Loneliness and Emotion Regulation

David A. Preece*[1,2], Amit Goldenberg[3], Rodrigo Becerra[2], Mark Boyes[1], Penelope Hasking[1], James J. Gross[4]

[1]Curtin University, School of Psychology, Perth, Australia.

[2]The University of Western Australia, School of Psychological Science, Perth, Australia.

[3]Harvard University, Harvard Business School, Boston, USA.

[4]Stanford University, Department of Psychology, Stanford, USA.

*Corresponding author: David Preece (email: david.preece@curtin.edu.au), Curtin University, School of Psychology, Kent Street, Bentley WA 6102, Australia.

Abstract

Loneliness is a risk factor for mental disorders and is a significant and growing public health issue, but to date, loneliness interventions have had limited success. We propose that an emotion regulation perspective might be useful for understanding loneliness and for suggesting new treatment targets. In this study, our aim was to test the basis for this proposal by examining whether individual differences in emotion regulation strategy use can explain significant variance in loneliness, and to establish what profile of strategy use might characterize loneliness. We administered a comprehensive battery of loneliness and emotion regulation questionnaires to 501 adults In a regression model, emotion regulation strategy use accounted for over half (52.2%) the variance in loneliness. A latent profile analysis revealed four profiles, with the "high loneliness" profile characterized cognitively by greater use of rumination, catastrophising, blame-attribution, and lesser use of cognitive reappraisal type strategies. Behaviorally, loneliness was characterised by greater use of expressive suppression, and regulating emotions by actively rejecting or withdrawing from others. We conclude that individual differences in emotion regulation may play an important role in explaining loneliness, and could therefore represent a promising treatment target.

Keywords: Loneliness, emotion regulation, strategies, profile

1. Loneliness and Emotion Regulation

Loneliness is a significant and growing public health issue (Cacioppo & Cacioppo, 2018). It is not synonymous with social isolation, and people with many social contacts can still report feeling disconnected and alone, just as people who are alone can report not feeling lonely (Hawkley & Cacioppo, 2010). Around 15-30% of adults report chronic or severe loneliness, a state associated with significantly increased risk of mental health problems (e.g., depression), physical illness (e.g., poor cardiovascular health), and premature mortality (Cacioppo et al., 2006). It is therefore important to have effective interventions for loneliness. Existing interventions have primarily targeted either improving social skills, or enhancing social supports, or increasing opportunities for social contact, or addressing maladaptive social cognitions (Masi et al., 2011). Unfortunately, to date, meta-analyses of loneliness interventions studies have found only small effect sizes overall (see Masi et al., 2011), highlighting the reality that loneliness interventions have, generally, so far not achieved the same efficacy as treatments for other social or behavioral difficulties.

Loneliness is most commonly defined and operationalised (i.e., using psychometric measures like the UCLA Loneliness scale; Russell, 1996) as a negative emotional state caused by the perception of unmet social needs (see Hawkley & Cacioppo, 2010). As such, because loneliness is a negative emotional state, this suggests that an emotion regulation framework might be useful both for understanding loneliness, and for developing more targeted and effective treatments for loneliness. Specifically, Gross's (2015) process model of emotion regulation delineates different categories of emotion regulation strategies based on how early they are activated in the emotion generation process (i.e., broad categories of situation selection, situation modification, attentional deployment, cognitive change, and response modulation), and hypothesises that different strategies from these categories will have different effects. That is, strategies will differ in how effective they are at down- or up-

regulating negative and positive emotions (see Gross & John, 2003). This emotion regulation framework has been widely and successfully applied in the broader mental health field, highlighting that individual differences in patterns of emotion regulation strategy use have important implications for well-being, interpersonal functioning, and psychopathology treatment (e.g., Aldao et al., 2010; Gross & John, 2003; Goldenberg et al., 2016; Preece et al., 2020; Sheppes et al., 2015). Emotion regulation strategy patterns have, for example, been found to robustly predict psychopathology symptoms (e.g., Aldao & Nolen-Hoeksema, 2012). It is therefore possible that an emotion regulation framework could have similar implications for understanding loneliness, however, this framework has not yet been comprehensively examined and applied in the context of loneliness.

To date, few studies have examined the links between loneliness and emotion regulation strategy usage. Of those available, studies have so far tended to focus on only a few regulation strategies, namely cognitive reappraisal and expressive suppression (e.g., O'Day et al., 2019; Verzeletti et al., 2016), or have only examined cognitive strategies in isolation (e.g., Vanhalst et al., 2018). These studies have shown, much like the wider mental health literature (Gross & John, 2003), that cognitive reappraisal is generally adaptive in terms of being associated with good outcomes (i.e., less loneliness), and expressive suppression is generally unhelpful in terms of being associated with poor outcomes (i.e., more loneliness). People do, though, often use a wide range of cognitive and behavioral strategies to regulate their emotions (i.e., types of cognitions or behaviors used to try to alter the trajectory of an unfolding emotional response; Aldao et al., 2010), so to gain a fuller understanding of the relationship between loneliness and emotion regulation, there is a need for further work exploring a wider breadth of emotion regulation strategies.

1.1. The Present Study

Our aim in this study was to examine links between loneliness and emotion

regulation. We did this by administering a battery of emotion regulation measures (assessing cognitive and behavioral emotion regulation strategies) and examining whether they explained significant variance in loneliness. We were also interested in mapping what profile of emotion regulation strategy usage might characterize loneliness.

2. Method

2.1. Participants and Procedure

Our sample comprised 501 adults (50.3% female)[1] with an average age of 46.92 years (SD=17.37, range=18-88). Participants were recruited by Qualtrics panels, an online survey recruitment company, to be representative of the general adult community in the United States. In terms of region, 21.4% were from the Midwest, 20.2% from the Northeast, 38.9% from the South, and 19.6% from the West. 14.2% had completed an associate's degree as their highest level of education, 19.6% a bachelor's degree, and 10.2% a post-graduate degree. Most reported their ethnicity as White or Caucasian (79.6%), Black or African American (7.6%), or Asian (4.0%). 8.0% were currently college students. All participants completed demographic questions (gender, age, education) as well as loneliness and emotion regulation measures as part of a larger battery of self-report questionnaires in an online anonymous survey.

2.2. Measures

We used the UCLA Loneliness scale (Russell, 1996) to operationalise loneliness because it is the most widely used measure of this construct and has well validated psychometric properties. We used the Emotion Regulation Questionnaire (ERQ; Gross &

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[1] Data collection took place in August 2019. The original data-set was N=508, however, to include gender as a covariate in our regression analysis, seven participants who identified their gender as non-binary were not included in the analysis. *A-priori* power analysis indicated that for our planned multiple regression analysis with 19 predictors, a minimum sample size of 153 would be required (specified for a medium effect size [f^2 =.15] and desired power level of .80).

John, 2003), Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski & Kraaij, 2007), and Behavioral Emotion Regulation Questionnaire (BERQ; Kraaij & Garnefski, 2019) to operationalise emotion regulation strategy use. These emotion regulation measures were selected because they are commonly used tools, and together they provide 16 well validated scale scores assessing a comprehensive range of emotion regulation strategies.

2.2.1. UCLA Loneliness Scale. The UCLA Loneliness scale (Russell, 1996) is a 20-item self-report measure of loneliness. Items are answered on a 4-point Likert scale, with higher scores indicating higher levels of loneliness. All items are summed into a total scale score. The UCLA Loneliness scale has demonstrated good validity and reliability (e.g., Russell, 1996), and had good internal consistency in our sample (Cronbach's α=.95).

2.2.2. Emotion Regulation Questionnaire. The ERQ (Gross & John, 2003) is a 10-item self-report measure of habitual use of two emotion regulation strategies: *cognitive reappraisal* ("When I want to feel less negative emotion, I change the way I'm thinking about the situation") and *expressive suppression* (e.g., "I control my emotions by not expressing them"). Items are answered on a 7-point Likert scale, with higher scores indicating more use of that strategy. It has demonstrated good validity and reliability (e.g., Preece et al., 2020), and both scale scores had good internal consistency in our sample (α=.75-.88).

2.2.3. Cognitive Emotion Regulation Questionnaire. The CERQ (Garnefski & Kraaij, 2007) is a 36-item self-report measure of nine cognitive-based emotion regulation strategies the respondent may use habitually when experiencing negative or unpleasant events: *self-blame* (e.g., "I feel that I am the one who is responsible for what has happened"), *acceptance* (e.g., "I think that I have to accept the situation"), *rumination* (e.g., "I am preoccupied with what I think and feel about what I experienced"), *positive refocusing* (e.g., "I think of pleasant things that have nothing to do with it"), *refocus on planning* (e.g., "I think about how I can best cope with the situation"), *positive reappraisal* (e.g., "I think that I can

become a stronger person as a result of what has happened"), *putting into perspective* (e.g., "I think that the other people go through much worse experiences"), *catastrophizing* (e.g., "I keep thinking about how terrible it is what I have experienced"), and *blaming others* (e.g., "I feel that others are responsible for what has happened"). Items are answered on a 5-point Likert scale, with higher scores indicating more use of that strategy. It has demonstrated good validity and reliability (e.g., Garnefski & Kraaij, 2007), and all scale scores had good internal consistency in our sample (α=.72-.85).

2.2.4. Behavioral Emotion Regulation Questionnaire. The BERQ (Kraaij & Garnefski, 2019) is a 20-item self-report measure of five behavioral-based emotion regulation strategies the respondent may use habitually when experiencing negative or unpleasant events: *seeking distraction* (e.g., "I set my worries aside by doing something else"), *withdrawal* (e.g., "I avoid other people"), *actively approaching* (e.g., "I take action to deal with it"), *seeking social support* (e.g., "I look for someone who can support me"), and *ignoring* (e.g., "I behave as if nothing is going on"). Items are answered on a 5-point Likert scale, with higher scores indicating more use of that strategy. It has demonstrated good validity and reliability (Kraaij & Garnefski, 2019), and all scale scores had good internal consistency in our sample (α=.77-.90).

2.3. Analytic Strategy

2.3.1. Correlation Matrix and Regression. Using JASP 0.12 software, we examined Pearson bivariate correlations, and conducted a hierarchical multiple regression analysis to examine whether habitual emotion regulation strategy usage predicted loneliness. The UCLA Loneliness scale total score was the criterion variable in our regression. In the first step, demographic variables (gender [male = 1, female = 0], age, and education level) were entered into the regression model to control for their potential effects. In the second step, all 16 of the ERQ, CERQ, and BERQ scale scores were entered as predictors.

2.3.2. Latent Profile Analysis. To examine patterns across individuals, we conducted a latent profile analysis using the TidyLPA package with *R* software (Rosenberg et al., 2018). Latent profile analysis is a modeling technique that identifies profiles (i.e., subgroups) of people within a dataset that have similar patterns across a set of variables (Hagenaars & McCutcheon, 2009). Our analysis included the UCLA Loneliness scale total score and the 16 scale scores of the ERQ, CERQ, and BERQ. All possible model types (i.e., 4) from the TidyLPA package were estimated, differing in allowed parameters for variances and covariances. Models had either: (1) equal variances, covariances fixed to 0; (2) varying variances, covariances fixed to 0; (3) equal variances, equal covariances; or (4) varying variances, varying covariances (Rosenberg et al., 2018). For each model type, solutions for 1 to 6 profiles were estimated and compared.[2]

The optimal solution was judged based on five common fit index values: the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Appropriate Weight of Evidence Criterion (AWE), Classification Likelihood Criterion (CLC), and Kullback Information Criterion (KIC) (for all of these fit indexes, lower values indicate a better fitting model). Of the individual fit index values, BIC has previously been found as the best performing indicator of an optimal solution, and so was prioritised here (see Nylund et al., 2007). We also report entropy values, which range from 0 to 1 (≥.80 being acceptable; Tein et al., 2013), with higher values indicating a higher certainty for classifying participants into the extracted profile categories.

3. Results

3.1. Correlation Matrix and Regression

Descriptive statistics for all measures are presented in Table 1. A Pearson correlation

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[2] If a 6 profile solution emerged as best, the analysis would be rerun with a higher number of profiles to check that a higher number of profiles would not have been superior.

matrix of all the loneliness, emotion regulation, and demographic variables is presented in Table S1 in the supplementary materials. In terms of bivariate correlations, with respect to cognitive strategies, loneliness was significantly associated ($p<.05$) with increased use of self-blaming, blaming others, rumination, acceptance, and catastrophizing, and decreased use of cognitive reappraisal type strategies (ERQ cognitive reappraisal, CERQ positive reappraisal, CERQ positive refocusing, CERQ refocus on planning). For behavioral strategies, loneliness was significantly associated with increased use of withdrawal, ignoring, and expressive suppression, and decreased seeking of social support, active approaching, and seeking distraction. With respect to demographic variables, loneliness was uncorrelated with gender, but associated with younger age and lower education level.[3]

In our hierarchical multiple regression analysis, the demographic variables alone accounted for 4.9% of the variance in loneliness. The addition of all the emotion regulation strategies into the model accounted for a statistically significant additional 52.2% of the variance in participants' loneliness levels (final model: $F[19, 481] = 33.645$, $p < .001$, $R^2 = .571$). As displayed in Table 2, eight of the emotion regulation strategies were unique predictors of loneliness. Cognitively, loneliness was associated with increased use of self-blaming, blaming others, and rumination, and decreased use of cognitive reappraisal type strategies (CERQ positive reappraisal, CERQ refocus on planning). Behaviourally, loneliness was associated with increased use of withdrawal and expressive suppression, and decreased seeking of social support. The other examined emotion regulation strategies were not significant unique predictors of loneliness.

---*Table 1*---

---*Table 2*---

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[3] Results stratified by gender are provided in supplementary Tables S2, S3, S4, and S5.

3.2. Latent Profile Analysis

Our latent profile analysis indicated that the data were well represented by a four profile solution (with equal variances, equal covariances). See Table S2 in the supplementary materials for fit index values for all tested models. The four-profile solution was optimal according to BIC, and also had a strong entropy value (.89), and theoretically meaningful distinctions between the extracted profiles. These four profiles varied in levels of loneliness and strategy usage (see Figure 1), and we refer to them here as the "high loneliness" (n=47), "high average loneliness" (n=54), low average loneliness" (n=349), and "low loneliness" (n=51) profiles. Relative to the "low loneliness" profile, the "high loneliness" profile was characterised by extremes in regulation strategy use patterns with increased use of self-blaming, rumination, catastrophising, and withdrawal, and decreased use of cognitive reappraisal type strategies and active approaching. The "low loneliness" profile displayed, generally speaking, the opposite pattern of extremes in high/low regulation strategy use. The "high average loneliness" and "low average loneliness" profiles tended to have a more even usage of strategies across the regulation categories (i.e., fewer extreme high and low scores within the profile), though the "high average loneliness" profile had more extreme elevations in catastrophising and other blaming.[4]

---*Figure 1*---

4. Discussion

Our aim in this study was to examine the links between habitual emotion regulation strategy usage and loneliness, considering a more comprehensive set of emotion regulation

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[4] An alternative method for deciding the number of profiles to extract is Akogul and Erisoglu's (2017) analytic hierarchy process. In this data-set, the Akogul and Erisoglu method identifies a 2-profile model as best; for completeness, this solution is displayed in the supplementary materials (see Figure S1). We prioritised the 4-profile solution over the 2-profile solution in this paper, because the 4-profile solution appeared more theoretically meaningful/interpretable; providing greater classification certainty (i.e., entropy) and making more nuanced distinctions between different loneliness profiles.

strategies than has previously been considered in the loneliness field. Overall, our results support the idea that the emotion regulation strategies people use are an important predictor of their loneliness levels, accounting for over half the variance in loneliness. Consistent with the specifications of the process model of emotion regulation (Gross, 2015), we found that different regulation strategies had differential relationships with loneliness, and that both cognitive and behavioral strategies appeared to play an important role.

4.1. Links Between Emotion Regulation Strategies and Loneliness

Cognitively, across our analyses, the habitual emotion regulation pattern linked to loneliness was characterised by more use of rumination, blame-attributions (to the self and others), and less use of cognitive reappraisal strategies or helpful thought reframing. Behaviourally, people with high loneliness also reported supressing expression of their emotions more (expressive suppression), and were more likely to try to regulate their emotions by actively rejecting or withdrawing from the social support of others, coupled with also being less likely to initiate the seeking of social support.

Our results are therefore consistent with previous loneliness studies that have mostly examined cognitive reappraisal and expressive suppression (e.g., O'Day et al., 2019; Verzeletti et al., 2016). Importantly, though, by examining a broader set of strategies our study reveals a more detailed profile of emotion regulation patterns characterising loneliness. Of particular note, our behavioural strategy findings reveal a potentially important paradox: people high in loneliness are, by definition, craving social connection to fill unmet interpersonal needs (Hawkley & Cacioppo, 2010), but simultaneously, our results suggest they are also frequently responding to negative emotions by supressing their expression and actively avoiding social contact. As such, these habitual emotion regulation patterns may perpetuate states of loneliness and social isolation. Our findings in this respect are consistent with contemporary loneliness theories (e.g., Cacioppo & Hawkley, 2009), which posit that

people high in loneliness may be cognitively hypervigilant for social threat, anticipating more negative social interactions, thus leading to socially avoidant behavior. Indeed, our cognitive emotion regulation strategy findings are also consistent with this view, whereby people with high loneliness do appear to rely on more unhelpful cognitive patterns to try to regulate negative emotions (e.g., increased rumination and self/other blaming, decreased cognitive reappraisal; see Garnefski & Kraaij, 2007).

4.2. Implications for Intervention

In the broader mental health field, profiles of emotion regulation strategy usage similar to this have been consistently linked to poor long-term outcomes, in terms of increased mental health disorder symptoms (e.g., depression, anxiety) and ineffectiveness in down-regulating negative emotions or up-regulating positive emotions (e.g., Gross & John, 2003; Kraaij & Garnefski, 2019). Correspondingly, many contemporary cognitive behavioral treatments for affective disorders target emotion regulation strategy use as a key transdiagnostic mechanism (in terms of trying to decrease use of unhelpful strategies and increase habitual use helpful ones), frequently finding good effect sizes in symptom reduction (e.g., Farchione et al., 2012).

Our results suggest that a similar emotion regulation focused approach might be fruitful for reducing loneliness: that is, psychotherapies specifically aiming to down-regulate loneliness via *decreasing* use of rumination, self/other blaming, expressive suppression, and behavioral withdrawal strategies, and *increasing* use of cognitive reappraisal and seeking of social support strategies (e.g., cognitive behavior therapy, dialectical behavior therapy, acceptance and commitment therapy; Hayes et al., 2006; Linehan et al., 2007; Mennin et al., 2013). Indeed, of the four main existing loneliness treatment approaches with outcome data (i.e., treatments primarily targeting improving social skills, or enhancing social supports, or increasing opportunities for social contact, or addressing maladaptive social cognitions),

meta-analysis indicates that those targeting maladaptive social cognitions within a cognitive therapy framework tend to have the largest effect sizes (see Masi et al., 2011). Studies like ours may therefore help to optimise the effectiveness of such treatments, by guiding the inclusion of a more comprehensive and targeted set of emotion regulation strategies.

4.3. Limitations and Future Directions

We think our study makes a useful contribution, however, some limitations will require further research. Firstly, our data are cross-sectional, so whilst the observed pattern of associations appears to make theoretical sense (Gross, 2015), future longitudinal studies are needed to determine the directionality of these relationships. Given our study examined only one sample, tests of replicability are also needed. Secondly, no information was available on the number of social contacts or quality of social environment participants had. It is possible that the emotion regulation strategies people use are influenced by the number of social contacts available to them, so ideally this variable would be useful to control in future work (e.g., Kearns & Creaven, 2017). Thirdly, corresponding to the ethnicity distribution of the population from which our sample was drawn (US Census Bureau, 2019), our sample was predominantly White. The adaptiveness of some regulation strategies (i.e., in terms of associations with long-term good or bad outcomes) can differ across cultures (e.g., expressive suppression generally having less problematic outcomes in Asian cultures; Soto et al., 2011), so further research will be important to determine the cross-cultural generalisability of the emotion regulation patterns that characterised loneliness in our sample. Fourthly, our analyses were specific to loneliness rather than a broader set of mental health variables (e.g., depression, anxiety, well-being). Emotion regulation strategy patterns have well established associations with other mental health constructs (e.g., Aldao et al., 2010, Sheppes et al., 2015), and future studies could expand on our work by directly comparing the extent to which emotion regulation patterns are shared or unique across loneliness and other mental

health constructs. Fifthly, by design, we were interested in general patterns of emotion regulation strategy use, rather than strategies used specifically to regulate loneliness or for specific contexts. We used this approach because it is common in the emotion regulation field, habitual regulation patterns have been linked with a variety of important long-term outcomes, and this approach is well facilitated by existing psychometric measures (e.g., Aldao et al., 2010; Gross & John, 2003). Nonetheless, future studies could expand on this by exploring the concordance between overall emotion regulation patterns and patterns specific to regulating loneliness. Such work could also complement self-report methodologies with the use of behavioral or experimental assessments of emotion regulation and loneliness (e.g., Gross & Levenson, 1993).

4.4. Conclusions

Our data suggest that the different cognitive and behavioral emotion regulation strategies people use account for substantial variance in loneliness. Whilst more studies are needed on this issue, these findings support that an emotion regulation framework may be useful to help conceptualise loneliness and potentially inform more targeted or optimised treatment approaches.

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Table 1
Descriptive Statistics and Cronbach's α Reliability Coefficients

Scale	M	SD	Range	Cronbach's α
UCLA Loneliness Scale				
Total score	47.26	13.62	20-79	.95
Emotion Regulation Questionnaire				
Cognitive reappraisal	28.79	7.35	6-42	.88
Expressive suppression	15.07	5.33	4-28	.75
Cognitive Emotion Regulation Questionnaire				
Self-blame	10.43	3.86	4-20	.80
Acceptance	11.95	3.49	4-20	.72
Rumination	11.05	3.77	4-20	.78
Positive refocusing	10.71	3.82	4-20	.82
Refocus on planning	12.87	3.86	4-20	.83
Positive reappraisal	12.63	4.08	4-20	.85
Putting into perspective	12.17	3.84	4-20	.79
Catastrophizing	8.81	3.76	4-20	.80
Blaming others	7.71	2.87	4-20	.77
Behavioral Emotion Regulation Questionnaire				
Seeking distraction	11.63	3.50	4-20	.77
Withdrawal	10.19	4.68	4-20	.90
Actively approaching	11.79	3.77	4-20	.85
Seeking social support	9.68	4.07	4-20	.88
Ignoring	9.06	3.85	4-20	.83

Table 2
Coefficients from the Final Model of a Hierarchical Multiple Regression Analysis of Emotion Regulation Strategy Scores Predicting Loneliness

Variable	Standardized β	Standard error	t	p
Gender	**-0.075**	**0.867**	**-2.345**	**0.019**
Age	-0.060	0.027	-1.770	0.077
Education	-0.043	0.306	-1.380	0.168
ERQ Cognitive reappraisal	-0.064	0.072	-1.633	0.103
ERQ Expressive suppression	**0.104**	**0.093**	**2.856**	**0.004**
CERQ Self-blame	**0.135**	**0.154**	**3.090**	**0.002**
CERQ Acceptance	0.003	0.157	0.073	0.941
CERQ Rumination	**0.094**	**0.164**	**2.074**	**0.039**
CERQ Positive refocusing	0.003	0.168	0.057	0.955
CERQ Refocus on planning	**-0.114**	**0.206**	**-1.962**	**0.050**
CERQ Positive reappraisal	**-0.150**	**0.192**	**-2.600**	**0.010**
CERQ Putting into perspective	0.014	0.158	0.318	0.750
CERQ Catastrophising	-0.023	0.154	-0.539	0.590
CERQ Blaming others	**0.155**	**0.170**	**4.342**	**< .001**
BERQ Seeking distraction	-0.022	0.168	-0.519	0.604
BERQ Withdrawal	**0.384**	**0.125**	**8.940**	**< .001**
BERQ Actively approaching	0.018	0.164	0.404	0.687
BERQ Seeking social support	**-0.169**	**0.126**	**-4.462**	**< .001**
BERQ Ignoring	-0.031	0.143	-0.762	0.446

Note. Significant predictors ($p<.05$) are bolded. ERQ=Emotion Regulation Questionnaire; CERQ=Cognitive Emotion Regulation Questionnaire; BERQ=Behavioral Emotion Regulation Questionnaire. Gender was coded 0=female, 1=male. Age was a continous variable. Education (highest level of completed education) was coded 1=none, 2=primary school, 3=some high school (not complete), 4=high school, 5=some college (no degree), 6=associate's degree, 7=bachelor's degree, 8=postgraduate degree.
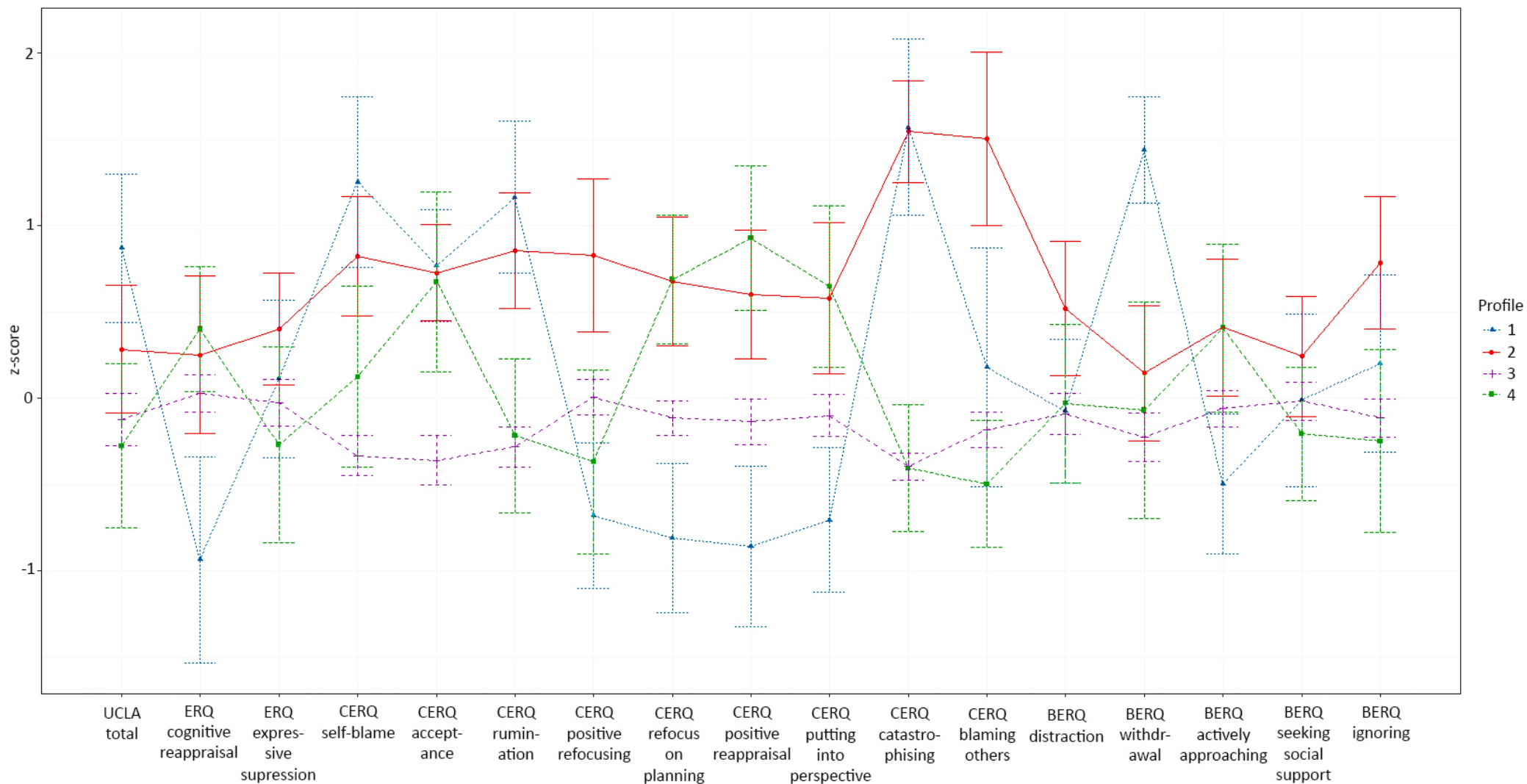
Figure 1. A visual representation of the 4-profile solution (equal variances, equal covariances) from the latent profile analysis. Profile 1 = "high loneliness", profile 2 = "high average loneliness", profile 3 = "low average loneliness", profile 4 = "low loneliness". Error bars are 95% confidence intervals. UCLA = UCLA Loneliness Scale, ERQ = Emotion Regulation Questionnaire, CERQ = Cognitive Emotion Regulation Questionnaire, BERQ = Behavioral Emotion Regulation Questionnaire.