. Hill and Castonguay (2017) have suggested that these effects broadly accounted for 8% of the outcome, a percentage that varied according to the initial patient’s psychological disturbance. To date, quantitative reviews highlight that therapist effects account for between 5 to 8% of the psychotherapy outcome (Baldwin & Imel, 2013; Barkham et al., 2017; Crits-Christoph et al., 1991; Johns et al., 2019).

Moreover, in a recent systematic review of therapist effects, Johns et al. (2019) discovered that these effects vary according to the type of study implemented, averaging 5% of outcomes in naturalistic settings, 2.4% in university counselling centres, and 8.2% in randomised control trials. The authors stated that from the pool of literature that met the inclusion criteria, most corresponded to applied research (85%), whereas the remaining studies resembled randomised control trial, and all of them but one implemented a multilevel modelling research design. The researchers also informed of a positive correlation between therapist effects and patient severity, meaning that the more severe the patient's diagnosis, the better the outcomes when treated by most effective therapists.

Falkenström et al. (2020) suggested that therapist effects can be ignored in longitudinal, within-patient research when the number of therapists is small or the included therapists treat unequal numbers of patients, as considering these effects in the statistical modelling may increase the risk of bias. In this research, the authors conducted a Monte Carlo simulation study, using multilevel and structural equation models. Moreover, the authors stated that ignoring random slopes led to biased standard errors when slope variance (i.e., the interaction between predictors) was large.
Meta-analyses of psychotherapeutic outcomes have revealed that theoretical approaches and related techniques accounted from between 0 to 5% of the total outcome variance (Lambert, 2013; Wampold & Imel, 2015), with the effect being more prominent for the most severe patients (Lambert, 2013). Wampold et al. (2017) stressed that numerous exogenous variables to psychotherapy, such as therapist’s age, gender, self-reported interpersonal skills, theoretical orientation, experience, and rated therapeutic competence, do not have a substantial impact on psychotherapeutic outcomes. Similarly, Delgadillo et al. (2020) reported that clinical experience, technical competence, and reflective ability were all unconnected features to psychotherapy results. Moreover, Leach (2005) emphasized that the development of a strong therapeutic alliance and the subsequent positive patient outcomes highly rely on effective communication skills, practitioner’s behaviour, collaboration, time, and trust. Lastly, Beutler et al. (2004) posed that contributions in psychotherapy research require scrutiny beyond the therapeutic approach and the patient’s diagnosis. Likewise, these authors stated that observable and inferred traits of the therapist have unfortunately seen the most significant decline in research.

Norcross and Lambert (2011) posit that there is converging evidence that the personality of the therapist is inextricably linked to the outcome of psychotherapy. Other scholars have argued that the therapist makes a more substantial contribution to the result of therapy than the patient (Baldwin et al., 2007; Wampold & Imel, 2015). Delgadillo et al. (2020) posed that it is possible to root some of the features that characterise effective therapists based on trait personality taxonomies. These authors studied therapist effects in a pooled sample of over 4000 patients to determine that therapists accounted for between 1% and 3% of overall outcome variance. However, this effect was larger when best-performing therapists were contrasted against average practitioners, as the difference in outcome variance was of 6%, favouring the most competent therapists, being this effect of moderate to large size ($g = .57$–
1.10). In addition, the scholars reported poorer outcomes in patients treated by therapists with above-average scores on agreeableness and openness to experience, both personality domains belonging to the five-factor personality paradigm, also known as OCEAN (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism).

Firth et al. (2020) discovered that therapist effects vary depending on the setting in which the psychological treatment is provided. The researchers reported significantly larger therapist effects on outcome variance in mental health primary (8.4%) and secondary care (4.1%), compared to university health centres (2.1%), voluntary organisations (2.3%), and workplace counselling (1.1%) therapeutic contexts. Here, primary care refers to general practitioner surgeries, community centres, as well as to Improving Access to Psychological Therapies (IAPT) programmes. Secondary care refers to more specialised mental health treatment for those suffering from more acute disorders. The authors concluded that especially the therapist’s effects in primary care are substantially distinct from other contexts and should be considered in the development of psychological intervention and delivery.

2.10–Patient Effects on the Psychotherapeutic Outcome

Adapting strategies to transdiagnostic (i.e., carrying different diagnoses) patient’s characteristics contributes significantly to psychotherapeutic outcomes, with small-to-medium effect sizes. Among these, culture (race/ethnicity; .50), therapy preferences (.28), and religion/spirituality (.13–.43) add more to successful outcomes than interventions tailored to patient diagnosis (Norcross & Lambert, 2019). These authors emphasize that nowadays, identical psychosocial treatment to patients is regarded as inappropriate. For instance, Shiner et al. (2017) studied a large cohort of war veterans experiencing PTSD (Post-traumatic stress disorder), determining that although gender match across patient and therapist dyads was not a
predictor of attrition in psychotherapy for women, it did have a predictive role for men, as men were less likely to continue treatment when matched with a male therapist.

Patient attachment style has been proposed as a predictor of psychotherapeutic outcomes, explaining a similar percentage of variance to other patient-related variables (Strauss & Petrowski, 2017). Levy et al. (2011) reported mean weighted correlations between patient attachment styles and psychotherapeutic outcomes of low-to-mid effect size ($d$ in the range of -.03 – -.46). Here, the anxious attachment style had the most substantial negative correlation with psychotherapeutic outcomes. In contrast, the effect of attachment security was relatively modest, nonetheless positive ($d = .37$).

Babl et al. (2020) studied the role of overall defensive functioning (ODF) in a sample of patients suffering from depression, anxiety and adjustment disorders through a randomised control design. ODF has been defined as automatic psychological processes which shield the individual from anxiety and other internal and external stressors (American Psychiatric Association, 2000). Vaillant (1971) classifies these processes into three-tier: adaptative, neurotic, and maladaptive. The authors reported that a higher number of adaptative defensive mechanisms was linked to less severe symptomatology during treatment, whereas a higher number of maladaptive defensive mechanisms was associated with more severe depressive and anxiety symptoms. Noticeable, the authors informed that an increase in adaptative mechanisms together with a decrease in maladaptive mechanisms through treatment was able to predict reductions in depressive symptoms. Likewise, a decrease in both neurotic and immature mechanisms was associated with reductions in anxiety symptoms.

Overall, the patient’s contribution to psychotherapeutic outcomes tends to be stronger than either any therapeutic approach or the therapeutic alliance, suggesting that future psychotherapy research should focus on the crucial patient’s characteristics intertwined with
the interpersonal processes determining psychotherapeutic outcomes (Lambert, 2013). For example, Gómez Penedo et al. (2020) discovered that patients suffering from depression reported a better alliance for sessions in which the patient and therapist’s affiliative behaviours were highly complementary. According to Sullivan’s (1953) dimensions of interpersonal behaviour, a relationship is considered complementary when it shows correspondence and reciprocity. The researchers reported that in the case of non-complementary conduct, patient affiliative behaviours (i.e., friendly) were positively associated with the alliance, meaning that the more affiliate behaviours from the patient, the stronger the alliance. This finding resembles former research which reported psychotherapy success largely relying on therapist flexibility and the ability of monitoring patient’s experience to the intended receptiveness (Bohart & Wade, 2013; Levitt et al., 2016).

2.11–Data Analysis for Assessing the Structure and Reliability of a Questionnaire

2.11.1–From Exploratory Factor Analysis to Exploratory Structural Equation Modelling

In factor analysis, factors are denominated latent or unmeasured variables, constituting the structure model in Structural Equation Modelling (SEM), whereas the items of a measure or observed variables constitute the measurement model comprising the baseline upon which latent variables are extracted (see Bollen, 1989). Therefore, these two levels are usually evaluated in terms of their distinctive structure when performing factor analysis. Exploratory methods, such as Exploratory Factor Analysis (EFA) are usually conducted to provide preliminary evidence of how the items load onto factors, whilst confirmatory methods, such as confirmatory factor analysis, allow checking former freely established loadings onto factors with higher constraints (Marsh et al., 2014).

Confirmatory Factor Analysis (CFA) permits confirming the previously studied internal psychometric structure of a questionnaire through Exploratory Factor Analysis
(EFA), at the expense of several assumptions (Kline, 1994). These CFA constrictions require that cross-loadings between factors are set to zero and items load only to distinctive uncorrelated factors, being this known as orthogonal simple structure, in contrast to the oblique simple structure, in which factors are allowed to correlate (McDonald, 2014). In practice, researchers frequently implement exploratory factor modelling when developing a new measure, which is later hard to settle when confirmatory factor analysis is conducted (e.g., Marsh et al., 2009). For instance, Marsh et al. (2014) argued that when counterexamples were requested to the claim that it is almost impossible to obtain an acceptable model fit with CFI to more than 2000 researchers from the field of SEM, not a single researcher was able to provide a suitable illustration.

Exploratory Structural Equation Modelling (ESEM) has been proposed as an efficient and more flexible alternative factor analytic approach for studying and confirming the internal structure of a questionnaire. CFA usually yields poor model fit, as orthogonal rotations are often considered unrealistic in psychological research (Morin et al., 2013). Marsh et al. (2014) posed that whilst ESEM remains a confirmatory approach, it is much less restrictive than CFA, which in turn allows for a better data fit for most psychological instruments that present cross-loadings. In this regard, they concluded that CFA usually produces inflated factor correlations, making it less suitable for assessing multidimensional constructs in comparison with ESEM. Illustrations of this point can be found in Tóth-Király et al. (2017), and chapter three of the present dissertation.

2.11.2–Bi-factor Versus Hierarchical Approaches in Factor Analysis

Bi-factor modelling is also known as general-specific or nested models (Holzinger & Swineford, 1937). In bi-factor modelling, the global or general factor is in pair with the remaining factors, allowing the items to load directly to the global and factor-level. It
contrasts with hierarchical factorial modelling—also denominated second-order—, where items cannot load onto the general factor directly, but only through their respective factors (see Chen et al., 2006; Reise, 2012). Although researchers in cognitive assessment have extensively studied bi-factor models (Gignac & Watkins, 2013; Gustafsson & Balke, 1993; Holzinger & Swineford, 1937; Luo et al., 1994), their applicability has proved useful in the psychometric assessment of non-cognitive constructs as well (Morin et al., 2015). As Reise (2012) posed, second-order and unidimensional models are nested within bi-factor modelling, meaning that researchers should prefer the least restricted model (i.e., bi-factor) instead of a constrained representation of it, which usually worsen model fit. An illustration of this argument can be found in Chen et al. (2006), where a bi-factor model fit significantly better than a hierarchical on quality of life. Chen et al. (2012) declared there are several reasons to recommend bi-factor modelling over second-order modelling, especially when testing the internal structure of multidimensional constructs. These authors argued that: 1) only bi-factor modelling can separate specific factors from the general factor, as the strength of the relationship between specific factors and the respective items is directly reflected in the factor loadings, whereas this cannot be tested in second-order models, since the specific factors are represented by the unique variances of the first-order factors, 2) only bi-factor modelling is able to identify if a facet still exists after partialling out the general factor, 3) bi-factor models can test mean differences on facets over and above the general factor, whereas in hierarchical modelling, only second-order latent means can be directly compared, 4) bi-factor modelling is more suitable when testing whether a subset of specific factors predicts external outcomes over and above the general factor, since specific factors are directly represented as independent variables whilst in second-order modelling they are not.
2.11.3–Reporting of Reliability Indexes

Regarding reliability, Zinbarg et al. (2005) has demonstrated that Omega (\(\omega\)) becomes the most appropriate reliability index when the focus of interest is the proportion of scale variance due to all common factors. In contrast, according to the authors, Omega hierarchical (\(\omega_h\)) allows examining the proportion of scale variance due to a general factor. Hence, it is informative to report these reliability statistics (\(\omega\) and \(\omega_h\)) and to contrast them, when appropriate, with the classical Alpha index at the global and factor-level. Likewise, Sijtsma (2009) posed that Cronbach’s Alpha is not a measure of internal consistency, and as such, does not convey information on the internal structure of a survey. As this author emphasised, Alpha suffers from random measurement error, being a more desirable strategy to report Alpha in addition to a greater lower bound (glb), such as Omega, as this will foster better reliability reporting practices.

2.12–The Role of Multiple Imputation

During the development of the studies included in the dissertation, multiple imputation was the preferred method for dealing with missing data across the studied datasets. According to Rubin (1987), “Multiple imputation is the technique that replaces each missing or deficient value with two or more acceptable values representing a distribution of possibilities” (p. 2). This author developed the original idea in the late ‘70s, which relies on a certain number of \(m\) values, representing each a dataset with imputed values ordered into vectors that sequentially replace the missing values as further imputations are conducted on the formerly imputed datasets. Allison (2000) stated that multiple imputation is one of the most attractive strategies for handling missing data in multivariate analysis.

There are a few methods available for imputing values, among them Conditional gaussian, Chained equations, Methods for monotone datasets, Maximum Likelihood-based
approaches, Weighting methods, and Bayesian approaches (see Horton & Kleinman, 2007). Enders et al. (2016) posed that as for multilevel analysis, joint imputation and chained equations have been found the two most appropriate, having each their pros and cons depending on the data and type of analysis intended. These authors concluded that the joint model is superior for data analysis portraying within and between cluster relations. In contrast, chained equations are more advantageous in random slope analyses, especially when the factor structure and parameters are invariant across levels, i.e., when measurement error is minimal. Multiple imputation by chained equations can be implemented in R through the MICE package (Van Buuren & Groothuis-Oudshoorn, 2011).

When performing multiple imputation, White et al. (2010) proposed including predictors with incomplete data in the imputation model, as this is advantageous for two reasons: 1) It makes more plausible the assumption of missing at random (MAR), thus reducing bias, and 2) It reduces the standard errors of the estimates in the model. Additionally, obtaining and pondering the fraction of the missing information (FMI) has been highlighted as an effective method to ascertain the validity of an imputation procedure, and it is recommended that reporting this index will gain efficiency (Madley-Dowd et al., 2019; Wagner, 2010).
Chapter 3: Validation and Adaptation of the TEIQue-SF in Chilean General and Clinical Population (Studies 1 and 2)

3.1–Introduction

The overall aim of the studies included in this chapter was to adapt and validate the TEIQue-SF (Trait Emotional Intelligence Questionnaire-Short Form) in Chilean Spanish for use in general and clinical populations. Thirty-eight participants assessed the translation before the pilot study. Subsequently, the author approached a pilot, a general and a clinical sample, comprising 525 individuals overall. There was specific interest in gathering local evidence of a) possible gender differences for the Global trait EI, b) reliability scores, c) internal factor structure, and d) measurement invariance for the general and clinical Chilean samples, were then compared to the original validation sample approached in the U.K. It is worth noting that previous work conducted by Pérez-González (2010) served as an impetus through the development of the Spanish-Chilean-TEIQue-SF. Therefore, the measure adapted in the dissertation expands on the measurement of trait EI in Spanish, mostly through their greater applicability to Latin-American Spanish population.

These studies represent the foundation upon which the subsequent chapters and respective investigations rely. This baseline is particularly relevant to the overall aim of the dissertation, as the first two studies provide sufficiently extensive psychometric evidence supporting the suitability of the Spanish-Chilean-TEIQue-SF for examining the trait EI construct locally. This reference allows for cross-cultural scrutiny of the invariability of the construct and variance comparison across countries and sociodemographic correlates, as

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presented in chapter four. In addition, the studies included in the present chapter permit comprehensive and reliable inspection of the trait EI effects in psychotherapy, as later described in chapter five. As announced in the literature review, preceding trait EI research in the region arrived at unbefitting local adaptations of trait EI measures (e.g., Neri-UrIBE & Juárez-García, 2016; Omar et al., 2014) or simply utilised foreign Spanish translations of well-regarded trait EI questionnaires in applied research without any local psychometric evidence with the population of interest (e.g., Veliz-Burgos et al., 2018; Veloso-Besio et al., 2013). Hence, the necessity of conducting this primary investigation providing psychometric evidence with a thoroughly adapted and validated short measure of trait EI is justified for the aims of the dissertation.

3.2–Method

3.2.1–Linguistic Adaptation and Pilot Sample

3.2.1.1–Participants. Firstly, thirty-eight people from the public assessed the linguistic and cultural translation of the original TEIQue-SF, as formerly produced by two certified translators. Secondly, a pilot sample of adults (N=70) was administered a paper questionnaire in high schools located in Santiago, which was deemed to resemble the distribution of trait EI in the community. Most participants were high-school teachers averaging forty years old, which the research team considered a knowledgeable audience for assessing the readability, layout, and overall suitability of the questionnaire. Hertzog (2008) has suggested that the sample size of pilot studies ranging from 10 to 40 observations are adequate in providing estimates with sufficient precision for a variety of possible research aims. Moreover, Lackey and Wingate (1998) have proposed that a pilot study should at least include 10% of the final study size. Therefore, the sample size of the pilot study complied with the two aforementioned criteria.
3.2.1.2–Measures. The translation of original TEIQue-SF, with 30 statements was tested in stage one, back-translated and harmonized before being administered to the pilot sample (stage two). This was the pilot Spanish-Chilean-TEIQue-SF questionnaire, which later evolved into the final adapted Spanish-Chilean-TEIQue-SF questionnaire. This last version of the measure is available in Appendix A1.

3.2.1.3–Design and procedure. A two-stage cross-sectional design through survey research was implemented. In the first stage, a linguistic adaptation of the TEIQue-SF to the Chilean context was carried out, where forward translation, reconciliation with the original scale, back translation and harmonization of versions preceded the implementation of qualitative techniques, i.e., cognitive debriefing interviews (eight) and focus groups (three in total, each with ten to fifteen participants). This approach allowed assessment of the structure, content, and language of the questionnaire with the population of interest. In the second stage, a validation sample was recruited.

Moreover, guidelines for implementing cognitive debriefing interviews were designed following the literature on linguistic and transcultural validations (Wild et al., 2005; Willis, 2006). An example of this is: “Could you tell me with your own words what is the meaning of statement 1 (read the statement)?” Finally, guidelines for implementing the focus group discussions were designed. An example of this is: “The coordinator must promote the reflection and discussion on emotional intelligence”. The guidelines for cognitive debriefings and focus groups are available in Appendices A2 and A3, respectively. The University College London-Research Ethics Committee approved the pilot study with project ID: 12971/00. Participants were approached face-to-face at this stage.
3.2.1.4—Data Analysis Plan. A descriptive analysis of the items was performed. Next, analyses of reliability were obtained for the general factor and the four factors through the Psych package in R (Revelle, 2017).

3.2.2—General Population Sample

3.2.2.1—Participants. A validation sample was approached in the cities of Santiago and Puerto Montt (N = 335), to administer the questionnaire to faculty in universities, evening students and people from the community, as it was presented directly by the researchers. Five additional questionnaires were disregarded through listwise deletion as they had the same pattern of response throughout the whole questionnaire and also were deleted five more that presented missing values. The sample was broadly balanced regarding gender (Women = 45%, Men = 35%, 19% did not disclose their gender, whilst 1% did not identify with either gender category). 90% of participants were under 50 years old (M = 33.41, SD = 11.39). Regarding their main occupation, most of them declared being students (27%) followed by those employed in the private sector (21%). A third block comprised high school teachers and university lectures (16%). Those employed in the public sector accounted for 6% of the sample. Unemployed and those who declared a not listed occupation accounted for 5% and 4% respectively. Seventy participants (21%) did not disclose their occupation. Regarding maximum educational attainment, 37% of participants had attained or were in the process of obtaining a secondary education qualification, 26% of them had obtained a higher education certification or university degree, and 16% held a postgraduate degree. The remaining 21% did not disclose their education. Participants did not receive any monetary recompense. The inclusion criterion was: (a) Adults, aged 18 years or above. The exclusion criteria were: (a) being a current mental health patient, and (b) having any diagnosis of severe psychopathology at the time of the study. The University College London-Research Ethics
Committee granted ethical approval for the research with project ID: 12971/00. The dataset is available at http://dx.doi.org/10.17632/gstrr47vpr.3

A power analysis was performed in STATISTICA statistical software version 10 (StatSoft, 2011) following the recommendations by MacCallum et al. (1999). Its purpose was to find a sample size sufficient to control for Type I and II errors. Specifically, the required sample size was 300 participants, taking an RMSEA of .06 over the Null Hypothesized RMSEA of .05, when the type I Error is set at .05, with 321 degrees of freedom, and the power goal was of .8. Since in this case, the parameters (items) are 30 and the factors stated in the literature for the questionnaire are four (i.e., Emotionality, Self-control, Sociability and Well-being), the solution to the formula yields 321 degrees of freedom. Therefore, the final power for study one with 335 cases was better than expected (.85). The large sample size in the general population sample will allow dealing with the lesser reliability of the TEIQue-SF compared to the full form, and thus, still account for the variance associated with the overall construct and its factors.

3.2.2.2–Measures. The Spanish-Chilean TEIQue-SF (see Appendix A1). The questionnaire comprises thirty statements and a Likert-7 response scale ranging from 1 (Completely Disagree) to 7 (Completely Agree).

3.2.2.3–Design and Procedure. A convenience sample design was implemented, where the researcher approached participants by two means: collective application (paper questionnaire), and online assessment through an anonymous Qualtrics form. Various institutions provided access to the participants at their work premises for collective application. For the online assessment, an anonymous Qualtrics link was distributed by email in institutions where members were likely to reach the inclusion criteria. The participants did not provide any personal data that could link their responses to their identity beyond informed
consents. The researcher explicitly instructed participants to choose the option that represented them most. Although the research was noninvasive, some participants might have felt uncomfortable with some statements due to their intrinsic relationship with personality. For those participants, as stated in the consent forms, withdrawal from the study was possible at any moment. Also, in the unlikely event that a participant underwent a severe disturbance when carrying out any of the planned research activities, adequate support could be requested at the nearest health emergency staff, a situation that was not informed to have happened.

Additionally, the study was appraised with the consensus-based standards for the selection of health status measurement instruments (COSMIN). The COSMIN study design checklist establishes criteria for assessing the methodological suitability of studies conducted in health settings to avoid potential risks or biases regarding reporting or samples size issues, which according to the authors prevents waste of resources or unethical behaviour in health research (Mokkink et al., 2019; see also Mokkink et al., 2010a; Mokkink et al., 2010b). An international panel of 57 specialists from Psychology, Epidemiology, Statistics, and Clinical Medicine developed the consensus, having all the experts conducted high-quality research in their respective fields as a pre-requisite to participate (Mokkink et al., 2010a).

This international standard provides a 4-point rating scale to understand the consequences of choices made in the design of the study, providing an overall rating of the research design (Mokkink et al., 2019). The four categories of the rating scale are: 1) very good, when the criterion is completely fulfilled, 2) adequate, when the studied criterion is attained with some limitations, 3) doubtful, when there are serious limitations to the design, and 4) inadequate, when the criterion examined does not comply with the minimal methodological requirements.
The clusters of analysis including all the applicable criteria to study design are: 1) general recommendations for the design of a study, 2) content validity, 3) structural validity, 4) internal consistency, 5) cross-cultural validity/measurement invariance, 6) criterion validity, 7) hypotheses testing for construct validity, 8) responsiveness and 9) translation process. Of especial interest for the development of the studies included in this chapter are the clusters on translation process, content and structural validity, and internal consistency. In all these clusters and across 12 criteria of translation process, 6 of internal consistency, and 6 of structural validity, the research was considered as of very good standard. For instance, regarding sample size, the highest-ranked category of very good requires seven times the number of items of the implemented questionnaire (i.e., 210 observations for the adapted measure) and 100 participants or more, a threshold that was abundantly exceeded in this study regarding the number of participants per items of the questionnaire, which was more than 11 times the number of items of the questionnaire.

3.2.2.4. Data protection measures. All the information was encrypted following the 256-bit encryption method, as recommended in “The Information Governance training” provided by UCL-ISG. Also, the data was stored in UCL desktop service (N drive) and UCL Pals building (Bedford Way 26, Room 200), and were only processed by the Principal researcher (Konstantinos Petrides) and the trainee (Pablo Pérez Díaz) for research purposes. One research assistant was in place for coordinating data collection whilst fieldwork was carried out. This assistant did not store nor analyse participants’ data. A risk assessment form was agreed upon between the trainee and the Principal Researcher. Safety measures regarding travelling, lodging and office conditions were all checked both in the U.K. and in Chile, as the trainee travelled to Chile to conduct data collection. A special mention of hazards whilst performing fieldwork was also included.
3.2.2.5–Data Analysis Plan. The Omega index of reliability was obtained for assessing and interpreting the internal consistency of the questionnaire (McDonald, 1999, 2014; Reise, 2012; Sijtsma, 2009; Zinbarg et al., 2005). Confirmatory Factor Analyses (CFA), and subsequently Exploratory Structural Equation Modelling (ESEM) were conducted for evaluating the internal factor structure of the questionnaire. Omega and Cronbach’s Alpha in R were obtained through the package Psych (Revelle, 2017). In Omega, the omegaSem function was implemented for reliability. This analysis yields a CFA upon which cross-loadings are modelled as a part of the general factor (Revelle, 2017). CFA models were also independently assessed in R by the package lavaan (Rosseel, 2012), whilst ESEM was implemented in Mplus version 8.1 (Muthén & Muthén, 2017). Additionally, Global trait EI gender-based analyses were performed.

Regarding factor analysis, CFA with ML estimator and modification indices (M.I) were firstly conducted to prove the expected unsuitability of CFA on the novel dataset, empirically. In a second step, ESEM with ML estimator, oblique rotations and M.I. were implemented. This progression from CFA to ESEM was chosen on several studies that have highlighted the methodological advantages ESEM has over EFA and CFA (Marsh et al., 2014). Likewise, Perera (2015) has provided further evidence in favour of ESEM when compared to EFA and CFA for exploring the multidimensional structure of the TEIQue-SF. In ESEM, bi-factor modelling was applied.

3.2.3–Clinical Population Sample

3.2.3.1–Participants. The sample comprised 120 patients in treatment at university mental health clinics in the cities of Santiago, Castro, and Puerto Montt. 69% of participants were women, 28% men, whilst 3% of the sample did not disclose their gender. 83% of participants were under 50 years old \( (M = 32.39, SD = 13.01) \). Two questionnaires were
disregarded through listwise deletion, as they presented missing values. Participants did not receive any monetary recompense. The inclusion criteria were: (a) aged 18 years at least, (b) being a current mental health patient within the approached mental health centres. Patients experiencing acute symptomatology from a severe psychiatric disorder were excluded from the study (e.g., Schizophrenia). Thus, all enrolled patients suffered from mild depressive or anxious symptomatology, which is in line with the admission patient profile of the university mental health clinics in Chile. For instance, De la Parra et al. (2019) illustrate that a typical mental health centre of this type in Santiago (composed of participants from middle and middle-low socioeconomic status) had more than 50% of patients diagnosed with depression over a period of ten years. This figure is congruent with those of the World Health Organisation (2017), highlighting that the greatest burden of mental health is attributable to depression and anxiety disorders. The University College London-Research Ethics Committee granted ethical approval for the research with project ID: 12971/00. The dataset is available at [http://dx.doi.org/10.17632/gstr47vpr.3](http://dx.doi.org/10.17632/gstr47vpr.3)

An Intraclass Correlation Coefficient (ICC) of .86 was obtained from a dataset provided by Cooper and Petrides (2010) through type A-ICCs (i.e., using an absolute agreement definition), upon which the power analysis for the sample was based. Cluster sample size estimations were conducted for achieving a power of .8. These calculations were based on a maximum target population of 1300 patients at university mental health clinics in the three cities according to MINEDUC’s figures (2017). From this population, a minimum sample size of 100 allowed dealing effectively (MacCallum et al., 1999) with the lower reliability that the TEIQue-SF shows in comparison to the full form, and thus, still account for the variance associated with the overall construct and its factors.

**3.2.3.2–Measures.** The Spanish-Chilean TEIQue-SF was utilised, as developed in the previous study.
**3.2.3.3–Design and Procedure.** Participants were assessed face-to-face by their mental health care providers in their respective mental health centres and usual consultation settings; this avoided the researcher contacting patients directly without their consent and the related ethical implications. Tailored in situ inductions were conducted with the psychotherapists working in the clinical centres where the data would be collected, emphasising that participants should choose the option that represented them most, and that they could leave the study at any time. For study two, the researcher implemented the same preventive measures regarding participant distress applied in study one.

As in study one, the consensus-based standards for the selection of health status measurement instruments (COSMIN) were implemented as a guideline (Mokkink et al., 2019). In all these clusters and across 12 criteria of translation process, 6 of internal consistency, and 5 of structural validity, the research was considered of a *very good* standard. There was only one criterion that could be labelled as *adequate*, which corresponded to the sample size of study two. The highest-ranked category of *very good* requires seven times the number of items of the implemented questionnaire (i.e., 210 observations in the case of adapted measure) and 100 participants or more. These criteria were only attained in study one.

The *adequate* description of the criterion requires at least five times the number of participants per item of the questionnaire (i.e., 150), and 100 or more participants overall. The first requirement of participants per item in this criterion is very close to the sample size of study two, with 120. Therefore, the sample size reached in study 2 was of exactly four times the number of items included in the questionnaire and exceeded the minimum of 100 participants required in the description of the criterion as *adequate*. The following description in the criterion (i.e., *doubtful*) corresponds to a design where the sample size is below 100 participants, although the requirement of five times the number of items remains.
Consequently, the structural validity for study two was considered *adequate* in this regard, as the descriptions of the ranked criterion resembled more this category than the highest *very good* and the immediately lower *doubtful*.

### 3.2.3.4–Data protection measures.
For study two, the researcher implemented the same data protection measures stated in study one.

### 3.2.3.5–Data Analysis Plan.
Internal consistency reliability analyses were performed through Omega \((\omega)\) and factor validity through bi-factor Exploratory Structural Equation Modelling (ESEM) in Mplus, version 8.1 (Muthén & Muthén, 2017). The *omegaSem* function was implemented for reliability with Omega, as described in the prior study. Cronbach’s Alpha and Omega indexes were obtained in R through the Psych package (Revelle, 2017). CFA modelling was not assessed for this sample, as it proved inadequate in study one. Finally, Global trait EI gender-based analyses were implemented, and a basic ESEM model amended through the introduction of modifications indices.

### 3.3–Results

#### 3.3.1–Pilot Sample Results

From the qualitative testing of the early adapted version of the questionnaire, changes were implemented to the readability of the translated items, instructions, and the included sociodemographic information. These amendments were most important for the different levels of the sociodemographic variables and less so for the readability of the items. All these modifications were made following consultation with the author of the instrument and the certified translators. The final version of the questionnaire was then applied to a sample comprised mostly adults high-school teachers. Descriptive statistics for this pilot sample \((N = 70)\) are displayed in Table 1.
Table 1. Descriptive Statistics for the TEI Measures in the Pilot General Sample

<table>
<thead>
<tr>
<th>Trait EI measure</th>
<th>Min</th>
<th>Max</th>
<th>M</th>
<th>SD</th>
<th>Skew</th>
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<tbody>
<tr>
<td>Global trait EI</td>
<td>2.90</td>
<td>5.40</td>
<td>4.09</td>
<td>0.44</td>
<td>0.46</td>
<td>0.92</td>
</tr>
<tr>
<td>Well-being</td>
<td>2.67</td>
<td>6.00</td>
<td>4.73</td>
<td>0.56</td>
<td>-0.39</td>
<td>1.95</td>
</tr>
<tr>
<td>Self-control</td>
<td>2.33</td>
<td>7.00</td>
<td>4.05</td>
<td>0.72</td>
<td>1.06</td>
<td>3.20</td>
</tr>
<tr>
<td>Emotionality</td>
<td>2.25</td>
<td>5.50</td>
<td>3.55</td>
<td>0.62</td>
<td>0.69</td>
<td>0.60</td>
</tr>
<tr>
<td>Sociability</td>
<td>2.83</td>
<td>6.50</td>
<td>4.12</td>
<td>0.75</td>
<td>0.94</td>
<td>1.44</td>
</tr>
</tbody>
</table>

*Note. EI = emotional Intelligence. Min = minimum, Max = maximum, M = mean, SD = standard deviation, Skew = skewness, Kurt = kurtosis.*

Reliability analysis revealed that the questionnaire was found reliable at the global \( \omega_{t} = .92 \) and factor-level (Well-being \( = 0.89 \), Self-control\( = 0.82 \), Emotionality \( = 0.72 \), Sociability\( = 0.66 \)) through the Omega total index. As predicted, compared to the Omega global output, \( \alpha = .89 \) was at the lower bound of the total reliability for the questionnaire. Furthermore, the proportion of scale variance due to the general factor (Global trait EI) was 47% \( (\omega_{h} = 47) \), regardless of the variance explained by the specific latent variables.

All items loaded either on the general factor or on at least one subscale factor, with the only exception being item 25, which did not correlate greater than .2, following Schmid and Leiman’s (1957) criterion, either at the general factor or the factor-level. The correlation for item 25 with the general factor was below .1, whereas the correlation with the factor Sociability was below .06. Therefore, statement 25 was reworded to make it more sensitive to the local context and boost its reliability in the larger study. The original Item 25 had an almost exact translation to Spanish. Thus, this item was reworded as: “In a discussion, I tend to give in even when I know I am right”. As discussed later, this proved to be an adequate substitution. The reason behind choosing this rewording relied heavily on the knowledge of the local context, the consideration of preceding TEIQue-SF translations from English to Spanish, and the weighting of the comments made by participants regarding the wording and local appropriateness of the item.
3.3.2–Results in the General Population Sample

3.3.2.1–Descriptive Statistics in the General Population Sample. Descriptive statistics for the trait EI factors in the general population sample are depicted in Table 2. As can be observed in Table 2, there is a common negative skewness which becomes more pronounced for the Well-being factor, where participants tended to score higher ($N = 335$).

3.3.2.2–Trait EI Gender Differences in the General Sample. There were no statistical differences with respect to gender for the Global trait EI factor: $t (115) = .114, p = .91$, with the test value of 5.01 ($MWomen$). Indeed, the means for the Global trait EI and descriptive statistics were strikingly similar: $MMen = 5.02, SD = .85, Skewness = -.30, Kurtosis = -.39, MWomen = 5.01, SD = .82, Skewness = -.33, Kurtosis = -.33$.

Table 2. Descriptive Statistics for the Trait EI Factors in the Chilean Samples

<table>
<thead>
<tr>
<th>Trait EI measure</th>
<th>Min</th>
<th>Max</th>
<th>M</th>
<th>SD</th>
<th>Skew</th>
<th>Kurt</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. General population sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
<td>2.40</td>
<td>6.80</td>
<td>5.03</td>
<td>0.85</td>
<td>-.19</td>
<td>-.54</td>
</tr>
<tr>
<td>Well-being</td>
<td>1.00</td>
<td>7.00</td>
<td>5.43</td>
<td>1.17</td>
<td>-.92</td>
<td>0.80</td>
</tr>
<tr>
<td>Self-control</td>
<td>1.33</td>
<td>7.00</td>
<td>4.76</td>
<td>1.05</td>
<td>-.15</td>
<td>-.14</td>
</tr>
<tr>
<td>Emotionality</td>
<td>2.13</td>
<td>7.00</td>
<td>4.98</td>
<td>1.03</td>
<td>-.22</td>
<td>-.51</td>
</tr>
<tr>
<td>Sociability</td>
<td>2.33</td>
<td>7.00</td>
<td>4.83</td>
<td>0.92</td>
<td>0.02</td>
<td>-.50</td>
</tr>
<tr>
<td>2. Clinical population sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
<td>2.63</td>
<td>6.80</td>
<td>4.75</td>
<td>0.08</td>
<td>0.46</td>
<td>-0.26</td>
</tr>
<tr>
<td>Well-being</td>
<td>1.50</td>
<td>7.00</td>
<td>5.05</td>
<td>0.11</td>
<td>-0.39</td>
<td>-0.47</td>
</tr>
<tr>
<td>Self-control</td>
<td>2.00</td>
<td>6.83</td>
<td>4.39</td>
<td>0.11</td>
<td>1.06</td>
<td>-0.70</td>
</tr>
<tr>
<td>Emotionality</td>
<td>2.13</td>
<td>6.88</td>
<td>4.88</td>
<td>0.09</td>
<td>0.69</td>
<td>-0.37</td>
</tr>
<tr>
<td>Sociability</td>
<td>1.33</td>
<td>6.33</td>
<td>4.63</td>
<td>0.08</td>
<td>0.94</td>
<td>1.24</td>
</tr>
</tbody>
</table>

Note. EI = emotional Intelligence. Min = minimum, Max = maximum, $M =$ mean, $SD =$ standard deviation, $Skew =$ skewness, $Kurt =$ kurtosis.

3.3.2.3–Reliability Analysis. These analyses revealed that the global score was highly reliable (see Taber, 2018), $\omega_t = .90$ and $\omega_h = 63$. Likewise, all factors showed good Omega reliability indices but Sociability, which displayed rather low-reliability indexes in comparison with other factors when assessed through omegaSem (Well-being = .84, Self-
control = .81, Emotionality = .63, Sociability = .41). As predicted by McDonald (1999, 2014), when compared to the omegaSem output, Cronbach’s Alpha was at the lower bound of the total reliability score for Global trait EI (α = .88).

Moreover, the proportion of scale variance due to the general factor (Global trait EI) indicated by $\omega_h$, was 63%, regardless of the variance explained by the remaining latent variables. Although Sociability had the lowest reliability score according to Omega, its reliability was somewhat higher by Cronbach’s Alpha index: $\alpha = .47, 95\% CI [.39, .56]$. The same was true for the second-lowest reliability score concerning Emotionality: $\alpha = .65, 95\% CI [.60, .71]$. Moreover, although less informative than omegaSem for factor analysis (since this analysis is based on an informed factor structure), the values of omega total were similar to factor-level Alphas (Well-being = .80, Self-control = .59, Emotionality = .65, Sociability = .46). It is worth mentioning that whilst omegaSem is sensitive to the internal modelled structure of a test, Alpha and omega total are not (Revelle, 2017). Therefore, the reliability indices for the factors Sociability and Emotionality may be labelled as adequate and acceptable, respectively (Taber, 2018).

### 3.3.2.4–Factor Analysis with the General Population Data
Here, CFA analyses were conducted first to prove the assumption of orthogonality was unfounded (see McDonald, 2014). They provided the psychometric basis for testing later the internal structure of the questionnaire through ESEM and oblique rotations.

#### 3.3.2.4.1–CFA Models with Modification Indices (M.I.)
For comparing different models with CFA, a second-order model (model 1) was contrasted to a bi-factor model (model 2) where all factors are correlated, following Morin et al.’s (2015) recommendations for analysing the factor structure of personality questionnaires. Firstly, a hierarchical, second-order model was tested (model 1), where each one of the factors was considered as a latent
variable on its own (with the corresponding items as indicators), whilst at the same time, all factors were considered indicators of a greater second-order factor (i.e., Global trait EI). The R syntax for the model is available in Appendix A4. Model 1 is depicted in figure 1.

When the proposed model was nested within the test base model with only one factor, the resultant fit was poor: Minimum function statistic for the baseline model (325, 335) = 2442.862, \( p < .001 \), Model Fit Test Statistic for the augmented model (295, 335) = 993.582, \( p < .001 \), \( CFI = 0.670 \), \( RMSEA = 0.084 \) 90% CI [0.078, 0.090] and \( SRMR = 0.092 \). The four factors loaded significantly onto the second-order factor (Global trait EI) at \( p < .001 \). Also, most items loaded significantly onto their keyed factor (\( p < .001 \)), with the exception of the two lowest loadings for the Sociability factor, regarding item 25 (\( p = .09 \)) and item 11 (\( p = .06 \)). The percentage of variance explained by the global factor was 50\%, followed by Well-being accounting (35\%), Self-control (23\%), Sociability (7\%), and Emotionality (6\%).

Subsequently, a bi-factor model (model 2) was tested. Here, a global factor enfolds all the items as a latent variable, and the factors are also latent variables on their own at the same level. The bi-factor model was nested within the test base model (one factor). The percentage of variance explained by the global factor was 57\%, and the factor-level latent variables were standardised. The statistics for goodness of fit showed a better fit for this last model than the higher-order previously presented: Minimum function statistic for the baseline model [(435, 335) = 3122.18 \( p < .001 \), Model Fit Test Statistic for the augmented model with one global factor and a four-factor-level [(379, 335) = 1020.19, \( p < .001 \)], \( CFI = 0.761 \), \( RMSEA = 0.071 \) 90% CI [0.066, 0.076] and \( SRMR = 0.081 \). The R syntax for the model is available in Appendix A5. Model 2 is depicted in figure 1.

These findings provided evidence for bi-factor modelling explaining better the internal structure of the Spanish-Chilean-TEIQue-SF. It is worth framing this conclusion on the matter
of fact that absolute fit indexes (e.g., RMSEA, SRMR) assess the extent to which the modelled covariance matrix matches the observed covariance matrix (i.e., baseline model), whereas incremental fit indexes (e.g., CFI, TLI) evaluate the degree to which the tested model is superior to an alternative model in replicating the observed covariance matrix (Chen, 2007), as compared above. Therefore, claiming differences based on the Chi-square statistic yields to incorrect interpretations, as this statistic is sensitive to sample size and violation of the normality assumption (Chen, 2007), whereas CFI is relatively independent of sample size (Hu & Bentler, 1998). This is why the overlap in 95% CIs between model 1 and model 2 suggests there is no statistical difference between the models, although in practice, they are not comparable given each model is based on a different set of observed variables, as warned by lavaan. Moreover, Little (1997) proposed three criteria for contrasting nested models: 1) the overall model fit is acceptable, 2) indexes of local misfit are uniformly and unsystematically distributed, and 3) the restricted model is substantially more meaningful and parsimonious than the baseline model. Based on these criteria, the contrast between model 1 and model 2 revealed that the overall model fit was closer to acceptable incremental values (i.e., .80) only for the bifactor model (model 2), since misspecification problems arose with the hierarchical model (model 1), given that lavaan warned that an estimated latent variable’s variance was negative for the factor Sociability, a situation that did not occur in model 2. Therefore, model 2 was more parsimonious than model 1, as to their respective nested baseline models. Regarding factor correlations, greater heterogeneity was found in model 2. Thus, non-significant loadings were observed for Well-being (item 5, \( p = .10 \); and 12, \( p = .36 \)), Self-control (item 4, \( p = .69 \)), Emotionality regarding items 16 (\( p = .73 \)) and 13 (\( p = .43 \)), and Sociability (item 11, \( p = .14 \)). At the Global trait EI factor this occurred for items 11 (\( p = .08 \)) and 25 (\( p = .06 \)). The results provided a basis for testing ESEM models with M.I. as the method of choice. The factor loadings for models 1 and 2 are available in Appendix A6.
3.3.2.4.2–ESEM Using ML Estimator and Oblique Rotations. The first basic ESEM (Model 3) ratified the appropriateness of bi-factor modelling. All latent variables were a set of EFA, and their variances were constrained at one. Therefore, this model is an exploratory rather than a confirmatory ESEM, as the last is presented in the literature as ESEM-within-CFA (EwC) (Marsh et al., 2014; Marsh, Nagengast, et al., 2013; Morin & Asparouhov, 2018; Morin et al., 2012). Likewise, the four factor-level was standardised on Global trait EI, as according to Muthén and Muthén (2017), “this puts the results in the metrics of an EFA” (p.105). The Mplus syntax for Model 3 is available in Appendix A7.

Model 3 showed a better fit to the models previously presented, reaching an acceptable to good fit: \( \chi^2 (295, 335) = 439.14, p < .001, CFI = 0.946, RMSEA = 0.038 \) 90% CI [0.030, 0.045] and SRMR = 0.033. Nevertheless, modification indices suggested the inclusion of two arguments for correlated errors: the first one, between item 18 and item 3 (items theoretically loading only on the general factor), and the second one, between item 21 (Sociability) and 17 (Emotionality). The former is theoretically appropriate because the re-specification of the model is intended to address two items not loading at the factor-level (18 and 3), which have been referred to as difficult to address when reaching up to the four factor-level structure in prior studies with the questionnaire using ESEM (Perera, 2015). Likewise, they point towards the same underlying facet (i.e., Self-motivation), as described in the full form of the questionnaire.

Model 4 is the re-specification of model 3, after the introduction of M.I. Here, items not theoretically associated with each of the factors were fixed at zero correlation, as recommended by Morin and Asparouhov (2018) in their ESEM-within-CFA (EwC) framework, since this allows complete CFA functionality with ESEM. The variance was set to 1 at the factor-level, and an oblique rotation was implemented, as in the preceding model. Model 4 is depicted in figure 2. The Mplus syntax for Model 4 is available in Appendix A8.
This last bi-factor ESEM model showed the best fit from all the models already presented: \( \chi^2 (293, 335) = 409.77, p < .001, CFI = 0.957, RMSEA = 0.034 \) 90% CI [0.026, 0.042] and \( SRMR = 0.032 \). Factor loadings are depicted in Table 3. Although most factor loadings were positive and did contribute significantly to their keyed factors, it is worth mentioning that some items did not load onto their keyed factor, but only on the Global trait EI factor. Moreover, as expected (see Cooper & Petrides, 2009), substantial cross-loadings were discovered between Global trait EI and the four-factor level: Global trait with Well-being (\( Z = 3.25, p = 0.001 \)), Self-control (\( Z = 4.50, p < 0.001 \)), Emotionality (\( Z = 3.99, p < 0.001 \)), and Sociability (\( Z = 4.95, p < 0.001 \)). At the factor level, there were also significant cross-loadings between Self-control and Emotionality (\( Z = 2.99, p = 0.01 \)), Self-control and Sociability (\( Z = 4.95, p < 0.001 \)), and finally between Emotionality and Sociability (\( Z = 3.19, p = 0.001 \)). Factor determinacies (i.e., the multiple correlations of the observed variables with the factor, see Grice, 2001) for the latent variables reached high values: Global trait EI (.949), Well-being (.776), Self-control (.832), Emotionality (.829), Sociability (.830). This evidence supports the validity of the overall factorial estimation.
Figure 1. Illustration of Higher-order and Bi-factor Models Obtained Through CFA in R

a.

b.
Note. (a) Model 1. Higher-order CFA model. (b) Model 2. Bi-factor CFA model. Both drawings were obtained through the R semPaths package. The thickness of the arrows in figure 1a depicts the magnitude of the standardised factor loadings. Green arrows depict positive correlations, whilst red arrows depict negative correlations.

Figure 2. Bi-factor ESEM With ML Estimator, Target Rotation and M.I. in General Population
Note. Only significant correlations are depicted with arrows. Fg stands for global trait EI, fs1 for well-being, fs2 for self-control, fs3 for emotionality and fs4 for sociability.
Table 3. Standardised Factor Loadings for the Spanish-Chilean-TEIQue-SF Items in General Population

<table>
<thead>
<tr>
<th>Item</th>
<th>Well-being</th>
<th>Self-control</th>
<th>Emotionality</th>
<th>Sociability</th>
<th>Global trait EI</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>.26</td>
<td></td>
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<tr>
<td>20</td>
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<td>27</td>
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<tr>
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<tr>
<td>7</td>
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<td>22</td>
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<td>8</td>
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<tr>
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<td>26</td>
<td>.60***</td>
<td></td>
<td>.35***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. All factor loadings in bold are significant. *p < .05, **p < .01, ***p < .001.
3.3.3—Results in the Clinical Population Sample

3.3.3.1—Descriptive Statistics in the Clinical Population Sample. Descriptive statistics for the trait EI factors in the clinical population sample are depicted in Table 2. As can be observed in Table 2, there was a slight common negative skewness that was more stressed for the Self-control factor, where participants tended to score higher.

3.3.3.2—Trait EI Gender Differences in the Clinical Sample. No statistical differences were revealed between women and men for the Global trait EI factor following a one-sample t-test in study two: $t (33) = .844, p = .41$, with test value of 4.78 ($M_{Women}$). Indeed, the means and descriptive statistics were similar: $MMen = 4.64, SD = .99, Skewness = -.29, Kurtosis = -.69, M_{Women} = 4.78, SD = .78, Skewness = .08, Kurtosis = -.25$.

3.3.3.3—Reliability Analysis. Reliability analysis revealed that the global score was highly reliable through $\omega_{sem}, \omega_{t} = .90$ and $\omega_{h} = 58$. In addition, all the factors tended to have fair to good Omega reliability indices when assessed through $\omega_{sem}$ (Well-being = .82, Self-control = .84, Emotionality = .49, Sociability = .71). Once more, Cronbach’s Alpha ($\alpha = .88$) was found to be at the lower bound of the total reliability for the questionnaire. The proportion of scale variance due to the general factor only (Global trait EI), as presented by $\omega_{h}$, was 58%. Although Emotionality had the lowest reliability score through Omega, its reliability was higher when assessed by the traditional Alpha index ($\alpha = .62, 95\% CI [.52,.72]$). Although less informative than $\omega_{sem}$ for factor analysis as mentioned in study one, the values of omega total were similar to factor-level Alphas (Well-being = .82, Self-control = .69, Emotionality = .63, Sociability = .48). $\omega_{sem}$ is sensitive to the internal modelled structure of a test, whereas Alpha and omega total are not (Revelle, 2017). As Taber (2018) notes, the reliability indices for the factors Emotionality and Sociability — both the lowest — may be described as acceptable and good, respectively. Moreover,
following the argumentation by this author, the results for Well-being and Self-control can be considered as robust.

### 3.3.3.4–Factor Analysis with the Clinical Data.

Based on the rationale previously described in study one, where CFA models proved unsuitable for studying the internal structure of the Spanish-Chilean-TEIQue-SF in general population, only ESEM models were tested with the clinical data.

#### 3.3.3.4.1–Bi-factor ESEM with ML Estimator and Target Rotation.

For assessing the factor structure through ESEM, a similar syntax to study one was applied (see Appendix A9). This model achieved a promising fit: $\chi^2(293, 335) = 424.707, p < .001$, $CFI = 0.874$, $RMSEA = 0.061$ 90% CI [0.047, 0.073] and $SRMR = 0.052$. Although most standardised loadings contributed to their keyed factors, some did not, and three items (i.e., 2, 11, and 25) did not load on the global factor at statistically significant levels. Modification indices suggested the inclusion of four correlated errors, all of them theoretically appropriate, as they concern items depicting the same underlying factors (i.e., items 16 and 13, and items 23 and 8 for Emotionality; items 22 and 7 for Self-control; items 12 and 27 for Well-being).

#### 3.3.3.4.2–Bi-factor ESEM with ML Estimator, Target Rotation, and Introduction of M.I.

This model is the re-specification of the one above, as depicted in figure 3. The Mplus syntax for this second model is available in Appendix A10. This model showed a better fit in comparison to the former: $\chi^2(291, 120) = 370.766, p < .001$, $CFI = 0.923$, $RMSEA = 0.048$ 90% CI [0.031, 0.062] and $SRMR = 0.048$. Factor loadings for the items are depicted in Table 4. Although most items contributed significantly to their keyed factors, item 25 did not. Furthermore, items 2, 11, 23 and 25 did not have statistically significant loadings onto the Global trait EI factor. Most items showed significant loadings at the factor-level. Consequently, the multidimensional factor structure replicated similarly as theoretically presented (see Petrides, Pita, et al., 2007). As in study 1, substantial cross-loadings were
Figure 3. Bi-factor ESEM With ML Estimator, Target Rotation and M.I. in Clinical Population

*Note.* Only significant correlations are depicted with arrows. Fg stands for global trait EI, fs1 for well-being, fs2 for self-control, fs3 for emotionality and fs4 for sociability.
Table 4. Standardised Factor Loadings for the Spanish-Chilean-TEIQue-SF Items in Clinical Population

<table>
<thead>
<tr>
<th>Item</th>
<th>Well-being</th>
<th>Self-control</th>
<th>Emotionality</th>
<th>Sociability</th>
<th>Global trait EI</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
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<td>11</td>
<td></td>
<td></td>
<td>.18</td>
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</table>

Note. All factor loadings in bold are significant. *p < .05, **p < .01, ***p < .001.
discovered between Global trait EI and the four-factor level, which was anticipated in the literature (see Cooper & Petrides, 2009): Global trait with Well-being ($Z = 3.89$, $p < 0.001$), Self-control ($Z = 2.95$, $p = 0.01$), Emotionality ($Z = 3.90$, $p < 0.001$), and Sociability ($Z = 4.29$, $p < 0.001$). At the factor level, there was also a significant cross-loading between Well-being and Sociability ($Z = 4.29$, $p < 0.001$). Lastly, factor determinacies for the latent variables reached slightly higher values when compared to the general sample: Global trait EI (.958), Well-being (.883), Self-control (.872), Emotionality (.876), Sociability (.871). The former provides robust evidence for the validity of the overall factorial estimation.

3.3.4–Multiple Group Measurement Invariance Results Between the UK and Chilean Samples

As can be observed in table 5, full measurement invariance analyses were performed between the Chilean samples and the UK validation sample (Cooper & Petrides, 2010). The scripts for these are available in Appendices A11 to A13. Measurement invariance was tested through three stages: Configural, Metric and Scalar (see Putnick & Bornstein, 2016), following the recommendations by Hu and Bentler (1999), Cheung and Rensvold (2002), Chen (2007), and Meade et al. (2008). Model fit was assessed, and decision rules were applied according to whether they complied or not with the type of invariance studied at each stage.

The analyses revealed that the questionnaire showed configural and metric invariance by the less stringent .9 cut-off for CFI, whilst RMSEA and SRMR were also lower than the currently accepted thresholds of .06 and .08 (Hu & Bentler, 1999), respectively; when testing the combined Chilean samples against the UK sample, and also when contrasting the general and clinical population samples against each other. The former, despite some of the metric and scalar analyses, yielded a higher $\Delta$CFI (around .02) than the traditional .01 cut-off
recommended by Cheung and Rensvold (2002), and Chen (2007). Although at the scalar level, the minimum CFI threshold of .9 was only achieved between the Chilean samples (Model 3 in Table 5), the RMSEA and SRMR indexes were below the accepted thresholds across the levels of invariance tested, and their $\Delta$RMSEA and $\Delta$SRMR were in the expected range for both group comparisons ($\leq .015$ and $\leq .030$, respectively; see Chen, 2007), providing general support for strong invariance. In this regard, Chen (2007) has stated that RMSEA and SRMR tend to over-reject invariant models, rendering another argument for considering the model as invariant up to the scalar level.

In summary, the trait EI latent variables were measured by the same items, factor loadings were equivalent, and item intercepts comparable across the UK and Chilean samples. Moreover, all fit statistics were within the expected boundaries when contrasting the two Chilean samples (i.e., general and clinical).
Table 5. Multiple Group Measurement Invariance Model Comparisons

<table>
<thead>
<tr>
<th>Models</th>
<th>$\chi^2$</th>
<th>$\Delta \chi^2$</th>
<th>df</th>
<th>CFI</th>
<th>$\Delta$ CFI</th>
<th>RMSEA</th>
<th>$\Delta$ RMSEA</th>
<th>RMSEALb</th>
<th>RMSEAUb</th>
<th>SRMR</th>
<th>$\Delta$ SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Configural</td>
<td>1506.16</td>
<td>—</td>
<td>879</td>
<td>0.917</td>
<td>—</td>
<td>0.046</td>
<td>—</td>
<td>0.050</td>
<td>0.036</td>
<td>—</td>
</tr>
<tr>
<td>Metric</td>
<td>2031.69</td>
<td>525.53</td>
<td>1129</td>
<td>0.880</td>
<td>0.037</td>
<td>0.049</td>
<td>0.003</td>
<td>0.046</td>
<td>0.053</td>
<td>0.054</td>
<td>0.018</td>
</tr>
<tr>
<td>Scalar</td>
<td>2253.93</td>
<td>222.24</td>
<td>1179</td>
<td>0.857</td>
<td>0.023</td>
<td>0.053</td>
<td>0.004</td>
<td>0.049</td>
<td>0.056</td>
<td>0.061</td>
<td>0.007</td>
</tr>
<tr>
<td>2</td>
<td>Configural</td>
<td>1121.93</td>
<td>—</td>
<td>586</td>
<td>0.927</td>
<td>—</td>
<td>0.043</td>
<td>—</td>
<td>0.039</td>
<td>0.047</td>
<td>0.032</td>
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<tr>
<td>Metric</td>
<td>1398.02</td>
<td>276.09</td>
<td>711</td>
<td>0.907</td>
<td>0.020</td>
<td>0.044</td>
<td>0.001</td>
<td>0.041</td>
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<td>0.044</td>
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<td>Scalar</td>
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<td>195.15</td>
<td>736</td>
<td>0.884</td>
<td>0.023</td>
<td>0.048</td>
<td>0.004</td>
<td>0.045</td>
<td>0.052</td>
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<tr>
<td>3</td>
<td>Configural</td>
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<td>—</td>
<td>584</td>
<td>0.946</td>
<td>—</td>
<td>0.039</td>
<td>—</td>
<td>0.031</td>
<td>0.046</td>
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<tr>
<td>Metric</td>
<td>1013.49</td>
<td>229.69</td>
<td>709</td>
<td>0.918</td>
<td>0.028</td>
<td>0.043</td>
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<td>0.037</td>
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<td>1053.43</td>
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<td>734</td>
<td>0.914</td>
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<td>0.044</td>
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<tr>
<td>4</td>
<td>Configural</td>
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<td>—</td>
<td>588</td>
<td>0.916</td>
<td>—</td>
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<td>—</td>
<td>0.042</td>
<td>0.050</td>
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<tr>
<td>Metric</td>
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<td>279.46</td>
<td>713</td>
<td>0.892</td>
<td>0.024</td>
<td>0.048</td>
<td>0.002</td>
<td>0.044</td>
<td>0.051</td>
<td>0.047</td>
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<td>Scalar</td>
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<td>0.021</td>
<td>0.051</td>
<td>0.003</td>
<td>0.048</td>
<td>0.055</td>
<td>0.053</td>
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</table>

Note. Model 1 = U.K. validation sample, $N = 537$; Chilean general population, $N = 335$; and Chilean clinical population, $N = 120$. Model 2 = U.K. validation sample and combined Chilean samples. Model 3 = Chilean general and clinical samples. Model 4 = U.K. validation sample and Chilean general population. $\chi^2$ = Chi square, $\Delta \chi^2$ = Chi square difference, df = degrees of freedom. CFI = comparative fit index, $\Delta$CFI = CFI difference, RMSEA = root mean square error of approximation, $\Delta$ RMSEA = RMSEA difference, RMSEALb = RMSEA lower bound, RMSEAUb = RMSEA upper bound. SRMR = standardized root mean residual.
3.4–Discussion

The scores of the Spanish-Chilean-TEIQue-SF version were examined and interpreted through CFA and ESEM using general and clinical participants. Reliability analyses confirmed the high reliability of the questionnaire, especially at the global level, which it was initially designed to assess (Petrides, 2009). The models implemented allowed contrasting a unidimensional interpretation of the Spanish-Chilean-TEIQue-SF with a multidimensional reading (one general plus a four factor-level). ESEM modelling confirmed the construct validity of the instrument, providing robust evidence for its multidimensionality through a bi-factor model. Measurement invariance analyses revealed a satisfactory fit for the UK and Chilean datasets, which allows for cross-cultural comparisons of latent means. Finally, the fit of the final model presented in study one was better than in previous ESEM and CFA validations of the TEIQue-SF (e.g., Cooper & Petrides, 2010; Jacobs et al., 2015; Laborde et al., 2016; Neri-Uribe & Juárez-García, 2016; Perera, 2015). The fit of the last ESEM model in the clinical sample was adequate, in line with preceding findings.

The present studies are the first to examine the TEIQue-SF factor structure through a bi-factor method, in contrast to the original proposed hierarchical second-order structure for trait EI measures (e.g., Cooper & Petrides, 2010; Petrides, 2009). The results are promising. Almost all items in the ESEM analysis of the Spanish-Chilean-TEIQue-SF loaded on their keyed factors in the Chilean samples. This was particularly true for the Global trait EI factor. On the contrary, the hierarchical models in the research, as presented in study one, had a more inadequate fit to the data and higher factor score indeterminacy when assessed in R through CFA. Hence, these factor scores had a lower correlation with the true factor scores than expected (see McDonald & Mulaik, 1979, for a review). In contrast, the exceptional fit found for the last bi-factor ESEM model in study one and the satisfactory fit for the final model in study two represents extraordinary evidence of the instrument’s construct validity.
compared to other EI measures (e.g., Siegling, Saklofske, et al., 2015). These results highlight the importance of working with this novel data analytic approach when assessing the factor structure of personality questionnaires, instead of the classical and often less promising results obtained through CFA modelling (Marsh et al., 2014).

Morin et al. (2015) illustrated the suitability of bi-factor models when assessing personality. There is agreement in the psychometrics community that bi-factor models are often less stringent than hierarchical models (Chen et al., 2006; Jennrich & Bentler, 2012; Reise, 2012). Also, the constraints imposed by hierarchical modelling often worsen model fit (Brunner et al., 2012; Chen et al., 2006; Reise, 2012). For instance, Marsh, Lüdtke, et al. (2013) have proposed that the use of item parcels, as usually implemented in hierarchical modelling, is likely to be unsuitable for scale development, latent means and measurement invariance, as even modest cross-loadings distort the relations between constructs when studied through CFA parcelling, camouflaging true relationships between items. This argument supports the implementation of item-level ESEM bi-factor modelling in the present studies as the method of choice, which has also proved advantageous compared to previous psychometric investigations with the measure in which CFAs were conducted (e.g., Feher et al., 2019; Laborde et al., 2016). This rationale was supported when contrasting the ESEM bi-factor models vis-à-vis hierarchical ESEM-within-CFA (see Appendix A14), due to hierarchical modelling—as anticipated—worsening model fit. Moreover, as Reise (2012) stated, bi-factor modelling is best suited for psychometric assessment of instruments primarily defined by a shared and robust trait, where multidimensionality is driven by well-established subdomains, as shown in the present Chilean studies with the TEIQue-SF.

No significant differences were found between women and men regarding trait EI means in the current Chilean studies. It has been argued that women could score higher than men in sociocultural contexts that support gender equality (see Fernández-Berrocal et al.,
In this regard, Petrides and Furnham (2000b) demonstrated that males tend to overestimate their trait EI when self-assessed through rating scales. These authors posed that women may tend to be self-derogatory when questioned on self-estimated trait EI, which could have happened in the Chilean general sample as well, even when using a well-established self-report measure like the TEIQue-SF.

As for Global trait EI, the findings were comparable to the original UK validation sample used in Cooper and Petrides (2010). In study one, Global trait EI and factor-level means for the TEIQue-SF were all above the values reported by Laborde et al. (2016) in Spain with university students. The most salient means differences were for Self-control (Mean difference = 0.32, d = .34), Sociability (Mean difference = 0.22, d = .25) and Global trait EI (Mean difference = 0.20, d = .26), although these differences were of small effect size. In contrast, the trait EI means in the clinical sample were very much comparable to Laborde et al., with the exception of Well-being (Mean difference = 0.28, d = .40), as this difference was of low-to-mid effect size. This trait was significantly diminished in study two, given that participants from clinical samples experience lower levels of Well-being than samples extracted from the community (e.g., Petrides et al., 2017). An example of this can be found in chapter five, where trait EI means from general population samples were contrasted with trait EI means taken from a typical clinical population sample. Moreover, it is worth noting that the clinical sample comprised patients suffering from common mental health disorders (i.e., depression and anxiety), which are the most prevalent diagnoses in clinical psychological settings, approximately affecting to 8% of the global population (World Health Organisation, 2017).

In summary, the Spanish-Chilean-TEIQue-SF was shown to be reliable and valid in the Chilean population. Regarding its factor validity, a model with a general factor plus a four-factor structure also revealed a better fit than a model with just one general factor. The
analyses supported latent-means invariance for the Spanish-Chilean-TEIQue-SF compared to the original measure. Finally, the advantage of having a validated and invariant brief trait EI measure in Spanish represents an opportunity from the practitioner perspective for precise psychological assessment in numerous settings, including clinical, educational, and organisational. These first psychometric studies with the TEIQue-SF in Chilean samples will allow for inference, pertinence, and comparability with other trait EI measures, related local adaptations, as well as informing trait EI means for specific populations in diverse research and professional settings.

3.4.1–Limitations and Future Directions

A limitation is the size of the samples in the two studies. Even though in study one, the sample size could be considered adequate for factor analysis according to Comrey and Lee (1992), and also fulfilled the requirement of 5 and 10 subjects per item based on the N:p ratio recommended by Gorsuch (1983) and Everitt (1975), respectively; Comrey and Lee (1992) advocate sample sizes of 500 or more for factor analysis. MacCallum et al. (1999) argue that when communalities are consistently low (i.e., below .5) but there is high overdetermination (i.e., six or more items loading onto one factor), as is the case with the TEIQue-SF, a sample size well over 100 should be enough for recovering the factor structure of a questionnaire. The COSMIN study design checklist implemented in studies one and two is congruent with the literature, as the quality of study one was higher than of study two, mainly due to the sample size differences between these. However, across several criteria of translation process, internal consistency, and structural validity, the methodological standard of the studies conducted in the present chapter can be labelled as satisfactory to very adequate.
It is worth noting that the reliability decreased from the pilot study in comparison to the general and clinical samples. This difference could be accounted for participants’ highest educational attainment, as 80% of participants in the pilot study had obtained a higher education or university degree in contrast to the two major studies, in which slightly more than 50% of participants were of comparable educational level. This tendency of more educated participants displaying higher reliability scores is noticeable in the general population sample, as the increase in reliability from participants having secondary education to those with a master’s degree was close to .1. Similarly, the increase in reliability in the clinical sample from participants having secondary education to those with higher education was of .04.

Another limitation regarding the results from the measurement invariance analyses is that the CFI changes (ΔCFI) between the models were mostly beyond the commonly accepted threshold of .01 (Hu & Bentler, 1999), even though the remaining fit statistics were in order across the studied levels of measurement invariance. Rutkowski and Svetina (2014) posed that relaxing this cut-off up to .02 is necessary when performing multigroup measurement invariance. Moreover, Putnick and Bornstein (2016) emphasised the current methodological restrictions for performing measurement invariance analysis, as they encouraged researchers to report it even when slight deviations from the standards could arise.

Future studies with trait EI measures can follow the rationale developed in this thesis, especially regarding the investigation of the TEIQue-SF factor structure through ESEM. From the research and literature perspective, trait EI will be now studied in Chile and nearby countries, contributing to the literature and related research in EI. In this respect, cross-cultural comparisons with the instrument in other Spanish background populations, especially in Latin-America, are encouraged. Additionally, future research is required with this
validated version of the questionnaire vis-à-vis other well-regarded personality measures (e.g., Big Five), as this will provide external validation to the Spanish-Chilean-TEIQue-SF.

The possibility of implementing such investigations in the region is enhanced by the studies presented here.
Chapter 4: Trait EI Construct Invariance Across Populations and Sociodemographic Characteristics (Study 3)

4.1–Introduction

The present chapter will explore the generalisability of the trait EI construct across populations and sociodemographic variables. It serves as a bridge between theory and research from the preceding chapter and the following clinical chapter. In chapter three, measurement invariance in both general and clinical population was attained up to the scalar level regarding the internal factor structure of the Spanish-Chilean-TEIQue-SF. This allows confident usage of the questionnaire in applied research settings in Chile and neighbour countries, given that the trait EI construct is measured with high equivalence by the Spanish-Chilean-TEIQue-SF compared to the original TEIQue-SF as to the questionnaires’ internal structure concerns. However, since other populations beyond those studied in chapter three, cultures, languages, as well as sociodemographic and economic peculiarities, may affect the interpretation and cross-cultural validity of trait EI, the present chapter will approach in further detail these scarcely addressed issues in the trait EI literature (e.g., Petrides & Furnham, 2006; Tsaousis & Kazi, 2013), by targeting two main aims. First, testing trait EI differences across important sociodemographic variables (i.e., gender, age, educational level, civil status, and occupation). Second, providing cross-cultural evidence of measurement invariance with the preceding sociodemographic features. Each included country has distinct characteristics, such as socio-political and geographic location, spoken language, culture, and economy, which creates a diversity suitable for studying measurement invariance transculturally (see Millsap, 2011). There are several implications for theory and research from the

approach chosen in this chapter. Theoretically, trait EI would prove pertinence in the literature regardless of the country where the research was conducted. Similarly, for practice, trait EI assessments conducted across populations with distinct sociodemographic features by the TEIQue-SF and the related country validations, such as the Spanish-Chilean-TEIQue-SF and the Brazilian validation, would obtain all equally valid and comparable findings, which is desirable for cross-cultural research and also for professional practice.

4.2–Method

4.2.1–Participants

The study included 2228 participants, 512 of whom were from Brazil (23%), 335 from Chile (15%), 515 from Italy (23%), and 866 from the U.K. (39%). All datasets but the Italian have been employed in former research: Cooper and Petrides (2010; UK), Perazzo et al. (2020; Brazil), and Pérez-Díaz and Petrides (2019; Chile), as described in chapter three of the present dissertation. From the pooled dataset, 1021 participants were women (46%), 1205 men (54%), and two undisclosed. Most participants were under thirty years old ($M = 28.22$, $SD = 11.38$, Minimum = 17, Maximum = 80). Regarding their main occupation, most were students (53%), followed by those employed in the private sector (24%). A third cluster comprised high-school teachers and university lecturers (7%). Those employed in the public sector accounted for 6% of the sample. The unemployed and those who declared a “non-listed” occupation accounted for 3% and 7% of the total sample, respectively. Regarding educational attainment, 47% of participants had obtained or were in the process of obtaining a higher education certificate or university degree, 34% had obtained a qualification of secondary education, 11% had completed primary education, whilst 9% held a postgraduate degree. Participants did not receive any compensation. The inclusion criterion was: (a) aged
17 years or above. The exclusion criteria were: (a) being a current mental health patient, and (b) having any diagnosis of severe psychopathology.

4.2.2– Measures

The TEIQue-SF questionnaire was administered in the U.K. (Cooper & Petrides, 2010; Petrides, 2009), Brazil (Perazzo et al., 2020), Chile (see chapter three of the dissertation), and Italy (Di Fabio & Palazzeschi, 2011). The Brazilian, Italian, English, and Italian versions of the TEIQue-SF comprise thirty statements and are responded on a 7-point Likert scale, ranging from 1 (Completely Disagree) to 7 (Completely Agree). All surveys included questions on the relevant sociodemographic variables.

4.2.3– Design and Procedure

In all four countries, participants completed paper-and-pencil or online versions of the questionnaires, collectively or individually. Pertinent local ethics boards approved all data collections. The University College London-Research Ethics Committee granted ethical approval for the Chilean (project ID: 12971/00) and U.K. samples, whereas the Brazilian sample received approval from the Human Research Ethics Committee of the Federal University of Minas Gerais, Brazil, under protocol number 67189617.2.1001.5149. The Italian sample received ethical clearance from the Ethics board of the University of Florence, Italy. Similar measures were followed regarding participant distress and discomfort in the four countries where the study was conducted. Adequate support could be requested at the nearest health emergency staff in each of the countries where the research was conducted.

Additionally, the study was evaluated with the consensus-based standards for the selection of health status measurement instruments (COSMIN), as described in further detail in section 3.2.2.3, chapter three. The COSMIN study design checklist establishes criteria for assessing the methodological suitability of studies conducted in health settings (Mokkink et
al., 2019; see also Mokkink et al., 2010a; Mokkink et al., 2010b). Of particular relevance for the development of the current study are the clusters of translation process, cross-cultural validity/measurement invariance, and internal consistency. In all these clusters and across 12 criteria for translation process, 7 for cross-cultural validity/measurement invariance, and 6 for internal consistency, the research was considered as of very good standard. The only exception in the transcultural measurement invariance analyses would be civil status, as this variable did not reach the minimum standard of 100 participants in the category divorced/separated, which would label this specific analysis as adequate. All the remaining cross-cultural validity criteria were largely surpassed, given the large sample size of the study and the likely cultural similarities within the same region samples (i.e., Latin-American versus European).

4.2.4. Data Protection Measures

For study three, the researcher implemented the same data protection measures stated in study one.

4.2.5. Data Analysis Plan

Multiple imputations by chained equations were implemented for treating missing values. These analyses were conducted in R, through the package MICE (Van Buuren & Groothuis-Oudshoorn, 2011). All the TEIQue-SF items in the original datasets were complete. However, values were missing for the sociodemographic variables gender (82, representing 3.68% of the observations), age (106, representing 4.76% of the observations), education (577, representing 25.90% of the observations), civil status (581, representing 26.07% of the observations) and occupation (582, representing 26.12% of the observations). To address these missing values, the researcher followed White et al.’ (2010) recommendation to include predictors with incomplete data in the imputation model, as this is
advantageous for two reasons: 1) It makes more plausible the assumption of missing at random (MAR), thus reducing bias, and 2) It reduces the standard errors of the estimates in the model. Therefore, 26 imputation models were performed, as this was the maximum percentage of missing values in any of the studied sociodemographic predictors. Regarding the imputation method, Predictive Mean Matching (PMM) was implemented for imputing numeric variables, Polytomous regression imputation (Polyreg) for unordered categoric variables, and Proportional odds (Polr) model for ordered variables (see Van Buuren & Groothuis-Oudshoorn, 2011).

The assumptions on the multivariate normal distribution and the homogeneity of variance were tested. Reliability was assessed through Cronbach’s Alpha and Omega in R through the Psych package (Revelle, 2017). The omegaSem function was implemented for reliability with Omega, as described in the preceding studies. Univariate analyses of variance (ANOVA) with post-hoc analyses and t-tests were conducted, as appropriate. Cohen’s (1998) $d$ and Cohen’s (1973) Eta-squared ($\eta^2$) were employed as measures of effect size, in addition to Hochberg’s $GT2$ as the post-hoc statistic. These effect size statistics and the post-hoc are recommended for comparing clusters of unequal size (Field, 2013).

Measurement invariance was tested across three stages: Configural, Metric and Scalar (see Putnick & Bornstein, 2016), following the recommendations by Hu and Bentler (1999), Cheung and Rensvold (2002), Chen (2007), and Meade et al. (2008). The model fit was appraised through MLR estimations (i.e., Maximum likelihood with robust standard errors). Afterwards, decision rules were applied to whether they attained or not with the type of studied invariance at each stage. This judgement was based on several critical criteria, such as sample size, requirements associated with each type of invariance, and specific thresholds of the fit statistics used for comparison (see Meade et al., 2008). In all cases, a base bi-factor
ESEM model was the starting point, as it proved suitable in former research with two of the included country datasets (see Perazzo et al., 2020; chapter three of the present dissertation, and Appendix A14). This model is depicted in Figure 4.

4.3–Results

It was first determined that the observations followed the multivariate normal distribution for Global trait EI through Q-Q plots (i.e., quantile-quantile). Additionally, the assumption of homogeneity of variances was met for all the sociodemographic variables but Age, as assessed by the Levene’s statistic (Gender, $F=2.32$, $df_1=2$, $df_2=2225$, $p = .10$; Age, $F = 8.51$, $df_1=2$, $df_2=2226$, $p = .01$; Education, $F = 1.70$, $df_1=4$, $df_2=2223$, $p = .15$; Civil status, $F = .98$, $df_1=4$, $df_2=2223$, $p = .42$; Occupation; $F = 1.75$, $df_1=5$, $df_2=2222$, $p = .12$).

Homogeneity of variances for Age was retained in each one of the countries, confirming the appropriateness of the analytic approach (Brazil, $F = 1.66$, $df= 510$, $p = .20$; Chile, $F = 3.17$, $df= 333$, $p = .08$; Italy; $F = 0.04$, $df= 513$, $p = .47$; U.K., $F = 0.18$, $df= 864$, $p = .67$).

4.3.1–Reliability Analyses

These analyses revealed that the Global trait EI score was highly reliable in the four datasets ($\omega_t = .90$). In addition, all trait EI factors had fair-to-good Omega reliability indices, except for Sociability (Well-being = .84, Self-control = .83, Emotionality = .64, Sociability = .35) when evaluated through omegaSem. As predicted (see Zinbarg et al., 2005), $\alpha = .88$, was at the lower bound of reliability for the Global trait EI score. The proportion of scale variance due to the general factor only (Global trait EI), as estimated by $\omega_h$, was 50%. As reported with the Chilean datasets in chapter three, Sociability had formerly shown the lowest Omega reliability, even though the estimate was higher when assessed by the traditional Alpha index ($\alpha = .61$, 95% CI [.58,.63]). As for the remaining factors, all showed somehow adequate Alphas (Taber, 2018): Well-being = .76, Self-control = .61, Emotionality = .67, although the
values were considerably lower than that of the Global trait EI score, which the TEIQue-SF was specifically designed to measure.

The values of omega total were similar to the abovementioned factor-level Alphas (Well-being = .78, Self-control = .62, Emotionality = .68, Sociability = .61). OmegaSem is sensitive to the internal modelled structure of a test, whereas Alpha and omega total are not; this explains the differences in the presented reliability scores (Revelle, 2017). Considering the lower-than-desired reliability scores at the factor-level, mean difference analyses were performed on Global trait EI since it showed a high internal consistency throughout.

4.3.2—Cross-cultural Comparisons of Global Trait EI

A preliminary one-way ANOVA was conducted with Global trait EI as the dependent variable and the four countries as the different levels of a between-subjects independent variable. This analysis showed that the variable country explained 6% of the variance in Global trait EI, which is considered a small-to-moderate effect size [$F (3, 2227) = 48.98, p < .001, \eta^2 = .06$]. Descriptive statistics of Global trait EI means in each country are depicted in Table 6.

4.3.3—Trait EI Mean Differences Across Sociodemographic Variables

After checking that Global trait EI scores followed the normal distribution, and the assumption of homogeneity of variances was met across the respective levels of the predictors, the countries were contrasted on the chosen sociodemographic variables. Possible interactions between sociodemographic predictors across the four countries were also examined through univariate analyses of variance (ANOVA). These analyses revealed the absence of two-way interactions between the chosen sociodemographic variables on Global trait EI, in any of the studied countries.
Figure 4. Illustration of the Base ESEM Bi-factor Model Tested Through Measurement Invariance Analyses Across Sociodemographic Variables

Note. Fg stands for global trait EI, fs1 for well-being, fs2 for self-control, fs3 for emotionality and fs4 for sociability. The TEIQue-SF items are t1 to t30.
### Table 6. Descriptive Statistics for the TEIQue-SF Datasets

<table>
<thead>
<tr>
<th>Trait EI measure</th>
<th>Min</th>
<th>Max</th>
<th>M</th>
<th>SD</th>
<th>Skew</th>
<th>Kurt</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Full cross-cultural dataset</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Global trait EI</td>
<td>2.00</td>
<td>7.00</td>
<td>4.85</td>
<td>0.77</td>
<td>-0.09</td>
<td>-0.28</td>
</tr>
<tr>
<td>Well-being</td>
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<td>7.00</td>
<td>5.28</td>
<td>1.06</td>
<td>-0.57</td>
<td>0.20</td>
</tr>
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<td>7.00</td>
<td>4.45</td>
<td>1.00</td>
<td>-0.11</td>
<td>0.01</td>
</tr>
<tr>
<td>Emotionality</td>
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<td>7.00</td>
<td>4.94</td>
<td>0.98</td>
<td>-0.31</td>
<td>-0.33</td>
</tr>
<tr>
<td>Sociability</td>
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<td>7.00</td>
<td>4.66</td>
<td>0.93</td>
<td>-0.06</td>
<td>-0.09</td>
</tr>
<tr>
<td>2. Brazil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
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<td>7.00</td>
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<td>1.18</td>
<td>-0.88</td>
<td>0.62</td>
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<td>4.14</td>
<td>1.08</td>
<td>-0.15</td>
<td>-0.35</td>
</tr>
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<td>5.15</td>
<td>0.89</td>
<td>-0.57</td>
<td>0.09</td>
</tr>
<tr>
<td>Sociability</td>
<td>1.67</td>
<td>7.00</td>
<td>4.57</td>
<td>0.94</td>
<td>-0.18</td>
<td>0.00</td>
</tr>
<tr>
<td>3. Chile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
<td>2.40</td>
<td>6.80</td>
<td>5.03</td>
<td>0.85</td>
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<td>-0.54</td>
</tr>
<tr>
<td>Well-being</td>
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<td>7.00</td>
<td>5.43</td>
<td>1.17</td>
<td>-0.92</td>
<td>0.80</td>
</tr>
<tr>
<td>Self-control</td>
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<td>7.00</td>
<td>4.76</td>
<td>1.05</td>
<td>-0.15</td>
<td>-0.14</td>
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<tr>
<td>Emotionality</td>
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<td>7.00</td>
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<td>-0.51</td>
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<td>Sociability</td>
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<td>7.00</td>
<td>4.83</td>
<td>0.92</td>
<td>0.02</td>
<td>-0.50</td>
</tr>
<tr>
<td>4. Italy</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Global trait EI</td>
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<td>4.53</td>
<td>0.74</td>
<td>0.41</td>
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</tr>
<tr>
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<td>7.00</td>
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<td>7.00</td>
<td>4.33</td>
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<td>-0.14</td>
<td>0.21</td>
</tr>
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<td>7.00</td>
<td>4.51</td>
<td>1.07</td>
<td>0.19</td>
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</tr>
<tr>
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<td>7.00</td>
<td>4.36</td>
<td>0.92</td>
<td>0.12</td>
<td>0.20</td>
</tr>
<tr>
<td>5. United Kingdom</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
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<td>7.00</td>
<td>5.41</td>
<td>0.90</td>
<td>-0.56</td>
<td>0.34</td>
</tr>
<tr>
<td>Well-being</td>
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<td>7.00</td>
<td>5.41</td>
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<td>0.34</td>
</tr>
<tr>
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<td>-0.04</td>
<td>-0.03</td>
</tr>
<tr>
<td>Emotionality</td>
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<td>7.00</td>
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<td>0.87</td>
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<td>0.22</td>
</tr>
<tr>
<td>Sociability</td>
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<td>7.00</td>
<td>4.82</td>
<td>0.89</td>
<td>-0.07</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

*Note.* All descriptive statistics refer to the pooled imputation dataset. EI = emotional intelligence. Min = minimum, Max = maximum, M = mean, SD = standard deviation, Skew = skewness, Kurt = kurtosis.
4.3.3.1—Gender and Age Differences in Trait EI. Except for Chile, all countries showed statistically significant Global trait EI gender differences, yet of small effect size. Regarding age, except for Italy, all countries showed statistically significant Global trait EI age differences, of small-to-mid effect size. These differences are depicted in Table 7. Age was treated as a categorical variable, which is a common practice for investigating measurement invariance (Millsap, 2011). Accordingly, two subsamples based on the quartiles of the age distribution were created. These were labelled as Younger (17-32), including participants from the minimum age up to quartile two (Q2); and Older (33-80), with participants from quartile three (Q3) up to the maximum age. Additionally, a Pearson correlation was performed between Global trait EI and age (as a continuous variable) on the merged dataset, which did not reach significance \[ r (2228) = .034, p = .11 \].

4.3.3.2—Trait EI Differences by Educational Attainment. The Chilean and Italian datasets revealed significant Global trait EI differences for educational attainment through ANOVA, although the U.K. dataset did not. The Brazilian dataset was excluded from these analyses, as it mainly comprised undergraduate students. These results are presented in Table 8. In Chile, higher educational attainment was linked to higher Global trait EI scores, as Hochberg’s GT2 revealed substantial differences in Global trait EI between participants with a secondary education certificate only and those with either a university or a master’s degree \( (d = 0.79, \text{ and } d = 0.81, \text{ respectively}) \). Similarly, in Italy, participants with a master’s degree scored significantly higher on Global trait EI, than those with a university degree \( (d = 1.09) \), those with a secondary education certificate only \( (d = 0.17) \), and those in the ‘others’ category \( (d = 0.20) \).
Table 7. Independent Samples t-Tests With Global Trait EI as the DV and Gender and Age as the Two IVs Across the Four Countries

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>df</th>
<th>MD</th>
<th>SE</th>
<th>p</th>
<th>d</th>
</tr>
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<tbody>
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<td>Brazil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>2.70</td>
<td>510</td>
<td>0.21</td>
<td>0.08</td>
<td>.007</td>
<td>0.27</td>
</tr>
<tr>
<td>Age</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Chile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.07</td>
<td>331</td>
<td>0.01</td>
<td>0.09</td>
<td>.948</td>
<td>0.01</td>
</tr>
<tr>
<td>Age</td>
<td>3.32</td>
<td>333</td>
<td>0.30</td>
<td>0.09</td>
<td>.001</td>
<td>0.37</td>
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<td></td>
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<td>Italy</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>2.85</td>
<td>513</td>
<td>0.19</td>
<td>0.07</td>
<td>.005</td>
<td>0.25</td>
</tr>
<tr>
<td>Age</td>
<td>0.72</td>
<td>513</td>
<td>0.05</td>
<td>0.07</td>
<td>.473</td>
<td>0.06</td>
</tr>
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<tr>
<td>Gender</td>
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<td>0.11</td>
<td>0.05</td>
<td>.019</td>
<td>0.16</td>
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<tr>
<td>Age</td>
<td>1.99</td>
<td>864</td>
<td>0.12</td>
<td>0.06</td>
<td>.046</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Note. The statistics for age in Brazil are not reported, as the clusters were severely unequal in size. $t = t$-test, $df =$ degrees of freedom, $MD =$ mean difference, $SE =$ standard error, $p = $ exact probability value, $d = $ Cohen's $d$ effect size statistic. All p-values are two-tailed.
Table 8. Global Trait EI Analyses of Variance (ANOVA) by Education, Civil Status, and Occupation

<table>
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<tr>
<th></th>
<th>Chile</th>
<th></th>
<th></th>
<th></th>
<th>Italy</th>
<th></th>
<th></th>
<th></th>
<th>United Kingdom</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>F</td>
<td>df</td>
<td>η2</td>
<td>M</td>
<td>SD</td>
<td>F</td>
<td>df</td>
<td>η2</td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>16.96**</td>
<td>3,331</td>
<td>0.133</td>
<td>5.39**</td>
<td>3,511 0.031</td>
<td>1.39</td>
<td>4.861</td>
<td>0.006</td>
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<tr>
<td>Secondary (a)</td>
<td>4.71</td>
<td>0.82</td>
<td>4.57</td>
<td>0.74</td>
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<td>4.93</td>
<td>0.74</td>
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</tr>
<tr>
<td>University (b)</td>
<td>5.33</td>
<td>0.75</td>
<td>4.06</td>
<td>0.41</td>
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<td>4.93</td>
<td>0.74</td>
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<td>Master (c)</td>
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<td>4.69</td>
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<td>0.74</td>
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<td>-</td>
<td>-</td>
<td></td>
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<td>0.74</td>
<td></td>
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</tr>
<tr>
<td>Other (e)</td>
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<td>0.92</td>
<td>4.54</td>
<td>0.76</td>
<td></td>
<td>4.93</td>
<td>0.74</td>
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<td><strong>Civil Status</strong></td>
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<td>4,330</td>
<td>0.064</td>
<td>4.96**</td>
<td>3,511 0.028</td>
<td>2.28</td>
<td>4.861</td>
<td>0.010</td>
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<tr>
<td>Single (f)</td>
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<td>0.86</td>
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<td>4.97</td>
<td>0.69</td>
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<td>In a relationship (g)</td>
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<td>Other (j)</td>
<td>4.56</td>
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<td>5.10</td>
<td>0.70</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Teacher/Lecturer (m)</td>
<td>5.48</td>
<td>0.69</td>
<td>5.49</td>
<td>0.65</td>
<td></td>
<td>5.09</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student (n)</td>
<td>4.83</td>
<td>0.86</td>
<td>4.75</td>
<td>0.74</td>
<td></td>
<td>4.94</td>
<td>0.69</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Unemployed (o)</td>
<td>5.08</td>
<td>0.77</td>
<td>4.06</td>
<td>0.35</td>
<td></td>
<td>4.96</td>
<td>0.75</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Other (p)</td>
<td>4.58</td>
<td>0.92</td>
<td>4.37</td>
<td>0.68</td>
<td></td>
<td>5.01</td>
<td>0.66</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note: The Brazilian dataset was excluded from these analyses, as it mainly comprised single undergraduate students. M = mean, SD = standard deviation, F = Fisher’s statistic, df = degrees of freedom, η2 = eta squared-effect size measure. All p-values are two-tailed. * p < .05. ** p < .01.
4.3.3.3–Trait EI Differences by Civil Status. The Chilean and the Italian datasets showed significant Global trait EI differences for civil status through ANOVA, although the U.K. did not. In Chile, significant differences in Global trait EI between married and single participants ($d = 0.58$) were found, as well as between married and divorced or separated participants ($d = 0.39$). In Italy, the largest trait EI differences were between married participants and those separated or divorced ($d = 1.41$), who also scored significantly lower than participants with a ‘non-listed’ civil status ($d = 1.81$). Single participants in Italy also showed significantly higher Global trait EI than those divorced or separated ($d = 1.29$). These results are presented in Table 8.

4.3.3.4–Trait EI Differences by Occupation. The Chilean and Italian datasets showed significant Global trait EI differences for occupation through ANOVA, although the U.K. did not. Significant differences in Global trait EI between teachers/lecturers and students were revealed in Chile, favouring these the former ($d = 0.83$). In Italy, teachers/lecturers scored significantly higher on Global trait EI than employees in the private sector ($d = 1.70$) and the unemployed ($d = 2.74$), whilst employees working in the public sector, as well as students, scored higher than employees in the private sector ($d = 1.07$ and $d = 0.55$, respectively). These results are presented in Table 8.

4.3.4–Measurement Invariance

The analyses revealed that trait EI, as measured by the TEIQue-SF, was invariant up to the scalar (latent means) level for gender, age, and education. The CFI reached the less stringent .9 cut-off threshold, with CFI changes across nested models below the .01 cut-off criterion recommended by Cheung and Rensvold (2002). Changes in the RMSEA and SRMR were within the ranges recommended by Chen (2007), i.e., $\leq .015$ and $\leq .030$, respectively. When gender invariance was tested separately for each country, the results showed non-invariance, especially at the scalar level. In these analyses, the CFI changes between the
nested models were considerably above .01, although the RMSEA and SRMR, were below 0.06 and 0.08, respectively, which are the recommended thresholds (see Hu & Bentler, 1999).

Concerning civil status and occupation, although these variables provided adequate evidence for metric invariance, the analyses revealed non-invariance at the scalar level, since the CFI changes between the models were above .01, which does not allow for a full cross-cultural comparison on trait EI even though the RMSEA and SRMR indices were again below 0.06 and 0.08 (see Hu & Bentler, 1999). Detailed results for these analyses are depicted in Table 9. The Mplus syntaxes for all the conducted measurement invariance analyses are presented from Appendices 15 to 21.
## Table 9. Multiple Group Measurement Invariance Comparisons by Sociodemographic Characteristics

<table>
<thead>
<tr>
<th>Models</th>
<th>χ²</th>
<th>Δ χ²</th>
<th>df</th>
<th>CFI</th>
<th>Δ CFI</th>
<th>RMSEA</th>
<th>Δ RMSEA</th>
<th>RMSEALb</th>
<th>RMSEAUb</th>
<th>SRMR</th>
<th>Δ SRMR</th>
</tr>
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<tbody>
<tr>
<td>1. Gender</td>
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</tr>
<tr>
<td>Configural</td>
<td>1336.48</td>
<td>—</td>
<td>578</td>
<td>0.949</td>
<td>—</td>
<td>0.034</td>
<td>—</td>
<td>0.032</td>
<td>0.037</td>
<td>0.025</td>
<td>—</td>
</tr>
<tr>
<td>Metric</td>
<td>1587.61</td>
<td>125.00</td>
<td>734</td>
<td>0.932</td>
<td>0.008</td>
<td>0.035</td>
<td>0.001</td>
<td>0.033</td>
<td>0.037</td>
<td>0.002</td>
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<tr>
<td>Scalar</td>
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<td>145.65</td>
<td>734</td>
<td>0.932</td>
<td>0.008</td>
<td>0.035</td>
<td>0.001</td>
<td>0.033</td>
<td>0.037</td>
<td>0.002</td>
<td>—</td>
</tr>
<tr>
<td>2. Women</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Configural</td>
<td>1971.99</td>
<td>—</td>
<td>1168</td>
<td>0.895</td>
<td>—</td>
<td>0.052</td>
<td>—</td>
<td>0.048</td>
<td>0.056</td>
<td>0.038</td>
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<tr>
<td>Metric</td>
<td>2447.10</td>
<td>475.11</td>
<td>1543</td>
<td>0.882</td>
<td>0.013</td>
<td>0.048</td>
<td>0.004</td>
<td>0.044</td>
<td>0.051</td>
<td>0.063</td>
<td>0.025</td>
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<tr>
<td>Scalar</td>
<td>2933.67</td>
<td>145.65</td>
<td>1543</td>
<td>0.882</td>
<td>0.013</td>
<td>0.048</td>
<td>0.004</td>
<td>0.044</td>
<td>0.051</td>
<td>0.063</td>
<td>0.025</td>
</tr>
<tr>
<td>3. Men</td>
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<td></td>
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<td>—</td>
<td>1168</td>
<td>0.891</td>
<td>—</td>
<td>0.052</td>
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<td>0.048</td>
<td>0.055</td>
<td>0.038</td>
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<td>599.54</td>
<td>1543</td>
<td>0.865</td>
<td>0.026</td>
<td>0.050</td>
<td>0.002</td>
<td>0.047</td>
<td>0.053</td>
<td>0.061</td>
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<td>512.62</td>
<td>1618</td>
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<td>0.057</td>
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<td>0.060</td>
<td>0.055</td>
<td>0.046</td>
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<tr>
<td>4. Age</td>
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<tr>
<td>Configural</td>
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<td>564</td>
<td>0.957</td>
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<td>—</td>
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<tr>
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<td>199.49</td>
<td>689</td>
<td>0.952</td>
<td>0.002</td>
<td>0.030</td>
<td>0.002</td>
<td>0.028</td>
<td>0.033</td>
<td>0.032</td>
<td>0.009</td>
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<td>133.70</td>
<td>714</td>
<td>0.945</td>
<td>0.007</td>
<td>0.032</td>
<td>0.002</td>
<td>0.030</td>
<td>0.034</td>
<td>0.033</td>
<td>0.001</td>
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<tr>
<td>5. Education</td>
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<td></td>
<td></td>
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<tr>
<td>Configural</td>
<td>2302.09</td>
<td>—</td>
<td>1164</td>
<td>0.925</td>
<td>—</td>
<td>0.042</td>
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<td>1539</td>
<td>0.922</td>
<td>0.003</td>
<td>0.037</td>
<td>0.005</td>
<td>0.035</td>
<td>0.040</td>
<td>0.045</td>
<td>0.014</td>
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<td>Scalar</td>
<td>2912.34</td>
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<td>1539</td>
<td>0.922</td>
<td>0.003</td>
<td>0.037</td>
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<td>0.035</td>
<td>0.040</td>
<td>0.045</td>
<td>0.014</td>
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<td>6. Civil status</td>
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<td>1460</td>
<td>0.897</td>
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<tr>
<td>Metric</td>
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<td>661.85</td>
<td>1960</td>
<td>0.892</td>
<td>0.005</td>
<td>0.046</td>
<td>0.005</td>
<td>0.044</td>
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<td>0.049</td>
<td>0.050</td>
<td>0.002</td>
</tr>
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<td>7. Occupation</td>
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</tr>
<tr>
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<td>1460</td>
<td>0.896</td>
<td>—</td>
<td>0.050</td>
<td>—</td>
<td>0.048</td>
<td>0.053</td>
<td>0.032</td>
<td>—</td>
</tr>
<tr>
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<td>524.23</td>
<td>1960</td>
<td>0.894</td>
<td>0.002</td>
<td>0.044</td>
<td>0.006</td>
<td>0.041</td>
<td>0.046</td>
<td>0.055</td>
<td>0.023</td>
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<td>322.76</td>
<td>2060</td>
<td>0.880</td>
<td>0.014</td>
<td>0.045</td>
<td>0.001</td>
<td>0.043</td>
<td>0.048</td>
<td>0.058</td>
<td>0.003</td>
</tr>
</tbody>
</table>

4.4–Discussion

The results revealed that despite some specific differences, the four studied datasets returned broadly similar results. ANOVA and follow-up pairwise comparisons exposed significant gender, age, and civil status differences in most countries. These results contrast with findings by Platsidou (2010), who reported non-significant effects for these sociodemographic variables on Global trait EI in a sample of 123 school teachers in Greece, which is one of the few studies that examined the relationship between trait EI and other sociodemographic variables beyond gender and age. It can be argued that the results of the present study may be more reliable due to the larger sample size, better gender balance (excluding the Brazilian sample), broader age range, and the utilisation of a highly conservative statistic for pairwise comparisons (Hochberg’s GT2), which is suitable for contrasting uneven groups.

The present study is methodologically comparable to Cooper and Petrides (2010), Pérez-Diaz & Petrides (2019), Siegling et al. (2014), and Ugarriza (2001), researchers who reported small effect size effects for gender or age through ANOVA and pairwise comparisons. One novelty of the implemented methodological approach pertains to the study of trait EI differences across civil status and occupation categories, for which no comparable designs have been found in the literature. Moreover, the COSMIN study design checklist supports the methodological quality of the study on several cross-cultural/measurement invariance and internal consistency criteria. Therefore, the methodological standard of the present study can be labelled as very good for most criteria.

Regarding educational attainment, the results show some similarity to those of Petrides et al. (2004), who have suggested that trait EI is positively associated with academic performance, particularly in vulnerable groups of students. Similarly, Perera and DiGiacomo (2013), and MacCann et al. (2020), conducted two independent meta-analyses on the
relationship between trait EI and academic performance, both concluding that trait EI has a positive effect, albeit causation cannot be claimed. These findings pose a challenge on the potential confounding variables affecting trait EI (e.g., socioeconomic status), and provide a basis for understanding Global trait EI differences across the levels of educational attainment found in Chile and Italy. Concerning occupation, the literature highlights that some professions, especially those related to leadership or educational roles, usually have higher levels of trait EI (Li et al., 2018; Platsidou, 2010; Siegling et al., 2014). The results of the present study are broadly consistent with these findings, as can be observed in the subsample of teachers/lecturers scoring higher on Global trait EI than other professionals both in Chile and Italy.

Regarding measurement invariance, the analyses support strong (i.e., scalar) cross-cultural invariance of trait EI (as measured by the TEIQue-SF) concerning age, gender, and education. The main advantages of the chosen approach in comparison to extant relevant research (e.g., Siegling, Furnham et al., 2015; Tsaousis & Kazi, 2013) are threefold. First, the implementation of a multidimensional baseline model, which included both the global and the factor-level of the construct, whereas former research had modelled either a global score or factor scores exclusively. Second, the richness of the datasets hereby presented, with participants coming from four different countries and being assessed in their respective native languages. Third, the strategy of testing for trait EI invariance beyond gender and age, which are the only two sociodemographic variables previously examined in this context.

Moreover, the measurement invariance analyses regarding trait EI are comparable with the extant cross-cultural literature of personality traits (see section 2.5.3, chapter two), as exemplified by the cross-cultural research on two of the most salient trait personality paradigms, this is, the Big Five-factor and the six-factor model (i.e., HEXACO). As posed by McCrae (2009), aggregate personality scores are limited in the literature. Therefore, the
contribution to the study of aggregate trait EI scores is one of the most substantial research pieces supporting the cross-culturally of the construct to date. The relevance is highlighted when the findings depicted in this chapter are contrasted with similar trait personality research conducted with Big Five and Six-factor measures, as most researchers did not obtain the required and crucial evidence of latent mean equivalence (see Byrne & Campbell, 2000). In contrast, the present study supported the cross-cultural mean equivalence (i.e., scalar invariance) of trait EI across countries and the studied sociodemographic variables of gender, age, and education.

In summary, the ANOVA and post-hoc comparisons yielded results that are broadly in line with extant literature on trait EI and sociodemographic variables. Across four different countries as well as gender, age, education, civil status and occupation, trait EI latent variables were shown to be operationalised by qualitatively the same items (i.e., Configural invariance), and to have equivalent factor loadings (i.e., Metric invariance). Factor intercepts were comparable across the variables: country, gender, age and education (i.e., Scalar invariance), although evidence of non-invariance was found in the factor intercepts of occupation and civil status. This finding suggests that latent trait EI means diverged substantially across the different levels of the abovementioned two variables, echoing the ANOVA results. Overall, the findings highlight the cross-cultural stability and validity of the trait EI construct, as measured by the TEIQue-SF, irrespective of cultural, linguistic, and other primary sociodemographic correlates.

4.4.1–Limitations and Future Research

The study is not without limitations. For instance, the sampling design was not representative, and the levels within the sociodemographic variables were of unequal size. The utilisation of Hochberg’s GT2 partially addressed this last limitation. Regarding the measurement invariance analyses, it is not possible to test all possible combinations of
variables. Therefore, a pragmatic approach was adopted since multiple mixtures are usually of limited theoretical interest (Millsap, 2011). Future research testing the invariability of trait EI may include other salient socioeconomic correlates, such as socioeconomic status, which were unable to be accounted for in the study. Furthermore, the original datasets included sociodemographic variables with a considerable percentage of missing values (i.e., education, civil status, and occupation), which the researcher aimed to counter by the implementation of multiple imputation, an efficient technique that produces asymptotically unbiased estimates and standard errors (White et al., 2010), and the appraisal of the fraction of missing information (see Madley-Dowd et al., 2019).

Regarding future research, the study described in this chapter serves as a foundation to continue scrutinising the role of trait emotional intelligence and its implications in widely different contexts, countries, and conditions. For instance, research regarding civil status and occupation may clarify if, under certain conditions, scalar invariance for the trait EI construct is also attainable on the different levels of these sociodemographic variables across countries, or if only metric invariance could be informed, as depicted in the present research. Moreover, the study of aggregate personality EI traits is fundamental for supporting the generalisability of the construct and emerges as especially valuable when the cross-cultural populations of interest are outside the usual scope of questionably generalisable WEIRD samples.
Chapter 5: Testing the Role of Trait EI in the Psychotherapeutic Setting (Study 4)

5.1–Introduction

Trait EI theory and its measures are utilised across a vast range of research and educational settings (Petrides et al., 2016). However, its potential utility within the psychotherapeutic context has yet to be examined. Accordingly, the overarching aim of the study presented in this chapter was to test the hypothesis that trait EI may have a significant beneficial effect on the psychotherapeutic outcome when tested longitudinally, after controlling for the impact of the therapeutic alliance from patients and therapists and extraneous variables. Among the latter, years of professional practice of the clinical provider, the idiosyncratic mental health centre effect, type of psychotherapy provided (Psychodynamic, Cognitive Behavioural Therapy, Integrative, Eclectic or Systemic), and cohort (i.e., period in which the patient was treated). The dependent variables were the overall psychotherapeutic outcome (OQ), symptom distress (SD), interpersonal relationships (IR), and social role (SR), whereas the independent variables were patient’s and therapist’s trait EI. The general hypotheses were: 1) Patient’s trait EI will have a positive longitudinal effect on the psychotherapeutic outcome, and 2) Therapist’s trait EI will have a positive longitudinal effect on the psychotherapeutic outcome. The specific hypotheses were: 1) There will be significant interactions between therapist’s trait EI independent variables and patient alliance measures exerting a positive effect on psychotherapeutic outcomes, 2) There will be significant interactions between patient’s trait EI independent variables and patient alliance measures exerting a positive effect on psychotherapeutic outcomes, 3) There will be meaningful interactions between patients and therapist’s trait EI independent variables.

exerting a positive effect on the overall psychotherapeutic outcome and symptom distress. The overall objective of the research was to test the causal effect of trait EI on the psychotherapeutic outcome in a longitudinal, multilevel, quasi-experimental design. Additionally, the specific objectives were: 1) To determine the most pertinent patient’s trait EI factors explaining the variance of clinical outcome, 2) To identify the most relevant therapist’s trait EI factors explaining the variation of clinical outcome, 3) To provide initial evidence for the incorporation of trait EI theory and instruments in mental health policy, in line with public health cost-efficiency approaches.

5.2–Method

5.2.1–Participants

Four university mental health centres were approached in Chile. Sixty-seven mental health patients and thirty-nine therapists with diverse therapeutic approaches agreed to participate in the research in their naturalistic psychotherapeutic settings. The main centre was located in the capital Santiago, contributing most patients (61.19%) and therapists (61.54%), two other centres were in the city of Talca, respectively adding 16.42% and 13.43% of patients, and 17.95% and 10.26% of therapists, and the last one was in the southern city of Temuco (patients = 8.96% and therapists = 10.26%). The University College London-Research Ethics Committee granted ethical approval for the research with project ID: 12971/00. Locally, the Scientific Ethics Committee of the Metropolitan-East-Health-Service branch (Chilean Ministry of Health) approved the protocol with project ID: 20202. The dataset and code are available at http://dx.doi.org/10.17632/py86m48kkh.1

The size of each centre was comparable, although some centres were able to include more dyads than others in the research. All therapists but one stated they received clinical supervision at the beginning of the study, meaning that their clinical work was overseen by an
experienced clinical trainer. Their preferred psychotherapeutic approaches varied (Systemic, \( n = 14 \); Psychodynamic, \( n = 8 \); CBT, \( n = 4 \); Integrative, \( n = 7 \); Humanistic, \( n = 3 \); and Eclectic, \( n = 3 \)). The sample comprised patients suffering from common mental health disorders (i.e., depression and anxiety). These syndromes are the most prevalent in mental health settings, affecting approximately 8% of the global population (World Health Organization, 2017).

Most therapists were on professional internships, which was a landmark towards their undergraduate Psychology degree. The number of years of professional practice varied among therapists. However, most were inexperienced (\( M = 2.03, SD = 0.60 \)), with 79.48% of them having two years or less of professional experience. In contrast, a substantially smaller fraction had practised between three and five years (10.26%), and an equal percentage (10.26%) declared having six or more years of professional practice. These two last groups of intermediate and experienced therapists usually performed both clinical and academic roles within the centres.

A multilevel power analysis suggested that the sample size required at the patient level would be 70, whilst 30 therapists would be expected at an upper level. The calculation was for a power of .90, 99% CI [.89–.91], an alpha of .01 (bilateral), and an effect measure of .34 (Hedges’ g) taken from extant relevant studies (Cooper & Petrides, 2010; Mackay et al., 2015; see chapter 3 of the dissertation). In performing this power estimation, the mean, standard deviation, and variance of Global trait EI from the local TEIQue-SF validation in clinical population were taken into consideration (see chapter 3 of the dissertation). This power analysis was conducted in the MLPowSim Software Package version 1.0 Beta 1 (Browne et al., 2009), and then simulated in R. The power for the total final sample of 67 patients and 39 therapists reached .92, 99% CI [.90–.93]. An additional power analysis, with
a trait EI effect size interval [.00–.33] from Andrei et al. (2016) ’s metanalytic findings yielded almost identical figures, .92, 99% CI [.90–.94].

5.2.2–Measures

5.2.2.1–Psychotherapeutic Outcome. The outcome questionnaire (OQ-45.2) developed by Lambert, Hansen, et al. (1996) has been validated and adapted for prospective psychotherapeutic research in Chile by De la Parra and Von Bergen (2006), see Appendix A22. The OQ-45.2 is a self-administered, five-point Likert scale, with a scoring range from 0 to 180, comprising three subscales: symptom distress (SD), interpersonal relationships (IR) and social role (SR), plus an overall outcome score (OQ). In Chile, the questionnaire demonstrated good evidence of test-retest reliability in patients through Cronbach’s alpha (OQ = .91, SD = .89, IR = .67, SR = .63), convergent validity vis-a-vis the DASS-21 scale (Depression, Anxiety and Stress Scale – 21), and sensitivity in measuring psychotherapeutic outcomes longitudinally (De la Parra & Von Bergen, 2006).

Psychometric evidence supporting the appropriateness of the OQ-45.2 for accurately studying psychotherapeutic outcomes across different populations and therapeutic settings has been highlighted in the extant literature (e.g., Lambert, Burlingame, et al., 1996; Vermeersch et al., 2000). The OQ-45.2 is a short self-report instrument especially intended for repeated measurement of patient status through psychotherapeutic treatment and at the termination of it (Lambert, Burlingame, et al., 1996). The instrument was developed from three crucial domains of psychotherapeutic outcome: interpersonal discomfort or symptomatic distress, interpersonal functioning, and social role performance, Lambert (1983). Lambert, Hansen, et al. (1996) highlighted that the questionnaire is intended to avoid artificial low ceiling effects, as this is the case in dichotomous measures that only assess presence or absence of psychopathology, instead of including items that point towards
positive mental states as the OQ does. Moreover, the instrument has concurrent validity with many well-regarded clinical symptomatology measures, such as the Symptom Checklist 90-Revised (SCL-90-R, Derogatis, 1994), Beck Depression Inventory (BDI, Beck et al., 1988), Zung Self-Rating Anxiety Scale (ZAS, Zung, 1971), Zung Self-Rating Depression Scale (ZSRDS, Zung, 1965), Manifest Anxiety Scale (TMA, Spielberger, 1983), State-Trait Anxiety Inventory (STAI, Spielberger, 1983), Inventory of Interpersonal Problems (IIP, Horowitz et al., 1988), Social Adjustment Scale (SAS, Weissman & Bothwell, 1976), among others (Lambert, Burlingame, et al., 1996). Sensitivity to change of the OQ-45.2 has been reported widely (e.g., De la Parra & Von Bergen, 2006; Vermeersch et al., 2000). Notably for the development of the present research, Anderson and Lambert (2001) posed that survival analyses of patients attending university-affiliated mental health clinics revealed that the median number of sessions required to attain clinically significant change was eleven. Moreover, those patients with higher levels of psychological distress at intake needed eight sessions more than patients experiencing lower levels of psychological disturbance to reach 50% of clinically significant change, as measured by the OQ-45.2. In addition, these changes remained after a follow-up of six months.

5.2.2.2–Trait Emotional Intelligence. The Spanish-Chilean TEIQue-SF questionnaire was utilised for assessing trait EI in patients and therapists (see chapter 3 of the dissertation). The Spanish-Chilean TEIQue-SF questionnaire is a locally adapted and validated measure comprising thirty statements, on a 7-point Likert scale, ranging from 1 (Completely Disagree) to 7 (Completely Agree). The Spanish-Chilean adaptation has shown a similar factor structure to the original TEIQue-SF (see chapter 3 of the dissertation and Appendix A1 for the questionnaire), as well as evidence of invariance across sociodemographic variables, including age, gender, and educational level (see chapter 4 of the dissertation).
5.2.2.3–The Working Alliance. The working alliance inventory (WAI) assesses both patient and therapist perspectives of the therapeutic alliance. The WAI is the most salient measure for evaluating the therapeutic relationship. It was developed by Horvath and Greenberg (1986, 1989) and adapted and validated in Chile by Santibañez (2001, 2003) for patients (WAI-P) and therapists (WAI-T). Patient and Therapist’s versions of the measure are included in Appendices A23 and A24. The questionnaire comprises 36 items and yields a global composite score (IAT-total) as well as scores on three distinct factors: bond, tasks, and goals. This three-factor structure is congruent with the theory formerly developed by Bordin (1979). The bond refers to the mutual trust, acceptance and confidence between patient and therapist, tasks relate to the means on which the proposed therapeutic goals will be pursued, whereas goals characterise the degree of agreement between the parts regarding the aims of treatment (Horvath & Greenberg, 1986, 1989). The questionnaire is reliable for both patients (patient-IAT-total, $\alpha = .90$; patient-bond-alliance, $\alpha = .67$; patient-tasks-alliance, $\alpha = .80$; patient-goals-alliance, $\alpha = .78$), and therapists (therapist-IAT-total, $\alpha = .93$; therapist-bond-alliance, $\alpha = .70$; therapist-tasks-alliance, $\alpha = .85$; therapist-goals-alliance, $\alpha = .88$) in Chilean mental health settings across psychotherapeutic approaches (Santibañez, 2003).

5.2.3–Design and Procedure

The research design is multilevel, quasi-experimental, and longitudinal. Shadish et al. (2002) defined quasi-experimental designs as experiments in which units are not randomly assigned. According to these authors, quasi-experiments serve a similar purpose to true experiments, as they test descriptive causal hypotheses on interventions to support counterfactual inference. In the present study, the units are twofold, first patients as the basic unit of analysis, and on an upper level, therapists. Although both units of analysis were not randomly selected, their longitudinal trait EI predictive effects were tested on the results of the psychological intervention and the alliance in the naturalistic setting. Outcomes were
assessed twice, at the beginning of the treatment as a baseline, and the end of it. Trait EI was evaluated once, before the start of the intervention. The therapeutic alliance was also assessed once, between four and six weeks after the beginning of the psychotherapy, as a second assessment of the alliance was logistically not feasible. An illustration of the research design is depicted in Figure 5.

Two samples of the general Chilean population of similar sociodemographic background and sample size to the sample of patients obtained for the present study were compared to ensure clinical participants statistically differed from the general population. These samples also had similar reliabilities to the trait EI factors in the clinical sample of the present study. The general population subsamples ($n_1 = 55$, $n_2 = 60$) were extracted from the validation of the Spanish-Chilean-TEIQue-SF in Chile (see chapter 3 of the dissertation). Each of them corresponded to a full and unaltered subset from locations approached in study 1. Finally, in study four, the researcher implemented similar participant distress and discomfort measures as in the previous studies of the dissertation. A greater emphasis was given to avoiding any possible distress and discomfort in clinical participants due to the alliance measures requested to patients and therapists. For instance, patients in the participating centres were required to hand in these alliance measures confidentially to the corresponding health coordinator in sealed envelopes. Participants were able to contact the research trainee (i.e., author of the dissertation) directly regarding the nature of the study, as indicated in the information sheet, although they seldomly approached the researcher by email, always with the intention of knowing more about the study aims. Moreover, the information was fully anonymised, as all participant’s data were coded, starting with a three-letter abbreviation identifying the centre, followed by the therapist’s allocated number and the patient’s number, which was only known by the respective health coordinator during data (e.g., CEP12 represents patient number two of therapist number one at centre CEP). This
system ensured confidentiality as a sort of double-blinding regarding patient and therapist’s identity.

Additionally, the study was appraised with the consensus-based standards for the selection of health status measurement instruments (COSMIN), which establishes criteria for assessing the methodological suitability of studies conducted in health settings to avoid potential risks or biases (Mokkink et al., 2019; see also Mokkink et al., 2010a; Mokkink et al., 2010b). This standard provides a 4-point rating scale to understand the consequences of choices made in the design of the study, providing an overall rating of the research design (Mokkink et al., 2019). The rating scale comprises four categories: 1) very good, 2) adequate, 3) doubtful, and 4) inadequate, as previously described (see section 3.2.2.3, chapter three).

The relevant criteria for the present study are described in the responsiveness cluster, as this allows appraisal of the validity of longitudinal research in before-and-after intervention designs. From eight criteria included in this cluster, seven matched the description of very good (i.e., criterion completely fulfilled), and only one matched with the description of adequate (i.e., attained with some limitations).

In detail, hypotheses were formulated according to the expected changes in outcomes, there was an adequate description of the intervention, and the time interval is appropriate as presented in the psychotherapeutic literature (see section 5.2.2.1, in the present chapter). Moreover, anything likely to have occurred during the treatment was adequately described, the patients were expected to change on their outcomes (as they did), the implemented statistical methods were appropriate, and the way missing items were handled was explicit. All these points scored the methodological rigour of the study as of very good standard according to the COSMIN checklist. However, the sample size was appraised as adequate, since samples between 50 to 99 patients fall in this category, whereas samples of a hundred patients or more are considered to be of a very good standard.
Figure 5. Illustration of the General Model and Variables Tested Throughout the Study

Note. This figure illustrates the independent, dependent and moderator variables tested in this multilevel longitudinal study. Independent trait EI variables are depicted at the left, alliance moderator variables are at the centre, along with the effect of the intervention (TIME), and the dependent outcome variables are at the beginning and the end of the psychotherapeutic intervention. Unidirectional lines represent main effects, whilst bidirectional lines represent interactions. All the tested models in the study included the effect of the intervention (TIME).

All participants were apprised of the conditions of the study (i.e., patients and therapists). They signed informed consent forms in which the possibility to withdraw from the study without giving any reason was explicit. Patients and therapists in the centres were invited to participate in the research through their health coordinator or head manager. The coordinators of the mental health centres were instructed to exclude from the study any patient who presented acute diagnosis or symptomatology (e.g., schizophrenia, severe personality disorder, bipolar affective disorder) or for whom it could be perilous to participate in the research. As the centres comprised a limited number of therapists, the practitioners were allowed to enrol multiple patients each. 58.97% of therapists enrolled one patient,
17.95% enrolled two patients, 15.38% enrolled three patients, and 7.69% enrolled four patients in the study.

5.2.4–Data Protection Measures

For study four, the researcher implemented the same data protection measures as in study one.

5.2.5–Data Analysis Plan

Multiple imputations by chained equations were implemented for treating missing values with the R package MICE (Van Buuren & Groothuis-Oudshoorn, 2011). White et al.’s (2010) recommendation to include predictors with incomplete data in the imputation model was followed, as this makes more plausible the assumption of missing at random (MAR), thus reducing bias and the standard error of parameter estimates in the model. Subsequently, Rubin’s (1987) recommendations were followed to obtain average values of the parameter estimates, which apply to longitudinal research designs as well (Spratt et al., 2010).

To ascertain the validity of the imputation procedure, given the high proportion of missing values for some of the imputed variables, the fraction of the missing information (FMI) across imputation models was examined. Scholars have recommended this as an index of efficiency gain, as it allows assessing reductions in standard errors in imputation analyses (Madley-Dowd et al., 2019; Wagner, 2010). Likewise, two reliability coefficients were calculated before and after multiple imputation: Cronbach’s Alpha (α) and Omega total (ωt), the latter a greater-lower-bound (glb) reliability index (see Sijtsma, 2009). The codes for the multiple imputation and merging procedures are in Appendices A24 and A25, respectively.

Multilevel linear modelling with grand mean-centred predictors was implemented at the patient level in R through the progressive introduction of random intercepts and slopes for
the included independent variables (see Dedrick et al., 2009, for a review). Given the prospective nature of the study, growth modelling, repeated measures analyses were conducted with a first-order autoregressive covariance structure (AR1), as this is the standard treatment of longitudinal data (see Field et al., 2012). These procedures were performed through the multilevel package (Bliese, 2016), and the extra functionality provided by the nlme package (Pinheiro et al., 2020), both in R version 3.6.3. The R Growth modelling scripts are in Appendix A27.

Multilevel linear models organise data hierarchically. Thus, through this approach, data is nested into different layers, which allows exploring cross-level effects. In other words, the method is advantageous since it makes possible to separate the sources of variance attributable to different levels of analysis (Vogt, 2011). For instance, if researchers wanted to examine the outcome of an educational programme in a primary school setting, they may account for the variability of children at a first level and their respective classrooms at a second level (Field, 2012). Multilevel modelling is always an improvement vis-à-vis classical regression methods, being indispensable for prediction, and helpful for causal inference and data reduction (Gelman, 2006). Likewise, Dedrick et al. (2009) noted that the main advantage of multilevel modelling compared to ordinary regression models concerns the ability to add cross-level error terms, which creates a more flexible covariance structure. In psychotherapy, Hill and Castonguay (2017) posited that multilevel modelling allows for the disentangling of patient and therapist contributions to the alliance and psychotherapeutic outcomes. Similarly, Constantino et al. (2017) suggested that multilevel modelling allows ascertaining therapist variability and its effects on patient’s processes and outcomes.

All analyses were performed with the restricted maximum likelihood estimator (REML) and the optim optimisation method. Following Aguinis et al. (2013), cross-level effects were explored, i.e., first testing lower-level direct effects, then cross-level direct
effects, and finally cross-level interaction effects. Several comparisons of the dependent variables across the different study subgroups were conducted to assess the generalizability and sensitivity of the findings (i.e., centre, cohort, type of psychotherapy provided), as recommended by Dedrick et al. (2009). The R scripts for all the figures implemented in the chapter are in Appendix A28. A correlation matrix of the variables included in the study is depicted in Figure 6, and the full correlation matrix is provided in Appendix A29.

5.3–Results

5.3.1–Percentage of Missing Values Across the Study Variables

Trait EI variables had 16.42% of missing values at the therapist level, and 4.5% at the patient level. The baseline outcome measure had 35.82% missing values for the global composite (OQ1), 14.93% (SD1), 26.87% (IR1), and 13.43% (SR1). The second outcome assessment had 47.76% of missing values for the global composite (OQ2), 43.28% (SD2), 46.27% (IR2), and 43.28% (SR2). The IAT measures were also subjected to multiple imputations, as the global alliance composite at the patient level (IAT-total-p) had 34.33% of missing values. IAT’s patient-bond-alliance had 28.36%, patient-tasks-alliance 28.36%, and patient-goals-alliance had 32.84%. For therapists, all alliance indices had 53.73% of missing values. Patient age and type of therapy had a small percentage of imputed variables in the final dataset (2.99% and 4.48%, respectively).
Figure 6. Correlation Matrix of the Variables Included in Study Four

Note: The correlation matrix has been arranged through hierarchical clustering order (hclust). GTEIp: patient global trait EI, WBp: patient Well-being, SCP: patient Self-control, EMP: patient Emotionality, SBp: patient Sociability. GTEIt: therapist global trait EI, WBT: therapist Well-being, SCT: therapist Self-control, EMT: therapist Emotionality, SBt: therapist Sociability. IAT_CONSTANT_p: patient-total-alliance, IAT_BOND_p: patient- bond-alliance, IAT_TASKS_p: patient-tasks-alliance, IAT_GOALS_p: patient-goals-alliance. OQ_CONSTANT_1: overall outcome time 1, OQ_SD_1: symptom distress time 1, OQ_IR_1: interpersonal relationships time 1, OQ_SR_1: social role time 1, OQ_CONSTANT_2: overall outcome time 2, OQ_SD_2: symptom distress time 2, OQ_IR_2: interpersonal relationships time 2, OQ_SR_2: social role time 2. Only significant correlations ($p < 0.01$) among variables are depicted.

5.3.2–Testing the Validity of the Multiple Imputation Model

Fifty-four imputations were performed ($m$), a number that corresponded to the maximum percentage of missing values in any of the variables in the dataset. In the multiple
imputation model, most FMI means (see Madley-Dowd et al., 2019, and the previous page for a definition of FMI) were in the expected range (.02–.40), with only one imputed variable having an FMI above .50 (Social Role, second measurement = .54). This suggests that the variability across the imputed datasets was mostly low, with the only exception of the second measurement of Social Role, which may be considered moderate in size. Madley-Dowd et al. (2019) proposed that an empirical standard error for an FMI up to 0.50 should be in the range 0.02-0.04, an interval that provides support for the validity of the overall imputation model.

5.3.3–Descriptive Statistics and Distributions

Descriptive statistics for the key variables in the analysis are depicted in Table 10. Normality was assessed through quantile-quantile (Q–Q) plots for each dependent variable at time 1 and 2. Values were in the range of -1.96 to 1.96 SDs indicating generally normal distributions (Field et al., 2012).

5.3.4–Reliability Analyses

Cronbach’s Alpha (α) and Omega total (ωt) indexes are reported in Appendix A30. All variables showed adequate reliability before and after multiple imputations, except for patient trait EI Emotionality and Self-control. Lower reliability scores at the factor-level are expected for the TEIQue-SF (e.g., Feher et al., 2019; Perazzo et al., 2020). In contrast, the global reliability scores exceeded .85 in the sample, which is congruent with the aforementioned literature and the brief format of the measure (e.g., Cooper & Petrides, 2010).
### Table 10. Descriptive Statistics for the Independent, Dependent, and Moderator Variables

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables (Trait EI)</strong></td>
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<tr>
<td><strong>Patients</strong></td>
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</tr>
<tr>
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<td>0.74</td>
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<td>1.26</td>
</tr>
<tr>
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<td>6.67</td>
<td>4.14</td>
<td>1.00</td>
</tr>
<tr>
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<td>6.50</td>
<td>4.37</td>
<td>0.84</td>
</tr>
<tr>
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<td>7.00</td>
<td>4.60</td>
<td>0.94</td>
</tr>
<tr>
<td><strong>Therapists</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global trait EI</td>
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<td>6.77</td>
<td>5.35</td>
<td>0.81</td>
</tr>
<tr>
<td>Well-being</td>
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<td>5.59</td>
<td>0.94</td>
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<td>0.94</td>
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<tr>
<td>Sociability</td>
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<td>6.67</td>
<td>5.14</td>
<td>0.82</td>
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<td><strong>Dependent Variables (OQ-45.2)</strong></td>
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<tr>
<td>First measure</td>
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<tr>
<td>Overall outcome</td>
<td>8.00</td>
<td>115.00</td>
<td>81.02</td>
<td>17.30</td>
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<td>76.00</td>
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<td>13.28</td>
</tr>
<tr>
<td>Interpersonal relationships</td>
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<td>32.00</td>
<td>21.30</td>
<td>5.50</td>
</tr>
<tr>
<td>Social role</td>
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<td>Second measure</td>
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<td>106.00</td>
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<td><strong>Moderator Variables (IAT)</strong></td>
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<tr>
<td><strong>Patients</strong></td>
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<td>246.00</td>
<td>199.00</td>
<td>31.27</td>
</tr>
<tr>
<td>Bond</td>
<td>25.00</td>
<td>84.00</td>
<td>69.18</td>
<td>10.26</td>
</tr>
<tr>
<td>Tasks</td>
<td>23.00</td>
<td>84.00</td>
<td>66.00</td>
<td>11.70</td>
</tr>
<tr>
<td>Goals</td>
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<td>83.00</td>
<td>63.75</td>
<td>11.43</td>
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<td><strong>Therapists</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Total alliance</td>
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<td>235.00</td>
<td>172.70</td>
<td>12.05</td>
</tr>
<tr>
<td>Bond</td>
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<td>80.00</td>
<td>65.74</td>
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<tr>
<td>Tasks</td>
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<td>81.00</td>
<td>53.97</td>
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<td>Goals</td>
<td>45.00</td>
<td>77.00</td>
<td>52.95</td>
<td>4.91</td>
</tr>
</tbody>
</table>

*Note.* All descriptive statistics refer to the pooled imputation dataset. Patients \( (n₁ = 67) \), Therapists \( (n₂ = 39) \). EI = emotional intelligence. Min = minimum, Max = maximum, \( M \) = mean, \( SD \) = standard deviation.
5.3.5–Mean Comparisons at Time one with Control Samples

Homogeneous subsets analyses were conducted through harmonic mean comparisons at the patient level with the non-imputed dataset \( n_1 = 64 \) for all the trait EI predictors and the two comparison samples taken from general Chilean population \( n_2 = 60, n_3 = 55 \), which had similar sociodemographic characteristics and sample size with the current clinical dataset (see chapter 3 of the dissertation).

These analyses confirmed that the two contrast samples taken from general Chilean population had significantly higher means on all trait EI predictors except Sociability, and thus constituted a homogeneous subset different from the clinical patient sample of the present study. As for Sociability, the means of these two general population samples were very alike \( M_2 = 4.96, M_3 = 4.98 \), and still higher than the present study’s sample \( M_1 = 4.61, p = 0.08 \). These results rendered evidence for considering the present sample as coming from genuine clinical population, clearly differentiated from the general population regarding trait EI means.

5.3.6–Examination of the Dependent Variables and the Later Introduction of Time

The properties of the outcomes were examined across models, which is usually described in the multilevel literature as the null model, since it includes only the regression of the repeated measure plus the random intercept at the patient level. From these analyses, intraclass correlation \( (ICC) \) estimates were obtained for each dependent variable in the OQ.45-2 questionnaire, as this is the suggested and most appropriate effect size measure in multilevel analysis (Lorah, 2018). These results indicated that 35\% of the variance in symptom distress (SD), 31\% in the overall outcome (OQ), 22\% in social role (SR), and 17\% in the interpersonal relationships (IR) can be explained by the response variability at the
patient level, as presented in Table 11. In comparison, 32% (SD), 30% (OQ), 14% (SR), and 6% (IR) can be explained by variability at the therapist level.

The fixed effects of time on the dependent variables across patients are illustrated in Figure 7. In the multilevel growth modelling literature, this is identified as Model time (see Aguinis et al., 2013; Bliese, 2016). These analyses revealed random variability across patients (i.e., unmodeled differences between the lower-level units of patients), supporting the modelling of a random intercept for the variable time. All models, except social role, remained significant when a random intercept was introduced at the patient level. These effects are depicted in Table 12.

5.3.7–Contextual Effects on the Dependent Variables

Contextual variables (i.e., centre effect, type of psychotherapeutic approach, cohort, and years of professional practice) were tested for their potential impact on the dependent variables. In line with the literature, the observed effects were limited. The centres accounted for less than 3% of the variance. All standardised effects were less than .02, except the impact of centre on interpersonal relationships, which reached .07. The type of psychotherapeutic approach implemented accounted for 16% of overall outcome variance (OQ), 14% of symptom distress (SD), 5% interpersonal relationships (IR) and 2% of social role (SR). All standardised effect sizes for these models were in the range of .01-.04, indicating minimal effects. As the data were collected in two different periods, the possible impact of temporal changes on the dependent variables was tested. Again, the effects were negligible, with ICCs in the range of .01-.27 and standardised effect sizes between .01 and .06. The years of professional practice were not significantly related to the dependent variables either, with ICCs in the interval .05-.08, and standardised effect sizes between .10 and .16. However, there was little variance in this variable, as its distribution was highly skewed due to most therapists were inexperienced.
5.3.8—Examination of Slope Variability

The time models above were tested with the inclusion of random effects across patients, meaning that individual regression coefficients were allowed to vary among patients. The examination of the slope variability focuses on the gradient of the multilevel regression lines, which indicates the strength of the relationship between variables (Vogt, 2011). At this step, there were no significant differences across the studied dependent variables compared to the models presented in Table 12. However, all models showed a slightly improved overall fit that was more substantial for symptom distress, where the fit statistics between the model with and without random slope variability approached statistical significance (\( p = .08 \)), favouring the fit of the former.

5.3.9—Predicting Intercept Variations at the Patient Level

At this stage, trait EI’s predictive effects were tested on the dependent variables through sequential modelling. This order corresponds to 1) the testing of lower-level direct effects, 2) the examination of the cross-level direct effects, and 3) the investigation of possible cross-level interactions (Aguinis et al., 2013). The same rationale was implemented with the alliance measures. These analyses were conducted with grand mean centring at the patient level and using autoregressive correlations (AR1).

The intercept is the point at which a regression line crosses the vertical axis (i.e., \( y \)) when the value on the horizontal axis (i.e., \( x \)) is zero. In other words, it is the predicted value of the dependent variable when the value of the independent variable is zero (Vogt, 2011). Patient intercept variations for the dependent variables are depicted in Appendix A31, whereas therapist intercept variations are illustrated in Appendix A32.

On the one hand, patient Global trait EI, Well-being and Self-control intercept variations were significant predictors of psychotherapeutic outcomes, meaning that variability
in these independent variables statistically explained psychotherapeutic outcomes to a significant degree. Specifically, the three patient-level trait EI variables predicted significant reductions in the overall outcome and symptom distress. In addition, non-significant reductions in outcomes were obtained for the remaining trait EI independent variables. These findings provided the first indications confirming the protective role of patient trait EI across the studied psychotherapeutic outcomes.

On the other hand, therapist trait EI intercept variations had a weaker effect on the psychotherapeutic outcome, confined mainly to the overall outcome and its interpersonal relationships aspect (see Appendix 32). All these relationships were in the unexpected direction where higher therapist trait EI was associated with worse psychotherapeutic outcomes. Specifically, therapist’s Global trait EI predicted a significant increase in the overall outcome, meaning that patient’s general psychological disturbance worsens across the studied outcome as a result of higher values of therapist’s Global trait EI from intake to the end of the study. The same applies to therapist’s Self-control and Sociability on the overall outcome, as well as to therapist’s Global trait EI, therapist’s Self-control, therapist’s Emotionality, and therapist’s Sociability on interpersonal relationships. All these trait EI independent variables significantly predicted an increase in the respective psychotherapeutic outcomes, meaning that patient’s psychological disturbance significantly increased. Finally, therapist’s Self-control also significantly predicted growth in patient’s scores of social role functionality, meaning that patients had significantly greater difficulties in social adjusting as a result of higher levels of therapist’s Self-control. Here, the strongest therapist trait EI effect was of therapist’s Sociability on interpersonal relationships, as can be appreciated in Appendix A32.
Figure 7. Pre and Post Dependent Variables Changes Across Patients: Model Time

A

Change in Overall outcome by time

B

Symptom distress change by time
Table 11. Variability of Outcome Measures Across Patients (Null Model)

<table>
<thead>
<tr>
<th>Type of effect</th>
<th>Model Overall outcome</th>
<th>Model Symptom distress</th>
<th>Model Interpersonal relationships</th>
<th>Model Social role</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>B0 = 77.06 SEB0 = 1.65 tB0 = 46.72*** df = 67</td>
<td>Fixed B0 = 42.81 SEB0 = 1.22 tB0 = 35.18*** df = 67</td>
<td>Fixed B0 = 20.36 SEB0 = 0.47 tB0 = 43.68*** df = 67</td>
<td>Fixed B0 = 13.89 SEB0 = 0.40 tB0 = 34.85*** df = 67</td>
</tr>
<tr>
<td>Random</td>
<td>B0 = 9.26 SEB0 = 13.89 df = 1130.25 AIC = 1138.92 BIC = 1124.26 ICC = 0.31</td>
<td>Random B0 = 7.14 SEB0 = 9.82 df = 1043.66 AIC = 1052.33 BIC = 1037.66 ICC = 0.35</td>
<td>Random B0 = 2.04 SEB0 = 4.56 df = 814.17 AIC = 822.84 BIC = 808.16 ICC = 0.17</td>
<td>Random B0 = 1.96 SEB0 = 3.69 df = 764.98 AIC = 773.65 BIC = 758.98 ICC = 0.22</td>
</tr>
</tbody>
</table>

Table 12. Psychotherapeutic Change Through Time by the Dependent Variables (Model Time)

<table>
<thead>
<tr>
<th>Type of effect</th>
<th>Model Overall outcome</th>
<th>Model Symptom distress</th>
<th>Model Interpersonal relationships</th>
<th>Model Social role</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B0</td>
<td>SEB0</td>
<td>tB0</td>
<td>B 1</td>
</tr>
<tr>
<td>Fixed</td>
<td>81.02</td>
<td>1.99</td>
<td>40.78***</td>
<td>-7.91</td>
</tr>
<tr>
<td>Random</td>
<td>10.01</td>
<td>12.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed</td>
<td>45.46</td>
<td>1.45</td>
<td>31.33***</td>
<td>-5.30</td>
</tr>
<tr>
<td>Random</td>
<td>7.57</td>
<td>9.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed</td>
<td>21.30</td>
<td>0.60</td>
<td>35.44***</td>
<td>-1.89</td>
</tr>
<tr>
<td>Random</td>
<td>2.21</td>
<td>4.39</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed</td>
<td>14.27</td>
<td>0.51</td>
<td>28.00***</td>
<td>-0.76</td>
</tr>
<tr>
<td>Random</td>
<td>1.97</td>
<td>3.68</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: B0: intercept, SEB0: standard error of the intercept, tB0: t-value of the intercept, B 1: Beta coefficient of TIME, SEB 1: standard error of TIME, tB 1: t-value of TIME, ß1: standardised beta coefficient of TIME, 95%CIß1: 95% confidence interval of the standardised coefficient of TIME, df: degrees of freedom, AIC: Akaike information criterion, BIC: Bayesian information criterion, -2LL: -2 log likelihood, ICC: intraclass correlation. * p < .05, ** p < .01, *** p < .001.
5.3.10–Predicting Slope Variations Between Time and the Independent Variables

5.3.10.1–Patient Trait EI Slope Variations. This section aims to determine whether trait EI independent variables can explain some of the variation in the time (x)-outcomes (y)slopes. Patient’s Global trait EI interacted with the effect of time on the overall outcome and symptom distress, meaning that patient’s Global trait EI moderated the effect of time on the overall outcome and symptom distress. Specifically, patients with low Global trait EI benefit substantially more from the psychological treatment than those with high trait EI at intake regarding the overall outcome (see Figure 8, panel A). Similarly, patients with low Global trait EI benefited substantially from the psychological intervention regarding symptom distress. In contrast, patients with high Global trait EI at intake showed a slight increase in the symptomatology at the end of the study (see Figure 8, panel B).

Patient Well-being also interacted with the effect of time on symptom distress and marginally with the overall outcome, meaning that patient’s Well-being moderated the effect of time on these outcomes. As with Global trait EI, patients low in Well-being showed a steeper reduction from intake to the end of the study on the overall outcome than those patients high in Well-being (see Figure 8, panel C). Likewise, patients with low Well-being benefited substantially from the psychological intervention regarding symptom distress, whereas patients high in Well-being at intake showed a slight increase in the symptomatology at the end of the treatment (see Figure 8, panel D).

Patient Self-control interacted with the effect of time on the overall outcome, as well as symptom distress, meaning that patient’s Self-control moderated the effect of time on these outcomes. Patients low in Self-control showed a steeper reduction on the overall outcome than those patients high in Self-control from intake to the end of the research (see Figure 8, panel E).
Likewise, patients with low Well-being benefited substantially from the psychological intervention regarding symptom distress, whereas patients high in Well-being at intake showed a slight improvement in the symptomatology from intake to the end of the study (see Figure 8, panel F).

Patient Emotionality interacted only with the effect of time on symptom distress, meaning that patient’s Emotionality moderated the effect of time on this outcome. Patients low in Emotionality showed a steeper reduction on symptom distress than those patients high in Emotionality from intake to the end of the study (see Figure 8, panel G). Finally, Patient Sociability interacted only with the effect of time on symptom distress, meaning that patient’s Sociability moderated the effect of time on this outcome. Patients low in Sociability showed a steeper reduction on symptom distress than those patients high in Sociability from intake to the end of the study (see Figure 8, panel H). All these results are illustrated in Figure 8, and full statistics are informed in Table 13.

### Table 13. Patients’ Trait EI Slope Variations

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>B</th>
<th>SEB</th>
<th>tB</th>
<th>Adj. p</th>
<th>β</th>
<th>95%CIβ</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>-2LL</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GTEIp*TIME</td>
<td>8.09</td>
<td>2.87</td>
<td>2.82*</td>
<td>.006</td>
<td>0.18</td>
<td>[0.05, 0.31]</td>
<td>65</td>
<td>1099.75</td>
<td>1125.55</td>
<td>1081.74</td>
<td>0.54</td>
</tr>
<tr>
<td>WBp*TIME</td>
<td>3.39</td>
<td>1.73</td>
<td>1.96</td>
<td>.054</td>
<td>0.13</td>
<td>[0.00, 0.26]</td>
<td>65</td>
<td>1105.02</td>
<td>1130.83</td>
<td>1087.02</td>
<td>0.59</td>
</tr>
<tr>
<td>SCp*TIME</td>
<td>4.78</td>
<td>2.16</td>
<td>2.21*</td>
<td>.031</td>
<td>0.14</td>
<td>[0.01, 0.27]</td>
<td>65</td>
<td>1106.90</td>
<td>1132.71</td>
<td>1089.90</td>
<td>0.58</td>
</tr>
<tr>
<td>GTEIp*TIME</td>
<td>8.36</td>
<td>1.90</td>
<td>4.39***</td>
<td>.001</td>
<td>0.26</td>
<td>[0.14, 0.37]</td>
<td>65</td>
<td>1001.39</td>
<td>1027.20</td>
<td>983.40</td>
<td>0.58</td>
</tr>
<tr>
<td>WBp*TIME</td>
<td>4.84</td>
<td>1.12</td>
<td>4.33***</td>
<td>.001</td>
<td>0.25</td>
<td>[0.14, 0.37]</td>
<td>65</td>
<td>997.81</td>
<td>1023.62</td>
<td>979.82</td>
<td>0.55</td>
</tr>
<tr>
<td>SCp*TIME</td>
<td>4.40</td>
<td>1.50</td>
<td>2.92**</td>
<td>.005</td>
<td>0.18</td>
<td>[0.06, 0.31]</td>
<td>65</td>
<td>1014.93</td>
<td>1040.74</td>
<td>996.94</td>
<td>0.62</td>
</tr>
<tr>
<td>EMp*TIME</td>
<td>3.85</td>
<td>1.84</td>
<td>2.09*</td>
<td>.041</td>
<td>0.13</td>
<td>[0.01, 0.26]</td>
<td>65</td>
<td>1024.85</td>
<td>1050.65</td>
<td>1006.84</td>
<td>0.66</td>
</tr>
<tr>
<td>SBp*TIME</td>
<td>3.60</td>
<td>1.70</td>
<td>2.18*</td>
<td>.033</td>
<td>0.14</td>
<td>[0.01, 0.27]</td>
<td>65</td>
<td>1026.28</td>
<td>1052.09</td>
<td>1008.28</td>
<td>0.66</td>
</tr>
</tbody>
</table>

**Figure 8.** *Patient’s trait EI Slope Variations Across Dependent Variables and Time*

- **A**: Graph showing the relationship between Global trait EI and TIME, differentiated by Low and High levels.
- **B**: Graph showing the relationship between Symptom distress and TIME, differentiated by Low and High levels.
- **C**: Graph showing the relationship between Quality of Life and TIME, differentiated by Low and High levels.
- **D**: Graph showing the relationship between Quality of Life and TIME, differentiated by Low and High levels.
5.3.10.2–Therapist’s Trait EI Slope Variations. Non-significant slope variations were found between therapist’s trait EI and time across outcomes, meaning that the longitudinal variability between therapists was negligible regarding outcomes changes.

5.3.11–Intercept and Slope Variations of Alliance Measures

Intercept variations were examined between the alliance and the outcome measures. These effects will be described in further detail when trait EI effects are contrasted with alliance effects, to avoid redundancy. Regarding slope variations, there were considerable effects of the alliance measures on the dependent variables, which especially relate to therapists.

Therapist total alliance interacted with time regarding symptom distress and social role, meaning that therapist total alliance moderated the effect of time on this outcome. Patients treated by therapists high in total alliance showed a steeper reduction in symptom distress than those patients treated by therapists low in total alliance from intake to the end of the study (see Figure 9, panel A). However, patients treated by therapists high in total alliance showed an increase in this outcome, i.e., poorer social adjustment at the end of the study compared to intake, whereas those patients treated by therapists low in total alliance showed a steep reduction in social role (see Figure 9, panel B).

Therapist tasks-alliance also interacted with time regarding symptom distress and social role, meaning that therapist tasks-alliance moderated the effect of time on these outcomes. Patients treated by therapists high in tasks-alliance showed a steeper reduction in symptom distress than those patients treated by therapists low in tasks-alliance from intake to the end of the study (see Figure 9, panel C). However, patients treated by therapists high in tasks-alliance showed an increase in this outcome, i.e., poorer social adjustment at the end of the study
compared to intake, whereas those patients treated by therapists low in tasks-alliance showed a steep reduction in social role, i.e., better social adjustment (see Figure 9, panel D).

Similarly, therapist goals-alliance interacted with time regarding symptom distress and social role, meaning that therapist goals-alliance moderated the effect of time on these outcomes. Patients treated by therapists high in goals-alliance showed a steeper reduction in symptom distress than those patients treated by therapists low in goals-alliance from intake to the end of the study (see Figure 9, panel E). However, patients treated by therapists high in goals-alliance showed an increase in social role (i.e., poorer social adjustment at the end of the study compared to intake), whereas those patients treated by therapists low in goals-alliance showed a steep reduction in social role, i.e., better social adjustment (see Figure 9, panel F).

Patient goals-alliance interacted with time regarding interpersonal relationships and social role, meaning that patient goals-alliance moderated the effect of time on these outcomes. Patients high in goals-alliance showed a steeper reduction in interpersonal relationships (i.e., better social adjustment) than those patients low in goals-alliance from intake to the end of the study (see Figure 9, panel G). Moreover, patients high in goals-alliance showed a steep reduction in social role (i.e., better social adjustment) from intake to the end of the study, whereas those patients low in goals-alliance showed an increase in social role (i.e., poorer social adjustment), from intake to the end of the study (see Figure 9, panel H). All these results are illustrated in Figure 9, and full statistics are informed in Table 14.
### Table 14. Slope Variations of Alliance Measures Across Outcomes

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>B</th>
<th>SEB</th>
<th>tB</th>
<th>Adj. p</th>
<th>95%CIβ</th>
<th>β</th>
<th>95%CIβ</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>-2LL</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>IAT-total-t*TIME</td>
<td>-0.28</td>
<td>0.13</td>
<td>2.21*</td>
<td>.080</td>
<td>[-0.27, -0.01]</td>
<td>-0.14</td>
<td>[-0.27, -0.01]</td>
<td>65</td>
<td>1037.50</td>
<td>1063.30</td>
<td>1019.50</td>
<td>0.68</td>
</tr>
<tr>
<td>IAT-tasks-t*TIME</td>
<td>-0.72</td>
<td>0.31</td>
<td>2.35*</td>
<td>.065</td>
<td>[-0.28, -0.02]</td>
<td>-0.15</td>
<td>[-0.28, -0.02]</td>
<td>65</td>
<td>1022.39</td>
<td>1059.20</td>
<td>1015.38</td>
<td>0.68</td>
</tr>
<tr>
<td>IAT-goals-t*TIME</td>
<td>-0.66</td>
<td>0.32</td>
<td>2.07*</td>
<td>.127</td>
<td>[-0.26, 0.00]</td>
<td>-0.13</td>
<td>[-0.26, 0.00]</td>
<td>65</td>
<td>1034.47</td>
<td>1060.28</td>
<td>1016.48</td>
<td>0.73</td>
</tr>
<tr>
<td>IAT-goals-p*TIME</td>
<td>-0.13</td>
<td>0.07</td>
<td>2.02*</td>
<td>.129</td>
<td>[-0.30, 0.01]</td>
<td>-0.15</td>
<td>[-0.30, 0.01]</td>
<td>65</td>
<td>818.55</td>
<td>844.36</td>
<td>800.56</td>
<td>0.72</td>
</tr>
<tr>
<td>IAT-total-t*TIME</td>
<td>0.13</td>
<td>0.05</td>
<td>2.49*</td>
<td>.023</td>
<td>0.18</td>
<td>[0.04, 0.33]</td>
<td>65</td>
<td>772.83</td>
<td>798.64</td>
<td>754.84</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>IAT-tasks-t*TIME</td>
<td>0.28</td>
<td>0.12</td>
<td>2.30*</td>
<td>.037</td>
<td>0.17</td>
<td>[0.02, 0.32]</td>
<td>65</td>
<td>770.26</td>
<td>796.07</td>
<td>752.26</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>IAT-goals-t*TIME</td>
<td>0.29</td>
<td>0.13</td>
<td>2.32*</td>
<td>.036</td>
<td>0.17</td>
<td>[0.02, 0.32]</td>
<td>65</td>
<td>770.05</td>
<td>795.86</td>
<td>752.06</td>
<td>0.73</td>
<td></td>
</tr>
<tr>
<td>IAT-goals-p*TIME</td>
<td>-0.11</td>
<td>0.06</td>
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<td>.103</td>
<td>-0.14</td>
<td>[-0.31, -0.01]</td>
<td>65</td>
<td>775.02</td>
<td>800.83</td>
<td>757.02</td>
<td>0.71</td>
<td></td>
</tr>
</tbody>
</table>

**Note.** B: Value of the interaction, SEB: standard error of the interaction, tB: t-value of the interaction, Adj. p = Adjusted p-value (FDR), β: standardised beta coefficient of the independent variable, 95%CIβ: 95% confidence interval of the standardised coefficients in the models, df: degrees of freedom, AIC: Akaiake information criterion, BIC: Bayesian information criterion, -2LL: -2 Log likelihood, ICC: Intraclass correlation. IAT-total-t: Therapists' total alliance, IAT-tasks-t: Therapists' tasks alliance, IAT-goals-t: Therapists' goals alliance, IAT-goals-p: Patients' goals alliance. * p < .05.

### 5.3.12–Trait EI Main Effects Vis-à-vis Alliance Main Effects

Here, models were constructed to account for 1) The combined effects of patient trait EI and patient alliance measures on the overall psychotherapeutic outcome and symptom distress, and 2) The combined cross-level effects of patient trait EI and therapist trait EI and alliance measures on the overall psychotherapeutic outcome and symptom distress. These outcomes were prioritised since they had a higher power for detecting effects in the relatively short intervention interval, as shown in the preceding analyses. Therefore, intercept variation was firstly explored, where fixed effects followed this general equation: MULTDV ~ TIME + Trait EI variable + IAT variable, and the effect of TIME was randomised across patients (~TIME | id). MULTDV refers to the dependent variable tested, for which four different objects were fitted in stacked format (i.e., long) to assess models for each outcome variable longitudinally. Secondly, slope variation
was investigated through this general equation: \( \text{MULTDV} \sim \text{TIME} + \text{Trait EI variable} \times \text{IAT variable} \), and the effect of TIME was also randomised across patients, as previously mentioned. Cross-level slope variations between patient Global trait EI and therapist Global trait EI replicated the same structure. All cross-level analyses included the grand mean centring of the level one variable (i.e., trait EI patient variable). Moreover, the correlation structure implemented in the analyses was AR (1), as informed in the method, which took the form of ~1 | id in all the multilevel equations implemented in the study.

5.3.12.1–Intercept Variations Between Trait EI and Alliance Measures. The effects of patient trait EI variables (i.e., Global trait EI, Well-being and Self-control) largely explained the variance of the overall outcome and symptom distress, as depicted in Appendices A31 and A32, respectively. In contrast, none of the alliance measures had a significant role. When trait EI patient independent variables were contrasted with the therapist alliance measures, the magnitude of the trait EI effects was unaltered from the previous analysis, as depicted in Appendices A33 and A34.

Therapist trait EI intercept variations had a weaker effect over psychotherapeutic outcomes in the earlier cross-level analyses. These effects remained broadly negligible across patient’s and therapist’s alliance measures, as well as to the psychological intervention (i.e., TIME). However, some exceptions should be highlighted. Therapist Global trait EI remained a significant predictor for the overall psychotherapeutic outcome, whereas patient total-alliance, patient bond-alliance and patient goals-alliance did not. Therefore, therapist Global trait EI was positively associated with the overall psychotherapeutic outcome, meaning that the higher therapist’s Global trait EI, the higher the overall outcome, and consequently the higher the patient’s psychological
disturbance from intake to the end of the study. In contrast, none of the alliance variables included in the model predicted this outcome significantly.

Similarly, therapist Self-control significantly predicted symptom distress compared to patient-total-alliance, and patient-goals-alliance, when these variables were introduced in the respective models. Therefore, therapist Self-control was positively associated with symptom distress, meaning that the higher therapist’s Self-control, the higher patient’s symptom distress from intake to the end of the study. However, the alliance measures did have a significant albeit modest predictive role in these contrasts. Likewise, therapist Self-control predicted symptom distress significantly when compared to patient-tasks-alliance. Moreover, therapist Self-control also predicted the overall outcome vis-à-vis patient-goals-alliance. Consequently, the higher therapist’s Self-control, the higher symptom distress and overall outcome. In both models, high scores of therapist Self-control predicted high values of patient’s psychological disturbance from intake to the end of the study. Here, none of the alliance variables included in the models predicted the outcomes significantly.

Therapist Emotionality did not predict the overall outcome significantly vis-à-vis alliance measures (see Appendices A33 and A34). However, therapist Sociability significantly predicted symptom distress when compared to patient goals-alliance, although this alliance variable had a stronger effect in the model. Therefore, therapist Sociability was positively associated with symptom distress, meaning that the higher therapist’s Sociability, the higher patient’s symptom distress from intake to the end of the study.

5.3.12.2–Slope Variations Between Trait EI and Alliance Measures. Interactions were tested between the trait EI independent variables and alliance measures on the overall outcome and symptom distress. The results revealed interactions between patient Self-control and
therapist total-alliance on symptom distress, meaning that therapist total-alliance moderated the effect of patient Self-control on this outcome. In other words, therapist total alliance longitudinally reduced the negative impact of excessive patient Self-control on symptom distress from intake to the end of the research.

In addition, therapist Global trait EI interacted with patient tasks-alliance and patient goals-alliance on symptom distress, meaning that patient tasks-alliance moderated the effect of therapist Global trait EI on this outcome. In other words, patient tasks-alliance longitudinally reduced the negative impact of excessive therapist Global trait EI on symptom distress from intake to the end of the research. With respect to the overall psychotherapeutic outcome, therapist Global trait EI significantly interacted with patient goals-alliance, meaning that patient goals-alliance moderated the effect of therapist Global trait EI on this outcome. In other words, patient goals-alliance longitudinally reduced the negative impact of excessive therapist Global trait EI on the overall outcome from intake to the end of the study.

At the factor-level of trait EI, therapist Well-being interacted with patient tasks-alliance on symptom distress and the overall outcome, meaning that patient tasks-alliance moderated the effect of therapist Global trait EI on these outcomes. These interactions predicted an attenuation in patient’s symptom distress and the overall outcome from intake to the end of the study. Likewise, therapist Well-being interacted with patient total-alliance and patient-goals-alliance on symptom distress and the overall outcome. Patient total-alliance and patient goals-alliance moderated the effect of therapist Well-being on these outcomes, as these interactions predicted a substantial diminution in patient’s symptom distress and the overall outcome from intake to the end of the study.
Therapist Self-control interacted significantly with patient tasks-alliance and patient goals-alliance on symptom distress. Patient tasks-alliance and patient goals-alliance moderated the effect of therapist Self-control on this outcome. These interactions predicted a substantial reduction in patient’s symptom distress from intake to the end of the study, as these alliance variables protected against the deleterious effects of therapist Self-control on outcomes. Similarly, therapist Sociability interacted with patient tasks-alliance and patient goals-alliance on symptom distress. These interactions were also significant for the overall outcome, meaning that patient tasks-alliance and patient goals-alliance moderated the effect of therapist Sociability on these outcomes. Once more, the interactions predicted a decrease in outcomes from intake to the end of the study, anticipating an improvement in patient’s psychological welfare. Therefore, these alliance variables also protected against the deleterious effects of therapist Sociability on outcomes. All these analyses are fully depicted in Table 15.

5.3.13–Cross-level Slope Variations Between Patient Global Trait EI and Therapist Global Trait EI

This step in the multilevel analysis examined if there was an interaction between patient and therapist trait EI on psychotherapeutic outcomes. For simplicity, reliability and consistency with the rationale and results formerly reported, the first examination was of the interaction of patient and therapist Global trait EI effects over the overall outcome and symptom distress, whilst the second was on the interaction between patient’s and therapist’s total alliances over the aforementioned outputs. These analyses confirmed the crucial role of trait EI for symptom distress and the overall outcome, which exceeded total alliance effects of both patients and therapists. The interaction effect between therapist and patient trait EI predicted changes in symptom distress better than the effects of the psychotherapeutic intervention in the augmented
model (i.e., the one including the interaction between therapist’s and patient’s alliances).

Therefore, the models including the main effects of time, therapist and patient’s trait EI, as well as the interaction between the last two on the overall outcome and symptom distress explained more variance than the augmented models formerly described, as proved by the goodness of fit statistics of these models portrayed in Table 16. These interactions are illustrated in Figure 10, where it is possible to observe that patients high in trait EI reached a steeper reduction of both the overall outcome and symptom distress from intake to the end of the study when treated by therapists high in trait EI in comparison with those patients low in trait EI treated by therapists low in trait EI.
**Table 15. Slope Variations between Trait EI and Alliance Measures on Outcomes**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>B</th>
<th>SEB</th>
<th>tB</th>
<th>Adj. p</th>
<th>β</th>
<th>95% CI β</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>-2LL</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SEB</td>
<td>tB</td>
<td>Adj. p</td>
<td>β</td>
<td>95% CI β</td>
<td>df</td>
<td>AIC</td>
<td>BIC</td>
<td>-2LL</td>
<td>ICC</td>
</tr>
<tr>
<td>GTEIt*IAT-goals-p</td>
<td>-0.33</td>
<td>0.14</td>
<td>2.59*</td>
<td>.018</td>
<td>-0.18</td>
<td>[-0.33, -0.03]</td>
<td>63</td>
<td>1114.52</td>
<td>1143.11</td>
<td>1094.52</td>
<td>0.84</td>
</tr>
<tr>
<td>WBt*IAT-tasks-p</td>
<td>-0.36</td>
<td>0.15</td>
<td>2.39*</td>
<td>.027</td>
<td>-0.23</td>
<td>[-0.43, -0.04]</td>
<td>63</td>
<td>1119.65</td>
<td>1148.25</td>
<td>1099.66</td>
<td>0.84</td>
</tr>
<tr>
<td>WBt*IAT-total-p</td>
<td>-0.13</td>
<td>0.05</td>
<td>2.05*</td>
<td>.024</td>
<td>-0.23</td>
<td>[-0.41, -0.04]</td>
<td>63</td>
<td>1122.35</td>
<td>1150.95</td>
<td>1102.36</td>
<td>0.84</td>
</tr>
<tr>
<td>WBt*IAT-goals-p</td>
<td>0.36</td>
<td>0.12</td>
<td>2.92**</td>
<td>.007</td>
<td>-0.23</td>
<td>[-0.38, -0.07]</td>
<td>63</td>
<td>1115.93</td>
<td>1144.53</td>
<td>1095.94</td>
<td>0.84</td>
</tr>
<tr>
<td>SBt*IAT-tasks-p</td>
<td>-0.37</td>
<td>0.15</td>
<td>2.49*</td>
<td>.017</td>
<td>-0.21</td>
<td>[-0.38, -0.04]</td>
<td>63</td>
<td>1113.49</td>
<td>1142.09</td>
<td>1093.50</td>
<td>0.84</td>
</tr>
<tr>
<td>SBt*IAT-goals-p</td>
<td>-0.44</td>
<td>0.13</td>
<td>3.38**</td>
<td>.001</td>
<td>-0.24</td>
<td>[-0.39, -0.10]</td>
<td>63</td>
<td>1105.70</td>
<td>1134.30</td>
<td>1085.70</td>
<td>0.85</td>
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</table>

**Model Symptom distress**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>B</th>
<th>SEB</th>
<th>tB</th>
<th>Adj. p</th>
<th>β</th>
<th>95% CI β</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>-2LL</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCP*IAT-total-t</td>
<td>-0.34</td>
<td>0.16</td>
<td>2.10*</td>
<td>.071</td>
<td>-0.33</td>
<td>[-0.65, -0.02]</td>
<td>63</td>
<td>1028.15</td>
<td>1056.75</td>
<td>1008.14</td>
<td>0.85</td>
</tr>
<tr>
<td>GTEIt*IAT-tasks-p</td>
<td>-0.24</td>
<td>0.12</td>
<td>2.07*</td>
<td>.046</td>
<td>-0.19</td>
<td>[-0.37, -0.01]</td>
<td>63</td>
<td>1033.50</td>
<td>1062.10</td>
<td>1013.50</td>
<td>0.83</td>
</tr>
<tr>
<td>GTEIt*IAT-goals-p</td>
<td>-0.27</td>
<td>0.10</td>
<td>2.78**</td>
<td>.007</td>
<td>-0.20</td>
<td>[-0.35, -0.06]</td>
<td>63</td>
<td>1027.91</td>
<td>1056.51</td>
<td>1007.90</td>
<td>0.84</td>
</tr>
<tr>
<td>WBt*IAT-tasks-p</td>
<td>-0.30</td>
<td>0.11</td>
<td>2.82**</td>
<td>.009</td>
<td>-0.27</td>
<td>[-0.46, -0.08]</td>
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<td>1032.24</td>
<td>1060.84</td>
<td>1012.24</td>
<td>0.84</td>
</tr>
<tr>
<td>WBt*IAT-total-p</td>
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<td>0.04</td>
<td>2.84**</td>
<td>.008</td>
<td>-0.26</td>
<td>[-0.44, -0.08]</td>
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<td>1034.63</td>
<td>1063.22</td>
<td>1014.62</td>
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<tr>
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<td>0.09</td>
<td>3.29**</td>
<td>.003</td>
<td>-0.25</td>
<td>[-0.40, -0.10]</td>
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<td>1027.52</td>
<td>1056.12</td>
<td>1007.52</td>
<td>0.84</td>
</tr>
<tr>
<td>SCt*IAT-tasks-p</td>
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<td>2.64*</td>
<td>.013</td>
<td>-0.28</td>
<td>[-0.49, -0.07]</td>
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<td>1030.40</td>
<td>1058.10</td>
<td>1010.40</td>
<td>0.84</td>
</tr>
<tr>
<td>SCt*IAT-goals-p</td>
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<td>0.01</td>
<td>3.35**</td>
<td>.001</td>
<td>-0.29</td>
<td>[-0.46, -0.12]</td>
<td>63</td>
<td>1024.15</td>
<td>1052.75</td>
<td>1004.16</td>
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</tr>
<tr>
<td>SBt*IAT-tasks-p</td>
<td>-0.27</td>
<td>0.11</td>
<td>2.37*</td>
<td>.021</td>
<td>-0.21</td>
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<td>1031.81</td>
<td>1060.41</td>
<td>1011.80</td>
<td>0.83</td>
</tr>
<tr>
<td>SBt*IAT-goals-p</td>
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<td>0.09</td>
<td>3.36**</td>
<td>.001</td>
<td>-0.25</td>
<td>[-0.39, -0.10]</td>
<td>63</td>
<td>1023.24</td>
<td>1051.84</td>
<td>1003.24</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Figure 9. Alliance Measures Slope Variations Across Dependent Variables and Time
Note. For the x-axis TIME, 0 represents the beginning of the psychological treatment and 1 represents the end of it. Panel A: therapist total-alliance slope on symptom distress. Panel B: therapist total-alliance slope on social role. Panel C: therapist tasks-alliance slope on symptom distress. Panel D: therapist tasks-alliance slope on social role. Panel E: therapist goals-alliance slope on symptom distress. Panel F: therapist goals-alliance on social role. Panel G: patient goals-alliance slope on interpersonal relationships. Panel H: patient goals-alliance slope on social role.
Table 16. Patient’s and Therapist’s Trait EI and Alliance Interactions on the Overall Outcome and Symptom Distress

<table>
<thead>
<tr>
<th>Predictors in the model</th>
<th>Model Overall outcome</th>
<th>Model Symptom distress</th>
</tr>
</thead>
<tbody>
<tr>
<td>TIME</td>
<td>B</td>
<td>SEB</td>
</tr>
<tr>
<td>TIME</td>
<td>-7.91</td>
<td>2.21</td>
</tr>
<tr>
<td>GTEIp</td>
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</tr>
<tr>
<td>GTEIt</td>
<td>3.93</td>
<td>1.80</td>
</tr>
<tr>
<td>GTEIp*GTEIt</td>
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<td>2.72</td>
</tr>
<tr>
<td>TIME</td>
<td>-5.30</td>
<td>1.58</td>
</tr>
<tr>
<td>GTEIp</td>
<td>-6.91</td>
<td>1.37</td>
</tr>
<tr>
<td>GTEIt</td>
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<td>1.25</td>
</tr>
<tr>
<td>GTEIp*GTEIt</td>
<td>-6.16</td>
<td>1.90</td>
</tr>
<tr>
<td>TIME</td>
<td>-7.91</td>
<td>2.21</td>
</tr>
<tr>
<td>GTEIp</td>
<td>-6.76</td>
<td>2.09</td>
</tr>
<tr>
<td>GTEIt</td>
<td>4.39</td>
<td>1.93</td>
</tr>
<tr>
<td>IAT-Total-p</td>
<td>0.51</td>
<td>1.24</td>
</tr>
<tr>
<td>IAT-Total-t</td>
<td>0.50</td>
<td>1.27</td>
</tr>
<tr>
<td>GTEIp*GTEIt</td>
<td>-5.17</td>
<td>3.04</td>
</tr>
<tr>
<td>IAT-T-p*IAT-T-t</td>
<td>-0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>TIME</td>
<td>-5.30</td>
<td>1.58</td>
</tr>
<tr>
<td>GTEIp</td>
<td>-6.76</td>
<td>1.45</td>
</tr>
<tr>
<td>GTEIt</td>
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<td>1.34</td>
</tr>
<tr>
<td>IAT-Total-p</td>
<td>-0.18</td>
<td>0.86</td>
</tr>
<tr>
<td>IAT-Total-t</td>
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<td>0.88</td>
</tr>
<tr>
<td>GTEIp*GTEIt</td>
<td>-5.88</td>
<td>2.11</td>
</tr>
<tr>
<td>IAT-T-p*IAT-T-t</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Figure 10. Patient’s and Therapist’s Global Trait EI Interactions Plot on the Overall Outcome and Symptom Distress

Note. Panel A: patient global trait EI and therapist global trait EI on overall outcome. Panel B: patient global trait EI and therapist global trait EI on symptom distress.
5.3.14–Cross-level Slope Variations Between Patient Factor-level Trait EI and Therapist Factor-level Trait EI

The last step in the multilevel analysis examined if there was any interaction between patient and therapist trait EI at the factor-level on the overall outcome and symptom distress. In addition to contrasting trait EI at the factor-level between the dyads, combinations of Global trait EI and factor-level scores were tested for interactions, which was more informative than direct factor-level interactions in most cases. These analyses followed a similar trend to the prior section. Factor-level trait EI cross-level interactions between patients and therapists were contrasted with patient’s and therapist’s alliance scores interactions on the overall outcome and symptom distress. Here, not only patient’s and therapist’s Global alliance interactions were tested, but also their factor-level scores, i.e., bond, tasks, and goals (see section 5.2.2.3, in the present chapter). As expected, taking account of the results described in table 16, none of the possible alliance interaction terms played a significant predictive role compared to the trait EI factor-level interactions terms in each of these models.

The interactions in these models are depicted in table 17 and illustrated in Figure 11. In these, the magnitude of the interaction effects was greater on symptom distress than the overall outcome. Likewise, all these moderations were of negative sign, meaning they reduced either the overall psychological distress or symptom distress of patients, as a product of trait EI moderation effects between patient and therapist.

Patient’s Well-being interacted with therapist’s Global trait EI on symptom distress, meaning that patients high in Well-being treated by therapists high in Global trait EI showed a steeper reduction on symptom distress than those patients low in Well-being treated by therapists low in Global trait EI from intake to the end of the study (see Figure 11, panel A).
Patient Well-being and therapist Well-being interacted at a substantial degree on symptom distress, meaning that therapist Well-being moderated the effect of patient’s Well-being on this outcome. Therefore, patients high in Well-being treated by therapists high in Well-being showed a steeper decrease in symptom distress than those patients low in Well-being treated by therapists low in Well-being EI from intake to the end of the research (see Figure 11, panel B).

Patient’ Sociability and therapist’ Well-being interacted significantly on the overall outcome, meaning that therapist’ Well-being moderated the effect of patient ‘Sociability on this outcome. Therefore, patients high in Sociability treated by therapists high in Well-being showed a steeper decrease in symptom distress than those patients low in Sociability treated by therapists low in Well-being from intake to the end of the study (see Figure 11, panel C).

Therapist’ Well-being interacted at a high degree with patient’ Global trait EI on symptom distress, meaning that therapist’ Well-being moderated the effect of patient’ Global trait EI on this outcome. Therefore, patients high in Global trait EI treated by therapists high in Well-being showed a steeper decrease in symptom distress than those patients low in Global trait EI treated by therapists low in Well-being from intake to the end of the research (see Figure 11, panel D). This model presented the best fit from all the trait EI factor-level interactions studied at this stage, and consequently explained the highest percentage of variance, as shown by the intraclass correlation coefficient, being even more substantial than the effect of the psychotherapeutic intervention (i.e., TIME), as can be appreciated in Table 17.

Patients ‘Global trait EI interacted with both therapist ‘Self-Control and Emotionality on symptom distress at a comparable degree, meaning that therapist’ Self-Control moderated the effect of patient’ global trait on this outcome. Therefore, patients high in Global trait EI treated
by therapists high in Self-Control showed a steeper decrease in symptom distress than those
patients low in Global trait EI treated by therapists low in Self-Control from intake to the end of
the research (see Figure 11, panel E). Similarly, patients high in Global trait EI treated by
therapists high in Emotionality showed a steeper decrease in symptom distress than those
patients low in Global trait EI treated by therapists low in Emotionality from intake to the end of
the research (see Figure 11, panel F).

Patient’ Global trait EI and therapist’ Well-being interacted on the overall outcome,
meaning that therapist’ Well-being moderated the effect of patient’ Global trait EI on this
outcome. Therefore, patients high in Global trait EI treated by therapists high in Well-being
showed a steeper decrease in the overall outcome than those patients low in Global trait EI
treated by therapists low in Well-being from intake to the end of the research (see Figure 11,
panel G).
Table 17. Patient’s and Therapist’s Factor-Level Trait EI Interactions on the Overall Outcome and Symptom Distress

<table>
<thead>
<tr>
<th>Predictors in the model</th>
<th>B</th>
<th>SEB</th>
<th>tB</th>
<th>Adj. p</th>
<th>β</th>
<th>95%CIβ</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>-2LL</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model Overall outcome</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME</td>
<td>-7.91</td>
<td>2.21</td>
<td>3.57***</td>
<td>.004</td>
<td>-0.24</td>
<td>[-0.37, -0.10]</td>
<td>66</td>
<td>1097.25</td>
<td>1136.80</td>
<td>1088.20</td>
<td>0.85</td>
</tr>
<tr>
<td>SBp</td>
<td>21.88</td>
<td>11.23</td>
<td>1.95</td>
<td>.075</td>
<td>-0.23</td>
<td>[-0.43, -0.04]</td>
<td>63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WBt</td>
<td>1.11</td>
<td>1.86</td>
<td>0.60</td>
<td>.553</td>
<td>0.06</td>
<td>[-0.15, 0.27]</td>
<td>63</td>
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<td></td>
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<tr>
<td>SBp*WBt</td>
<td>-4.66</td>
<td>2.08</td>
<td>2.24*</td>
<td>.058</td>
<td>-0.24</td>
<td>[-0.46, -0.03]</td>
<td>63</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| **Model Symptom Distress** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -5.30 | 1.58   | -3.36** | .004  | -0.22 | [-0.35, -0.09] | 66   | 1007.57 | 1036.17 | 987.58  | 0.87 |
| WBp                     | 9.92  | 6.04   | 1.64  | .140   | -0.40 | [-0.57, -0.23] | 63   |          |          |         |      |
| GTEIt                   | 1.59  | 1.24   | 1.29  | .204   | 0.11  | [-0.06, 0.26]  | 63   |          |          |         |      |
| WBp*GTEIt               | -2.62 | 1.10   | -2.38* | .040   | -0.22 | [-0.40, -0.04] | 63   |          |          |         |      |

| **Model Overall outcome** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -7.91 | 2.21   | 3.57*** | .004  | -0.24 | [-0.37, -0.10] | 66   | 1098.01 | 1126.60 | 1078.00 | 0.86 |
| GTEIp                   | 24.87 | 12.63  | 1.97*** | .072  | -0.34 | [-0.52, -0.17] | 63   |          |          |         |      |
| WBt                     | 2.70  | 1.54   | 1.75  | .090   | 0.15  | [-0.02, 0.32]  | 63   |          |          |         |      |
| GTEIp*WBt               | -5.84 | 2.25   | 2.60* | .024   | -0.24 | [-0.43, -0.06] | 63   |          |          |         |      |

| **Model Symptom Distress** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -5.30 | 1.58   | -3.36** | .004  | -0.22 | [-0.35, -0.09] | 66   | 1008.15 | 1036.75 | 988.16  | 0.87 |
| WBp                     | 9.59  | 5.64   | 1.70  | .125   | -0.39 | [-0.56, -0.21] | 63   |          |          |         |      |
| WBt                     | 1.15  | 1.07   | 1.08  | .287   | 0.09  | [-0.08, 0.25]  | 63   |          |          |         |      |
| WBp*WBt                 | -2.38 | 0.95   | -2.51* | .030   | -0.23 | [-0.41, -0.05] | 63   |          |          |         |      |

| **Model Symptom Distress** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -5.30 | 1.58   | -3.36** | .004  | -0.22 | [-0.35, -0.09] | 66   | 1006.59 | 1035.19 | 986.58  | 0.87 |
| GTEIp                   | 23.98 | 8.71   | 2.75** | .011  | -0.42 | [-0.59, -0.26] | 63   |          |          |         |      |
| WBt                     | 1.22  | 1.06   | 1.14  | .257   | 0.09  | [-0.07, 0.26]  | 63   |          |          |         |      |
| GTEIp*WBt               | -5.54 | 1.55   | -3.57*** | .002  | -0.31 | [-0.49, -0.14] | 63   |          |          |         |      |

| **Model Symptom Distress** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -5.30 | 1.58   | -3.36** | .004  | -0.22 | [-0.35, -0.09] | 66   | 1010.84 | 1039.44 | 990.84  | 0.87 |
| GTEIp                   | 12.12 | 7.87   | 1.54  | .172   | -0.43 | [-0.60, -0.09] | 63   |          |          |         |      |
| SCt                     | 1.27  | 1.09   | 1.16  | .250   | 0.10  | [-0.07, 0.28]  | 63   |          |          |         |      |
| GTEIp*SCt               | -3.94 | 1.65   | -2.39* | .040   | -0.23 | [-0.43, -0.04] | 63   |          |          |         |      |

| **Model Symptom Distress** |       |        |      |        |       |        |      |          |          |         |      |
| TIME                    | -5.30 | 1.58   | -3.36** | .004  | -0.22 | [-0.35, -0.09] | 66   | 1013.29 | 1041.89 | 993.30  | 0.87 |
| GTEIp                   | 12.21 | 7.99   | 1.53  | .176   | -0.41 | [-0.58, -0.24] | 63   |          |          |         |      |
| EMt                     | 0.61  | 1.12   | 0.55  | .587   | 0.05  | [-0.13, 0.22]  | 63   |          |          |         |      |
| GTEIp*EMt               | -3.59 | 1.52   | -2.37* | .021   | -0.20 | [-0.38, -0.03] | 63   |          |          |         |      |

Note. B: slope of the independent variable, SEB: standard error of the independent variable, tB: t-value of the independent variable, Adj. p = Adjusted p-value (FDR), β: standardised beta coefficient of the independent variable, 95%CIβ: 95% confidence interval of the standardised coefficients in the models, df: degrees of freedom, AIC: Akaike information criterion, BIC: Bayesian information criterion, -2LL: -2 Log likelihood, ICC: intraclass correlation, GTEIp: patients’ global trait EI, WBp: patients’ well-being, SBp: patients’ sociability, GTEIt: therapists’ global trait EI, WBt: therapists’ well-being, SCt: therapists’ self-control, EMt: therapists’ emotionality. * p < .05, ** p < .01, *** p < .001.
Figure 11. Patient’s and Therapist’s Factor-Level Trait EI Interactions Plots on the Overall Outcome and Symptom Distress
5.4 Discussion

The present study investigated the role of trait emotional intelligence in psychotherapy. The research contributes to the examination of the relational patterns and psychotherapeutic outcomes of patient-therapist dyads, as claimed of great need in the clinical literature (e.g., Schattner & Tishby, 2018). The findings suggest a beneficial effect of patient trait EI on psychopathology, even after accounting for the effect of psychological treatment on psychotherapeutic outcomes, similar to what Petrides et al. (2017) have suggested from earlier research. Thus, supporting the first general hypothesis suggesting beneficial patient trait EI effects on outcomes. The adverse effects of therapist trait EI on outcomes are counterintuitive and do not support at first glance the second general hypothesis proposing advantageous therapist trait EI effects on outcomes. However, later stages in the data analytic approach suggested otherwise, as the interaction between patient and therapist trait EI reduced most psychotherapeutic outcomes, being thus valuable for patient’s psychological welfare.

Moreover, the counterintuitive findings regarding therapist trait EI on outcomes can be understood under the belief-importance theory (i.e., BELIMP, see Petrides, 2010, 2011a). According to Petrides (2010), personality traits confer a propensity to perceive convergences and divergences between individuals’ beliefs regarding goals and the importance that their place on these goals. Within this framework, belief and importance are envisioned as two coordinates defining the BELIMP plane, which is composed of four quadrants (i.e., hubris, motivation, depression, and apathy). Therefore, therapists high in hubris may be less likely to recognise divergences on treatment goals and their importance to psychotherapy, especially when paired with patients high in depression (which is theoretically linked to big five’s neuroticism). Similarly, therapists high in motivation may be less likely to engage in concealed treatment goals
with those patients high in apathy (which is theoretically equivalent to big five’s low in extraversion, i.e., introversion). In other words, therapists high in trait EI may unintentionally affect patient outcomes through their excessive hubris, whereas those high in consciousness may affect patient outcomes through their excessive sense of achievement and assertiveness. Petrides (2010) have provided evidence on the stance that high scorers on global trait EI suffer from exaggerated pride or self-confidence, and that high scorers on conscientiousness are spatially at the extreme of those scoring high in apathy, which in terms of trait EI would be considered as low global trait EI. Thus, supporting the abovementioned hypotheses regarding a mismatch between patient and therapist that can be traced to unique personality factor space’s relationships replicating in psychotherapy.

Although alliance measures had a mostly tangential role in predicting psychotherapeutic outcome, the interaction between therapist’s alliance measures and the effects of time predicted all outcome variables other than the overall outcome (see Figure 9). Similarly, the interaction between therapist trait EI independent variables and patient alliance measures predicted more outcome variance than the interaction between patient trait EI independent variables and any alliance measure studied. This supported the first specific hypothesis, which stated that there would be meaningful interactions between therapist’s trait EI and patient’s alliance; and provided less substantial support for the second specific hypothesis, claiming there would be significant interactions between patient’s trait EI independent variables and patient’s alliance. Moreover, the study of the interaction between trait EI and the alliance provides a novel pathway for comprehending the relationship between the alliance and other relational constructs in psychotherapy, which has been claimed as urgently necessary in the alliance literature (e.g., Horvath, 2018b). Perhaps, this relates to the distinction between trait and state alliance as
defined by Zilcha-Mano (2017), in which the trait elements refer to the stable characteristics of the therapeutic relationship, whereas the state elements depict the more volatile session by session relational turns of the relationship during therapy. This interpretation would be certainly in line with the findings hereby portrayed for patients, as patient trait EI effects followed the same direction that patient alliance regarding psychotherapeutic outcomes. In this regard, state elements of the alliance were not registered in the study, and consequently, their relationship to trait EI on psychotherapeutic outcomes remains unexplored.

Moreover, given that the differential patient effects in the extant psychotherapy literature have been shown to depend on a number of transdiagnostic patient characteristics, such as culture, therapy preferences, religion, attachment style, overall defensive functioning, and affiliative behaviours, as presented in chapter two, it seems sensible to envisage the mismatch of patient and therapist trait EI in the therapeutic setting as a potential source of alliance disruption, not explained by the interaction between patient and therapist alliance variables (Table 16). For instance, Pizer (1998) posed that beyond the negotiation of goals and tasks, which are explicit in the therapeutic dialogue, the consideration of dyads’ wishes and expectations may exert a role on psychotherapeutic outcomes. This is congruent with the earlier findings of Arora et al. (2011), who suggested that practitioner trait EI effects on outcomes are circumscribed to the specific professional and interpersonal scenario in which they are deployed, as these authors examined trait effects in medical undergraduates at surgical settings. This early finding has been confirmed for psychotherapy by Firth et al. (2020) and Johns et al. (2019), researchers that informed of therapist effects varying on the type of health facility in which patients are treated.

In the present study, the psychotherapeutic settings in which the psychological intervention was implemented were fairly homogeneous between university mental health
centres. Therefore, therapist effects were likely to be explained by personality traits and the interpersonal interactions between patient and therapist, as depicted by the data analytic approach based on trait EI and the alliance. This approach is consistent with Beutler et al. (2004), who have advocated for research aimed to examine therapist effects beyond therapeutic approaches or patient diagnosis, as traditionally conducted, and focus instead on observable and latent traits of the therapist, as implemented in the present research through the study of trait effects across psychotherapeutic dyads. Further evidence of trait therapist effects on psychotherapeutic outcomes has been recently provided by Delgadillo et al. (2020). These authors reported worse outcomes when patients were treated by therapists high in agreeableness and openness to experience, which resembles the somewhat iatrogenic main effect of therapist trait EI described earlier in this chapter. Perhaps, it is more interesting for the clinical practitioner how these effects translated into a reduction of patient’s psychological disturbance when patient and therapist trait EI variables interacted, as well as when trait independent variables interacted with alliance measures. This highlights the point made by Norcross and Lambert (2019) regarding the difficulty in establishing causal paths between the therapeutic alliance and outcomes, which becomes more intricate when introducing the interplay of dyadic personality measures as performed in the present chapter. Future research may elucidate whether this hypothesis remains viable and empirically valid.

Regarding the third specific hypothesis, which stated that there would be meaningful interactions between patient’s and therapist’s trait EI variables on the overall psychotherapeutic outcome and symptom distress, the findings herein reported provided support for this claim across global and factor-level trait independent variables. Moreover, patient and therapist’s Global trait EI remained significant predictors for symptom distress and the overall outcome
even after the inclusion of patient and therapist alliance effects, and their interaction. The effect of this interaction on symptom distress was of comparable magnitude to the psychological intervention (i.e., TIME), as presented in Table 16. This finding illustrates how strongly patient trait EI and therapist trait EI converge, accounting for a noticeable amount of outcome variance not previously reported in the psychotherapy literature, albeit anticipated in the trait EI literature (e.g., Petrides et al., 2017). Similarly, the interaction between patient Global trait EI and therapist Well-being on symptom distress accounted for substantial variance, as more discrete interplays between other trait variables did when the model included at least one trait EI factor-level independent variable (see Table 17, and Figure 11). It is convenient framing these interactions between emotional intelligences through the BELIMP framework, as previously presented (see Petrides, 2010). Therefore, it is possible to infer that patient Global trait EI somehow compensates the negative effects of therapist Global trait EI on outcomes.

Remarkably, patient trait EI consistently explained more outcome variance than therapist trait EI, in line with the substantial contribution from patient’s personality to psychotherapeutic outcomes, which largely submerged the effects of the therapeutic alliance and the theoretical psychotherapeutic approach (Lambert, 2013; Norcross & Lambert, 2019). Nonetheless, therapist Global trait EI, Self-control and Sociability, negatively predicted the overall outcome and interpersonal relationships (see Appendix A32), rendering support to therapist’s effects supported by trait EI. Here, it is worth recalling that the higher the score, the worse the psychotherapeutic outcome for patients. Therefore, the impact and direction on the outcomes was distinguishable whether it derived from patient trait EI or therapist trait EI, as the former were significant on the overall outcome and symptom distress mostly, and the latter typically affected the overall outcome and interpersonal relationships.
Theoretically and statistically, trait well-being and state well-being are linked (e.g., Martins et al., 2010, and section 2.2 of the dissertation). As presented in Figure 6 and Appendix A29, patient Well-being (trait EI) was negatively and substantially correlated to the symptoms scale (i.e., OQ_SD_1, $r = -.65$) and overall outcome of the dependent variable (i.e., OQ_TOTAL_1, $r = -.45$), as it was patient Global trait EI (i.e., OQ_SD_1, $r = -.60$; OQ_TOTAL_1, $r = -.50$), and patient Self-control (i.e., OQ_SD_1, $r = -.48$; OQ_TOTAL_1, $r = -.42$). However, it is worth highlighting that although trait well-being is correlated and lexically identical to state well-being, the former refers to personality dispositions towards fulfilment and happiness (see Petrides, 2009, and section 2.2 of the dissertation), whereas the latter refers to a critical balance between positive and negative affect, which is driven by cognitive evaluations, instead of personality dispositions (Toussaint & Friedman, 2009). For instance, overall outcome (i.e., OQ_TOTAL) in the OQ-45.2 questionnaire correlates very highly ($r = .81$, Lambert, Hansen et al. 1996) with Friedman’s Well-being scale (1994), which assesses state well-being. However, in the present study, the zero-order correlation between trait Well-being and the overall outcome was much lower (i.e., OQ_TOTAL), being close to a halve of what Lambert et al. reported when comparing Friedman’s Well-being scale with the OQ-45.2. This is a shred of evidence that although the two Well-being constructs resemble, they are not the same.

A trend of large effect sizes was observed for the trait EI independent variables when the dependent variables examined in the multilevel models were overall outcome and symptom distress. This tendency was especially noticeable when including the effects of patient and therapist’s Global trait EI and excluding alliance measures (Table 16), as well as when studying trait EI interaction effects between patients and therapists on both the overall outcome and symptom distress, as displayed in Table 17 and Figure 10. The contribution of patient’s trait EI
to these outcomes was robust at the factor level for Well-being as well as to Self-control corroborating the findings of former studies conducted with the TEIQue-SF (Siegling, Furnham, et al., 2015). Thus, these predictors, along with Global trait EI, played a substantial role in explaining patient’s symptomatology and the overall psychotherapeutic outcome. The contribution of therapist’s trait EI at the factor-level is novel. The findings concerning therapist-trait EI’ main effects failed to provide full support to the second general hypothesis (i.e., a positive effect of therapist trait EI on psychotherapeutic outcomes). However, they did sustain the third specific hypothesis, stating that meaningful interactions between patient’s and therapist’s trait EI independent variables would predict substantial reductions on the overall psychotherapeutic outcome and symptom distress, and thus an improvement in patient’s psychological welfare. The difference in these outcomes from intake to the end of the study is greatly reduced between patients with low trait EI and those with high trait EI when treated by therapists high in trait EI, as illustrated in Figure 10.

Studying psychotherapeutic processes in their naturalistic settings offers important advantages in comparison to experimental designs, which are potentially unfeasible to apply to the research aims herein explored. For instance, although the lack of randomisation is a limitation of the present study, approaching psychotherapeutic dyads with minimal intervention presented an opportunity for studying the phenomenon with greater ecological validity (Cook & Campbell, 1979; Shadish et al., 2002). Additionally, the COSMIN study design checklist supports the methodological quality of the study and its comparability with typical longitudinal research, as the methodological standard of the study included in the present chapter can be labelled as very adequate for most criteria, with the only exception of the sample size criterion which lowers the quality to the adequate category.
Homogeneous subset analyses revealed that the sample in the current investigation was distinctly different in trait EI means from two sociodemographic comparable samples drawn from general population. This renders additional support for the inclusion of trait EI measures as potential predictors of psychotherapeutic outcomes, since the present investigation’s findings suggest that clinical populations experience lowers levels of trait EI before any psychological treatment has taken place. Moreover, the extent of the trait EI prospective effects are large (after the intervention starts) compared to the alliance and the anticipated beneficial effects of the psychological intervention across therapists and centres.

In summary, the present investigation of the trait EI effects on psychotherapeutic outcomes reveals that both patient and therapist’s trait emotional intelligence play a substantial role in explaining the outcome of psychotherapy, independently of alliance and other contextual correlates. Theoretically, the research contributes to the therapeutic factor model accounting for formerly unexplained outcome variance. It accomplishes this by unravelling the previously unexplored role of patient’s and therapist’s trait EI regarding psychotherapeutic outcomes and the interplay of trait EI effects with the alliance. In practice, the revealed trait EI effects on psychotherapeutic outcomes command for serious consideration of the construct in the genesis, maintenance, and evolution of psychological treatment. Therefore, the inclusion of trait EI measures in psychotherapy to assess the suitability of patients to psychotherapy is supported, as high trait EI individuals would benefit less from treatment than those with low trait EI, and to avoid therapists could exert a deleterious effect on outcomes as a result of excessively low or high trait EI.
5.4.1—Limitations and Future Research

A limitation of the study was not following up a general population control group to longitudinally compare trait EI and psychological outcomes between this group and the studied clinical sample. This inclusion could have yielded further evidence for or against the temporal stability of trait EI across samples and inform on potential interactions between participants’ history and the psychological treatment (Cook & Campbell, 1979). However, scholars have the assured knowledge after several decades of compelling research that psychotherapy works and is no longer a subject of debate (Norcross & Lambert, 2019; Wampold & Imel, 2015). In the present study, this was demonstrated through the noticeable changes across psychotherapeutic outcomes from intake to final assessment.

Likewise, given that trait EI is defined as a stable personality characteristic, as opposed to a state (see Petrides, 2009), it seems unlikely trait EI changes among patients might bias the results. Indeed, potential trait EI changes among patients, if assessed longitudinally, should align with the results of the intervention (i.e., psychotherapeutic outcomes), as demonstrated in the present study. Notwithstanding, a second trait EI measurement at the end of treatment could have been informative to prove this statement empirically, as this would have allowed a crossed panel model to bolster the inference of causality regarding trait EI effects in psychotherapy. According to Kenny (1975, 2014), a cross-lagged panel correlation is a method in SEM (i.e., structural equation modelling) that allows testing spuriousness by comparing cross-lagged correlations from a variable measured two or more times (i.e., longitudinally).

Regarding the sample size of the multilevel analysis, Maas and Hox (2005) have indicated that Maximum Likelihood estimations lead to unbiased point estimates and accurate asymptotic standard errors for the first level. Nevertheless, these might suffer from slightly
higher bias from second level onwards with samples comprised of groups lower than fifty clusters. Future research is needed to replicate these findings, and to rule out threats of the design that were not possible to control in the current study. For instance, a sample size closer or over 100 individuals at the patient level and 50 at the therapist level, a suitable control group for pre and post-test measures, the inclusion of external validating measures regarding outcomes (e.g., Beck Depression Inventory, Beck et al., 1988; Symptom Checklist 90-R, Derogatis, 1994; WHO-5, Topp et al., 2015), and randomisation would be desirable in forthcoming research.
Chapter 6: Summary of the Research

6.1–Introduction

The present dissertation examined key issues contributing to an accurate examination of the role of trait EI in psychotherapy. In this regard, each study was built on the former and altogether contributed to the trait EI literature from a novel perspective. First, the advances in the psychometric investigation of the internal structure of the TEIQue-SF in Latin-America through ESEM and bi-factor modelling provided a fresh, robust, and updated interpretation of the factor structure of this short measure of trait EI in general and clinical populations, which also informed on construct equivalence with the original measure when measurement invariance was conducted at the global and factor-level. Earlier investigations in the region with other trait EI measures and the same TEIQue-SF were unable to provide evidence of comparable value (e.g., Neri-Uribe & Juárez-García, 2016).

Second, cross-cultural research is challenging to implement. Measures in different countries may have variations in the way items are written and in their fundamental meaning, which may prevent comparability across populations. Local bureaucratic barriers may also take a toll on the appropriate comparability across countries. For example, if ethical approval is not obtained according to the research schedule, some researchers may lose the opportunity of including country data in the research. Similarly, substantial differences regarding the temporal interval in which data are collected might bias results. Moreover, the coordination between researchers located in various geographical and time zones, speaking each a distinct native language, may again become an obstacle for conducting this type of endeavours.
Consequently, the additional evidence supporting the invariance of the trait emotional intelligence construct across key sociodemographic variables (i.e., gender, age, and educational attainment) is a novel contribution, informing on the universality of trait EI. It complements what the extant literature had scarcely anticipated about the invariability of the construct regarding gender and age, beyond its proven applicability to WEIRD samples (as discussed in section 2.5.1, chapter two), albeit measurement invariance was not fully supported for civil status and occupation, as there was heterogeneity across the strata of the examined countries, which was especially higher in these variables. Moreover, the findings from chapter four are not limited to measurement invariance only, as the most traditional method for contrasting trait EI means across countries was implemented with univariate analyses of variance. This allowed a straightforward reference to the literature studying sociodemographic differences across populations, albeit measurement error affecting ANOVA (as portrayed in Table 8, chapter four). In contrast, measurement invariance permitted an examination of the role exerted by these sociodemographic correlates on trait EI without this flaw.

Third, having the assured knowledge that the trait EI measure administered in Chile is valid, reliable, and invariant compared to the original TEIQue-SF, the final examination of the role of trait EI in psychotherapy sets the ground for future research addressing psychotherapeutic outcomes, by demonstrating the longitudinal interplay of patient’s trait EI and psychotherapist’s trait EI in predicting therapeutic outcomes. This is the main contribution of the dissertation for personality and clinical psychology research. The systematic investigation of trait EI effects across distinct psychotherapeutic outcomes allowed analysis of the trait EI effects compared to the effects of the alliance and the psychological intervention. This role was formerly unexplored
either in the personality or psychotherapeutic literature. Table 18 summarises the contributions of the dissertation by chapter, as presented at the end of section 6.2.

6.2–Conclusions on the research propositions

6.2.1–Research Propositions Studied in Chapter Three

Studies one and two in chapter three examining the internal factor structure of the Spanish-Chilean-TEIQue-SF fulfilled the gap regarding the use of locally untested foreign trait EI measures. Similarly, these pieces of research added to previously poorly-fitting local trait EI validations in the region, whilst confirming the propositions on the appropriateness of the test when studied through ESEM, bi-factor modelling, and measurement invariance in two fairly large local samples, extracted from general and clinical settings. Examples of unsatisfactory validations in Latin-America are found in Omar et al. (2014) and Neri-Uribe and Juárez-García (2016), as the original factor structure of the TEIQue-SF was not replicated in these studies.

Moreover, the implementation of a blend of linguistic and quantitative techniques during the early linguistic adaptation of the Spanish-Chilean-TEIQue-SF was advantageous. The involvement of professional translators, high-school teachers, as well as other experts in the field that assessed the layout of the questionnaire and provided their valuable feedback, together with the early assessment of reliability in the pilot sample, were all aspects that greatly contributed to the successful development of the studies described in chapter three.

The adopted ESEM-bi-factor interpretation is novel regarding trait EI measures. It responds to the modern advances in the literature stressing the methodological advantages of these approaches for studying the factor structure of a questionnaire in comparison to the classic CFA modelling and hierarchical interpretation of the factor structure (Marsh et al., 2014; Morin
et al., 2015; Perera, 2015). These benefits mainly relate to bi-factor and ESEM being respectively more flexible than a hierarchical interpretation and CFA modelling. This feature permits a more precise psychometric interpretation of most psychological questionnaires presenting factor or facet cross-loadings. Likewise, the presentation of extensive reliability scores for the Spanish-Chilean-TEIQue-SF through Omega, omegaSem and omega total is a psychometric advancement to the classic Cronbach’s Alpha reliability index, whose weaknesses have been extensively discussed in the literature and the present dissertation (e.g., Revelle, 2017, Sjitsma, 2009; Zinbarg et al., 2005).

These foregoing features are non-trivial. They raise the standards regarding psychometric reporting practices and allow for a more sophisticated, up-to-date inspection of psychometric evidence supporting the validity and reliability of personality instruments, and especially of trait EI questionnaires. They also permit more flexible and precise modelling across several statistical hypotheses, as demonstrated in the examination of factor structure measurement invariance in chapter four, which comes as a natural extension of the basic ESEM-bi-factor model tested across several nested invariance models of increasing restrictiveness. Regarding this, it is important to notice that according to current standards, measurement invariance is no longer a desirable or optional analysis providing marginal support for the comparability of a questionnaire across countries or populations, but a fundamental procedure required for demonstrating equivalence between the adapted and the original measure. For instance, Ziegler and Bensch (2013) declared that an instrument lacking any evidence of measurement invariance becomes utterly useless, being always of superior calibre for researchers to provide with some sort of proof of it. This explains why in the progression of the dissertation, measurement invariance was
firstly tested at the factor structure in chapter three, and later expanded to sociodemographic correlates and country comparability in general population data, as described in chapter four.

6.2.2–Research Propositions Studied in Chapter Four

The third study in chapter four provided a comprehensive cross-cultural investigation of trait EI construct invariability across four countries, two European and two Latin-American as well as across five sociodemographic variables (i.e., gender, age, educational level, civil and occupational status). This piece of research filled a void in the literature regarding measurement invariance evidence supporting the invariability of trait EI across different populations and sociodemographic variables, albeit non-invariance was observed for civil and occupational status. Likewise, the research contributed to accumulate cross-cultural evidence on trait EI mean differences supported by formerly unexplored sociodemographic variables, such as educational level, civil and occupational status. Other country-level sociodemographic variables beyond the five analysed in chapter four, are subject to future trait EI cross-cultural investigations. The extant literature had only examined the role of gender on trait EI means through measurement invariance (e.g., Siegling, Furnham et al., 2015; Tsaousis & Kazi, 2013). These two additions to the literature prepared the ground for the examination of trait EI effects in the psychotherapeutic context in chapter five, regardless of possible trait EI mean differences across sociodemographic variables, the presence of scalar non-invariance regarding civil status and occupation, and the potential inclusion of other relevant sociodemographic variables (e.g., socioeconomic status), which did not deter from generalising trait EI findings, despite participants’ sociodemographic differences, as demonstrated in chapter four.
Moreover, aggregate personality scores are scarce in the personality literature (McCrae, 2009; Schmitt et al., 2007), and they are even scarcer in the trait EI literature, as previously introduced. Hence, the usefulness and comparability of the research portrayed in this chapter. Similar cross-cultural personality examinations with well-regarded taxonomies, such as the Big Five and the Six-factor models have rarely attained latent mean equivalence, as study three did for the levels of several sociodemographic variables (cf., Ion et al., 2017; Schmitt et al., 2007; Thielmann et al., 2020). In addition, comparability within and between regions was reached. Latent means resemblance between neighbouring countries was anticipated in the literature (see Allik & McCrae, 2004), as it was the case for the two Latin-American, and the two Europeans countries included in study three. This finding establishes a trace with theoretical approaches linking culture and psychological likeness within geographical regions (e.g., LeVine, 2001; Saucier & Goldberg, 2001).

The findings reporting measurement invariance up to the scalar level for gender, age, and educational achievement, are novel and informative for theory and applied research alike. They allow assessing trait EI confidently with the TEIQue-SF, regardless of mean differences in the aforementioned variables. Likewise, the reported non-invariance for civil and occupational status besides being enlightening for theory, sets the target for future applied research in numerous settings to investigate the impact of these sociodemographic variables on trait EI means in further detail. For instance, different statistical treatment regarding occupational status may yield contrasting results given the virtually infinite combinations that can be drawn for different careers. The way these categories are finally merged, as a result of allocating participants’ responses to predefined groups, could account for potential changes regarding measurement invariance at any of the studied levels (i.e., configural, metric, scalar), especially given the
unbalanced sample size of those groups. Further research is required to either corroborate or refute the sociodemographic differences reported through ANOVAs, which suggested a small-to-moderate effect attributable to the country in which the data was collected regarding Global trait EI mean discrepancies, as well as substantial trait EI variability between the various levels of education, civil status, and occupation across countries.

6.2.3–Research Propositions Studied in Chapter Five

Chapter five examined the propositions comprised in study four. This chapter was explorative in nature, as little prior empirical work assessed the role of trait EI in the extant psychotherapeutic literature. Consequently, the tested hypotheses and chosen methodological approach aimed to portray a complete picture of fixed and random trait EI effects from patient, therapist, and their respective alliance measures. This goal was attained by including the effect of the psychological treatment as a basal independent variable in all the tested multilevel regression models. Upon this base, the effects of trait EI independent variables and the alliance were progressively tested in each of the studied models. These independent variables explained intercept and slope variations, in addition to cross-level interactions across several conditions. All of which confirmed the anticipated magnitude of the trait EI effects on psychotherapeutic outcomes.

These steps depicted the role of trait EI on psychotherapeutic outcomes layer by layer, in such a way that each of the steps involved in the multilevel modelling construction was evident, verifiable, and derived from the development of a basic model to the construction of more complicated representations through the introduction of random intercepts, slopes and cross-level interactions. In addition, comprehensive reliability coefficients, standard errors, and the variance
components of the models were all reported as recommended in the multilevel literature (see Aguinis et al., 2013). The findings described in this chapter suggest in their overall interpretation that trait EI effects coming from the patient-therapist dyad explained substantial psychotherapeutic outcome variance.

Nonetheless, these effects were of different magnitude depending on whether they emanated from the patient or the therapist, as patient’s trait EI effects were markedly stronger than therapist’s effects. Perhaps most surprising are the opposite trait EI effects on psychotherapeutic outcomes, whether they emanated from the patient or the therapist. Thus, patient trait EI was associated with improved psychological well-being at the end of the intervention, whilst therapist trait EI was associated with worsened patient’s emotional welfare at the termination of treatment. Further scrutiny of the role of trait EI at the therapist level is required, where possible moderation and mediation analyses may clarify matters in the context of multilevel designs with larger sample sizes at both levels, which are unreliable to assess with study four’s dataset given its relatively small sample size.

Patient and therapist alliance measures could play a role as mediators of trait EI effects on psychotherapeutic outcomes, as the early findings presented in chapter five suggest, although this requires further examination. Despite the effects of the alliance on psychotherapeutic outcomes were discrete (i.e., of low magnitude), in line with the extant literature (e.g., Horvath, 2011), there were some noticeable interactions between the alliance and trait EI, which expand the current understanding of the relational patterns embedded in the therapeutic relationship. These interactions are not accountable for the alliance as formerly studied, and in this regard, they contribute to the extended role of the therapeutic relationship beyond its previously characterised elements in the literature (see Horvath, 2018a, 2018b).
### Table 18. Summary Listing of the Contributions by Chapter

<table>
<thead>
<tr>
<th>Chapter Three (Studies one and two)</th>
<th>Chapter Four (Study three)</th>
<th>Chapter Five (Study four)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First investigation of the internal structure of the TEIQue-SF through bi-factor ESEM modelling.</td>
<td>First cross-cultural trait EI mean differences for civil status across three country datasets.</td>
<td>Evidence of a tangential role of alliance measures in predicting psychotherapeutic outcomes.</td>
</tr>
<tr>
<td>Construct invariance between the original TEIQue-SF and the adapted/validated form in Chile.</td>
<td>First cross-cultural study of trait EI occupational mean differences across three country datasets</td>
<td>Interaction effect between therapist alliance measures and the impact of treatment on most psychotherapeutic outcomes</td>
</tr>
<tr>
<td>Successful linguistic adaptation and validation of the Spanish-Chilean-TEIQue-SF in general and clinical populations.</td>
<td>Robust evidence of trait EI measurement invariance across gender, age, and education. Less robust evidence supporting the invariance of trait EI regarding civil status and occupation.</td>
<td>Evidence of meaningful interaction between patient and therapist Global trait EI on the overall psychotherapeutic outcome and symptom distress</td>
</tr>
</tbody>
</table>

### 6.3–Implications for Theory

The implications of the studies included in the dissertation are manifold. First, the bi-factor modelling of trait EI is novel, and as demonstrated in the first and second studies, not only convenient but methodologically desirable (see Reise, 2012). The classic hierarchical (second-
order) conceptualisation of trait EI (see Petrides, 2009) yielded a slightly worse model fit than the preferred bi-factor approach examined across chapters three and four when modelled through ESEM, as presented in Appendix A17. In this table, the differences between a hierarchical and a bi-factor interpretation were larger for the clinical sample portrayed in study two than for the general sample depicted in study one. Hence, it appears that these differences accentuate as a result of smaller sample size and consequently, larger standard errors. In any case, both interpretations of the internal factor structure seem comparable across large samples (i.e., more than 300 individuals), as the contrast between the results informed in section 3.3.2.4.2 for the final bi-factor interpretation in the general population, and those portrayed in Appendix A17 for the hierarchical reading suggest.

ESEM also contributes theoretically to the comprehension of trait EI. It allows modelling with greater flexibility the internal factor structure of trait EI measures, as proved with the Spanish-Chilean-TEIQue-SF (see chapter three of the dissertation), the Brazilian validation of the measure (Perazzo et al., 2020) and the cross-cultural measurement invariance across sociodemographic variables and countries portrayed in chapter four. Indeed, ESEM permits a more precise re-interpretation of the internal structure of several psychological measures, which often feature multiple cross-loadings (Marsh et al., 2014). The technique allows standardising the variance of each factor in its basic form, as well as fixing the correlation of those items not theoretically loading to some of the factors, setting a specific type of rotation, estimator, and item correlated uniqueness. In its most advance presentation (i.e., ESEM-within-CFA, EwC), each item is fixed to an explicit factor loading according to the previously obtained estimates from the basic ESEM model (see Marsh et al., 2014). This level of sophistication is rarely seen in the literature when building or adapting personality measures, which is an important contribution of
this dissertation that enhances the psychometric background of the trait EI construct as measured by the Spanish-Chilean-TEIQue-SF.

Another theoretical contribution to the literature is the provision, for the first time in the region, of South-American trait EI means, as these not only allow for comparability with other countries (as demonstrated in chapter four) but also inform on two well-defined populations, this is general and clinical populations. This distinction is pertinent and has numerous theoretical implications and practical advantages. For instance, the differences reported in trait EI means between the pilot, general and clinical samples studied in chapter three, together with the general population means reported in chapter four, and the clinical means reported in chapter five, all point to significantly lower clinical means (see also Petrides, Hudry, et al., 2011). If we return to the trait EI definition, it is possible to conjecture that each of these populations is characterised by a peculiar emotional self-perception and social effectiveness (see Van der Linden et al., 2017). This distinctiveness supports the comparison of trait EI means from general population with those of the clinical sample in study four, since this allowed demonstrated a distinctive emotional self-perception and social effectiveness in each group, providing support to the clinical pertinence of approaching patients in their naturalistic settings regarding trait EI.

The cross-cultural research base of trait EI has also been substantially enhanced as a result of the studies portrayed in chapter three and four. First, the availability of a short, invariant measure of trait EI, translated into local Spanish, with a complete validation in Chilean general and clinical population, serves the purpose of filling the gap in the region regarding trait EI assessment. Due to Latin-America being mostly a Spanish speaking continent, which predisposes the neighbouring countries to similar personality means (Allik & McCrae, 2004), the impact of the research increases. Therefore, emotional intelligence researchers based in nearby countries
may benefit from the use of the Spanish-Chilean-TEIQue-SF or use it as a tool for future local validations, as was partially the case with the Brazilian validation (Perazzo et al., 2020). This piece of research used the same ESEM model proposed in the Spanish-Chilean validation, which provided further evidence for the use of the short measure in the region. In addition, this research served from the theoretical and methodological interpretations crafted in the Chilean validations, such as the measurement invariance analyses presented in chapters three and four. Hence, having a wider comprehension of emotional self-perception and social effectiveness beyond the usually studied WEIRD samples, i.e., western, educated, industrialised, rich, and democratic populations (Henrich et al., 2010), is fundamental for sustaining the universality of trait EI and expanding its application to new arenas, despite the WEIRDless samples (i.e., Brazil and Chile) included in study three cannot be claimed as purely non-WEIRD populations.

Similarly, the contribution of chapter four in terms of aggregate trait EI scores is significant in documenting the universality of the trait EI construct, especially as this was proven across dissimilar regions of the world. The findings portrayed in study three highlight that regardless of sociocultural differences accounting for trait EI variability across countries and geographical regions (i.e., Latin-America versus Europe), the expected universality of the trait EI construct is supported. This is in line with comparable trait EI literature (e.g., Siegling, Furnham, et al., 2015; Tsaousis & Kazi, 2013), as well as with research in the extended trait personality field, supporting the universality of the Big Five-factor model (e.g., McCrae et al., 2005, Schmitt et al., 2007) and to less extent of the HEXACO six-factor model of personality (e.g., Ion et al., 2017; Thielmann et al., 2020).

The formerly unexplored role of trait EI in psychotherapy stands out as a logical extension of the influence of emotionally based self-perceptions, and in a wider representation,
the effect of personality on psychopathology and psychotherapy. It is worth remembering that
the consolidation of psychotherapy as effective psychological treatment has been supported ever
since Eysenck (1952) first rang the alarm on the effects of psychoanalytic and eclectic
therapeutic interventions nearly seventy years ago; when he concluded that training clinical
psychologists in psychotherapy was pointless. A vast amount of quality research conducted since
that publication has proven otherwise, as psychotherapy has demonstrated to be effective with a
standard mean difference of .70, which is considered a relatively large effect (see Munder et al.,
2019; Smith & Glass, 1977; Smith et al., 1980). Nowadays, as introduced in the literature review
and chapter five, the effectiveness of psychotherapy is no longer a topic of debate (Norcross &
Lambert, 2019).

Patient’s trait EI and therapist’s trait EI effects, along with the quality of the alliance had
the greatest predictive value regarding psychotherapeutic outcomes in study four. These results
contributed theoretically to the unexplained outcome variance. Moreover, an overall
improvement in patients’ psychotherapeutic outcomes after brief psychological eclectic
interventions conducted in different university mental health centres was demonstrated.
Additionally, trait EI and alliance contributions from patient and therapist to psychotherapeutic
outcomes were progressively tested. As expected, trait EI predicted psychotherapeutic outcome
changes, with the impact of patient’s trait EI stronger than the role of therapist’s trait EI in most
outputs. These findings supported the overall aim of the study and the implied assertion that the
role of the therapeutic alliance on psychotherapeutic outcomes, although present, could have
been somehow overrated in the extant literature, compared to the influence of well-established
personality characteristics, such as trait EI. This stance is congruent with Beutler et al.’s (2004)
plead for scrutiny of patient and therapist’s personality traits contributing to psychotherapeutic
outcomes, as the study of these trait effects on outcomes has declined in recent years in favour of randomised control trials (RCT), which are primarily focused on the effectiveness of the psychological intervention. The findings reported in chapter five justify the inclusion of trait EI as a predictor of psychotherapeutic outcomes in the clinical psychology literature and encourage researchers to carefully consider trait EI effects when accounting for psychotherapeutic outcome variance, especially in longitudinal, multilevel designs.

The trait EI therapist effects, as presented in Appendix A32, pose a call to the therapist’s emotionality. They inform that some trait EI predictors from the therapist exert a substantial influence on psychotherapeutic outcomes, as the higher of these traits, the higher the psychological disturbance of the patient, especially on the overall outcome and interpersonal relationships. Here, the role of therapist’s Global trait EI, therapist’s Self-control and therapist’s Sociability explained most outcome variance. Among these contrasts, the most substantial was of therapist’s Sociability regarding interpersonal relationships. These results pertain to both patient and therapist effects in the literature and advise on a possible disparity of emotional constellations from patient and therapist that encounter each other in psychotherapy. The source of this discrepancy may point towards a construct different than the alliance, in which the emotionality of patient and therapist either align or diverge with the expected consequences for the course of treatment. In this regard, it is easier to understand therapist trait EI effects in interaction with patient trait effects, as presented in Table 16 and Figure 10 (chapter five), as the interaction between patient and therapist trait EI contributed to a significant reduction in the overall outcome and symptom distress (i.e., the lower the outcome, the higher patient’s psychological wellbeing).
The interactions at the factor level depicted in Table 17 and Figure 11 in chapter five provided further scrutiny over patient and therapist trait EI links. These confirmed the contribution of patient’s Global trait EI, Well-being and Sociability, which interacted with therapist’s Global trait EI, Well-being, Self-control and Emotionality. The most substantial of these interactions related to the combined effect of patient’s Global trait EI and therapist’s Well-being on symptom distress, meaning that patients high in Global trait EI experienced a steeper decrease in psychological distress when treated by a therapist high in Well-being. Again, this builds new knowledge regarding patient and therapist trait EI effects. It is also informative for practice, as will be discussed in the following section.

6.4–Implications for Policy and Practice

Some implications for policy and practice were previously presented in the various chapter discussions. This section will expand on these suggestions. Table 19 summarises the implications of the dissertation for policy and practice by chapter, as presented at the end of the current segment.

First, the local validation of the Spanish-Chilean-TEIQue-SF permits mental health policymakers in Chile and neighbouring Spanish-speaking countries to include a valid and reliable measure for quick assessment of emotional self-perceptions. Although trait EI questionnaires are not designed for purposes of psychopathological diagnosis, they do inform extensively on individuals’ emotional perceptions, which is crucial for psychological practice in educational, organisational, clinical, and other health settings.

In education, the Spanish-Chilean-TEIQue-SF may be used for rapid self-assessment in the context of Psychology undergraduate, postgraduate or even college curriculum, where
students eager to have a screening of their emotionality may benefit from its use. This evaluation might be the first approximation to Psychology for them and consequently, trigger their desire to know more about the subject or serve as an example of a locally validated measure. The examination of the TEIQue-SF in Chile could also be of especial relevance for those students interested in obtaining local examples of CFA-ESEM comparisons, as well as for those scholars and apprentices in the field of Quantitative Psychology in need of literature, examples, or coding from a bi-factor internal structure questionnaire for future research or course assignment.

The questionnaire could help those students in doubt of requesting mental health care, and thus be informative should the result deviate significantly from the mean of the general population sample depicted in study one (e.g., less than two standard deviations from it). Similarly, those with high scores as a result of the evaluation may reinforce their self-esteem and consequently recognise to a higher degree their emotional strengths. However, as a word of caution, the TEIQue-SF is not intended as a diagnostic tool, and specific diagnostic instruments applied by a trained clinician should follow it, especially in the presence of very low scores, to avoid as much as possible, potential iatrogenic effects (i.e., undesirable consequences to patient from the assessment). In any case, there are multiple practical perspectives in which groups from the community may engage and obtain new insights from the questionnaire, as participants repeatedly expressed their curiosity about the questionnaire’s underlying construct and levels of measurement during the process of data collection for study one, the former pilotage and the linguistic adaptation with high-school teachers that preceded it.

In business settings, the questionnaire may be used for monitoring employees’ overall emotional self-perceptions, sense of wellbeing, and self-control, as conducted by a workplace wellbeing department, given the reliable scores of these factors in each of the studies included in
the dissertation. These actions are far from being invasive if employees can self-manage the results of their own trait EI assessments in an online platform or mobile application, and voluntarily consent to share the results of such evaluations to the wellbeing department or directly to their healthcare provider only. These evaluations may well act as part of socio-emotional prevention policy, framed under *corporate social responsibility* schemes (see Aguinis & Glavas, 2012, for a review). Moreover, given that the Spanish-Chilean-TEIQue-SF was found invariant regarding its internal structure, across sociodemographic variables, and even cross-culturally, the possibilities of use in organisational settings are vast, including the utilisation in cross-country strategic research in Spanish-speaking countries.

In clinical and health settings, trait EI may serve as a first screening into patient emotionality, as the results in chapter five inform. Moreover, the interactions between the client and the practitioner depicted in the prior chapter suggest that practitioner’s emotionality greatly influences the outcome. Consequently, having a first assessment of the clinical or health dyad at intake is beneficial and informative as a prognosis in these settings. For instance, a steeper improvement in psychological disturbance can be forecasted for those patients with lower levels of trait EI at intake. In contrast, more modest improvements can be expected for patients with higher levels of trait EI at intake, making their inclusion into a therapeutic process less justifiable, although still beneficial—especially when treated by a therapist high in trait EI—, as presented in Figures 10 and 11. In practice, this is relevant for policy, as interventions are costly for the health system and the same users, especially if out-of-pocket payments are made. Additionally, attrition is more likely to occur in courses of treatment with patients in less need of psychological support (Hunsley et al., 1999).
On the other hand, patient goals-alliance, therapist total-alliance, therapist tasks-alliance and therapist goal-alliance interacted with the effect of the intervention (TIME), as illustrated in Figure 9, chapter five. These interactions were all in the expected direction of the higher alliance, the steeper the decrease in patient’s psychological disturbance, except for the effects of the aforementioned therapist alliance variables on social role. As for these variables, the higher the alliance, the poorer the patient’s performance in social environments (i.e., work, family, and leisure). Here, it may be the case that the higher alliance emanating from the therapist acted as a barrier on the patient’s social performance, as therapists reporting low levels of alliance did achieve a similar decrease in psychological disturbance regarding symptom distress, as shown in Figure 9, Panels A, C, and E, chapter five. Likewise, the same trend occurred when patient goals-alliance interacted with the effect of the psychological treatment (i.e., TIME) on interpersonal relationships and social role, which is also illustrated in the same figure, panels G and H. Overall, these results inform practitioners and mental health policymakers on the importance of the alliance, especially when contrasted with the effects of trait EI, as presented in Table 16, chapter five.

Finally, the strong interaction between patient and therapist Global trait EI on the overall psychotherapeutic outcome and symptom distress is paramount for understanding trait EI effects in clinical and other health settings, where the emotionality of both patient and provider exert a substantial role on the output of the professional relationship.

Table 19. Summary Listing of Implications for Policy and Practice by Chapter

<table>
<thead>
<tr>
<th>Chapter three (Studies one and two)</th>
<th>Chapter four (Study three)</th>
<th>Chapter five (Study four)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first psychometric studies with the TEIQue-SF in Chilean samples allow for</td>
<td>The large sample size of the study allowed for precise cross-cultural inferences with</td>
<td>The revealed protective effect of patient trait EI on psychopathology deserves</td>
</tr>
<tr>
<td><strong>inference and comparability research in educational, organisational, and health/clinical settings.</strong></td>
<td><strong>reduced standard errors, higher reliability, better gender balance, broader age range, and the utilisation of a highly conservative statistic for pairwise comparisons. All these features provide robust support for the utilisation of the TEIQue-SF in cross-cultural research.</strong></td>
<td><strong>consideration by mental health care providers, as to policy and practice in clinical and health settings.</strong></td>
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<tr>
<td><strong>The possibility of measuring with a validated and invariant brief trait EI measure in Spanish represents an opportunity from the practitioner perspective for precise psychological assessment.</strong></td>
<td><strong>The small effect size for gender or age effects through ANOVA yields further support to the invariability of trait EI (as verified through multigroup measurement invariance), across countries and sociodemographic variables, being this extendable to policy and research. For instance, practitioners can confidently and accurately assess trait EI across a wide range of participants, regardless of their age or gender. The same applies to those applied researchers aiming to examine populations with skewed sociodemographic correlates.</strong></td>
<td><strong>The adverse effect of therapist trait EI on psychotherapeutic outcomes is especially informative for clinicians. It suggests that a potential mismatch of emotional profiles emanating from patients and therapists may be counterproductive regarding psychotherapeutic outcomes.</strong></td>
</tr>
<tr>
<td><strong>Facilitates the study of trait EI in Chile and nearby countries by educational, organisational, and health/clinical applied researchers.</strong></td>
<td><strong>Even the large samples taken from very homogenous populations, such as the Brazilian and Italian samples, had marginal deviations from the overall pool of population samples regarding model fit, when contrasted through the base ESEM bi-factor model throughout configural, metric and scalar measurement invariance. This robustness of the construct allows for practical trait EI assessment across a wide range of settings and populations of interest.</strong></td>
<td><strong>Due to trait EI substantially explained outcome variance, whereas alliance measures had a tangential role in predicting psychotherapeutic outcome; mental health policy should embrace trait EI effects and therefore, include trait EI measures in future clinical and health research.</strong></td>
</tr>
</tbody>
</table>
Psychometrically based cross-cultural comparisons with the instrument in other Spanish background populations, especially in Latin-America, will now be possible.

The findings highlight the cross-cultural stability and validity of trait EI, as measured by the TEIQue-SF, irrespective of cultural, linguistic, and other primary sociodemographic correlates. This is of great importance for policy and research.

The interaction between patient and therapist Global trait EI on the overall psychotherapeutic outcome and symptom distress is paramount for understanding trait EI effects in clinical and other health settings.

6.5–Limitations and Strengths of the Research

The detailed limitations of each study are expressed in the respective chapters. Overall, these restrictions relate to sample size, unequal size of groups, and use of non-probabilistic samples, without randomisation of the participants. The sample size restrictions especially applied to study four, even though the power analysis performed for this research yielded an expected and final power beyond .9, which limits the probability of Type II error, i.e., not detecting an effect when this is present in the population of interest. Regarding Type I error (i.e., falsely claiming an effect when this is not present in the population of interest), the error was somehow reduced with the calculation, when appropriate, of adjusted p-values controlling the False Discovery Rate (FDR), i.e., the proportion of erroneously rejected null hypotheses when simultaneously testing multiple comparisons, (Benjamini & Hochberg, 1995).

Less substantial limitations regarding sample size concerned the first two studies, as some authors recommend a sample size of over 500 individuals to recall the internal factor structure of a questionnaire (see Comrey & Lee, 1992). Nevertheless, given that the internal structure of the questionnaire was replicated almost identically in the Brazilian validation of the TEIQue-SF (Perazzo et al., 2020), this research served as a replication of the original bi-factor ESEM interpretation depicted in the two first studies of the dissertation. On the other hand, the
use of non-probabilistic sampling is less preferred than random probabilistic sampling, although this shortcoming was addressed by the inclusion of large sample sizes in study one and especially in study three, which reduced the sampling error (see Corbetta, 2003). The clinical samples utilised in study two and four suffered from higher sampling error compared to the general population samples of studies one and three. However, the standard deviations of the trait EI independent variables in the samples analysed in studies two and four are comparable to Petrides et al. (2017), researchers that informed of trait EI effects on irrational beliefs and psychopathology in psychiatric outpatients. These limitations are acknowledged, although they do not deter from the implications of the findings.

The strengths are multiple. First, the contribution to the trait EI literature, which was highlighted during the course of publication, as the manuscripts addressed relevant topics for personality and individual differences research, previously underdeveloped or neglected. For instance, adapting brief measures, such as the TEIQue-SF, has several benefits for educational, organisational, and clinical/health psychological assessment, as well as to cross-cultural and local research, as demonstrated throughout the dissertation. The study of emotional intelligence beyond WEIRD samples, or at the very least in WEIRDless samples as described in section 2.5.1, is imperative. True generalisability of any psychological construct cannot be claimed in the absence of evidence-based quality research across abundant and wide-ranging populations. The same applies to the highlighted role of measurement invariance in guaranteeing construct comparability across populations, as reviewed in section 2.5.2, chapter two. Finally, the approach taken for disentangling the role of trait EI in psychotherapeutic outcomes is novel. It has full comparability with the extant psychotherapy literature, further informing on these practically unexplored effects on psychopathology during psychological treatment.
Second, the use of modern and sophisticated statistical analyses throughout the dissertation is probably the greatest contribution from the data analytical perspective, as this point was also highlighted throughout the peer-reviewing processes in which the outlets from the current dissertation were submitted for review. For instance, the implementation of ESEM modelling, omega as reliability index, measurement invariance, and multilevel analysis, were all statistically appropriate procedures, which were strategically implemented through a theory-driven approach in each one of the studies comprised in the dissertation.

6.6–Implications for Methodology

Several methodological advantages can be stressed from the dissertation. First, the blend of qualitative and quantitative strategies in the Chilean adaptation and validation of the TEIQue-SF. Second, the early assessment of the validation of the questionnaire with a highly enlightening pilot sample comprised of high-school teachers. Third, the informative and fundamental role of conducting cross-cultural research testing invariability, cross-cultural equivalence, and comparability of the trait EI construct with large samples. Fourth, the expansion of trait EI assessment in Latin-American populations, as presented throughout the dissertation. Fifth, the high methodological standards implemented throughout the dissertation and corroborated by the COSMIN study design checklist across the criteria depicted in the clusters of translation process, internal consistency, structural validity, cross-cultural validity/measurement invariance and validity of longitudinal research. These points are valuable aspects of the research design, advantageous for theory, research, and practice.

The overall contrast regarding trait EI means between general and clinical populations is also methodologically insightful regarding the trait EI construct, as proven across the studies of
the dissertation. It reveals that samples obtained from the community display higher trait EI means compared to clinical samples, which applies to the global trait and the factor-level (i.e., Well-being, Self-control, Emotionality and Sociability). It implies in practice that the trait emotional intelligence of clinical populations is expected to be diminished when compared to people from the community, which is linked to psychopathology (Petrides et al., 2017) and psychotherapeutic outcomes as inspected in study four, chapter five. This discrepancy in trait EI means, along with the findings reported in the literature, justify a distinct understanding and treatment of the trait EI effects in forthcoming clinical population research. Similarly, several multilevel applications modelling trait EI as a predictor may prove useful in explaining outcomes in wide-ranging applied research, even in relatively small size cohorts, as conducted in chapter five. These ideas will be expanded in the following section.

6.7–Implications for Future Research

Future studies in Latin-American general population should include trait EI as a variable of interest, as the suitability of the construct was verified under several conditions in chapters three and four. Moreover, the predictive role of trait EI on several health outcomes has been claimed higher compared to other emotional intelligence taxonomies and their respective measures in the literature (see sections 2.2 and 2.7 in chapter two), ratifying its appropriateness in psychological research. This goal may be enhanced in the region with the Spanish-Chilean-TEIQue-SF and other trait EI measures, such as the Brazilian adaptation (see Perazzo et al., 2020) and the Spanish adaptation of the TEIQue and the TEIQue-SF (see Pérez-González, 2010). The trait EI studies conducted in Latin-America to date are mostly portrayed through the chapters of the present dissertation. Therefore, it is expected they indirectly contribute to either
the creation of new trait EI measures or the adaptation of other trait EI measures suited for
different populations, such as children and adolescents, organisational forms, among others.

Upcoming cross-cultural and measurement invariance investigations can further explore
the role of several sociodemographic variables on trait EI, as studied in chapter four. For
instance, future research from the author of the dissertation and colleagues will replicate the
research design portrayed in chapter four with clinical samples from Chile, Peru, and possibly
two other countries. This research will expand the already proven measurement invariance of
trait EI across sociodemographic correlates in the general population, whilst informing on the
direction of trait EI mean differences driven by sociodemographic predictors, as depicted in the
fourth chapter of the dissertation. It is expected that these studies further elucidate on the
suitability of trait EI in clinical populations, which is partially addressed in this dissertation
through studies two and four. Moreover, this enquiry will provide a fresh opportunity for either
confirming or disproving trait EI non-invariance across the various levels of civil status and
occupation, as portrayed in chapter four.

Forthcoming clinical psychology, as well as other health studies, should include trait EI
as a variable of interest, given the results portrayed in studies two and four and the support from
previous research. For instance, concerning study two, the surprisingly good fit of the tested
ESEM bi-factor models is unequivocal evidence of the appropriateness of trait EI measures in
providing an accurate psychological screening of clinical populations, especially when
considering the relatively small sample analysed in this study. Moreover, a replication of study
four with larger sample size, more intermediate outcomes and alliance measures across time, a
control group for the effect of the intervention, more trait EI measurements across time and
budgeting supporting the scale-up of the project would allow confirming the already portrayed
trait EI effects on psychotherapeutic outcomes. In addition, the extant literature suggests that the alliance is key for understanding psychotherapeutic outcomes. For this reason, if we add the role of the alliance to the aforementioned potential independent variables, the possibilities for future research are endless. As shown in chapter four, it is likely to find several interactions between other personality-based independent variables and the alliance.

Experimental and quasi-experimental research with trait EI and neurophysiological correlates would also be advantageous, as they would offer a more rounded comprehension of the trait EI effects. In this regard, an improvement on the design presented in study four could include subjective and objective stress correlates, similarly to what Mikolajczak et al. (2007) researched through experimental design, Sarrionandia and Mikolajczak (2020) reported in metanalytic research, and what Arora et al. (2011) investigated with medical practitioners. This approach would yield additional causal information that could relate to specific passages of the psychotherapeutic process and their relationship to patient and therapist’ trait EI, as well as to the alliance, especially if longitudinal, multilevel designs are implemented, and potential interactional effects are studied in depth.

Furthermore, recent investigations comprising Big Five measures stress the rather non-beneficial role of some components of this paradigm on psychotherapeutic outcomes when coming from the therapist. Specifically, when in excess, therapist agreeableness and openness to experience account for a negative burden on psychotherapeutic outcomes (see Delgadillo et al., 2020, and section 2.9 in chapter two). These findings have an almost direct relationship to the unexpected results regarding therapist trait EI reported in chapter five, as this variable negatively predicted psychotherapeutic outcomes, meaning that the higher Global trait EI, the poorer the outcomes.
Moreover, given that the dark triad as described in section 2.7, chapter two, strongly correlates with trait EI; careful prospective consideration of the positive association between narcissism and trait EI on psychotherapeutic outcomes may provide a more comprehensive interpretation of the adverse therapist’ trait EI effects on psychotherapeutic outcomes described in chapter five, especially if this is conducted through longitudinal multilevel analysis. In other words, is the narcissistic component of therapist trait EI explaining poorer psychotherapeutic outcomes? Similarly, given that Machiavellianism and psychopathy are negatively related to trait EI, further research including these two variables along with trait EI in statistical modelling on psychotherapeutic outcomes, may inform on potentially unexplored interactional effects. For instance, higher levels of Machiavellianism and psychopathy in patients should predict poorer psychotherapeutic outcomes, and therefore, these variables should correlate negatively with trait EI, in line with the literature. Likewise, patients higher in trait EI could cancel out the effects of therapist Machiavellianism and psychopathy, although this relationship may be hard to prove in practice. Perhaps, it is more valuable to inquire whether therapists high in trait EI may overrule the negative effects on psychotherapeutic outcomes of patients high in Machiavellianism and psychopathy. Moreover, Heym et al. (2020) have recently introduced the construct of dark empath, which characterises individuals high in dark traits (as described in the dark triad paradigm) in the presence of high empathy, which adds additional complexity to the role of personality traits on psychotherapy outcomes, and the role of the psychotherapeutic relationship in it.

Considering the research design and findings portrayed in chapter five, potentially interesting future investigation could compare the predictive role of ability EI and trait EI on psychotherapeutic outcomes. This would allow disentangling whether one or the other is a stronger predictor of outcomes in psychotherapy, as well as documenting hypothetically differential effects
from the two types of EI emanating from patient or therapist, similarly as reported in chapter five for trait EI. In addition, given that the trait EI measurement method resembles typical performance, it would be interesting to test if any incremental effect could be observed on psychotherapeutic outcomes after introducing ability EI measures, as these are based on maximal performance.

Another potential pathway for research involves the role that trait EI may exert on the outcomes of specific populations of patients. For instance, since personality disorders have found negatively linked to trait EI (see section 2.7, chapter two), it may be the case that patient trait EI mediates the effects of personality disorders on psychotherapeutic outcomes and that therapist trait EI moderates the effect of personality disorders on outcomes. It would be worth testing these hypotheses and compare the extent of the trait EI effects on such populations. For example, regarding personality disorders, probably the magnitude of these effects might be stronger depending on the type of personality disorder studied, as some of these may be more susceptible to trait EI effects than others, and the direction that these effects take can substantially differ from patient to therapist.

As previously described, several algorithms may be tailored for different populations, diagnoses, personality traits, type of complaint, as well as the level of engagement in the psychotherapeutic process, exemplified by the role that patient and therapist alliance had on psychotherapeutic outcomes. Patients suffering from diverse syndromes and conditions, such as autism, cancer, alexithymia, drug addictions, among others, can be studied after adapting the basal research design implemented in study four to these populations according to what works best, albeit tailored interventions to specific diagnosis have reported minimal incremental effects in the psychotherapeutic literature (see section 2.10, chapter 2). More importantly, the present dissertation and the extant literature provide a ground for further experimental investigation of
patient-therapist dyads matched by their trait EI and other well-regarded trait taxonomies (e.g., the big five model of personality) to disentangle additional personality-based effects on psychotherapy outcomes and other health-related outputs.

The present theory-driven building research on the trait EI construct and its effects on psychotherapeutic outcomes confirmed the overall hypothesis that the interaction between patient effects and therapist effect is more complex and powerful than previously suggested, even when compared to the alliance. The dissertation built on previous research that highlighted the suitability of trait EI for explaining health and life satisfaction outcomes, as well as to the need of studying in further detail the emotional personality-based grid on which the interpersonal exchanges between patient and therapist develop in psychotherapy (e.g., Balb et al., 2020, Beutler et al., 2004, Gómez Penedo et al., 2020). In the dissertation, the role of trait emotional intelligence emerged as significant for explaining the outcome in psychotherapy, which sets the foundation for further related research.
References


https://doi.org/10.1002/jclp.1056

https://doi.org/10.2298/PSI1301005A


https://doi.org/10.1097/ACM.0b013e31822bd7aa


https://doi.org/10.1177%2F1073191105283504


https://doi.org/10.1037/0022-006X.75.6.842


https://doi.org/10.1016/j.paid.2018.09.020


[https://doi.org/10.1080/10503307.2020.1731927](https://doi.org/10.1080/10503307.2020.1731927)


*Behavioral and Brain Sciences, 33*, 61–135.

https://doi.org/10.1017/S0140525X0999152X


https://doi.org/10.1016/j.paid.2020.110172


Horvath, A. O., & Bedi, R. P. (2002). The alliance. In J. C. Norcross (Ed.), *Psychotherapy relationships that work: Therapist contributions responsiveness to patients*


https://doi.org/10.1037/1082-989X.3.4.424

https://doi.org/10.1080/10705519909540118


https://doi.org/10.1080/00223891.2016.1187155


http://dx.doi.org/10.1097/00005053-198308000-00005

https://doi.org/10.1016/j.bbapap.2014.09.014

https://doi.org/10.2753/rpo1061-0405440604

https://doi.org/10.1027/1614-2241.1.3.86

https://doi.org/10.1037/1082-989X.4.1.84


[https://doi.org/10.1016/j.psyneuen.2007.07.009](https://doi.org/10.1016/j.psyneuen.2007.07.009)

[https://doi.org/10.4324/9780203821961](https://doi.org/10.4324/9780203821961)

[http://www.mifuturo.cl/index.php/donde-y-que-estudiar/buscador-de-carreras](http://www.mifuturo.cl/index.php/donde-y-que-estudiar/buscador-de-carreras)


https://doi.org/10.1037/10306-010


http://doi.org/10.1111/j.1600-0447.2011.01711.x


https://doi.org/10.1037/a0021554


https://doi.org/10.3389/fpsyg.2019.01116


https://doi.org/10.1016/S0191-8869(98)00001-4


Barbaranelli, C., Beer, A., Borg-Cunen, M. A., Bratko, D., Brunner-Sciarrà, M.,
Reflect Mean Personality Trait Levels in 49 Cultures. *Science, 310*, 96–100.
https://doi.org/10.1126/science.1117199

Thielmann, I., Akrami, N., Babarović, T., Belloch, A., Bergh, R., Chirumbolo, A., Čolović, P.,
HEXACO–100 Across 16 Languages: A Large-Scale Test of Measurement Invariance.
*Journal of Personality Assessment, 102*(5), 714–726.
https://doi.org/10.1080/00223891.2019.1614011


https://doi.org/10.1159/000376585


https://doi.org/10.18637/jss.v045.i03

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https://doi.org/10.1002/sim.4067


[https://doi.org/10.1037/a0040435](https://doi.org/10.1037/a0040435)

[https://doi.org/10.1037/0000093-006](https://doi.org/10.1037/0000093-006)

Zinbarg, R. E., Revelle, W., Yovel, I., & Li, W. (2005). Cronbach’s, α Revelle’s β and McDonald’s ωH: Their relations with each other and two alternative conceptualizations of reliability. *Psychometrika, 70*(1), 123–133.  
[https://doi.org/10.1007/s11336-003-0974-7](https://doi.org/10.1007/s11336-003-0974-7)

[https://doi.org/10.1037/0022-3514.65.4.757](https://doi.org/10.1037/0022-3514.65.4.757)

Appendices
# Table of Appendices

A 1: The Spanish-Chilean TEIQue-SF ..............................................................272

A 2: Research Guidelines for Conducting Cognitive Interviews on the TEIQue-SF. ..............................................274

A 3: Research Guidelines for Conducting Focus Groups Discussions on the TEIQue-SF. .................................275

A 4: Model 1. Higher-order CFA Syntax with MI in the General Population Sample .............................................275

A 5: Model 2. Bi-factor CFA Syntax with MI in the General Population Sample ..................................................275

A 6: Factor Loadings of the CFA Models (Models 1 and 2) ..................................................................................276

A 7: Model 3. First Bi-factor ESEM without M.I. in the General Population Sample .............................................277

A 8 : Model 4. Bi-factor ESEM with ML Estimator Target Rotation and Introduction of M.I. in the General Population Sample .............................................................................................................277

A 9: Bi-factor Exploratory Structural Equation Modeling (ESEM) using ML Estimator and Oblique Rotation (Target) in the Clinical Population Sample .........................................................................................277

A 10: Bi-factor ESEM with ML, Target Rotation and the Introduction of M.I. in the Clinical Population Sample .............................................................................................................................................278

A 11: Multiple Group Configural Invariance Between Population Samples .................................................................278

A 12: Multiple Group Metric Invariance Between Population Samples .................................................................280

A 13: Multiple Group Metric Invariance Between Population Samples .................................................................281

A 14: Additional First-order and Hierarchical Multidimensional Analyses With the Spanish-Chilean-TEIQue-SF .................................................................................................................................................283

A 15: Age Measurement Invariance Mplus Syntax .......................................................................................................284

A 16: Gender Measurement Invariance Mplus Syntax ..................................................................................................284

A 17: Women Measurement Invariance across Countries Mplus Syntax ......................................................................285

A 18: Men Measurement Invariance across Countries Mplus Syntax ...........................................................................286
A 19: Educational Level Measurement Invariance Mplus Syntax ................................................................. 287
A 20: Civil Status Measurement Invariance Mplus Syntax ........................................................................... 288
A 21: Occupation Measurement Invariance Mplus Syntax ......................................................................... 289
A 22: Chilean Adaptation and Validation of the Outcome Questionnaire (OQ-45.2) ......................... 290
A 23: Chilean Adaptation and Validation of the Working Alliance Inventory (WAI)-Patient Version .... 291
A 24: Chilean Adaptation and Validation of the Working Alliance Inventory (WAI)-Therapist Version 295
A 25: R Code for Multiple Imputation ........................................................................................................ 299
A 26: SPSS Merge Syntaxes of the Imputed Datasets ................................................................................. 299
A 27: R Growth Modelling Scripts Implemented in Chapter Five ......................................................... 301
A 28: R Scripts for Figures Implemented in Chapter Five ........................................................................... 366
A 29: Full Correlation Matrix of the Dataset Utilised in Chapter Five ...................................................... 376
A 30: Reliability Coefficients Before and After Multiple Imputation for the Measures Implemented in Chapter Five ........................................................................................................................................ 377
A 31: Patient’s trait EI Intercept Variations Across the Outcome Measures ............................................. 378
A 32: Therapist’s trait EI Intercept Variations Across the Outcome Measures ........................................ 379
A 33: Intercept Variations of Patient’s trait EI and Alliance Measures on the Overall Outcome ........... 380
A 34: Intercept Variations of Patient’s trait EI and Alliance Measures on Symptom Distress ............... 381
A 35: Intercept Variations of Patient’s trait EI and Therapist’s Alliance Measures on the Overall Outcome 382
A 36: Intercept Variations of Patient’s trait EI and Therapist’s Alliance Measures on Symptom Distress 383
A 1: The Spanish-Chilean TEIQue-SF

Cuestionario de inteligencia emocional de rasgo, versión corta (sigla en inglés: TEIQue-SF)

**Instrucciones:** Por favor, responda cada una de las siguientes afirmaciones encerrando en un círculo el número que mejor refleje su grado de acuerdo o desacuerdo con cada afirmación. No piense demasiado el significado exacto de las afirmaciones. Trabaje rápido y trate de responder con la mayor precisión posible. No hay respuestas correctas ni incorrectas. Hay siete posibles respuestas para cada afirmación que van desde “Completamente en desacuerdo” (número 1) hasta “Completamente de acuerdo” (número 7).

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Para mí no es un problema expresar mis emociones con palabras.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>2. Con frecuencia, me resulta difícil ver las cosas desde el punto de vista de otra persona.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>3. En general, soy una persona muy motivada.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>4. Por lo general, me resulta difícil controlar mis emociones.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>5. Por lo general, encuentro que la vida no es placentera.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>6. Puedo tratar con la gente de manera assertiva.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>7. Tiendo a cambiar de opinión con frecuencia.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>8. Muchas veces, no puedo darme cuenta de qué emoción siento.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>9. Creo que tengo una serie de buenas cualidades.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>10. Con frecuencia, me resulta difícil defender mis derechos.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>11. Por lo general, puedo influir en la manera en que otras personas se sienten.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>12. En general, tengo una perspectiva pesimista sobre la mayoría de las cosas.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>13. Los que están cerca de mí se quejan con frecuencia de que no los trato bien.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>14. Con frecuencia, me resulta difícil adecuar mi vida según las circunstancias.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>15. En general, soy capaz de lidiar con el estrés.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>16. Con frecuencia, me resulta difícil mostrar mi afecto hacia los que están cerca de mí.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>17. Normalmente, soy capaz de “ponerme en los zapatos del otro” y experimentar sus emociones.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>18. Normalmente, me resulta difícil mantenerme motivado(a).</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>19. Normalmente, puedo encontrar la manera de controlar mis emociones cuando quiero.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>20. En general, estoy satisfecho(a) con mi vida.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>21. Me describiría a mí mismo(a) como un(a) buen(a) mediador(a).</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>22. Tiendo a comprometerme con cosas de las que después me arrepiento.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>23. Con frecuencia, hago una pausa y pienso en mis sentimientos.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>24. Creo que estoy lleno(a) de fortalezas personales.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>25. En una discusión tiendo a ceder, incluso cuando sé que tengo la razón.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>26. Pareciera que no tengo ninguna influencia sobre los sentimientos de otras personas.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>27. Por lo general, creo que las cosas van a salir bien en mi vida.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>28. Me resulta difícil relacionarme bien, incluso con aquellos cercanos a mí.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>29. Por lo general, soy capaz de adaptarme a nuevos entornos.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>30. Los demás me admirarán por mantener la calma.</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
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</tr>
</tbody>
</table>

Para obtener más información sobre el programa de investigación en inteligencia emocional de rasgo, visite: www.psychometriclab.com

Tenga presente que cualquier uso comercial de este instrumento está estrictamente prohibido.
<table>
<thead>
<tr>
<th>PREGUNTAS -PARTE 2</th>
<th>Sobre usted</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. ¿Cuál es su sexo?</td>
<td>□ MASCULINO  □ FEMENINO  □ OTRO</td>
</tr>
<tr>
<td>2. ¿Cuál es su año de nacimiento?</td>
<td>☑ 19...</td>
</tr>
<tr>
<td>3. Usted se crió principalmente en un(a)...</td>
<td>□ Ciudad grande □ Ciudad □ Pueblo  □ Otro(a)</td>
</tr>
<tr>
<td>4. ¿Con qué mano escribe de forma natural?</td>
<td>□ DERECHA □ IZQUIERDA</td>
</tr>
<tr>
<td>5. ¿Cuál es su orden de hijo? (por ej. Primer hijo, segundo hijo...)</td>
<td>□ 1er  □ 2do  □ 3er  □ 4to  □ 5to  □ 6º o +</td>
</tr>
<tr>
<td>6. ¿Cuántos hijos ha tenido?</td>
<td>□ Ninguno □ 1 □ 2 □ 3 □ 4 □ 5 □ 5+</td>
</tr>
<tr>
<td>7. ¿Cuál es su estado civil?</td>
<td>□ Soltero/a □ Vive en pareja □ Casado/a, sin hijos □ Casado/a, con hijos en el colegio □ Casado/a sin hijos en el colegio □ Divorciado(a)/ Separado(a) □ Viudo/a □ Otro/a</td>
</tr>
<tr>
<td>8. ¿Cuál es su actividad actual?</td>
<td>□ Sector privado, industria □ Sector privado, empresa de servicios □ Fuerzas armadas □ Servicio de salud □ Otro sector público □ Servicio social/voluntariado □ Docente □ Estudiante □ Cesante □ Otro</td>
</tr>
<tr>
<td>9. ¿A qué nivel educacional llegó?</td>
<td>□ Educación Media □ Educación Superior o similar □ Título Universitario o similar □ Estudios de magíster o máster en ciencias □ Máster en administración de empresas □ Doctorado □ Otro</td>
</tr>
<tr>
<td>10. ¿Cómo describiría su origen étnico?</td>
<td>□ Mestizo □ Blanco □ Mapuche/Huilliche □ Negro – ascendencia americana □ Negro – ascendencia africana □ Asiático (Chino, Japonés, Coreano, etc.) □ Indio (origenario de India) □ Otra etnia originaria de Chile □ Otro</td>
</tr>
<tr>
<td>11. ¿Cuál es la tendencia religiosa de su familia?</td>
<td>□ Cristiana – Protestante □ Cristiana – Católica romana □ Cristiana – Otra □ Musulmana □ Hinduista □ Judaíta □ Budista □ Otra creencia □ Ninguna</td>
</tr>
<tr>
<td>12. ¿Con cuál religión diría usted que se siente más identificado hoy en día?</td>
<td>□ Cristiana – Protestante □ Cristiana – Católica □ Cristiana – Otra □ Musulmana □ Hinduista □ Judaíta □ Budista □ Otra creencia □ Ninguna</td>
</tr>
<tr>
<td>13. ¿Cuál es su sueldo bruto mensual?</td>
<td>□ Menos de CL$350.000  □ Entre CL$350.001 y CL$700.000  □ Entre CL$700.001 y CL$1.000.000  □ Entre CL$1.000.001 y CL$1.400.000  □ Entre CL$1.400.001 y CL$1.750.000  □ Entre CL$1.750.001 y CL$2.000.000  □ Entre CL$2.001.001 y CL$2.450.000  □ Entre CL$2.451.001 y CL$3.000.000  □ Más de CL$3.000.000.</td>
</tr>
<tr>
<td>14. ¿Qué tan religioso/a es usted?</td>
<td>□ 1= Nada de religiosa/□ 4= El promedio □ 7= Muy religiosa/a  □ 0= No aplica</td>
</tr>
<tr>
<td>15. ¿Cuáles son sus ideas políticas?</td>
<td>En una escala de 1 a 7, donde: □ 1= Muy de izquierda □ 4= Ninguna □ 7= Muy de derecha</td>
</tr>
<tr>
<td>16. ¿Qué tan feliz está en su trabajo?</td>
<td>En una escala de 1 a 7, donde: □ 1= Nada de feliz □ 4= El promedio □ 7= Muy feliz □ 0= No aplica</td>
</tr>
<tr>
<td>17. ¿Qué tan bueno/a es usted en su área de trabajo?</td>
<td>Esciba el número</td>
</tr>
<tr>
<td>18. ¿Cuántas horas al mes dedica usted al trabajo voluntario (no remunerado)?</td>
<td>Esciba el número</td>
</tr>
<tr>
<td>19. ¿Es el español su idioma materno?</td>
<td>□ SÍ □ NO</td>
</tr>
<tr>
<td>20. ¿Cuál es su cargo? (Si no aplica, entonces por favor escriba 0)</td>
<td>☑ 0...</td>
</tr>
</tbody>
</table>
A 2: Research Guidelines for Conducting Cognitive Interviews on the TEIQue-SF.

1- Could you tell me in your own words the instruction you have just read and heard?
2- Can you tell me in your own words, what is the meaning of statement 1? (read statement)

Repeat the same question for the remaining 29 statements.

3- What does it mean the word “emotion” to you?
4- In many of the statements, the word: “feelings” are used. What do you think about this word? Do you think is right to use it or would you rather use another one?
5- What does it mean to you “to get into someone’s shoes”?
6- Does question number eight apply to your own experience? How distant is the situation provided in the sentence of your own experience? Would you say this depends on something else?
7- Does question number twenty-eight apply to your own experience? How distant is the situation provided in the sentence to your own experience? Would you say this depends on something else?
8- You have just told me that this does depend on something else (if applicable). Can you tell me upon which this depends on?
9- Is it ok to you to talk about emotions and feelings or do you feel strange talking about these issues? How do these questions make you feel?
10- What do you think about the word “motivated”? Do you think is fine to use it or would you rather use another word?
11- Regarding the possible answers for the questions, do you think it was rather hard or easy to find the answer you wanted among the possible responses?
12- Can you tell me what comes to your mind when I tell you “completely disagree”?
13- Can you tell me what comes to your mind when I tell you “disagree”?
14- Can you tell me what comes to your mind when I tell you “completely agree”?
15- Can you tell me what comes to your mind when I tell you “agree”?

Adapted following the recommendations by Wild et al. (2005), and Willis (2005).
A 3: Research Guidelines for Conducting Focus Groups Discussions on the TEIQue-SF.

- Each group must compose of ten to fifteen participants and one coordinator.
- All the groups must be registered audio-visually by the coordinator.
- First, the coordinator must provide a short induction to the construct (trait emotional intelligence) and to the TEIQue-SF questionnaire.
- The coordinator must encourage the reflexion and discussion on emotional intelligence.
- The coordinator must encourage the reflexion and discussion on the layout of the questionnaire, its statements and their meaning.
- The coordinator must encourage the reflexion and discussion on the statements of the questionnaire and their meaning.
- The coordinator must encourage the reflexion and discussion on the range of possible answers to the statements.
- The coordinator must actively lead the questions and dynamics to the participants in the groups, making sure all of them share their ideas on the topics approached.
- The coordinator must read each one of the statements, after which he must ask the group if these enunciations are understandable or not.
- After the discussions have been performed, a summary of the most important ideas and conclusions of the meeting is expected to be provided by each one of the group participants.

Adapted following the recommendations by Wild et al. (2005), and Willis (2005).

A 4: Model 1. Higher-order CFA Syntax with MI in the General Population Sample

```r
model3 <- ‘ well_being =~ t5+ t20 + t9 + t24 + t12 + t27; self_control =~ t4+ t19 + t7 + t22 + t15+ t30; emotionality =~ t1+ t16 + t2 + t17+ t8 + t23 + t13 + t28; sociability =~ t6 + t21+ t10 + t25 + t11 + t26; teiglob =~ well_being + self_control + emotionality + sociability ‘
```

A 5: Model 2. Bi-factor CFA Syntax with MI in the General Population Sample

```r
model4 <- ‘tot_tei =~ t1+t2+t3+t4+t5+t6+t7+t8+t9+t10+t11+t12+t13+t14+t15+t16+t17+ t18+t19+t20+t21+t22+t23+t24+t25+t26+t27+t28+t29+t30; well_being =~ t5 + t20 + t9 + t24 + t12 + t27; self_control =~ t4 + t19 + t7 + t22 + t15 + t30; emotionality =~ t1 + t16 + t2 + t17 + t8 + t23 + t13 + t28; sociability =~ t6 + t21 + t10 + t25 + t11 + t26’
```
### Table A6: Factor Loadings of the CFA Models (Models 1 and 2).

| Well_being =~ | Estimate | Std.Error | Z-value | p (>|z|) | Std.lv | Std.all |
|--------------|----------|-----------|---------|---------|--------|---------|
| t5           | 1.00     | 0.92      | 0.45    |          |        |         |
| t20          | 1.30     | 0.17      | 7.49    | 0.00    | 1.19   | 0.72    |
| t9           | 0.95     | 0.14      | 7.07    | 0.00    | 0.87   | 0.62    |
| t24          | 1.15     | 0.15      | 7.52    | 0.00    | 1.05   | 0.72    |
| t12          | 1.18     | 0.17      | 6.79    | 0.00    | 1.09   | 0.57    |
| t27          | 1.28     | 0.17      | 7.95    | 0.00    | 1.17   | 0.74    |
| Self_control =~ |        |           |         |         |        |         |
| t4           | 1.00     | 1.01      | 0.52    |          |        |         |
| t19          | 0.64     | 0.12      | 5.54    | 0.00    | 0.64   | 0.40    |
| t7           | 0.99     | 0.15      | 6.57    | 0.00    | 1.00   | 0.52    |
| t22          | 0.75     | 0.14      | 5.52    | 0.00    | 0.76   | 0.40    |
| t15          | 0.79     | 0.13      | 5.98    | 0.00    | 0.80   | 0.45    |
| t30          | 0.65     | 0.13      | 5.03    | 0.00    | 0.66   | 0.36    |
| Emotionality =~ |       |           |         |         |        |         |
| t1           | 1.00     | 0.79      | 0.42    |          |        |         |
| t16          | 1.18     | 0.21      | 5.58    | 0.00    | 0.92   | 0.45    |
| t2           | 0.83     | 0.18      | 4.56    | 0.00    | 0.65   | 0.33    |
| t17          | 1.00     | 0.18      | 5.59    | 0.00    | 0.78   | 0.45    |
| t8           | 1.31     | 0.22      | 5.89    | 0.00    | 1.02   | 0.49    |
| t23          | 0.45     | 0.14      | 3.22    | 0.00    | 0.35   | 0.21    |
| t13          | 1.33     | 0.21      | 6.28    | 0.00    | 1.05   | 0.57    |
| t28          | 1.50     | 0.24      | 6.38    | 0.00    | 1.18   | 0.59    |
| Sociability =~ |       |           |         |         |        |         |
| t6           | 1.00     | 0.60      | 0.39    |          |        |         |
| t21          | 1.30     | 0.20      | 6.35    | 0.00    | 0.78   | 0.55    |
| t10          | 1.31     | 0.25      | 5.30    | 0.00    | 0.79   | 0.39    |
| t25          | 0.32     | 0.19      | 1.70    | 0.09    | 0.19   | 0.10    |
| t11          | 0.30     | 0.16      | 1.89    | 0.06    | 0.18   | 0.11    |
| t26          | 1.13     | 0.22      | 5.13    | 0.00    | 0.68   | 0.37    |

---

Note: Std. Error = Standard Error, Z-value = Z-statistic, values above 1.96 are deemed significant. Std.lv = Standardised latent value parameter, Std.all = Completely standardised model parameter. All factors are depicted with the logical symbol representing the regression function.
A 7: Model 3. First Bi-factor ESEM without M.I. in the General Population Sample

VARIABLE:
NAMES ARE t1-t30;
MODEL: fg f1 f2 f3 f4 BY t1-t30 (*1);
ANALYSIS:
ROTATION = BI-GEOMIN;
OUTPUT: STDY; SAMPSTAT; MODINDICES(ALL); FSCEOEFFICIENT; FSDETERMINACY;

A 8 : Model 4. Bi-factor ESEM with ML Estimator Target Rotation and Introduction of M.I. in the General Population Sample

MODEL:
f
fg BY t1 t2 t3 t4 t5 t6 t7 t8 t9 t10 t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0 t2~0 t17~0 t8~0
t23~0 t13~0 t28~0 t3~0 t14~0 t18~0 t29~0(*1);
T18 WITH T3;
T21 WITH T17;

ANALYSIS:
ROTATION = TARGET;
OUTPUT: STDY; SAMPSTAT; MODINDICES(ALL); FSCEOEFFICIENT; FSDETERMINACY;

A 9: Bi-factor Exploratory Structural Equation Modeling (ESEM) using ML Estimator and Oblique Rotation (Target) in the Clinical Population Sample

MODEL:
f
fg BY t1 t2 t3 t4 t5 t6 t7 t8 t9 t10 t11 t12 t13 t14 t15 t16 t17 t18 t19 t20 t21 t22 t23 t24 t25 t26
t27 t28 t29 t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0 t2~0 t17~0 t8~0
t23~0 t13~0 t28~0 t6~0 t21~0 t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t1~0 t16~0 t2~0 t17~0 t8~0
t23~0 t13~0 t28~0 t6~0 t21~0 t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t5~0 t20~0 t9~0 t24~0
t12~0 t27~0 t6~0 t21~0 t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t3~0 t14~0 t18~0 t29~0(*1);

ANALYSIS:
ROTATION = TARGET;
OUTPUT: STDY; SAMPSTAT; MODINDICES(ALL); FSCOEFFICIENT;
FSDETERMINACY;

A 10: Bi-factor ESEM with ML, Target Rotation and the Introduction of M.I. in the Clinical Population Sample

MODEL:
fg BY t1 t2 t3 t4 t5 t6 t7 t8 t9 t10 t11 t12 t13 t14 t15 t16 t17 t18 t19 t20 t21 t22 t23 t24 t25 t26 t27 t28 t29 t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t6~0 t21~0 t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0 t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0 t9~0 t24~0 t12~0 t27~0 t4~0 t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0 t3~0 t14~0 t18~0 t29~0(*1);
T16 WITH T13;
T22 WITH T7;
T23 WITH T8;
T12 WITH T27;

ANALYSIS:
ROTATION = TARGET;
OUTPUT: STDY; SAMPSTAT; MODINDICES(ALL); FSCOEFFICIENT;
FSDETERMINACY;

A 11: Multiple Group Configural Invariance Between Population Samples

MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1); FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);
[t1-t30];
t1-t30;
[fg@0]; [FS1@0]; [FS2@0]; [FS3@0]; [FS4@0];

MODEL GENERAL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);
[t1-t30];
t1-t30;
t18 WITH t3(c1);
t21 WITH t17(c2);
[fg@0]; [FS1@0]; [FS2@0]; [FS3@0]; [FS4@0];

MODEL CLINICAL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
A 12: Multiple Group Metric Invariance Between Population Samples

MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
2~0 t17~0 t8~0 t23~0 t13~0 t28~0
16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);
MODEL GENERAL:
t1-t30;
t1-t30;
t18 WITH t3(c1);
t21 WITH t17(c2);
MODEL CLINICAL:
t1-t30;
t1-t30;
t16 WITH t13(d1);
t22 WITH t7(d2);
t23 WITH t8(d3);
t12 WITH t27(d4);
A 13: Multiple Group Metric Invariance Between Population Samples
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);
MODEL CLINICAL:
  t1-t30;
  t16 WITH t13(d1);
  t22 WITH t7(d2);
  t23 WITH t8(d3);
  t12 WITH t27(d4);
  [fg*]; [fs1*]; [fs2*]; [fs3*]; [fs4*];
A 14: Additional First-order and Hierarchical Multidimensional Analyses With the Spanish-Chilean-TEIQue-SF

<table>
<thead>
<tr>
<th>Models</th>
<th>$\chi^2$</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA</th>
<th>RMSEALb</th>
<th>RMSEAUb</th>
<th>SRMR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study 1: General population sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. First-order factor-level ESEM</td>
<td>522.92</td>
<td>323</td>
<td>0.926</td>
<td>0.043</td>
<td>0.036</td>
<td>0.050</td>
<td>0.037</td>
</tr>
<tr>
<td>2. First-order factor-level ESEM with M.I.</td>
<td>492.44</td>
<td>319</td>
<td>0.935</td>
<td>0.040</td>
<td>0.033</td>
<td>0.047</td>
<td>0.036</td>
</tr>
<tr>
<td>3. Second-order ESEM-within-CFA with M.I.</td>
<td>457.94</td>
<td>319</td>
<td>0.948</td>
<td>0.036</td>
<td>0.028</td>
<td>0.043</td>
<td>0.035</td>
</tr>
<tr>
<td>4. Reported model 4. Bifactor ESEM with M.I.</td>
<td>409.77</td>
<td>293</td>
<td>0.957</td>
<td>0.034</td>
<td>0.026</td>
<td>0.042</td>
<td>0.032</td>
</tr>
</tbody>
</table>

$\chi^2$ difference between Models 3 and 4. 48.17** 26

<table>
<thead>
<tr>
<th>Study 2: Clinical population sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. First-order factor-level ESEM</td>
</tr>
<tr>
<td>2. First-order factor-level ESEM with M.I.</td>
</tr>
<tr>
<td>3. Second-order ESEM-within-CFA with M.I.</td>
</tr>
<tr>
<td>4. Reported model 2. Bifactor ESEM with M.I.</td>
</tr>
</tbody>
</table>

$\chi^2$ difference between Models 3 and 4. 59.96*** 26

*Note.* Chilean general population, $N = 335$; and Chilean clinical population, $N = 120$. *M.I.* = Modification indices. *ESEM within-CFA* = ESEM tested within CFA framework. $\chi^2$ = Chi Squared, df = degrees of freedom, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation, RMSEALb = RMSEA Lower bound, RMSEAUb = Upper bound. SRMR = Standardized root mean residual. Models 3 and 4 represent the more accurate and definite descriptions of CFA and ESEM representations of the Spanish-Chilean-TEIQque-SF’s internal structure in the general and clinical population samples. **$p < 0.01$, ***$p < 0.001$. 
A 15: Age Measurement Invariance Mplus Syntax
VARIABLE:
names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation agec;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is agec (1=Young 2=Senior);
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
sampstat;
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);

A 16: Gender Measurement Invariance Mplus Syntax
VARIABLE:
names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is gender (1=Woman 2=Man);
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
sampstat;
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);

A 17: Women Measurement Invariance across Countries Mplus Syntax
VARIABLE:
names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is group (1=Chile 2=Brazil 3=UK 4=Italy);
USEOBSERVATIONS = gender EQ 1
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
SAMPLE;
MODINDICES(ALL);
MODEL:
fg BY t1-t30 (*1);

FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);

A 18: Men Measurement Invariance across Countries Mplus Syntax

VARIABLE:
  names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is group (1=Chile 2=Brazil 3=UK 4=Italy);
USEOBSERVATIONS = gender EQ 2

ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
sampstat;

MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
A 19: Educational Level Measurement Invariance Mplus Syntax

VARIABLE:
names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
     t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
     t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
     gender age group education civilstatus occupation agec;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
     t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
     t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is education (1=secondary 2=university 3=master 5=other);
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT: sampstat;
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
A 20: Civil Status Measurement Invariance Mplus Syntax

VARIABLE:
names = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation agec;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is civilstatus (1=single 2=relationship 3=married 4=divorced/separated 5=other);
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
sampstat;
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
A 21: Occupation Measurement Invariance Mplus Syntax

VARIABLE:
names= t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30
gender age group education civilstatus occupation agec;
usevar = t1 t2 t3 t4 t5 t6 t7 t8 t9 t10
t11 t12 t13 t14 t15 t16 t17 t18 t19 t20
t21 t22 t23 t24 t25 t26 t27 t28 t29 t30;
grouping is occupation (1=private 2=public 3=teacher 4=student 5= unemployed 6=other);
ANALYSIS:
ESTIMATOR = MLR;
ROTATION = TARGET (orthogonal);
MODEL = CONFIGURAL METRIC SCALAR;
OUTPUT:
sampstat;
MODEL:
fg BY t1-t30 (*1);
FS1 BY t5 t20 t9 t24 t12 t27 t4~0 t19~0
t7~0 t22~0 t15~0 t30~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0
t28~0 t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS2 BY t4 t19 t7 t22 t15 t30 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t1~0
t16~0 t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t6~0 t21~0 t10~0
t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS3 BY t1 t16 t2 t17 t8 t23 t13 t28 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t5~0
t20~0 t9~0 t24~0 t12~0 t27~0 t6~0 t21~0
t10~0 t25~0 t11~0 t26~0 t3~0 t14~0 t18~0 t29~0(*1);
FS4 BY t6 t21 t10 t25 t11 t26 t5~0 t20~0
t9~0 t24~0 t12~0 t27~0 t4~0
t19~0 t7~0 t22~0 t15~0 t30~0 t1~0 t16~0
t2~0 t17~0 t8~0 t23~0 t13~0 t28~0
t3~0 t14~0 t18~0 t29~0(*1);
A 22: Chilean Adaptation and Validation of the Outcome Questionnaire (OQ-45.2)

Cuestionario de resultados OQ-45.2

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<th>Cásc</th>
<th>A veces</th>
<th>Con frecuencia</th>
<th>Casi siempre</th>
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Desarrollado por Michael Lambert, Ph. D. y Gary M. Burdanga, Ph. D. 
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Para mayor información contácte a Guillerme de la Parra C. o Alejandro van der Eerden M. 
R. MAX: gdelparra@help.net
R. MAX: awd@derg.net
A 23: Chilean Adaptation and Validation of the Working Alliance Inventory (WAI)-Patient Version

Inventario de Alianza de Trabajo

Forma P

Instrucciones

En las siguientes páginas se plantean una serie de afirmaciones que describen algunas de las diferentes maneras en que una persona puede pensar o sentir acerca de su psicoterapeuta (psicólogo). A medida que lea las afirmaciones, cuando en el texto aparezca una __________, inserte mentalmente el nombre de su psicoterapeuta (psicólogo).

Bajo cada una de las afirmaciones hay una escala con puntaje de 1 a 7:

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<td>5</td>
<td>6</td>
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<tr>
<td>Nunca</td>
<td>Casi nunca</td>
<td>ocasionalmente</td>
<td>A veces</td>
<td>Frecuentemente</td>
<td>Casi siempre</td>
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</table>

Si la afirmación describe la manera que usted piensa (o siente) siempre, marque el número 7; si esto nunca le sucede marque el número 1. Use los números existentes entremedio para describir las variaciones entre estos extremos.

Este cuestionario es CONFIDENCIAL; ni su terapeuta ni el consultorio verán sus respuestas.

Trabaje rápido; queremos conocer sus primeras impresiones.
(POR FAVOR NO OLVIDE RESPONDER TODOS LOS ITEMS)

Gracias por su cooperación.

I.A.T.: Adaptación a Chile (Santibañez, 2000)

Puntajes: T: _______  M: _______  V: _______
<table>
<thead>
<tr>
<th></th>
<th>1. Me siento incómodo (a) con __________</th>
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<td></td>
<td>2. Creo que __________ y yo estamos de acuerdo respecto de las cosas que yo necesitaré hacer en la terapia para cambiar mi situación.</td>
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<td>3. Siento que me aproblemoy me tienen preocupado (a) los resultados de estas sesiones.</td>
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<td>4. Lo que estoy haciendo en terapia me aporta nuevas perspectivas para mirar mi problema.</td>
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<td>5. Piensoy __________ y yo nos entendemos.</td>
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<td>6. Siento que __________ percibe adecuadamente cuáles son mis metas.</td>
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<td>7. Encuentro confuso lo que estoy haciendo en terapia.</td>
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<td>8. Creo que __________ me estima.</td>
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<td>9. Desearía que __________ y yo pudiéramos clarificar el objetivo de nuestras sesiones.</td>
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<td>10. Estoy en desacuerdo con __________ acerca de lo que yo debería lograr en terapia.</td>
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<td>11. Creo que el tiempo que __________ y yo estamos juntos en la (s) sesión (es) no es aprovechado de modo eficiente.</td>
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<td>12. Me da la impresión que __________ no entiende lo que yo estoy tratando de lograr en la terapia.</td>
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<td>13. Tengo claro cuáles son mis responsabilidades en la terapia.</td>
<td>Nunca</td>
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<tr>
<td>14. Las metas de estas sesiones son importantes para mí.</td>
<td>Nunca</td>
</tr>
<tr>
<td>15. Encuentro que lo que _______ y yo hacemos en terapia no se relaciona con mis problemas actuales.</td>
<td>Nunca</td>
</tr>
<tr>
<td>16. Siento que las cosas que hago en la terapia me van a ayudar a lograr los cambios que deseo.</td>
<td>Nunca</td>
</tr>
<tr>
<td>17. Creo que ________ está genuinamente preocupado (a) por mi bienestar.</td>
<td>Nunca</td>
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<tr>
<td>18. Tengo claridad respecto a lo que ________ quiere que yo haga en estas sesiones.</td>
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<td>19. Siento que ________ y yo nos respetamos mutuamente.</td>
<td>Nunca</td>
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<td>20. Siento que ________ no es completamente sincero (a) en sus sentimientos hacia mí.</td>
<td>Nunca</td>
</tr>
<tr>
<td>22. ________, y yo estamos trabajando para lograr metas terapéuticas establecidas de mutuo acuerdo.</td>
<td>Nunca</td>
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<td>23. Siento que ________ me aprecia.</td>
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<td>24. Creo que ________, y yo estamos de acuerdo sobre lo que para mí es importante trabajar.</td>
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25. Como resultado de estas sesiones, tengo más claro como podría cambiar.

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26. Creo que _________ y yo confiamos uno en el otro.

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27. Me da la impresión que _________ y yo tenemos ideas diferentes acerca de cuáles son mis problemas.

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28. Mi relación con _________ es muy importante para mí.

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29. Tengo la sensación que si yo digo o hago cosas incorrectas, _________ va a dejar de trabajar conmigo.

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30. Pienso que _________ y yo trabajamos juntos (as) en establecer metas para mi terapia.

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31. Estoy frustrado (a) por las cosas que estoy haciendo en terapia.

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32. Creo que hemos establecido un buen acuerdo sobre cuál es el tipo de cambios que serían buenos para mi.

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33. Siento que las cosas que _________ me pide que haga no tienen sentido.

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34. No sé qué resultados esperar de mi psicoterapia.

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35. Creo que la manera en que estamos trabajando con mi problema es correcta.

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36. Siento que _________ se preocupa por mí incluso cuando hago cosas que él (ella) no aprueba.

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### Inventario de Alianza de Trabajo

**Forma T**

**Instrucciones**

En las siguientes páginas se plantean una serie de afirmaciones que describen algunas de las diferentes maneras en que una persona puede pensar o sentir acerca de su paciente (cliente). A medida que lea las afirmaciones, cuando en el texto aparezca una ____________, inserte mentalmente el nombre de su paciente (cliente).

Bajo cada una de las afirmaciones hay una escala con puntaje de 1 a 7:

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Si la afirmación describe la manera que usted piensa (o siente) siempre, marque el número 7; si esto nunca le sucede marque el número 1. Use los números existentes entremedio para describir las variaciones entre estos extremos.

**Este cuestionario es CONFIDENCIAL; ni su paciente ni el consultorio verán sus respuestas.**

Trabaje rápido; queremos conocer sus primeras impresiones.

**POR FAVOR NO OLVIDE RESPONDER TODOS LOS ITÉMENS**

Gracias por su cooperación.


I.A.T.: Adaptación a Chile (Santibañez, 2000)

---

Puntajes: T: _______  M: _______  V: _______

IAT (T) p. 1
1. Me siento incómodo (a) con __________.

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2. Creo que __________ y yo estamos de acuerdo acerca de los pasos necesarios para mejorar su situación.

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3. Tengo ciertas dudas acerca de los resultados de estas sesiones.

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4. Creo que mi paciente y yo tenemos confianza que nuestro desempeño en la terapia es útil.

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5. Siento que realmente entiendo a __________.

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6. __________ y yo tenemos una percepción común de sus metas.

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7. Me da la impresión que __________ encuentra confuso lo que estamos haciendo en terapia.

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8. Creo que __________ me aprecia.

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9. Siento necesidad de clarificarle el sentido de nuestras sesiones a __________.

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10. Tengo algunos desacuerdos con __________ acerca de los objetivos de estas sesiones.

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11. Creo que el tiempo que __________ y yo estamos pasando juntos no es usado eficientemente.

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12. Tengo dudas acerca de lo que estamos tratando de lograr en la terapia.

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13. Yo soy claro y explícito con ______ acerca de cuáles son sus responsabilidades en la terapia.

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14. Las metas actuales de estas sesiones son importantes para mi.

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15. Encuentro que lo que ______ y yo estamos haciendo en terapia no está relacionado con sus reales preocupaciones.

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16. Tengo confianza en que las cosas que hacemos en terapia ayudarán a ______ a lograr los cambios que él (ella) desea.

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17. Estoy genuinamente preocupado (a) por el bienestar de ______.

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18. Tengo claro lo que espero que ______ haga en estas sesiones.

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19. Pienso que ______ y yo nos respetamos el uno al otro.

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20. Siento que yo no soy completamente honesto (a) acerca de mis sentimientos hacia ______.

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21. Confío en mi habilidad para ayudar a ______.

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22. Creo que estamos trabajando hacia el logro de las metas mutuamente acordadas.

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23. Yo aprecio a ______ como persona.

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24. Creo que ______ y yo estamos de acuerdo sobre lo que es importante trabajar.

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25. Pienso que un resultado de estas sesiones es que ________ tiene más claro cómo puede cambiar.

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26. Siento que ________ y yo hemos logrado una confianza mutua.

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27. Pienso que ________ y yo tenemos ideas diferentes acerca de cuáles son sus problemas reales.

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28. Nuestra relación es importante para ________.

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29. Creo que ________ teme que si él (ella) dice o hace cosas incorrectas, yo dejaría de trabajar con él (ella).

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30. ________ y yo hemos colaborado en establecer las metas para esta (s) sesión (es).

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31. Siento que ________ está frustrado (a) por lo que le estoy pidiendo que haga en terapia.

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32. Hemos establecido un buen acuerdo acerca de los cambios que serían buenos para ________.

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33. Pienso que las cosas que estamos haciendo en terapia no tienen mucho sentido para ________.

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34. Creo que ________ no sabe qué esperar como resultado de la psicoterapia.

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35. Me da la impresión que ________ cree que la manera como estamos trabajando con su problema es correcta.

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36. Respeto a ________ incluso cuando hace cosas que yo no apruebo.

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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nunca</td>
<td>Casi nunca</td>
<td>Ocasionalmente</td>
<td>A veces</td>
<td>Frecuentemente</td>
<td>Casi siempre</td>
<td>Siempre</td>
</tr>
</tbody>
</table>
A 25: R Code for Multiple Imputation

```r
library(foreign)
library(mice)
library(VIM)
library(semPlot)
library(semTools)

setwd("C:\Users\Pablopd\Dropbox\R_Scripts")

MISCO <- read.spss('C:\Users\Pablopd\Dropbox\R_Scripts\Dataset Study 4 (RECODED) - Final-ML.sav',
                    use.value.labels = TRUE, to.data.frame = TRUE)
str(MISCO)
summary(MISCO)
p <- function(x) {sum(is.na(x))/length(x)*100}
apply(MISCO, 2, p)
md.pattern(MISCO)
md.pairs(MISCO)

#MICE
impute <- mice(MISCO[,3:30], m = 54, seed = 123)
print(impute)
head(impute$loggedEvents, 2)
tail(impute$loggedEvents, 2)
outlist <- as.character(impute$loggedEvents[, "out"])
write.csv(outlist, file = 'outlistloggedeventsfull.csv', row.names=TRUE)
mat <- complete(impute, 'long')
write.csv(mat, file = 'imputedlongtherapy.csv', row.names=TRUE)

fmiresults <- fmi(impute, method = "saturated", group = NULL, ords = NULL,
                   varnames = NULL, exclude = NULL, fewImps = FALSE)
warnings()
print(fmiresults)
write.csv(fmiresults, file = 'fmiresultsFINAL1.csv', row.names=TRUE)
```

A 26: SPSS Merge Syntaxes of the Imputed Datasets

#case 1, only for missing values of patients

```sql
SORT CASES BY @.id(A) @.imp(A).

* OMS.
DATASET DECLARE finalagreggated.
OMS
```
/SELECT TABLES
/IF COMMANDS=['Frequencies'] SUBTYPES=['Statistics']
/DESTINATION FORMAT=SAV NUMBERED=TableName_ 
OUTFILE='finalaggregated' VIEWER=NO
/COLUMNS SEQUENCE=[RALL CALL LALL].

SORT CASES BY @.id.
SPLIT FILE SEPARATE BY @.id.

FREQUENCIES VARIABLES=age WBT SCT EMT SBT GTEIT IAT1Bt IAT1Tt IAT1Gt 
IAT1TOTALt GTEIp WBp SCp EMp SBp 
IATBONDP IATTASKSP IATGOALSP IATTOTALP SD1 IR1 SR1 OQTOTAL1 SD2 IR2 
SR2 OQTOTAL2 
/FORMAT=NOTABLE 
/STATISTICS=MEAN 
/ORDER=ANALYSIS.

* OMSEND.
OMSEND TAG=['$Id1'].

#case 2, only for missing values of therapists
SORT CASES BY @.id(A) @.imp(A).

* OMS.
DATASET DECLARE typeoftherapyonly.
OMS
/SELECT TABLES
/IF COMMANDS=['Frequencies'] SUBTYPES=['Statistics']
/DESTINATION FORMAT=SAV NUMBERED=TableNumber_ 
OUTFILE='typeoftherapyonly' VIEWER=NO
/COLUMNS SEQUENCE=[RALL CALL LALL].

SORT CASES BY @.id.
SPLIT FILE SEPARATE BY @.id.

FREQUENCIES VARIABLES= age WBT SCT EMT SBT GTEIT IAT1Bt IAT1Tt IAT1Gt 
IAT1TOTALt GTEIp WBp SCp EMp SBp 
IATBONDP IATTASKSP IATGOALSP IATTOTALP SD1 IR1 SR1 OQTOTAL1 SD2 IR2 
SR2 OQTOTAL2 typeoftherapy 
/FORMAT=NOTABLE 
/STATISTICS=MEAN MODE 
/ORDER=ANALYSIS.

* OMSEND.
OMSEND TAG=['$Id1'].

A 27: R Growth Modelling Scripts Implemented in Chapter Five

library(foreign)
library(lavaan)
library(semPlot)
library(semTools)
library(multilevel)
library(nlme)
library(lattice)
library(dplyr)
library(rlang)
library(effectsize)
library(parameters)

MULTI<-ead.spss(’C:\Users\Pablopd\Dropbox\R_Scripts\Finalaggregated.sav’,
  use.value.labels= TRUE, to.data.frame = TRUE)

summary(MULTI)

##################### EXAMINE THE DV ACROSS ID (PATIENTS) ########################

#Examine the DV with OQ
Null.Model.OQ <- lme(MULTDV~1, random=~1|id, data=UNIV.OQ,
control=list(opt="optim"))
VarCorr(Null.Model.OQ)
85.7804/(85.7804+193.0036) #icc
summary(Null.Model.OQ)

#Examine the DV with SD
Null.Model.sd <- lme(MULTDV~1, random=~1|id, data=UNIV.SD, control=list(opt="optim"))
VarCorr(Null.Model.sd)
50.95509/(50.95509+96.50238) #icc
summary(Null.Model.sd)

#Examine the DV with IR
Null.Model.ir <- lme(MULTDV~1, random=~1|id, data=UNIV.IR, control=list(opt="optim"))
VarCorr(Null.Model.ir)
4.156066/(4.156066+20.798555) #icc
summary(Null.Model.ir)

#Examine the DV with SR
Null.Model.sr <- lme(MULTDV~1, random=~1|id, data=UNIV.SR, control=list(opt="optim"))
VarCorr(Null.Model.sr)
3.846543/(3.846543+13.589175) #icc
summary(Null.Model.sr)

#########################EXAMINE THE DV ACROSS YOPP#################################

#Examine the DV with OQ
Null.Model.OQ <- lme(MULTDV~1, random=~1|YOPP, data=UNIV.OQ, control=list(opt="optim"))
VarCorr(Null.Model.OQ)
summary(Null.Model.OQ)
17.24955/(17.24955+270.50332) #icc
effectsize(Null.Model.OQ)

#Examine the DV with SD
Null.Model.sd <- lme(MULTDV~1, random=~1|YOPP, data=UNIV.SD, control=list(opt="optim"))
VarCorr(Null.Model.sd)
12.97793/(12.97793+142.90903) #icc
effectsize(Null.Model.sd)
19.7262/(19.7262+129.5803)

#Examine the DV with IR
Null.Model.ir <- lme(MULTDV~1, random=~1|YOPP, data=UNIV.IR, control=list(opt="optim"))
VarCorr(Null.Model.ir)
1.222182/(1.222182+24.276281) #icc
effectsize(Null.Model.ir)

#Examine the DV with SR
Null.Model.sr <- lme(MULTDV~1, random=~1|YOPP, data=UNIV.SR, control=list(opt="optim"))
VarCorr(Null.Model.sr)
1.041849/(1.041849+16.792726) #icc
effectsize(Null.Model.sr)

#########################EXAMINE THE DV ACROSS CENTRES###########################

#Examine the DV with OQ
Null.Model.OQ <- lme(MULTDV~1, random=~1|Centre, data=UNIV.OQ, control=list(opt="optim"))
VarCorr(Null.Model.OQ)
summary(Null.Model.OQ)
0.03149279/(0.03149279+278.13174828) #icc
effectsize(Null.Model.OQ)
#Examine the DV with SD
Null.Model.sd <- lme(MULTDV~1, random=~1|Centre, data=UNIV.SD, control=list(opt="optim"))
VarCorr(Null.Model.sd)
1.977918/(1.977918+146.067646) #icc
effectsize(Null.Model.sd)

#Examine the DV with IR
Null.Model.ir <- lme(MULTDV~1, random=~1|Centre, data=UNIV.IR, control=list(opt="optim"))
VarCorr(Null.Model.ir)
0.6752319/(0.6752319+24.4865880) #icc
effectsize(Null.Model.ir)

#Examine the DV with SR
Null.Model.sr <- lme(MULTDV~1, random=~1|Centre, data=UNIV.SR, control=list(opt="optim"))
VarCorr(Null.Model.sr)
0.02966091/(0.02966091+17.39051477) #icc
effectsize(Null.Model.sr)

#Examine the DV across Therapists

#Examine the DV with SD
Null.Model.OQ <- lme(MULTDV~1, random=~1|Therapist, data=UNIV.OQ, control=list(opt="optim"))
VarCorr(Null.Model.OQ)
85.97612/(85.97612+205.27732) #icc
effectsize(Null.Model.OQ)

#Examine the DV with IR
Null.Model.ir <- lme(MULTDV~1, random=~1|Therapist, data=UNIV.IR, control=list(opt="optim"))
VarCorr(Null.Model.ir)
3.519709/(3.519709+21.686690) #icc
effectsize(Null.Model.ir)

#Examine the DV with SR

Null.Model.sr <- lme(MULTDV~1, random=~1|Therapist, data=UNIV.SR, control=list(opt="optim"))
VarCorr(Null.Model.sr)
1.071934/(1.071934+16.420135) #icc
effectsize(Null.Model.sr)

#########################EXAMINE THE DV ACROSS COHORTS##########################

#Examine the DV with OQ

Null.Model.OQ <- lme(MULTDV~1, random=~1|Cohort, data=UNIV.OQ, control=list(opt="optim"))
VarCorr(Null.Model.OQ)
30.6087/(30.6087+263.1353) #icc
effectsize(Null.Model.OQ)

#Examine the DV with SD

Null.Model.sd <- lme(MULTDV~1, random=~1|Cohort, data=UNIV.SD, control=list(opt="optim"))
VarCorr(Null.Model.sd)
4.22074/(4.22074+145.00540) #icc
effectsize(Null.Model.sd)

#Examine the DV with IR

Null.Model.ir <- lme(MULTDV~1, random=~1|Cohort, data=UNIV.IR, control=list(opt="optim"))
VarCorr(Null.Model.ir)
7.863565/(7.863565+21.068917) #icc
effectsize(Null.Model.ir)

#Examine the DV with SR

Null.Model.sr <- lme(MULTDV~1, random=~1|Cohort, data=UNIV.SR, control=list(opt="optim"))
VarCorr(Null.Model.sr)
0.002154065/(0.002154065+17.406801599) #icc
effectsize(Null.Model.sr)

#########################EXAMINE THE DV ACROSS TYPE OF PSYCHOTHERAPY##########################
# Examine the DV with OQ

Null.Model.OQ <- lme(MULTDV~1, random=~1|typeoftherapy, data=UNIV.OQ, na.action = na.omit, control=list(opt="optim"))
VarCorr(Null.Model.OQ)
47.69245/(47.69245+249.82384) #icc
effectsize(Null.Model.OQ)
summary(Null.Model.OQ)

# Examine the DV with SD

Null.Model.sd <- lme(MULTDV~1, random=~1|typeoftherapy, na.action = na.omit, data=UNIV.SD, control=list(opt="optim"))
VarCorr(Null.Model.sd)
21.65667/(21.65667+133.82237) #icc
effectsize(Null.Model.sd)

# Examine the DV with IR

Null.Model.ir <- lme(MULTDV~1, random=~1|typeoftherapy, data=UNIV.IR, na.action = na.omit, control=list(opt="optim"))
VarCorr(Null.Model.ir)
1.270729/(1.270729+24.070012) #icc
effectsize(Null.Model.ir)

# Examine the DV with SR

Null.Model.sr <- lme(MULTDV~1, random=~1|typeoftherapy, data=UNIV.SR, na.action = na.omit, control=list(opt="optim"))
VarCorr(Null.Model.sr)
0.377048/(0.377048+17.134785) #icc
effectsize(Null.Model.sr)

# Model Time

# Model time with OQ

Null.Model.OQ.1 <- lme(MULTDV~TIME, random=~1|id, data=UNIV.OQ, control=list(opt="optim"))
summary(Null.Model.OQ.1)
effectsize(Null.Model.OQ.1, robust=TRUE)
VarCorr(Null.Model.OQ.1)
100.1781/(100.1781+164.2084)

# Model time with SD
Null.Model.sd.1 <- lme(MULTDV~TIME, random=~1|id, data=UNIV.SD, control=list(opt="optim"))
summary(Null.Model.sd.1)
effectsize(Null.Model.sd.1, robust=TRUE)
VarCorr(Null.Model.sd.1)
57.35791/(57.35791+83.69486)

#Model time with IR

Null.Model.ir.1 <- lme(MULTDV~TIME, random=~1|id, data=UNIV.IR, control=list(opt="optim"))
summary(Null.Model.ir.1)
effectsize(Null.Model.ir.1, robust=TRUE)
VarCorr(Null.Model.ir.1)
4.900637/(4.900637+19.305673)

#Model time with SR

Null.Model.sr.1 <- lme(MULTDV~TIME, random=~1|id, data=UNIV.SR, control=list(opt="optim"))
summary(Null.Model.sr.1)
effectsize(Null.Model.sr.1, robust=TRUE)
VarCorr(Null.Model.sr.1)
3.888324/(3.888324+13.505629)

#Model slope variability with OQ

Model.OQ.2 <- update(Null.Model.OQ.1, random=~TIME|id)
anova(Null.Model.OQ.1, Model.OQ.2)
effectsize(Model.OQ.2, robust=TRUE)

#Model slope variability with SD

Model.sd.2 <- update(Null.Model.sd.1, random=~TIME|id)
anova(Null.Model.sd.1, Model.sd.2)
effectsize(Model.sd.2, robust=TRUE)

#Model slope variability with IR

Model.ir.2 <- update(Null.Model.ir.1, random=~TIME|typeoftherapy/id)
anova(Null.Model.ir.1, Model.ir.2)
summary(Model.ir.2)
effectsize(Model.ir.2, robust=TRUE)
# Model slope variability with SR

Model.sr.2 <- update(Null.Model.sr.1, random=~TIME|id)
anova(Null.Model.sr.1, Model.sr.2)
effectsize(Model.sr.2, robust=TRUE)

####################### Predicting intercept variation - Level 2###############################

### Unsure whether to leave or remove AR1 as it was not significant before

####################### Predicting intercept variation - Level 2- with GTEIp(Patient), GRAND MEAN CENTERING###############################

# Model time with OQ

UNIV.OQ$GTEIp<- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(244.0885/(244.0885+42.1642))

# Model time with SD

UNIV.SD$GTEIp<- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(124.9107/(124.9107+21.23954)) #icc

# Model time with IR

UNIV.IR$GTEIp<- UNIV.IR$GTEIp-mean(UNIV.IR$GTEIp)
Model.ir.6 <- lme(MULTDV~TIME+GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(28.875271/(28.875271+4.865034)) #icc

# Model time with SR

UNIV.SR$GTEIp<- UNIV.SR$GTEIp-mean(UNIV.SR$GTEIp)
Model.sr.6 <- lme(MULTDV~TIME+GTEIp, random=~TIME|id, correlation=corAR1(), 
data=UNIV.SR, control=list(opt="optim"))
summary(Model.sr.6)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(20.118438/(20.118438+3.444007)) #icc

## Predicting intercept variation- Level 2- with Wellbeing(Patient),GRAND MEAN CENTERING ######

#Model time with OQ
UNIV.OQ$WBp<- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp, random=~TIME|id, correlation=corAR1(), 
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(242.72879/(242.72879+42.84406))

#Model time with SD
UNIV.SD$WBp<- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp, random=~TIME|id, correlation=corAR1(), 
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.82135/(126.82135+20.28422))

UNIV.IR$WBp<- UNIV.IR$WBp-mean(UNIV.IR$WBp)
Model.ir.6 <- lme(MULTDV~TIME+WBp, random=~TIME|id, correlation=corAR1(), 
data=UNIV.IR, control=list(opt="optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust=FALSE)
VarCorr(Model.ir.6)
(28.903855/(28.903855+4.850742))

UNIV.SR$WBp<- UNIV.SR$WBp-mean(UNIV.SR$WBp)
Model.SR.6 <- lme(MULTDV~TIME+WBp, random=~TIME|id, correlation=corAR1(), 
data=UNIV.SR, control=list(opt="optim"))
summary(Model.SR.6)
effectsize(Model.SR.6, robust=TRUE)
VarCorr(Model.SR.6)
(20.10275 /(20.10275 + 3.45185))
## Predicting intercept variation - Level 2 - with Self-control(Patient), GRAND MEAN CENTERING####

# Model time with OQ

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp, random = ~TIME|id, correlation = corAR1(),
  data = UNIV.OQ, control = list(opt = "optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust = FALSE)
VarCorr(Model.OQ.6)
(240.85397/(240.85397 + 43.78147))

# Model time with SD

UNIV.SD$SCp <- UNIV.SD$SCp - mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV ~ TIME + SCp, random = ~TIME|id, correlation = corAR1(),
  data = UNIV.SD, control = list(opt = "optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust = TRUE)
VarCorr(Model.sd.6)
(122.19762/(122.19762 + 22.59609))

# Model time with IR

UNIV.IR$SCp <- UNIV.IR$SCp - mean(UNIV.IR$SCp)
Model.ir.6 <- lme(MULTDV ~ TIME + SCp, random = ~TIME|id, correlation = corAR1(),
  data = UNIV.IR, control = list(opt = "optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust = FALSE)
VarCorr(Model.ir.6)
(28.876556/(28.876556 + 4.864391))

# Model time with SR

UNIV.SR$SCp <- UNIV.SR$SCp - mean(UNIV.SR$SCp)
Model.SR.6 <- lme(MULTDV ~ TIME + SCp, random = ~TIME|id, correlation = corAR1(),
  data = UNIV.SR, control = list(opt = "optim"))
summary(Model.SR.6)
effectsize(Model.SR.6, robust = TRUE)
VarCorr(Model.SR.6)
(20.104858/(20.104858 + 3.450797))

# Predicting intercept variation - Level 2 - with Emotionality(Patient), GRAND MEAN CENTERING####
# Model time with OQ

UNIV.OQ$EMp <- UNIV.OQ$EMp - mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV ~ TIME + EMp, random = ~TIME|id, correlation = corAR1(),
data = UNIV.OQ, control = list(opt = "optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust = FALSE)
VarCorr(Model.OQ.6)
(236.91358/(236.91358 + 45.75166))

# Model time with SD

UNIV.SD$EMp <- UNIV.SD$EMp - mean(UNIV.SD$EMp)
Model.SD.6 <- lme(MULTDV ~ TIME + EMp, random = ~TIME|id, correlation = corAR1(),
data = UNIV.SD, control = list(opt = "optim"))
summary(Model.SD.6)
effectsize(Model.SD.6, robust = TRUE)
VarCorr(Model.SD.6)
(119.0540/(119.0540 + 24.1679))

# Model time with IR

UNIV.IR$EMp <- UNIV.IR$EMp - mean(UNIV.IR$EMp)
Model.IR.6 <- lme(MULTDV ~ TIME + EMp, random = ~TIME|id, correlation = corAR1(),
data = UNIV.IR, control = list(opt = "optim"))
summary(Model.IR.6)
effectsize(Model.IR.6, robust = FALSE)
VarCorr(Model.IR.6)
(28.866429/(28.866429 + 4.869455))

UNIV.SR$EMp <- UNIV.SR$EMp - mean(UNIV.SR$EMp)
Model.SR.6 <- lme(MULTDV ~ TIME + EMp, random = ~TIME|id, correlation = corAR1(),
data = UNIV.SR, control = list(opt = "optim"))
summary(Model.SR.6)
effectsize(Model.SR.6, robust = TRUE)
VarCorr(Model.SR.6)
(20.182590/(20.182590 + 3.411931))

# Predicting intercept variation - Level 2 - with Sociability(Patient), GRAND MEAN CENTERING####

# Model time with SD

UNIV.SD$SBp <- UNIV.SD$SBp - mean(UNIV.SD$SBp)
Model.sd.6 <- lme(MULTDV ~ TIME + SBp, random = ~TIME|id, correlation = corAR1(),
data = UNIV.SD, control = list(opt = "optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(118.59811/(118.59811+24.39584))

#Model time with OQ

UNIV.OQ$SBp <- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.47074/(236.47074+45.97308))

#Model time with IR

UNIV.IR$SBp <- UNIV.IR$SBp-mean(UNIV.IR$SBp)
Model.IR.6 <- lme(MULTDV~TIME+SBp, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.IR, control=list(opt="optim"))
summary(Model.IR.6)
effectsize(Model.IR.6, robust=FALSE)
VarCorr(Model.IR.6)
(28.97212/(28.97212+4.81661))

UNIV.SR$SBp <- UNIV.SR$SBp-mean(UNIV.SR$SBp)
Model.SR.6 <- lme(MULTDV~TIME+SBp, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.SR, control=list(opt="optim"))
summary(Model.SR.6)
effectsize(Model.SR.6, robust=TRUE)
VarCorr(Model.SR.6)
(20.165980/(20.165980+3.420236))

######Predicting intercept variation- Level 2- with GTEIT, GRAND MEAN CENTERING#

#Model time with SD

UNIV.SD$GTEIT <- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.SD.6 <- lme(MULTDV~TIME+GTEIT, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
summary(Model.SD.6)
effectsize(Model.SD.6, robust=FALSE)
VarCorr(Model.SD.6)
(117.94723/(117.94723+24.72128))

#Model time with OQ
UNIV.OQ$GTEIT <- UNIV.OQ$GTEIT - mean(UNIV.OQ$GTEIT)
Model.OQ.6 <- lme(MULTDV ~ TIME + GTEIT, random = ~TIME|id, correlation = corAR1(),
data = UNIV.OQ, control = list(opt = "optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust = TRUE)
VarCorr(Model.OQ.6)
(236.82484/(236.82484+45.79603))

# Model time with IR

UNIV.IR$GTEIT <- UNIV.IR$GTEIT - mean(UNIV.IR$GTEIT)
Model.ir.6 <- lme(MULTDV ~ TIME + GTEIT, random = ~TIME|id, correlation = corAR1(),
data = UNIV.IR, control = list(opt = "optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust = TRUE)
VarCorr(Model.ir.6)
(29.159589/(29.159589+4.722875))

# Model time with SR

UNIV.SR$GTEIT <- UNIV.SR$GTEIT - mean(UNIV.SR$GTEIT)
Model.SR.6 <- lme(MULTDV ~ TIME + GTEIT, random = ~TIME|id, correlation = corAR1(),
data = UNIV.SR, control = list(opt = "optim"))
summary(Model.SR.6)
effectsize(Model.SR.6, robust = TRUE)
VarCorr(Model.SR.6)
(20.23195/(20.23195+3.38725))

########### Predicting intercept variation - Level 2 - with Wellbeing-Therapist, GRAND MEAN CENTERING

# Model time with OQ

UNIV.OQ$WBT <- UNIV.OQ$WBT - mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV ~ TIME + WBT, random = ~TIME|id, correlation = corAR1(),
data = UNIV.OQ, control = list(opt = "optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust = FALSE)
VarCorr(Model.OQ.6)
(235.75662/(235.75662+46.33014))

# Model time with SD

UNIV.SD$WBT <- UNIV.SD$WBT - mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV ~ TIME + WBT, random = ~TIME|id, correlation = corAR1(),
data = UNIV.SD, control = list(opt = "optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
\((117.88352/(117.88352+24.75313))\)

#Model time with IR

\(\text{UNIV.IR}\$WBT <- \text{UNIV.IR}\$WBT-mean(UNIV.IR\$WBT)\)

Model.ir.6 <- lme(MULTDV~TIME+WBT, random=~TIME|id, correlation=corAR1(),
  data=UNIV.IR, control=list(opt="optim"))

summary(Model.ir.6)
effectsize(Model.ir.6, robust=FALSE)
VarCorr(Model.ir.6)
\((28.966834/(28.966834+4.819252))\)

#Model time with SR

\(\text{UNIV.SR}\$WBT <- \text{UNIV.SR}\$WBT-mean(UNIV.SR\$WBT)\)

Model.sr.6 <- lme(MULTDV~TIME+WBT, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SR, control=list(opt="optim"))

summary(Model.sr.6)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
\((20.118438/(20.118438+3.444007))\)

#Predicting intercept variation- Level 2- with Self-control-Therapist, GRAND MEAN CENTERING#

#Model time with OQ

\(\text{UNIV.OQ}\$SCT <- \text{UNIV.OQ}\$SCT-mean(UNIV.OQ\$SCT)\)

Model.OQ.6 <- lme(MULTDV~TIME+SCT, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))

summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
\((235.75662/(235.75662+46.33014))\)

#Model time with SD

\(\text{UNIV.SD}\$SCT <- \text{UNIV.SD}\$SCT-mean(UNIV.SD\$SCT)\)

Model.sd.6 <- lme(MULTDV~TIME+SCT, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))

summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
# Model time with IR

\[
\text{UNIV.IR} \cdot \text{SCT} \leftarrow \text{UNIV.IR} \cdot \text{SCT} - \text{mean(UNIV.IR} \cdot \text{SCT})
\]

Model.ir.6 <- lme(MULTDV~TIME+SCT, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.IR, control=list(opt="optim"))

summary(Model.ir.6)

effectsize(Model.ir.6, robust=FALSE)

VarCorr(Model.ir.6)

(28.966834/(28.966834+4.819252))

# Model time with SR

\[
\text{UNIV.SR} \cdot \text{SCT} \leftarrow \text{UNIV.SR} \cdot \text{SCT} - \text{mean(UNIV.SR} \cdot \text{SCT})
\]

Model.sr.6 <- lme(MULTDV~TIME+SCT, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SR, control=list(opt="optim"))

summary(Model.sr.6)

effectsize(Model.sr.6, robust=TRUE)

VarCorr(Model.sr.6)

(20.328910/(20.328910+3.338771))

##### Predicting intercept variation - Level 2 - with Emotionality-Therapist, GRAND MEAN CENTERING #######

# Model time with OQ

\[
\text{UNIV.OQ} \cdot \text{EMT} \leftarrow \text{UNIV.OQ} \cdot \text{EMT} - \text{mean(UNIV.OQ} \cdot \text{EMT})
\]

Model.OQ.6 <- lme(MULTDV~TIME+EMT, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.OQ, control=list(opt="optim"))

summary(Model.OQ.6)

effectsize(Model.OQ.6, robust=FALSE)

VarCorr(Model.OQ.6)

(234.95287/(234.95287+46.73202))

# Model time with SD

\[
\text{UNIV.SD} \cdot \text{EMT} \leftarrow \text{UNIV.SD} \cdot \text{EMT} - \text{mean(UNIV.SD} \cdot \text{EMT})
\]

Model.sd.6 <- lme(MULTDV~TIME+EMT, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SD, control=list(opt="optim"))

summary(Model.sd.6)

effectsize(Model.sd.6, robust=FALSE)

VarCorr(Model.sd.6)

(117.39352/(117.39352+24.99813))

# Model time with IR
UNIV.IR$EMT <- UNIV.IR$EMT - mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV ~ TIME + EMT, random = ~ TIME|id, correlation = corAR1(),
data = UNIV.IR, control = list(opt = "optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust = FALSE)
VarCorr(Model.ir.6)
(29.111189/(29.111189 + 4.747075))

# Model time with SR

UNIV.SR$EMT <- UNIV.SR$EMT - mean(UNIV.SR$EMT)
Model.sr.6 <- lme(MULTDV ~ TIME + EMT, random = ~ TIME|id, correlation = corAR1(),
data = UNIV.SR, control = list(opt = "optim"))
summary(Model.sr.6)
effectsize(Model.sr.6, robust = TRUE)
VarCorr(Model.sr.6)
(20.328910/(20.328910 + 3.338771))

######### Predicting intercept variation - Level 2 - with Sociability, GRAND MEAN CENTERING###########

# Model time with OQ

UNIV.OQ$SBT <- UNIV.OQ$SBT - mean(UNIV.OQ$SBT)
Model.OQ.6 <- lme(MULTDV ~ TIME + SBT, random = ~ TIME|id, correlation = corAR1(),
data = UNIV.OQ, control = list(opt = "optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust = FALSE)
VarCorr(Model.OQ.6)
(234.95287/(234.95287 + 46.73202))

# Model time with SD

UNIV.SD$SBT <- UNIV.SD$SBT - mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV ~ TIME + SBT, random = ~ TIME|id, correlation = corAR1(),
data = UNIV.SD, control = list(opt = "optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust = FALSE)
VarCorr(Model.sd.6)
(117.39352/(117.39352 + 24.99813))

# Model time with IR

UNIV.IR$SBT <- UNIV.IR$SBT - mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV ~ TIME + SBT, random = ~ TIME|id, correlation = corAR1(),
data = UNIV.IR, control = list(opt = "optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust = FALSE)
data=UNIV.IR, control=list(opt="optim"))
summary(Model.ir.6)
effectsize(Model.ir.6, robust=FALSE)
VarCorr(Model.ir.6)
(29.111189/(29.111189+4.747075))

#Model time with SR

UNIV.SR$SBT<- UNIV.SR$SBT-mean(UNIV.SR$SBT)
Model.sr.6 <- lme(MULTDV~TIME+SBT, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
summary(Model.sr.6)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(20.328910 /(20.328910+3.338771))

########################### Predicting SLOPE VARIATIONs- Level 2- with GTEIp, GRAND MEAN CENTERING#############################

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
### Predicting SLOPE VARIATIONs- Level 2- with WBp, GRAND MEAN CENTERING###

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*WBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(optim))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=FALSE)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*WBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(optim))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)

# Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*WBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(optim))
round(summary(Model.ir.6)$tTable, dig=5)

effectsize(Model.OQ.6, robust=FALSE)

VarCorr(Model.OQ.6)
(227.03974/(227.03974+45.23527))

### Predicting SLOPE VARIATIONs- Level 2- with SCp, GRAND MEAN CENTERING###

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*SCp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(optim))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=FALSE)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*SCp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(optim))
round(summary(Model.sd.6)$tTable, dig=5)
effectsizer(Model.sd.6, robust=FALSE)

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*SCp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*SCp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

############################### Predicting SLOPE VARIATIONs- Level 2- with EMp (PATIENT), GRAND MEAN CENTERING###############################

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*EMp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsizer(Model.sd.6, robust=FALSE)

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*EMp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with IR

Model.IR.6 <- lme(MULTDV~TIME*EMp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.IR.6)$tTable, dig=5)

#Model time with SR

Model.SR.6 <- lme(MULTDV~TIME*EMp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.SR.6)$tTable, dig=5)

############################### Predicting SLOPE VARIATIONs- Level 2- with SBp (PATIENT), GRAND MEAN CENTERING###############################
#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with IR

Model.IR.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.IR.6)$tTable, dig=5)

#Model time with SR

Model.SR.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.SR.6)$tTable, dig=5)

######################## Predicting SLOPE VARIATION (PATIENT),
GRAND MEAN CENTERING##########################

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(216.78271/(216.78271+40.13081))

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(93.4074/(93.4074+18.83383))
Predicting SLOPE VARIATIONs - Level 2 - with GTEIT, GRAND MEAN CENTERING

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*GTEIT, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*GTEIT, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

# Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*GTEIT, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

# Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*GTEIT, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

Predicting SLOPE VARIATIONs - Level 2 - with WBT, GRAND MEAN CENTERING

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*WBT, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*WBT, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

# Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*WBT, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*WBT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

############################ Predicting SLOPE VARIATIONs- Level 2- with SCT, GRAND MEAN CENTERING##############################
#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*SCT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*SCT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*SCT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*SCT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

################################### Predicting SLOPE VARIATIONs- Level 2- with EMT, GRAND MEAN CENTERING###################################
#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*EMT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*EMT, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with IR

Model.IR.6 <- lme(MULTDV~TIME*EMT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.IR.6)$tTable, dig=5)

#Model time with SR

Model.SR.6 <- lme(MULTDV~TIME*EMT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.SR.6)$tTable, dig=5)

##############################################################
# Predicting SLOPE VARIATIONs- Level 2- with SBT, GRAND MEAN CENTERING
##############################################################

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*SBT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*SBT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with IR

Model.IR.6 <- lme(MULTDV~TIME*SBT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.IR.6)$tTable, dig=5)

#Model time with SR

Model.SR.6 <- lme(MULTDV~TIME*SBT, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.SR.6)$tTable, dig=5)

##############################################################
# Predicting SLOPE VARIATIONs- Level 2- with IATTOTALP, GRAND MEAN CENTERING
##############################################################
# Model time with OQ

Model.OQ.6 <- lme(MULTDV ~ TIME*IATTOTALP, random=~TIME|id,
correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV ~ TIME*IATTOTALP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

effectsize(Model.sd.6, robust=FALSE)

# Model time with IR

Model.ir.6 <- lme(MULTDV ~ TIME*IATTOTALP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

# Model time with SR

Model.sr.6 <- lme(MULTDV ~ TIME*IATTOTALP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

############################ Predicting SLOPE VARIATIONs - Level 2 - with IATTOTALt, GRAND MEAN CENTERING###############################

# Model time with OQ

Model.OQ.6 <- lme(MULTDV ~ TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV ~ TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

effectsize(Model.sd.6, robust=FALSE)

# Model time with IR

Model.ir.6 <- lme(MULTDV ~ TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

# Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=FALSE)

#################################################################
Predicting SLOPE VARIATIONs- Level 2- with IATBONDP, GRAND MEAN CENTERING
#################################################################

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

# Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

# Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)

#################################################################
Predicting SLOPE VARIATIONs- Level 2- with IATTASKSP, GRAND MEAN CENTERING
#################################################################

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD
```R
Model.sd.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

# Model time with IR
Model.ir.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
effectsize(Model.ir.6, robust=TRUE)

# Model time with SR
Model.sr.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=TRUE)

##################### Predicting SLOPE VARIATIONS - Level 2- with IATGOALSP, GRAND MEAN CENTERING ##########################

# Model time with OQ
Model.OQ.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD
Model.sd.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)

# Model time with IR
Model.ir.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
effectsize(Model.ir.6, robust=TRUE)

# Model time with SR
Model.sr.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
```
effectsize(Model.sr.6, robust=FALSE)

########################## Predicting SLOPE VARIATIONs- Level 2- with IATBONDP

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(28.33374/(28.33374+4.781312))

########################## Predicting SLOPE VARIATIONs- Level 2- with IATTASKSP

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(19.315204/(19.315204+3.378973))

########################## Predicting SLOPE VARIATIONs- Level 2- with IATGOALSP, GRAND MEAN CENTERING

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(27.481138/(27.481138+4.707039))

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(18.98978/(18.98978+3.347084))
Predicting SLOPE VARIATIONs- Level 2- with IATTASKSP, GRAND MEAN CENTERING

#Model time with SR
#Model time with SR-try type of therapy#

Model.sr.6 <- lme(MULTDV~TIME*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(19.315204/(19.315204+3.378973))

Predicting SLOPE VARIATIONs- Level 2- with IATTOTALt, GRAND MEAN CENTERING

#Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

#Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=TRUE)

#Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

#Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=FALSE)

Predicting SLOPE VARIATIONs- Level 2- with IATBt, GRAND MEAN CENTERING
# Model time with OQ

```r
Model.OQ.6 <- lme(MULTDV~TIME*IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
```

# Model time with SD

```r
Model.sd.6 <- lme(MULTDV~TIME*IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
```

# Model time with IR

```r
Model.ir.6 <- lme(MULTDV~TIME*IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
```

# Model time with SR

```r
Model.sr.6 <- lme(MULTDV~TIME*IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
```

# Predicting SLOPE VARIATIONs - Level 2 - with IATTt, GRAND MEAN CENTERING

# Model time with OQ

```r
Model.OQ.6 <- lme(MULTDV~TIME*IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
```

# Model time with SD

```r
Model.sd.6 <- lme(MULTDV~TIME*IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
effectsize(Model.sd.6, robust=TRUE)
round(summary(Model.sd.6)$tTable, dig=5)
```

# Model time with IR

```r
Model.ir.6 <- lme(MULTDV~TIME*IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)
```
# Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATTt, random=~TIME|id, correlation=corAR1(),
                data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=5)
effectsize(Model.sr.6, robust=FALSE)

Predicting SLOPE VARIATIONs- Level 2- with IATGOALSt, GRAND MEAN CENTERING

# Model time with OQ

Model.OQ.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)

# Model time with SD

Model.sd.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)

# Model time with IR

Model.ir.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=5)

# Model time with SR

Model.sr.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)

BEYOND IAT ANALYSES

Predicting intercept variation- Level 2- with GTEIp(Patient), GRAND MEAN CENTERING

# Model time with SD

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(124.7582/(124.7582+21.3158))

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATBt, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(124.72669/(124.72669+21.33155))

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATTt, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(124.82925/(124.82925+21.28027))

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATGt, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(124.85481/(124.85481+21.26749))

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(124.92903/(124.92903+21.23038))

UNIV.SD$GTEIp <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp+IATBONDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(125.10040/(125.10040+21.14469))

UNIV.SDSGTEIp <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp+IATTASKSP, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(125.10040/(125.10040+21.14469))

UNIV.SDSGTEIp.2 <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp.2+IATTASKSP, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(125.10040/(125.10040+21.14469))

UNIV.SDSGTEIp <- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp+IATTASKSP, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(125.10040/(125.10040+21.14469))

# Model time with OQ

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(243.58859/(243.58859+42.41416))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))

UNIV.OQS$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
 data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.72444/(243.72444+42.34623))
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.62977/(243.62977+42.39357))

UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATGt, random=~TIME|id,
correlation=corAR1(),
        data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.6193/(243.6193+42.3988))

UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
        data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.87619/(243.87619+42.27035))

UNIV.OQ$GTEIp <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
        data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(244.00400/(244.00400+42.20645))

UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
        data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(244.00400/(244.00400+42.20645))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(243.94362/(243.94362+42.23664))

## Predicting intercept variation - Level 2 - with Wellbeing(Patient), GRAND MEAN CENTERING #######

# Model time with SD

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATTOTALt, random=~TIME|id,
correlation=corAR1(),
   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(126.74252/(126.74252+20.32364))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATBTt, random=~TIME|id,
correlation=corAR1(),
   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(126.61672/(126.61672+20.38633))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATTt, random=~TIME|id,
correlation=corAR1(),
   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.83392/(126.83392+20.27793))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATGt, random=~TIME|id,
correlation=corAR1(),
   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.88063/(126.88063+20.25458))
UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATTOTALP, random=~TIME|id, correlation=corAR1(),
                 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsze(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.79412/(126.79412+20.29784))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATBONDP, random=~TIME|id, correlation=corAR1(),
                 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsze(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.95124/(126.95124+20.21927))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATTASKSP, random=~TIME|id, correlation=corAR1(),
                 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsze(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(126.63673/(126.63673+20.37653))

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2+IATGOALSP, random=~TIME|id, correlation=corAR1(),
                 data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsze(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(126.92213/(126.92213+20.23383))

#Model time with OQ

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATTOTALt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsze(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(242.31692/(242.31692+43.04999))
UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATTb, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizemodel.Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.5263/(242.5263+43.08213))

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATTt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizemodel.Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.42177/(242.42177+42.99757))

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATGt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizemodel.Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.35867/(242.35867+43.02912))

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATTOTALP, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizemodel.Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.59659/(242.59659+42.91016))

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATBONDP, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizemodel.Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.56402/(242.56402+42.92644))
UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATTASKSP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizer(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(242.68688/(242.68688+42.86502))

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2+IATGOALSP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsizer(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(242.68376/(242.68376+42.86658))

## Predicting intercept variation- Level 2- with Self-control(Patient), GRAND MEAN CENTERING####

#Model time with SD

UNIV.SD$SCp<- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATTOTALt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsizer(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(122.47712/(122.47712+22.45633))

UNIV.SD$SCp<- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATBt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsizer(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(122.01967/(122.01967+22.68506))

UNIV.SD$SCp<- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATTt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsizer(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(122.5817/(122.5817+22.40402))

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATGt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(122.45355/(122.45355+22.46812))

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATTOTALP, random=~TIME|id,
                   correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(122.17411/(122.17411+22.60784))

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATBONDP, random=~TIME|id,
                   correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(122.1306/(122.1306+22.6296))

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATTASKSP, random=~TIME|id,
                   correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(122.07350/(122.07350+22.65814))

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp+IATGOALSP, random=~TIME|id,
                   correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(122.36757/(122.36757+22.51111))
# Model time with OQ

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp + IATTOTALt, random = ~ TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(240.68719/(240.68719+43.86486))

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp + IATTt, random = ~ TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(240.40397/(240.40397+44.00647))

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp + IATBt, random = ~ TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(240.83672/(240.83672+43.79009))

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp + IATGt, random = ~ TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(122.45355/(122.45355+22.46812))

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV ~ TIME + SCp + IATTOTALP, random = ~ TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(240.84227/(240.84227+43.78732))

UNIV.OQ$SCp <- UNIV.OQ$SCp - mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV~TIME+SCp+IATBONDP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(240.63990/(240.63990+43.88851))

UNIV.OQ$SCp<-
UNIV.OQ$SCp-mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV~TIME+SCp+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(241.01902/(241.01902+43.69894))

UNIV.OQ$SCp<-
UNIV.OQ$SCp-mean(UNIV.OQ$SCp)
Model.OQ.6 <- lme(MULTDV~TIME+SCp+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(240.85536/(240.85536+43.78077))

# Predicting intercept variation- Level 2- with Emotionality(Patient), GRAND MEAN CENTERING####

#Model time with SD

UNIV.SD$EMp<-
UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATTOTALt, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.31967 /(119.31967 +24.03506))

UNIV.SD$EMp<-
UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.91113/(118.91113+24.23933))
UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATTt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.36933/(119.36933+24.01023))

UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATGt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.29329/(119.29329+24.04825))

UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATTOTALP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.55603/(119.55603+23.91688))

UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATBONDP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.65176/(119.65176+23.86901))

UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATTASKSP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.14513/(119.14513+24.12233))

UNIV.SD$EMp <- UNIV.SD$EMp-mean(UNIV.SD$EMp)
Model.sd.6 <- lme(MULTDV~TIME+EMp+IATGOALSP, random=~TIME|id, correlation=corAR1(),
               data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.75715/(119.75715+23.81632))

# Model time with OQ

UNIV.OQ$EMp <- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATTOTALt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.63681/(236.63681+45.89005))

UNIV.OQ$EMp <- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATTOTALt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.48978/(236.48978+45.96356))

UNIV.OQ$EMp <- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATTt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.64117/(236.64117+45.88787))

UNIV.OQ$EMp <- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATGt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.55775/(236.55775+45.92958))

UNIV.OQ$EMp <- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATTOTALP, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(236.97376/(236.97376+45.72157))

UNIV.OQ$EMp<- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATBONDp, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.15457/(237.15457+45.63117))

UNIV.OQ$EMp<- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATASKSP, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.69281/(236.69281+45.86205))

UNIV.OQ$EMp<- UNIV.OQ$EMp-mean(UNIV.OQ$EMp)
Model.OQ.6 <- lme(MULTDV~TIME+EMp+IATGOALSP, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.10572/(237.10572+45.65559))

# Predicting intercept variation- Level 2- with Sociability(Patient), GRAND MEAN CENTERING####

#Model time with SD

UNIV.SD$SBp<- UNIV.SD$SBp-mean(UNIV.SD$SBp)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATTOTALt, random=~TIME|id, correlation=corAR1(), data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.76869/(118.76869+24.31055))

UNIV.SD$$SBp$$<- UNIV.SD$$SBp$$-mean(UNIV.SD$$SBp$$)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATBt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.37340/(118.37340+24.50819))

UNIV.SD$$SBp$$<- UNIV.SD$$SBp$$-mean(UNIV.SD$$SBp$$)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATTt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.84041/(118.84041+24.27469))

UNIV.SD$$SBp$$<- UNIV.SD$$SBp$$-mean(UNIV.SD$$SBp$$)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATGt, random=~TIME|id, correlation=corAR1(),
               data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.83154/(118.83154+24.27912))

UNIV.SD$$SBp$$<- UNIV.SD$$SBp$$-mean(UNIV.SD$$SBp$$)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATTOTALP, random=~TIME|id,
                  correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.03731/(119.03731+24.17624))

UNIV.SD$$SBp$$<- UNIV.SD$$SBp$$-mean(UNIV.SD$$SBp$$)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATTASKSP, random=~TIME|id, 
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(118.59236/(118.59236+24.39871))

UNIV.SD$SBp< UNIV.SD$SBp-mean(UNIV.SD$SBp)
Model.sd.6 <- lme(MULTDV~TIME+SBp+IATGOALSP, random=~TIME|id, 
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.10233/(119.10233+24.14373))

#Model time with OQ

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(236.07925/(236.07925+46.16883))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATBt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(235.96294/(235.96294+46.22698))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATTt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.09341/(236.09341+46.16176))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATGt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(235.96294/(235.96294+46.22698))
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.10718/(236.10718+46.15486))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(236.4629/(236.4629+45.9770))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATBONDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(236.55645/(236.55645+45.93023))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATTASKDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(236.4049/(236.4049+46.0060))

UNIV.OQ$SBp<- UNIV.OQ$SBp-mean(UNIV.OQ$SBp)
Model.OQ.6 <- lme(MULTDV~TIME+SBp+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(236.60972/(236.60972+45.90359))

################ Predicting intercept variation- Level 2- with GTEIT, GRAND MEAN CENTERING####################

#Model time with SD
UNIV.SD$GTEIT <- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.sd.6 <- lme(MULTDV~TIME+GTEIT+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.8539/(118.8539+24.26792))

UNIV.SD$GTEIT <- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.sd.6 <- lme(MULTDV~TIME+GTEIT+IATBONDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$GTEIT <- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.sd.6 <- lme(MULTDV~TIME+GTEIT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.8539/(118.8539+24.26792))

#Model time with OQ

UNIV.OQ$GTEIT <- UNIV.OQ$GTEIT-mean(UNIV.OQ$GTEIT)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIT+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.62036/(237.62036+45.39827))

UNIV.OQ$GTEIT <- UNIV.OQ$GTEIT-mean(UNIV.OQ$GTEIT)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIT+IATBONDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(237.68579/(237.68579+45.36556))

UNIV.SR$GTEIT<- UNIV.SR$GTEIT-mean(UNIV.SR$GTEIT)
Model.sr.6 <- lme(MULTDV~TIME+GTEIT+IATTASKSP, random=-~TIME|id,
correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(20.275138/(20.275138+3.365657))

UNIV.OQ$GTEIT<- UNIV.OQ$GTEIT-mean(UNIV.OQ$GTEIT)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIT+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.75180/(237.75180+45.33255))

############ Predicting intercept variation- Level 2- with WBT, GRAND MEAN CENTERING#####################

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT+IATTOTALP, random=~TIME|id,
correlation=corAR1(), data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.8539/(118.8539+24.26792))

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT+IATBONDP, random=~TIME|id,
correlation=corAR1(), data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT+IATGOALSP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
efffectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.8539/(118.8539+24.26792))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT+IATTOTALP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
efffectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.62036/(237.62036+45.39827))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT+IATBONDP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
efffectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(237.68579/(237.68579+45.36556))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT+IATGOALSP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
efffectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(237.75180/(237.75180+45.33255))

UNIV.SR$WBT<- UNIV.SR$WBT-mean(UNIV.SR$WBT)
Model.sr.6 <- lme(MULTDV~TIME+WBT+IATTASKSP, random=~TIME|id, correlation=corAR1(),
   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
efffectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(20.275138/(20.275138+3.365657))

######## Predicting intercept variation- Level 2- with Self-control-Therapist, GRAND MEAN
CENTERING################
# Model time with SD

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV ~ TIME + SCT + IATTOTALt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.20064/(119.20064+24.09458))

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV ~ TIME + SCT + IATGt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.09157/(119.09157+24.14911))

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV ~ TIME + SCT + IATBt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.77844/(118.77844+24.30567))

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV ~ TIME + SCT + IATTt, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.16337/(119.16337+24.11321))

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV ~ TIME + SCT + IATTOTALP, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.47363/(119.47363+23.95808))

UNIV.SD$SCT <- UNIV.SD$SCT - mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV~TIME+SCT+IATBONDp, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.4872/(119.4872+23.9513))

UNIV.SD$SCT<- UNIV.SD$SCT-mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV~TIME+SCT+IATASKSp, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.97690/(118.97690+24.20644))

UNIV.SD$SCT<- UNIV.SD$SCT-mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV~TIME+SCT+IATGOALSp, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.7130/(119.7130+23.8384))

# Model time with OQ

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATTOTALt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(119.20064/(119.20064+24.09458))

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATGt, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(119.09157/(119.09157+24.14911))

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATBt, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(118.77844/(118.77844+24.30567))

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATTt, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.16337/(119.16337+24.11321))

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATTOTALP, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(237.99000/(237.99000+45.21345))

UNIV.OQ$SCT<- UNIV.OQ$SCT-mean(UNIV.OQ$SCT)
Model.OQ.6 <- lme(MULTDV~TIME+SCT+IATGOALSP, random=~TIME|id, correlation=corAR1(), data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(237.99000/(237.99000+45.21345))
## Model time with SR

\[
\frac{352}{238.63909/(238.63909+44.88891)}
\]

### Model time with SR

\[
\text{UNIV.SR}\$\text{SCT} < - \text{UNIV.SR}\$\text{SCT} - \text{mean(UNIV.SR}\$\text{SCT})
\]

Model.sr.6 <- lme(MULTDV~TIME+SCT+IATTOTALt, random=~TIME|id, correlation=corAR1(),
                     data=UNIV.SR, control=list(opt="optim"))

round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)

VarCorr(Model.sr.6)

\[
\frac{20.43841/(20.43841+3.28402)}
\]

UNIV.SR\$SCT <- UNIV.SR\$SCT - mean(UNIV.SR\$SCT)

Model.sr.6 <- lme(MULTDV~TIME+SCT+IATGt, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SR, control=list(opt="optim"))

round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)

VarCorr(Model.sr.6)

\[
\frac{20.422498/(20.422498+3.291977)}
\]

UNIV.SR\$SCT <- UNIV.SR\$SCT - mean(UNIV.SR\$SCT)

Model.sr.6 <- lme(MULTDV~TIME+SCT+IATBt, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SR, control=list(opt="optim"))

round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)

VarCorr(Model.sr.6)

\[
\frac{20.353042/(20.353042+3.326705)}
\]

UNIV.SR\$SCT <- UNIV.SR\$SCT - mean(UNIV.SR\$SCT)

Model.sr.6 <- lme(MULTDV~TIME+SCT+IATTt, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SR, control=list(opt="optim"))

round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)

VarCorr(Model.sr.6)

\[
\frac{20.420805/(20.420805+3.292823)}
\]

UNIV.SR\$SCT <- UNIV.SR\$SCT - mean(UNIV.SR\$SCT)

Model.sr.6 <- lme(MULTDV~TIME+SCT+IATBONDP, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.SR, control=list(opt="optim"))

round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)

VarCorr(Model.sr.6)

\[
\frac{20.330493/(20.330493+3.337979)}
\]
UNIV.SR$SCT <- UNIV.SR$SCT - mean(UNIV.SR$SCT)
Model.sr.6 <- lme(MULTDV~TIME+SCT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(20.375537/(20.375537+3.315457))

UNIV.SR$SCT <- UNIV.SR$SCT - mean(UNIV.SR$SCT)
Model.sr.6 <- lme(MULTDV~TIME+SCT+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=TRUE)
VarCorr(Model.sr.6)
(20.398808/(20.398808+3.303822))

######### Predicting intercept variation- Level 2- with Sociability Therapist, GRAND MEAN CENTERING#################

UNIV.SD$SBT <- UNIV.SD$SBT - mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV~TIME+SBT+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(118.37649/(118.37649+24.50665))

UNIV.SD$SBT <- UNIV.SD$SBT - mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV~TIME+SBT+IATBONDP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(118.37649/(118.37649+24.50665))

UNIV.SD$SBT <- UNIV.SD$SBT - mean(UNIV.SD$SBT)
Model.SD.6 <- lme(MULTDV~TIME+SBT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.SD.6)$tTable, dig=3)

UNIV.SD$SBT <- UNIV.SD$SBT - mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV~TIME+SBT+IATGOALSP, random=~TIME|id, correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(119.0311/(119.0311+24.17933))

#Model time with IR

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATTOTALt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.95368/(29.95368+4.32583))

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATGt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.972210/(29.972210+4.31656565))

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATTt, random=~TIME|id, correlation=corAR1(),
    data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.972210/(29.972210+4.31656565))

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATBONDP, random=~TIME|id, correlation=corAR1(),
    data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATGOALSP, random=~TIME|id, correlation=corAR1(),
               data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)

#Model time with SR

UNIV.SR$SBT<- UNIV.SR$SBT-mean(UNIV.SR$SBT)
Model.sr.6 <- lme(MULTDV~TIME+SBT+IATTASKSP, random=~TIME|typeoftherapy/id,
                   correlation=corAR1(),
                   data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATTASKSP, random=~TIME|id,
                  correlation=corAR1(),
                  data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)

UNIV.SR$SBT<- UNIV.SR$SBT-mean(UNIV.SR$SBT)
Model.sr.6 <- lme(MULTDV~TIME+SBT+IATGOALSP, random=~TIME|typeoftherapy/id,
                  correlation=corAR1(),
                  data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)

UNIV.IR$SBT<- UNIV.IR$SBT-mean(UNIV.IR$SBT)
Model.ir.6 <- lme(MULTDV~TIME+SBT+IATGOALSP, random=~TIME|id,
                  correlation=corAR1(),
                  data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)

######### Predicting intercept variation- Level 2- with Emotionality Therapist, GRAND MEAN CENTERING################

#Model time with SD

UNIV.SD$EMT<- UNIV.SD$EMT-mean(UNIV.SD$EMT)
Model.sd.6 <- lme(MULTDV~TIME+EMT+IATTOTALP, random=~TIME|id,
                  correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)

UNIV.SD$EMT<- UNIV.SD$EMT-mean(UNIV.SD$EMT)
Model.sd.6 <- lme(MULTDV~TIME+EMT+IATTOTALP, random=~TIME|id,
                  correlation=corAR1(),
                  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(118.37649/(118.37649+24.50665))
UNIV.SD$EMT <- UNIV.SD$EMT - mean(UNIV.SD$EMT)
Model.sd.6 <- lme(MULTDV~TIME+EMT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$EMT <- UNIV.SD$EMT - mean(UNIV.SD$EMT)
Model.sd.6 <- lme(MULTDV~TIME+EMT+IATGOALSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
effects.size(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.0311/(119.0311+24.17933))

#Model time with OQ

UNIV.OQ$EMT <- UNIV.OQ$EMT - mean(UNIV.OQ$EMT)
Model.OQ.6 <- lme(MULTDV~TIME+EMT+IATTOTALP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effects.size(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(118.37649/(118.37649+24.50665))

UNIV.OQ$EMT <- UNIV.OQ$EMT - mean(UNIV.OQ$EMT)
Model.OQ.6 <- lme(MULTDV~TIME+EMT+IATBONDP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effects.size(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(118.37649/(118.37649+24.50665))

UNIV.OQ$EMT <- UNIV.OQ$EMT - mean(UNIV.OQ$EMT)
Model.OQ.6 <- lme(MULTDV~TIME+EMT+IATTASKSP, random=~TIME|id,
correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effects.size(Model.OQ.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.0311/(119.0311+24.17933))

#Model time with IR

UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATTOTALt, random=~TIME|id, 
correlation=corAR1(),
        data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.95368/(29.95368+4.32583))

UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATGt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.972210/(29.972210+4.316565))

UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATBt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
effectsize(Model.ir.6, robust=TRUE)
VarCorr(Model.ir.6)
(29.972210/(29.972210+4.316565))

UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATBONDP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
UNIV.IR$EMT <- UNIV.IR$EMT-mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV~TIME+EMT+IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.IR, control=list(opt="optim"))
round(summary(Model.ir.6)$tTable, dig=3)
UNIV.IR$EMT <- UNIV.IR$EMT - mean(UNIV.IR$EMT)
Model.ir.6 <- lme(MULTDV ~ TIME + EMT + IATGOALSP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.IR, control = list(optim = "optim"))
round(summary(Model.ir.6)$tTable, dig = 3)

########################Predicting Slope variation (interaction) - Level 2 - with GTEIp(Patient), GRAND MEAN CENTERING########################

# Model time with SD
UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATTOTALP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.SD, control = list(optim = "optim"))
round(summary(Model.sd.6)$tTable, dig = 3)

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATTASKSP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.SD, control = list(optim = "optim"))
round(summary(Model.sd.6)$tTable, dig = 3)

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATGOALSP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.SD, control = list(optim = "optim"))
round(summary(Model.sd.6)$tTable, dig = 3)

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATGOALSP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.SD, control = list(optim = "optim"))
round(summary(Model.sd.6)$tTable, dig = 3)

UNIV.SD$GTEIp.2 <- UNIV.SD$GTEIp - mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATTOTALP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.SD, control = list(optim = "optim"))
round(summary(Model.sd.6)$tTable, dig = 3)

# Model time with OQ
UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp - mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV ~ TIME + GTEIp.2 * IATTOTALP, random = ~ TIME | id,
correlation = corAR1(),
    data = UNIV.OQ, control = list(optim = "optim"))
round(summary(Model.OQ.6)$tTable, dig = 3)

UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp - mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2*IATGOALSP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

UNIV.OQ$GTEIp.2 <- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp.2*IATTASKSP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

## Predicting Slope variation (interaction) - Level 2 - with Wellbeing(Patient), GRAND MEAN CENTERING ######

# Model time with SD

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2*IATTOTALP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2*IATBONDP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

UNIV.SD$WBp.2 <- UNIV.SD$WBp-mean(UNIV.SD$WBp)
Model.sd.6 <- lme(MULTDV~TIME+WBp.2*IATTASKP, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)
# Model time with OQ

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2*IATTOTALP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2*IATBONDP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

UNIV.OQ$WBp.2 <- UNIV.OQ$WBp-mean(UNIV.OQ$WBp)
Model.OQ.6 <- lme(MULTDV~TIME+WBp.2*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)

## Predicting Slope variation (interaction) - Level 2 - with Self-control(Patient), GRAND MEAN CENTERING####

# Model time with SD

UNIV.SD$SCp <- UNIV.SD$SCp-mean(UNIV.SD$SCp)
Model.sd.6 <- lme(MULTDV~TIME+SCp*IATTOTALt, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(123.20464/(123.20464+22.09257))

# Predicting Slope variation (interaction) - with Sociability(Patient), GRAND MEAN CENTERING####

# Model time with SD

UNIV.SD$SBp <- UNIV.SD$SBp-mean(UNIV.SD$SBp)
Model.sd.6 <- lme(MULTDV~TIME+SBp*IATTOTALt, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=3)

############################ Slope variation (interaction) - Level 2 - with GTEIT, GRAND MEAN CENTERING################################

#Model time with SD

UNIV.SD$GTEIT<- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.sd.6 <- lme(MULTDV~TIME+GTEIT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.33027/(119.33027+24.02976))

UNIV.SD$GTEIT<- UNIV.SD$GTEIT-mean(UNIV.SD$GTEIT)
Model.sd.6 <- lme(MULTDV~TIME+GTEIT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(120.86010/(120.86010+23.26484))

#Model time with OQ

UNIV.OQ$GTEIT<- UNIV.OQ$GTEIT-mean(UNIV.OQ$GTEIT)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(239.99387/(239.99387+44.21151))

############################ Slope variation (interaction) - Level 2 - with Wellbeing-Therapist, GRAND MEAN CENTERING############################

#Model time with SD

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.95073/(119.95073+23.71953))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=3)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(237.85313/(237.85313+45.28189))

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT*IATTOTALP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(120.62871/(120.62871+23.38054))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT*IATTOTALP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(238.53502/(238.53502+44.94094))

UNIV.SD$WBT<- UNIV.SD$WBT-mean(UNIV.SD$WBT)
Model.sd.6 <- lme(MULTDV~TIME+WBT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(121.29468/(121.29468+23.04755))

UNIV.OQ$WBT<- UNIV.OQ$WBT-mean(UNIV.OQ$WBT)
Model.OQ.6 <- lme(MULTDV~TIME+WBT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
       data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(239.71422/(239.71422+44.35134))

###### Predicting Slope variation (interaction)- Level 2- with Self-control-Therapist, GRAND MEAN CENTERING##################################

#Model time with SD

UNIV.SD$SCT <- UNIV.SD$SCT-mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV~TIME+SCT*IATTASKSP, random=~TIME|id, correlation=corAR1(),
             data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(120.51041/(120.51041+23.43969))

UNIV.SD$SCT <- UNIV.SD$SCT-mean(UNIV.SD$SCT)
Model.sd.6 <- lme(MULTDV~TIME+SCT*IATGOALSP, random=~TIME|id, correlation=corAR1(),
             data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(122.14567/(122.14567+22.62206))

##Model time with SR

UNIV.SR$SCT <- UNIV.SR$SCT-mean(UNIV.SR$SCT)
Model.sr.6 <- lme(MULTDV~TIME+SCT*IATGOAL, random=~TIME|id, correlation=corAR1(),
             data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(20.55767/(20.55767+3.22439))

########## Predicting Slope variation (interaction)- Level 2- with Sociability Therapist, GRAND MEAN CENTERING###################################

#time with SD

UNIV.SD$SBT <- UNIV.SD$SBT-mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV~TIME+SBT*IATTASKSP, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(119.24757/(119.24757+24.07111))

UNIV.SD$SBT<- UNIV.SD$SBT-mean(UNIV.SD$SBT)
Model.sd.6 <- lme(MULTDV~TIME+SBT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
round(summary(Model.sd.6)$tTable, dig=5)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(121.4448/(121.4448+22.9725))

#time with OQ

UNIV.OQ$SBT<- UNIV.OQ$SBT-mean(UNIV.OQ$SBT)
Model.OQ.6 <- lme(MULTDV~TIME+SBT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
round(summary(Model.OQ.6)$tTable, dig=5)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(239.72975/(239.72975+44.34357))

UNIV.OQ$SBT<- UNIV.OQ$SBT-mean(UNIV.OQ$SBT)
Model.OQ.6 <- lme(MULTDV~TIME+SBT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(243.16014/(243.16014+42.62838))

UNIV.SR$SBT<- UNIV.SR$SBT-mean(UNIV.SR$SBT)
Model.sr.6 <- lme(MULTDV~TIME+SBT*IATTASKSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(20.374573/(20.374573+3.315939))

UNIV.SR$SBT<- UNIV.SR$SBT-mean(UNIV.SR$SBT)
Model.sr.6 <- lme(MULTDV~TIME+SBT*IATGOALSP, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
round(summary(Model.sr.6)$tTable, dig=3)
effectsize(Model.sr.6, robust=FALSE)
VarCorr(Model.sr.6)
(20.374573/(20.374573+3.31593))

########## TRAIT EI PSYCHOTHERAPIST AND PATIENTS#################

#time with SD
UNIV.SD$GTEIp<- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+GTEIp*GTEIT, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=TRUE)
VarCorr(Model.sd.6)
(128.01413/(128.01413+19.68783))

#time with OQ
UNIV.OQ$GTEIp<- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+GTEIp*GTEIT, random=~TIME|id,
correlation=corAR1(),
    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=TRUE)
VarCorr(Model.OQ.6)
(248.4593/(248.4593+39.9788))

#time with SD
UNIV.SD$GTEIp<- UNIV.SD$GTEIp-mean(UNIV.SD$GTEIp)
Model.sd.6 <- lme(MULTDV~TIME+IATTOTALP*IATTOTALt+GTEIp*GTEIT,
    random=~TIME|id, correlation=corAR1(),
    data=UNIV.SD, control=list(opt="optim"))
summary(Model.sd.6)
effectsize(Model.sd.6, robust=FALSE)
VarCorr(Model.sd.6)
(127.46001/(127.46001+19.96489))

#time with OQ
UNIV.OQ$GTEIp<- UNIV.OQ$GTEIp-mean(UNIV.OQ$GTEIp)
Model.OQ.6 <- lme(MULTDV~TIME+IATTOTALP*IATTOTALt+GTEIp*GTEIT, random=~TIME|id, correlation=corAR1(),
                    data=UNIV.OQ, control=list(opt="optim"))
summary(Model.OQ.6)
effectsize(Model.OQ.6, robust=FALSE)
VarCorr(Model.OQ.6)
(247.3861/(247.3861+40.5154))

A 28: R Scripts for Figures Implemented in Chapter Five

library(foreign)
library(semPlot)
library(semTools)
library(multilevel)
library(nlme)
library(lattice)
MULTI<-read.spss('C:\Users\Pablopd\Dropbox\R _Scripts\Finalaggregated.sav',
                   use.value.labels= TRUE, to.data.frame = TRUE)

#Figure 6
my_data <- MULTI[, c(8:33)]
c_matrix <- rcorr(as.matrix(my_data))
c_matrix
flattenCorrMatrix <- function(cormat, pmat) {
  ut <- upper.tri(cormat)
  data.frame(
    row = rownames(cormat)[row(cormat)[ut]],
    column = rownames(cormat)[col(cormat)[ut]],
    cor = (cormat)[ut],
    p = pmat[ut]
  )
}
flattenCorrMatrix(c_matrix $r, c_matrix $P)
corrplot(c_matrix $r, type="upper", order="hclust",
          p.mat = c_matrix $P, sig.level = 0.01, insig = "blank")

#Fig7A
#Growth ilustration OQ
UNIV.OQ <-make.univ(MULTI, MULTI[,32:33])
names(UNIV.OQ)
xyplot(MULTDV~TIME|as.factor(id),data=UNIV.OQ[1:134,],
       type=c("p", "r", "g"), col="blue", col.line="black",
       pfactor=TRUE, xlab = "Years", ylab = "Score", panel=
       panel.linexylo)

xlab=list(label="Time", cex=2),
ylab=list(label="Overall outcome", cex=2),
main="Change in Overall outcome by time",
par.settings=list(par.main.text=list(cex=2)),
scales=list(x=list(at=c(0,1), labels=c(0,1))))

# Fig 7B
# Growth illustration SD
UNIV.SD <- make.univ(MULTI, MULTI[, 26:27])
names(UNIV.SD)

xyplot(MULTDV~TIME|as.factor(id), data=UNIV.SD[1:134,],
   type=c("p", "r", "g"), col="blue", col.line="black",
   xlab="Time", ylab="Symptom distress", main="Symptom distress change by time",
   scales=list(x=list(at=c(0,1), labels=c(0,1))))

# Fig 7C
# Growth illustration IR
UNIV.IR <- make.univ(MULTI, MULTI[, 28:29])
names(UNIV.IR)

xyplot(MULTDV~TIME|as.factor(id), data=UNIV.IR[1:134,],
   type=c("p", "r", "g"), col="blue", col.line="black",
   xlab=list(label="Time", cex=2),
   ylab=list(label="Interpersonal relationships", cex=2),
   main="Change in Interpersonal relationships by time",
   par.settings=list(par.main.text=list(cex=2)),
   scales=list(x=list(at=c(0,1), labels=c(0,1))))

# Fig 7D
# Growth illustration SR
UNIV.SR <- make.univ(MULTI, MULTI[, 30:31])
names(UNIV.SR)

xyplot(MULTDV~TIME|as.factor(id), data=UNIV.SR[1:134,],
   type=c("p", "r", "g"), col="blue", col.line="black",
   xlab=list(label="Time", cex=2),
   ylab=list(label="Social role", cex=2),
   main="Change in Social role by time",
   par.settings=list(par.main.text=list(cex=2)),
   scales=list(x=list(at=c(0,1), labels=c(0,1))))

# Figure 8

# Predicting SLOPE VARIATIONs - Level 2 - with GTEIp, GRAND MEAN CENTERING#

# Model time with OQ
Model.OQ.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
   data=UNIV.OQ, control=list(opt="optim")))
#8A
TDAT <- data.frame(GTEIp=c(3.65, 5.13),
                   TIME=c(0,0,1,1),
                   G.GTEIp=c("Low","High"))

TDAT$MULTDV <- predict(Model.OQ.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.GTEIp, MULTDV,
                           ylab="Overall outcome",
                           col = c("green4", "red3"),
                           trace.label = deparse(substitute(Patient-Global.trait.EI))))

mean(UNIV.OQ$GTEIp)
sd(UNIV.OQ$GTEIp)
4.39 + 0.74
#5.13
4.39 - 0.74
#3.65

#Model time with SD
Model.sd.6 <- lme(MULTDV~TIME*GTEIp, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.SD, control=list(opt="optim"))

#8B
TDAT <- data.frame(GTEIp=c(3.65, 5.13),
                   TIME=c(0,0,1,1),
                   G.GTEIp=c("Low","High"))

TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.GTEIp, MULTDV,
                           col = c("green4", "red3"), ylab="Symptom distress",
                           trace.label = deparse(substitute(Patient-Global.trait.EI))))

############################ Predicting SLOPE VARIATIONs- Level 2- with WBp, GRAND MEAN CENTERING###############################

#Model time with OQ
Model.OQ.6 <- lme(MULTDV~TIME*WBp, random=~TIME|id, correlation=corAR1(),
                   data=UNIV.OQ, control=list(opt="optim"))

#8C
TDAT <- data.frame(WBp=c(3.22, 5.74),
                   TIME=c(0,0,1,1),
                   G.WBp=c("Low","High"))

TDAT$MULTDV <- predict(Model.OQ.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.WBp, MULTDV,
                           col = c("green4", "red3"), ylab="Overall outcome",
                           trace.label = deparse(substitute(Patient-Wellbeing))))
mean(UNIV.OQ$WBp)
sd(UNIV.OQ$WBp)
4.48 + 1.26
#5.74
4.48 - 1.26
#3.22

#Model time with SD
Model.sd.6 <- lme(MULTDV~TIME*WBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))

#8D
TDAT <- data.frame(WBp= c(3.22, 5.74),
                  TIME=c(0,0,1,1),
                  G.WBp=c("Low","High"))
TDATSMULTDV <- predict(Model.sd.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.WBp, MULTDV,
col = c("green4", "red3"), ylab="Symptom distress",
trace.label = deparse(substitute(Patient-Wellbeing))))

mean(UNIV.OQ$WBp)
sd(UNIV.OQ$WBp)
4.48 + 1.26
#5.74
4.48 - 1.26
#3.22

##################### Predicting SLOPE VARIATIONs- Level 2- with SCp, GRAND MEAN CENTERING####################

#Model time with OQ
Model.OQ.6 <- lme(MULTDV~TIME*SCp, random=~TIME|id, correlation=corAR1(),
data=UNIV.OQ, control=list(opt="optim"))

#8E
TDAT <- data.frame(SCp= c(3.15, 5.13),
                  TIME=c(0,0,1,1),
                  G.SCp=c("Low","High"))
TDATSMULTDV <- predict(Model.OQ.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.SCp, MULTDV,
col = c("green4", "red3"), ylab="Overall outcome",
trace.label = deparse(substitute(Patient-Self-control))))

mean(UNIV.OQ$SCp)
sd(UNIV.OQ$SCp)
4.14 + 0.99
# Model time with SD

Model.sd.6 <- lme(MULTDV ~ TIME*SCp, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))

# 8F

TDAT <- data.frame(SCp= c(3.15, 5.13),
  TIME=c(0,0,1,1),
  G.SCp=c("Low","High"))

TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)

with (TDAT, interaction.plot(TIME, G.SCp, MULTDV,
  col = c("green4", "red3"), ylab="Symptom distress",
  trace.label = deparse(substitute(Patient-Self-control))))

mean(UNIV.OQ$SCp)
sd(UNIV.OQ$SCp)

4.14 + 0.99
#5.13
4.14 - 0.99
#3.15

# Predicting SLOPE VARIATIONs- Level 2- with EMp (PATIENT), GRAND MEAN CENTERING#

# Model time with SD

Model.sd.6 <- lme(MULTDV ~ TIME*EMp, random=~TIME|id, correlation=corAR1(),
  data=UNIV.SD, control=list(opt="optim"))

# 8G

TDAT <- data.frame(EMp= c(3.53, 5.21),
  TIME=c(0,0,1,1),
  G.EMp=c("Low","High"))

TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)

with (TDAT, interaction.plot(TIME, G.EMp, MULTDV,
  ylab="Symptom distress",
  col = c("green4", "red3"),
  trace.label = deparse(substitute(Patient-Emotionality))))

mean(UNIV.SD$EMp)
sd(UNIV.SD$EMp)

4.37 + 0.84
#5.21
Predicting SLOPE VARIATIONs - Level 2 - with SBp (PATIENT), GRAND MEAN CENTERING

# Model time with SD
Model.sd.6 <- lme(MULTDV~TIME*SBp, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))

#8H
TDAT <- data.frame(SBp= c(3.67, 5.53),
TIME=c(0,0,1,1),
G.SBp=c("Low","High"))
TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)

#Predicting SLOPE VARIATIONs - Level 2 - with IATTOTALt, GRAND MEAN CENTERING#

# Model time with SD (8A)
Model.sd.6 <- lme(MULTDV~TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))

#(9A)
TDAT <- data.frame(IATTOTALt= c(160.66, 184.68),
TIME=c(0,0,1,1),
G.IATTOTALt=c("Low","High"))
TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)

mean(UNIV.SD$SBp)
sd(UNIV.SD$SBp)

4.60 + 0.93
#5.53
4.60 - 0.93
#3.67
172.67 + 12.01
#184.68
172.67 - 12.01
#160.66

#Model time with SR

Model.sr.6 <- lme(MULTDV ~ TIME*IATTOTALt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))

#(9B)
TDAT <- data.frame(IATTOTALt= c(160.61, 184.73),
TIME=c(0,0,1,1),
G.IATTOTALt=c("Low","High"))
TDAT$MULTDV <- predict(Model.sr.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATTOTALt, MULTDV,
col = c("green4", "red3"), ylab="Social role",
trace.label = deparse(substitute(Therapist-IAT.TOTAL))))
mean(UNIV.SD$IATTOTALt)
sd(UNIV.SD$IATTOTALt)

172.67 + 12.06
#172.67
172.67 - 12.06
#52.38

#Model time with SD

Model.sd.6 <- lme(MULTDV ~ TIME*IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))

#(9C)
TDAT <- data.frame(IATTt= c(48.96, 58.98),
TIME=c(0,0,1,1),
G.IATTt=c("Low","High"))
TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATTt, MULTDV,
col = c("green4", "red3"), ylab="Symptom distress",
trace.label = deparse(substitute(Therapist-IAT.TASKS))))
mean(UNIV.SD$IATTt)
sd(UNIV.SD$IATTt)

53.97 + 5.01
#58.98
53.97 - 5.01
#48.96

#Model time with SR
Model.sr.6 <- lme(MULTDV~TIME*IATTt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))

#(9D)
TDAT <- data.frame(IATTt=c(48.96, 58.98),
                   TIME=c(0,0,1,1),
                   G.IATTt=c("Low","High"))
TDAT$MULTDV <- predict(Model.sr.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATTt, MULTDV,
col = c("green4", "red3"), ylab="Social role",
trace.label = deparse(substitute(Therapist-IAT.TASKS))))
mean(UNIV.SD$IATTt)
sd(UNIV.SD$IATTt)
53.97 + 5.01
#58.98
53.97 - 5.01
#48.96

#Model time with SD

#(9E)
Model.sd.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SD, control=list(opt="optim"))

TDAT <- data.frame(IATGt=c(48.06, 57.84),
                   TIME=c(0,0,1,1),
                   G.IATGt=c("Low","High"))
TDAT$MULTDV <- predict(Model.sd.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATGt, MULTDV,
col = c("green4", "red3"), ylab="Symptom distress",
trace.label = deparse(substitute(Therapist-IAT.GOALS))))
mean(UNIV.SD$IATGt)
sd(UNIV.SD$IATGt)
52.95 + 4.89
#57.84
52.95 - 4.89
#48.06

#Model time with SR
Model.sr.6 <- lme(MULTDV~TIME*IATGt, random=~TIME|id, correlation=corAR1(),
data=UNIV.SR, control=list(opt="optim"))

#(9F)
TDAT <- data.frame(IATGt=c(48.06, 57.84),
                   TIME=c(0,0,1,1),
                   G.IATGt=c("Low","High"))
```r
TDAT$MULTDV <- predict(Model.sr.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATGt, MULTDV,
    col = c("green4", "red3"),
    ylab="Social role",
    trace.label = deparse(substitute(Therapist-IAT.GOALS))))
mean(UNIV.SD$IATGt)
sd(UNIV.SD$IATGt)
52.95 + 4.89
#57.84
52.95 - 4.89
#48.06

#Model time with IR
Model.ir.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
    data=UNIV.IR, control=list(opt="optim"))
#(9G)
TDAT <- data.frame(IATGOALSP= c(52.38, 75.14),
    TIME=c(0,0,1,1),
    G.IATGOALSP=c("Low","High"))
TDAT$MULTDV <- predict(Model.ir.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATGOALSP, MULTDV,
    col = c("green4", "red3"), ylab="Interpersonal relationships",
    trace.label = deparse(substitute(Patient-IAT.GOALS))))
mean(UNIV.SD$IATGOALSP)
sd(UNIV.SD$IATGOALSP)
63.76 + 11.38
#75.14
63.76 - 11.38
#52.38

#Model time with SR
Model.sr.6 <- lme(MULTDV~TIME*IATGOALSP, random=~TIME|id, correlation=corAR1(),
    data=UNIV.SR, control=list(opt="optim"))
#(9H)
TDAT <- data.frame(IATGOALSP= c(52.38, 75.14),
    TIME=c(0,0,1,1),
    G.IATGOALSP=c("Low", "High"))
TDAT$MULTDV <- predict(Model.sr.6, TDAT, level=0)
with (TDAT, interaction.plot(TIME, G.IATGOALSP, MULTDV,
    col = c("green4", "red3"), ylab="Social role",
    trace.label = deparse(substitute(Patient-IAT.GOALS))))
mean(UNIV.SD$IATGOALSP)
sd(UNIV.SD$IATGOALSP)
63.76 + 11.38
```
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<th>Em t</th>
<th>SBt</th>
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A 29: Full Correlation Matrix of the Dataset Utilised in Chapter Five

A 30: Reliability Coefficients Before and After Multiple Imputation for the Measures Implemented in Chapter Five

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Note. GTEIp = patient global trait EI , WBp = patient Well-being, SCp = patient Self-control , EMp = patient Emotionality , IAT-Tp = patient-total-alliance, IAT-Bp = patient-bond-alliance, IAT-Tab = patient-tasks-alliance, IAT-Gp = patient-goals-alliance, Q-T1 = overall outcome time 1, Q-SD1 = symptom distress time 1, Q-IR1 = interpersonal relationships time 1, Q-SR1 = social role time 1, Q-T2 = overall outcome time 2, Q-SD2 = symptom distress time 2, Q-IR2 = interpersonal relationships time 2, Q-SR2 = social role time 2. GTEIt = therapist global trait EI , WBit = therapist Well-being , SCT = therapist Self-control , EMt = therapist Emotionality , IAT-Tt = therapist-total-alliance, IAT-Bt = therapist-bond-alliance, IAT-Tat = therapist-tasks-alliance, IAT-Gt = therapist-goals-alliance.
A 31: Patient’s trait EI Intercept Variations Across the Outcome Measures

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<th>( AIC )</th>
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**Model Symptom distress**

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**Model Interpersonal relationships**

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**Model Social role**

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Note. \( B_0 \): intercept, \( SEB_0 \): standard error of the intercept, \( tB_0 \): t-value of the intercept, \( B_1 \): TIME, \( SEB_1 \): standard error of TIME, \( tB_1 \): t-value of TIME, \( \beta_0 \): standardised intercept, \( df \): degrees of freedom, \( AIC \): Akaike information criterion, \( BIC \): Bayesian information criterion, \( -2LL \): -2 log likelihood, ICC: intraclass correlation. GTEIp: patient global trait EI, WBp: patient Well-being, SCp: patient Self-control, EMp: patient Emotionality, SBp: patient Sociability. * \( p < .05 \), ** \( p < .01 \), *** \( p < .001 \).
A 32: Therapist’s trait EI Intercept Variations Across the Outcome Measures

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**Model Symptom distress**

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**Model Interpersonal relationships**

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**Model Social role**

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*Note. $B_0$: intercept, $SEB_0$: standard error of the intercept, $tB_0$: t-value of the intercept, $\beta_0$: standardised intercept, df: degrees of freedom, $AIC$: Akaike information criterion, $BIC$: Bayesian information criterion, -2LL: -2 log likelihood, ICC: intraclass correlation. GTEIt: therapist global trait EI, WBt: therapist Well-being, SCt: therapist Self-control, EMt: therapist Emotionality, SBt: therapist Sociability. * $p < .05$, ** $p < .01$, *** $p < .001$. 
A 33: Intercept Variations of Patient’s trait EI and Alliance Measures on the Overall Outcome

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A 34: Intercept Variations of Patient’s trait EI and Alliance Measures on Symptom Distress

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## A 35: Intercept Variations of Patient’s trait EI and Therapist’s Alliance Measures on the Overall Outcome

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[Note: The table above presents the results of a statistical analysis comparing the intercept variations of patient's trait EI and therapist's alliance measures with various outcome measures. The table includes the intercept ($B_0$), standard error of the intercept (SE$B_0$), $t$-value of the intercept ($tB_0$), degrees of freedom ($df$), Akaike information criterion (AIC), Bayesian information criterion (BIC), $-2$ log likelihood ($-2LL$), and intraclass correlation (ICC) for different models. The models are categorized under GTEIp, WBp, SCp, EMp, and SBp, with specific measures such as IAT-total-t, IAT-bond-t, IAT-tasks-t, and IAT-goals-t. The significance levels are indicated by * ($p < .05$), ** ($p < .01$), and *** ($p < .001$).]
### A 36: Intercept Variations of Patient’s trait EI and Therapist’s Alliance Measures on Symptom Distress

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