Investigating the short-term predictability of psychological distress by mental well-being in individuals using N-of-1 analysis of observational data collected in an experience sampling study

Abstract

Previous research has extensively examined the relationship between mental well-being and psychological distress, suggesting that they are associated yet distinct constructs. However, most studies have focused on either concurrent associations or long-term predictive relationships, neglecting the short-term predictability of well-being on distress. Moreover, traditional approaches have analysed group-level associations, assuming consistency across individuals. To investigate the individual-level short-term predictability of distress by well-being, this study utilized time series analysis, accounting for autocorrelation and time trends. Data from four university students previously participating in a two-week experience sampling study were selected for n-of-1 analyses as proposed by McDonald et al. (2020). Momentary self-reports of well-being and distress were collected three times per day. The variables were examined through visual inspection of individual scatter plots, variability and stationarity assessments, and autocorrelation analyses to develop dynamic regression models which control for time trends and autocorrelation structures in the data. The results showed that well-being did not significantly predict anxiety or depression for any of the four participants, suggesting the absence of a short-term predictability on the individual level. This can have important implications for research and practice as it questions the role well-being plays, for example, in positive psychology interventions. However, the null findings could also be attributed to variations across individuals as well as to methodological limitations, including the limited number of data points, a potentially inappropriate choice of the lag interval, the volatility of the constructs, and challenges to accurately measure them, which highlights the need for meticulous design and warrants further research.

Introduction

Background and Relevance of Mental Health

Mental disorders are among the top ten causes of burden of disease worldwide and constitute an increasingly important public health issue (GBD 2019 Mental Disorders Collaborators, 2022). Among mental disorders, depressive and anxiety disorders account for the largest proportion of disease burden, at 28.8% and 31.1%, respectively (GBD 2019 Mental Disorders Collaborators, 2022). In the World Health Organization's (WHO) European Region, the estimated prevalence of mental disorders was 110 million in 2015, corresponding to 12% of its total population (World Health Organization, 2019). However, common mental disorders such as depression and anxiety are treatable and potentially preventable (Mendelson & Eaton, 2018; World Health Organization, 2004a). An exact understanding of how these disorders develop and progress over time in individuals can contribute to adequate interventions for treatment and prevention (Ariens et al., 2020; Kazdin & Blase, 2011).

Traditionally, health has been defined solely in terms of the absence of disease (Ryff & Singer, 2010). However, the WHO introduced a more comprehensive definition about half a century ago, expanding the concept of health beyond the mere absence of illness. According to the WHO, health is "a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity" (Callahan, 1973). This definition emphasizes that health cannot be adequately described by focusing solely on illness and should not be viewed separately from subjective experience. Instead, the positive aspects of well-being should be considered while recognizing the interconnectedness of physical, mental, and social dimensions in defining overall health. However, this conception has long been largely neglected in both research and practice (World Health Organization, 2004b).

In this respect, a new area of research has emerged aimed at decreasing the burden linked to prevalent mental disorders (Herron & Trent, 2000). This novel approach, known as the dual-continua model, proposes that mental health and mental illness are not opposing points on a single spectrum, but instead, are two moderately interrelated yet primarily distinct continua (Huppert & Whittington, 2003; Keyes, 2005, 2007; Westerhof & Keyes, 2010).

First, the mental illness continuum ranges from severe mental illness to the absence of psychopathology and is measured by the degree of psychological distress. Psychological distress usually refers to a state of emotional suffering characterized by a non-specific set of psychological symptoms, such as depression, anxiety, or stress (Dohrenwend et al., 1980; Drapeau et al., 2012; Kessler et al., 2002). Second, the mental health continuum ranges from languishing to flourishing (Keyes, 2002). Regarding mental well-being, there are two distinguishable components: hedonic and eudaimonic well-being (Deci & Ryan, 2008; Ryan & Deci, 2001; Waterman, 1993). The former involves experiencing positive emotions and feeling content with life (Diener, 1984; Diener et al., 1999; Kahneman et al., 1999). The latter comprises aspects such as self-acceptance, autonomy, and purpose in life (Ryff, 1989; Ryff & Keyes, 1995).

In conclusion, this two-continua model implies that a person may experience a mental disorder while also having low levels of positive mental health. However, in contrast to the traditional mono-continuum notion of mental health, it also entails that someone with a mental disorder may have higher than average levels of positive mental health. As an illustration, a study by Bergsma et al. (2011) found that more than two-thirds of individuals who had been diagnosed with a mental disorder reported feeling happy often, usually, or always within the past four weeks.

Previous Research on the Relationship between Well-being and Distress

Numerous cross-sectional studies, utilizing both correlational and confirmatory factor analysis methods, have shown the distinctiveness or discriminant validity of distress and well-being (c. f. Kraiss et al., 2022). In their scoping review, Iasiello and Van Agteren (2020) concluded that these studies have typically revealed moderate correlations between measures of well-being and distress as well as a consistent superior fit of a correlated bifactorial model compared to a unifactorial model of mental health. However, even though they are essentially distinct constructs, well-being and distress are not completely independent of each other, but are related in a complex way.

This relationship has already been investigated in various nomothetic studies. As such, mental well-being is suggested to have various positive consequences, including better physical health (Huppert, 2009) and life longevity (Andrews et al., 2001; Xu & Roberts, 2010). Moreover, numerous longitudinal studies indicate that high levels of well-being can lower the chance of psychological distress later in life (Grant et al., 2013; Keyes et al., 2010; Lamers et al., 2015; Schotanus-Dijkstra et al., 2016; Wood & Joseph, 2010). Furthermore, multiple studies found that well-being can predict recovery from psychological distress (Iasiello et al., 2019; Leamy et al., 2011; Schotanus-Dijkstra et al., 2019).

However, our understanding of the relationship between mental well-being and psychological distress is still limited due to previous studies being either cross-sectional or longitudinal with a small number of measurement points. To study dynamic changes within individuals, intensive longitudinal data involving rather high numbers of observations per individual over time is needed (Hamaker & Wichers, 2017). The experience sampling method (ESM), also known as ecological momentary assessment (EMA), is a technique now commonly utilized to gather intensive longitudinal data about participants' current subjective experiences (Csikszentmihalyi & Larson, 2014; Stone & Shiffman, 1994). Recent technological advances, such as the omnipresence of smartphones, have greatly facilitated the possibilities for gathering repeated self-reports with relatively high measurement densities (Berkel et al., 2017; Raento et al., 2009). ESM enables real-time research in ecologically valid contexts, meaning that assessments occur within the natural variations of daily life without modulating it (Myin-Germeys & Kuppens, 2021). Moreover, participants are assessed prospectively, whereby retrospective biases are reduced (Ebner-Priemer et al., 2009), which may be particularly relevant for volatile concepts such as psychological distress.

A recent ESM study by Kraiss et al. (2022) already examined the relationship between distress and mental well-being within individuals and found convincing evidence that the dual continua model appears to be valid within individuals when analysed at the group level. However, they also found significant variation among individuals, suggesting that the dual continua model may not apply universally. These results indicate that the relationship between distress and well-being may differ among individuals. Drawing conclusions at the individual level based on group-level findings can lead to ecological fallacies (Curran & Bauer, 2011), since such inferences require associations to be consistent across individuals (De Luca Picione, 2015; Salvatore & Valsiner, 2010). This assumption of statistical ergodicity may not be accurate as generally only few individuals are accurately represented by the average patterns found in nomothetic studies (Estes & Todd Maddox, 2005; Fisher et al., 2018; Hamaker et al., 2005; Molenaar, 2004; Molenaar & Campbell, 2009). While theories and models in clinical psychology, including the dual continua model of mental health, are often studied through a nomothetic approach (Kwasnicka & Naughton, 2020; McDonald et al., 2017; Zuidersma et al., 2020), there is a growing recognition that there are significant differences among individuals in the aetiology, pathogenesis, and treatment of psychological disorders and their symptoms (Hofmann & Hayes, 2019; Moskow et al., 2023; Ozomaro et al., 2013; Wium-Andersen et al., 2017; Wright & Woods, 2020). Nevertheless, despite their potential benefits, a systematic review by McDonald et al. (2017) found that single-subject research designs, commonly referred to as N-of-1 studies, are not yet widely employed in health psychology and behavioural medicine. Such studies can provide rich data on individual patterns of change over time that may not be captured by traditional group-level studies (Kwasnicka & Naughton, 2020).

Beside the lack of idiographic analyses, another issue is that virtually all research examining the relationship between well-being and distress has focused on either the concurrent, or the long-term predictive associations over several months or years based on a low number of data points. Although Kraiss et al. (2022) employed intensive longitudinal data, their analyses only examined concurrent associations between well-being and distress while no conclusions regarding temporal precedence were drawn. To the author's knowledge, no study has yet explored the short-term predictability of mental well-being on psychological distress in terms of dynamic changes occurring during the same day. Utilizing intensive longitudinal data obtained via the ESM, time series analysis might be well suited to model predictive associations between variables for individuals (Ariens et al., 2020). Time series analysis is a set of techniques that has been only infrequently applied in psychology and involves analysing a large number of repeated measurements from a single subject to determine how measurements can be anticipated from previous measurement points by various factors (Hamaker & Dolan, 2009; Jebb et al., 2015). Understanding the short-term predictability of distress by well-being may significantly contribute to the theory underlying the dual continua model as well as its practical applications. For example, the model is widely employed as a framework for positive psychology interventions (PPIs; Iasiello & Van Agteren, 2020). PPIs are typically designed to enhance well-being factors, with the belief that they have the potential to positively influence both continua from the dual continua model (Schotanus-Dijkstra et al., 2017). There exist some theories about how and why well-being can have a positive impact on distress. For instance, Trompetter et al. (2017) propose that self-compassion, which is particularly present in individuals with high levels of mental well-being, creates a friendly and accepting environment for negative experiences, and can thus act as an adaptive strategy for emotion regulation and resilience against psychological distress.

Research Aim

The current study conducts a post hoc analysis of the study by Kraiss et al. (2022) and investigates the short-term predictability of psychological distress by mental well-being in individuals. To address the limitations outlined above, the current study aims to explore the potential temporal precedence of well-being in relation to distress using an N-of-1 observational design. Considering the lack of quantitative idiographic analyses in clinical psychological research, this study seeks to bridge this gap by utilizing time series analysis of intensive longitudinal data collected through the ESM. By examining the short-term dynamics between well-being and distress, this study contributes to our understanding of intra-individual affective processes underlying the dual continua model of mental health. Previous nomothetic research has generally shown moderate associations between well-being and distress in both a concurrent and long-term relationship. In case a short-term predictive relationship between the two constructs exists at the individual level, significant results are expected to be found, at least for some participants. The (non-)existence of such a relationship may have relevant implications for the theory and application of the dual continua model. For example, it could provide indications for the working mechanism of PPIs.

Methods

Participants

Sample

The current study is a secondary analysis of the experience sampling dataset which was previously used by Kraiss et al. (2022). To acquire participants for this ESM study, a convenience sampling approach was utilized, which has the advantage of recruiting participants who are readily available, accessible, and willing to participate (Etikan et al., 2016). Two psychology students recruited participants as part of their bachelor theses (Möller, 2020; Völker, 2020) through informal contacts via WhatsApp or in person from their network. Out of the individuals who were contacted, 83% agreed to participate in the study, yielding 35 university students from different countries, mostly Germany (Völker, 2020).

Selection

In the current study, out of the 35 participants, 25 were omitted because they completed less than 90 percent of the measurement points. This threshold was chosen in correspondence to the guideline put forth by McDonald et al. (2020), as the amount of missing data influences estimates of autocorrelation. Additionally, two were excluded due to lack of variability in the variables of interest (floor effect) as observed in Excel after applying a colour gradient, since the presence of sufficient variability is crucial for examining potential relationships between the variables (Jebb et al., 2015). For the remaining eight participants, individual scatter plots were created for depression and anxiety, respectively, as outcome variables and lagged well-being as the predictor variable using the Statistical Package for Social Sciences (SPSS) version 28.0.1.0 software. Based on variability of the variables and a potentially predictive relationship seen in these plots (see Figure 1), visual inspection resulted in four participants being selected for further analysis.

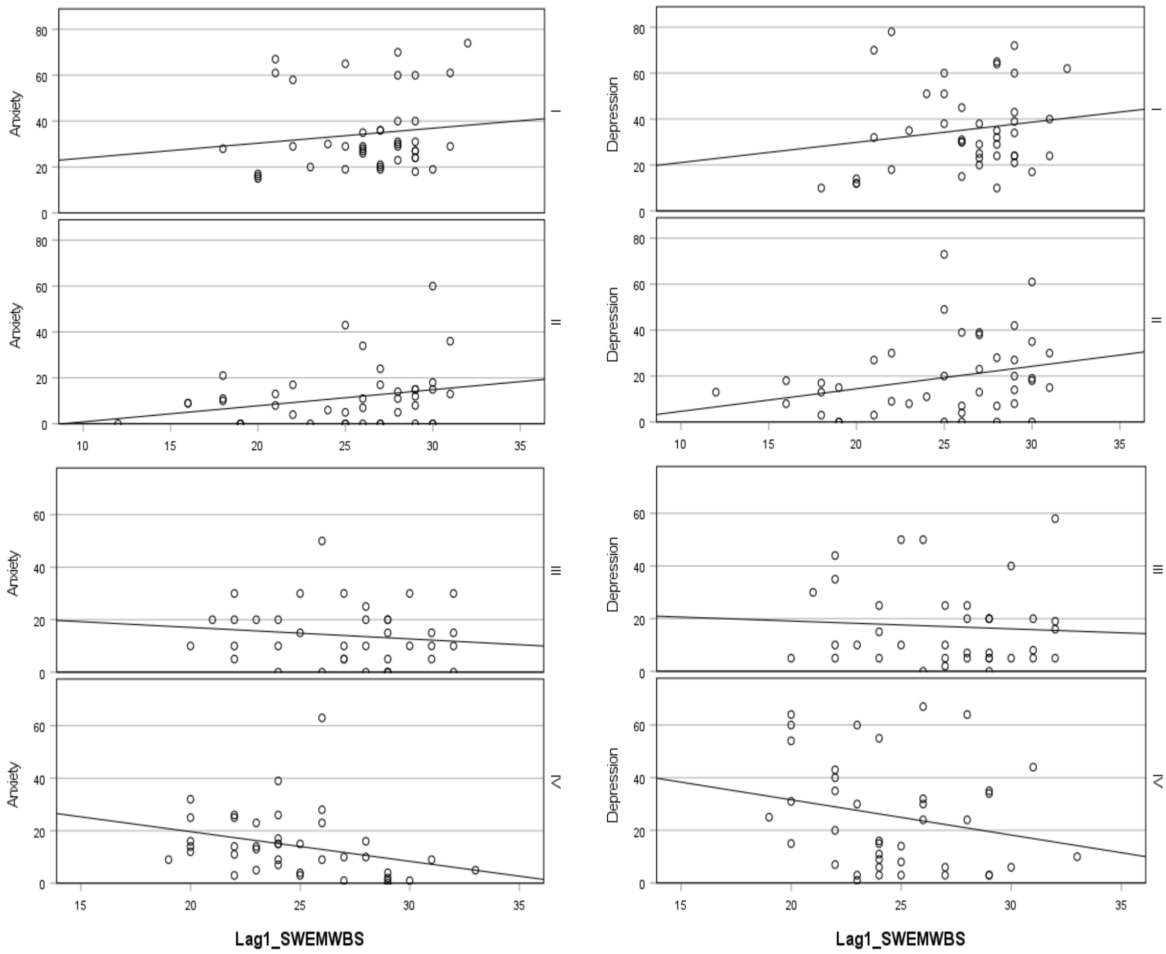

Figure 1:
Scatter Plots with Anxiety (left) and Depression (right) as outcome and one-lagged Well-being as predictor variables for participants I to IV (from top to bottom, as labelled on the right-hand side)

Data Collection

Momentary self-reports of mental well-being and psychological distress were assessed using the experience sampling method (ESM) for intensive longitudinal data (Bolger & Laurenceau, 2013). During the measurement period from April 6th to April 19th, 2020, participants were asked a set of identical questions via the Ethica App on their smartphones and were instructed to respond as soon as possible for the sake of accuracy. The prompts occurred as per an interval contingent scheme (c. f. Conner & Lehman, 2012) three times a day at 10 a.m. (morning), 3 p.m. (afternoon), and 8 p.m. (evening), yielding a maximum of 42 data points per individual over two weeks.

Measures

Psychological Distress

Psychological distress was assessed using two of the most common types of symptoms, i.e., depression and anxiety (Drapeau et al., 2012; Mirowsky & Ross, 2003). In the scientific literature, there has been some discussion on the conceptualization and measurement of psychological distress. According to the review by Dohrenwend et al. (1980), screening scales for psychological distress usually include questions about various cognitive, behavioural, emotional, and psychophysiological symptoms that are commonly found in people with different types of mental disorders. Despite the diverse content, most of the symptoms on these scales are highly associated with a single principal factor. Accordingly, people with different types of mental disorders usually score high on this core dimension of non-specific distress. The seminal tripartite model, proposed by Clark and Watson (1991), also supports this idea of an underlying non-specific distress factor that exists across different mental disorders such as depression and anxiety. The model further explicates that in addition to the underlying distress, depression and anxiety are characterized by a divergent symptomatology such as anhedonia (specific depression) and physiological hyperarousal (specific anxiety), respectively. Accordingly, depression and anxiety are treated separately in this study. Each of the two types of symptom was assessed using a single item, i.e., '*How anxious do you feel right now?*' and '*How down do you feel right now?'*, respectively. Participants answered each question by indicating the intensity of that feeling on Visual Analogue Scale (VAS) ranging from 0 ('*Not anxious/ down at all*') to 100 ('*Extremely anxious/ down*').

VASs have been demonstrated to be a suitable instrument for evaluating short-term changes in both anxiety (Rossi & Pourtois, 2012) and depressive feelings (Moullec et al., 2011), respectively. Furthermore, it has been suggested that VASs may be advantageous over discrete scales because they can achieve a higher measurement level, avoid systematic bias due to scale coarseness, and potentially elicit more extreme responses (Kuhlmann et al., 2017; Myin-Germeys & Kuppens, 2021).

Mental Well-being

The Short Warwick-Edinburgh Mental Well-being Scale (SWEMWBS; Stewart-Brown et al., 2009), a condensed version consisting of seven items derived from the original 14-item Warwick-Edinburgh Mental Well-being Scale (WEMWBS; Tennant et al., 2007), was utilized to measure mental well-being. While the WEMWBS captures both main dimensions of well-being, i.e., eudaimonia and hedonia (Ryan & Deci, 2001), the SWEMWBS places greater emphasis on eudaimonic well-being at the benefit of enhanced scaling properties and reduced participant burden (Ng Fat et al., 2017). The SWEMWBS exhibited a strong correlation (r_s >.95) with the WEMWBS (Stewart-Brown et al., 2009) and performed similarly in a national survey in England (Ng Fat et al., 2017). Furthermore, the SWEMWBS has shown adequate validity and reliability in people with depression, anxiety spectrum disorders and schizophrenia in Singapore (Vaingankar et al., 2017). The positively worded items of the SWEMWBS, for example, '*I've been feeling useful.*', referred to the past two hours and were answered on a 5-point Likert scale ('*None of the time'* to '*all of the time'*) in the current study. A total well-being score was created by aggregating the seven items, yielding a value between 7 and 35 for each measurement point. Since one participant (respondent IV) once missed completing one item, the mean value of the other six items of the same measurement point was inserted for this item.

Data Analysis

Data analysis was performed using SPSS and in accordance with the framework for N-of-1 analyses of intensive longitudinal observational data developed by McDonald et al. (2020). The procedures described below outline the general approach followed in the study, with separate analyses conducted for each participant and outcome variable. Specifically, N-of-1 analyses for four participants were performed, resulting in a total of eight dynamic regression models.

Dataset Preparation

Potentially missing data points were identified and imputed to ensure the integrity of the time series data. Measurement points were only missing for one participant (respondent III), who failed to complete three measurement points (7.1 %). As suggested by McDonald (2020), if missing data is minimal (i.e., less than 10%) a simple imputation method can be applied. Accordingly, the mean value of the two previous and two subsequent data points was utilized for imputation.

Assessment of Variability and Stationarity

To examine the variability and centrality of the outcome variables, descriptive statistics including mean, standard deviation, and range were computed and evaluated. Next, individual time series plots were created for the outcome and predictor variables, respectively. Visual inspection of the plots offers initial insights into the overall behaviour of the variables such as potential time-related patterns and thereby help guide further analysis and modelling decisions (Park et al., 1990).

To assess stationarity in the data, this study examined whether the statistical properties of the outcome variables, including mean, variance, and autocorrelation, remained constant over time. The assumption of stationarity was important to be approximately met for making valid predictions in the subsequent dynamic regression analysis. To evaluate stationarity, the time-series data was partitioned into two equal-sized segments, representing each week of measurement. Descriptive statistics were then compared between the two segments to assess any notable differences.

To further investigate for time trends, a standard linear regression model was applied for each individual with time as the predictor and state depression and anxiety as the outcome variables, respectively. When a significant linear time trend was identified for a participant, the time variable was incorporated as a predictor in their final dynamic regression model.

Regarding periodicity, a potential association between the time of the day at time of measurement (morning, afternoon, evening) and the three variables of interest (depression, anxiety, well-being) was suspected. Therefore, one-way ANOVAs were performed with morning, afternoon, and evening as the group factor.

Autocorrelation Analysis

The presence of autocorrelation in the predictor and the two outcome variables was investigated by utilizing the 'Autocorrelation' function in SPSS. The output included two correlograms, respectively: one for the autocorrelation function (ACF) and one for the partial autocorrelation function (PACF). The ACF represents the correlation between consecutive data points. If any of the bars in the ACF exceed the 95% confidence limit, it suggests the presence of autocorrelation, implying the need for controlling this effect. The PACF provides insights on lag selection by identifying residual autocorrelation when all preceding lags are included. The plot's point where partial autocorrelations converge to zero indicates the appropriate number of lags. Lagged variables of the two outcome variables were created in accordance with the autocorrelation structure identified. To confirm the adequacy of the specified autocorrelation structure, the lagged variables were entered into a regression model, and the correlograms of the residuals were examined to ensure that they exhibited characteristics of "white noise," indicating the absence of any remaining autocorrelation (Jebb et al., 2015).

Dynamic Regression Analysis

To assess the within-person short-term predictive relationship of state well-being on psychological distress, a dynamic regression model was developed, where depression and anxiety, respectively, were entered as dependent variables. As independent variables, beside one-lagged well-being, if applicable to the respective participant, the model included appropriately lagged outcome variables to address autocorrelation, as well as other time-dependent variables to account for time trends. Moreover, a post-model check was performed to examine whether the ordinary least squares regression assumptions, such as linearity, normality, and heteroscedasticity, hold for the model. This was done by visually inspecting a histogram and normal probability plot of the residuals as well as a scatterplot of the residuals vs. the predicted values.

Results

The results of the n-of-1 analyses of the four selected participants are presented below. First, a comprehensive report for participant I is provided, structured according to the methods section. This is followed by a summary of participants II, III and IV, as the analyses were carried out analogously to each other.

Participant I

Assessment of Variability and Stationarity

When examining the centrality and variability of the two outcome variables, anxiety and depression had similar means and standard deviations over the two-week measurement period (see Table 1). Furthermore, anxiety scores ranged from 15 to 74 and depression scores from 10 to 78. Visual inspection of the time series plots of the variables of interest revealed a sufficient degree of variability for outcome and predictor variables while no clear time dependent pattern could be identified (c.f. Figure 2). Notably, anxiety scores appeared particularly volatile up to time point 22, after which they stayed relatively low whereas depression scores remained volatile over the entire measurement period.

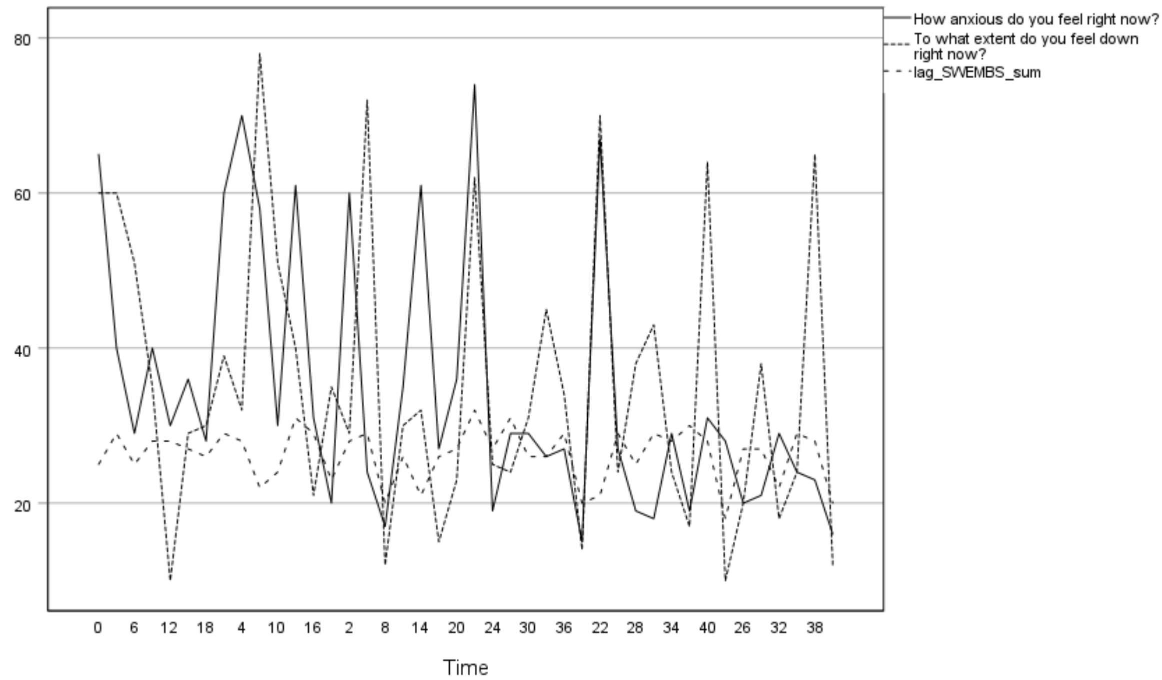

Figure 2
Time Series Plot for Anxiety, Depression and Well-being for Participant I

Table 1

Descriptive Statistics for the Outcome Variables of both Weeks of Measurement for Participants I to IV

Participant		Minimum		Maximum		Mean			Standard Deviation		
	Week	1	2	1	2	1 & 2	1	2	1 & 2	1	2
I	Anxiety	17	15	70	74	35.4	40.9	28.1	16.9	16.5	14.9
	Depression	10	10	78	70	34.5	37.3	33.4	18.5	18.6	18.5
II	Anxiety	0	0	60	43	11.2	13.8	8.6	12.8	15.0	10.0
	Depression	0	0	61	71	19.1	18.6	19.7	17.0	15.5	18.8
III	Anxiety	0	0	30	50	12.8	8.5	17.1	11.4	9.0	12.2
	Depression	0	0	58	50	15.0	9.7	20.3	14.5	12.8	14.6
IV	Anxiety	0	2	28	63	14.6	10.0	19.4	12.0	8.1	13.7
	Depression	1	11	44	67	26.0	12.8	39.2	20.3	12.9	17.8

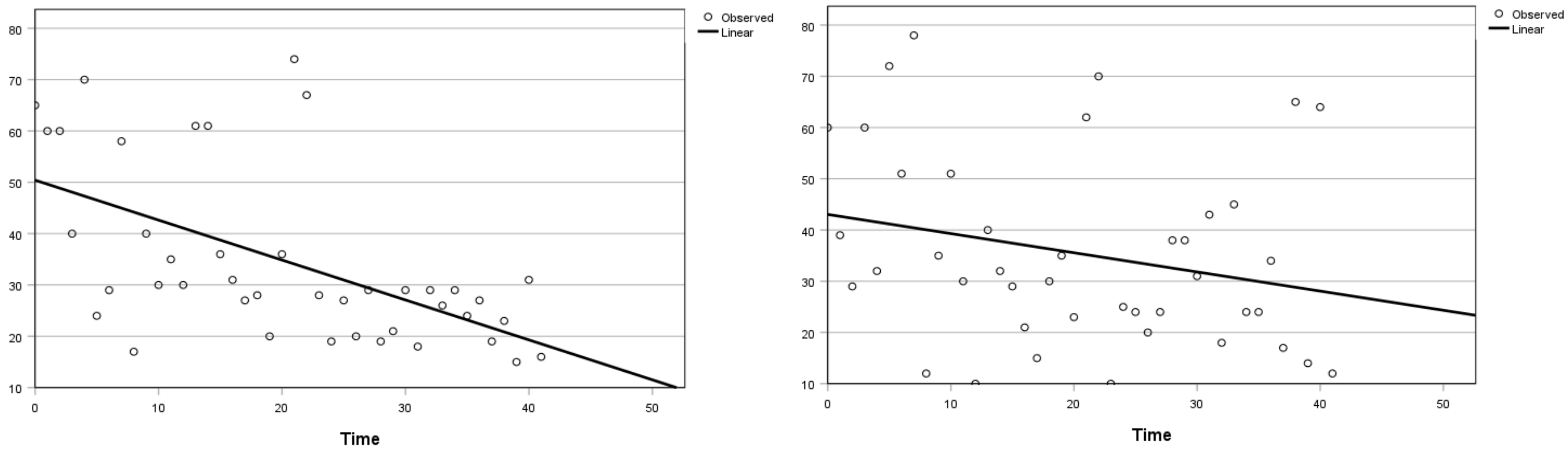

Figure 3:

Time Plots for Anxiety (left) and Depression (right) for Participant I

To examine the outcome variables for stationarity in terms of time trends, their mean, standard deviation, minimum, and maximum were compared between measurement weeks one and two. In this respect, both outcome variables, i.e., depression and anxiety, appeared to be relatively stationary (see Table 1). Nevertheless, time plots displayed linear trends (see Figure 3) and the linear regression model revealed a significant moderate time trend for the anxiety whereas it was not significant for the depression variable (see Table 2). Therefore, the time variable was included as an independent variable in the dynamic regression model for anxiety, but not for depression. To assess the outcome measures for a potential periodic pattern, ANOVAs with Morning, Afternoon, and Evening as factor groups were carried out and showed no evidence of periodicity regarding at what time of the day the measurement took place for both anxiety and depression (see Table 2).

Table 2

Results from the stationarity assessments for trends (linear regression) and periodicity (ANOVA)

Participant	Variable	Linear regression		ANOVA	
		R^2	*p*-value	$F(2, 39)$	*p*-value
I	Anxiety	.32	< .001	.89	.419
	Depression	.06	.112	1.72	.193
II	Anxiety	.25	.138	1.10	.344
	Depression	.00	.997	.46	.634
III	Anxiety	.07	.088	.73	.490
	Depression	.04	.219	.40	.672
IV	Anxiety	.18	.005	1.38	.262
	Depression	.45	< .001	.25	.778

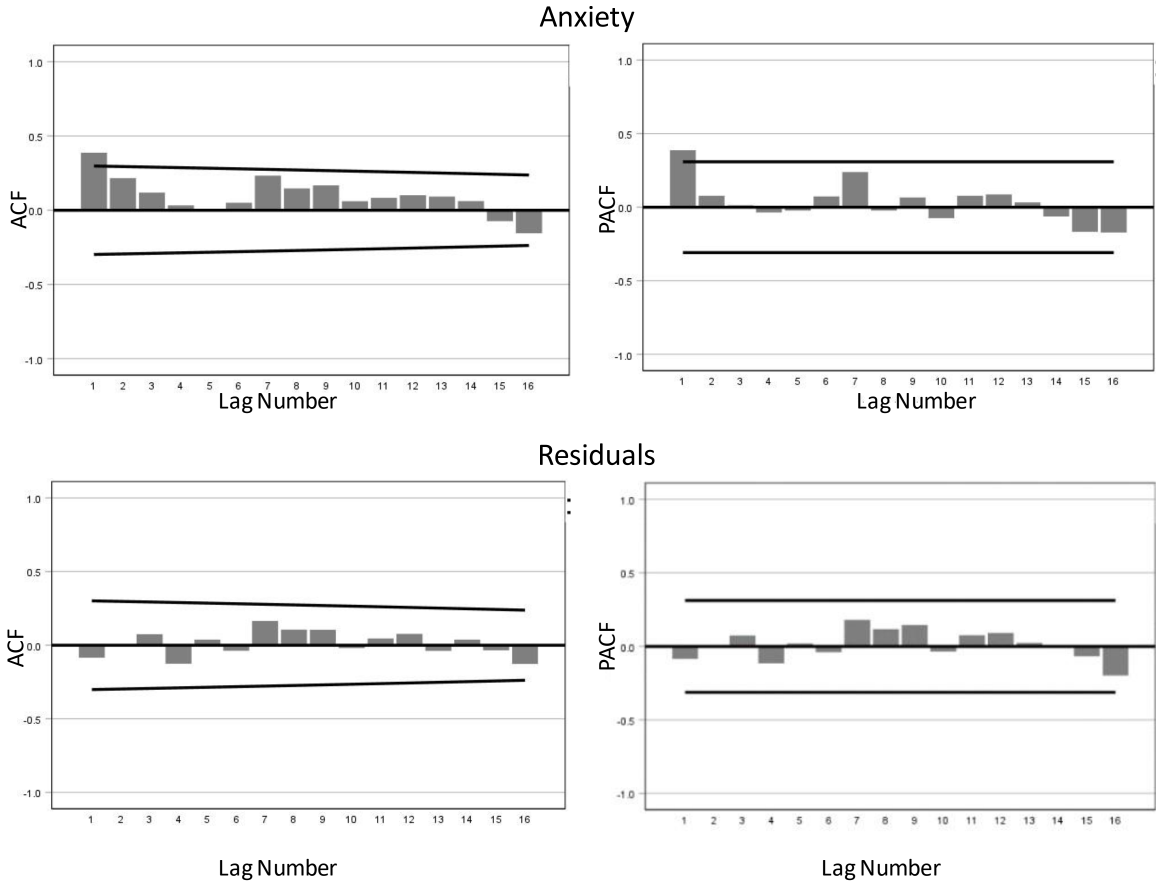

Figure 4
ACF (left) and PACF (right) plots of the anxiety variable (top) and the unstandardized residuals (bottom) after accounting for lag 1 for Respondent I

Autocorrelation Analysis

Figure 4 above shows the correlogram (ACF) and partial correlogram (PACF) for lags 1 to 16 of the anxiety variable. The ACF plot revealed an autocorrelation value for the first lag ($\rho_{1, A}$ = .39, $p_{1, A}$ = .009) which was not within the 95% CI, indicating that autocorrelation exists and needs to be controlled in the dynamic regression model. The PACF plot displayed a similar pattern, where only the bar for lag 1 exceeded the bounds of the 95% confidence interval ($\rho_{1, A}$ = .39). At lag 2, the partial autocorrelation coefficient converged to 0 ($\rho_{2, A}$ = .08). Accordingly, the first lag of the anxiety variable was included in the final regression model. Checking whether autocorrelation has been adequately specified, no remaining significant autocorrelation was found in the residuals after including lag 1 in the regression model (see Figure 4). Concerning depression, neither the ACF nor PACF showed evidence of significant autocorrelation (see Figure 6 in Appendix A), implying that autocorrelation could be neglected for this outcome measure in the final dynamic regression analysis.

Dynamic Regression Analysis

Dynamic regression was conducted with one-lagged well-being as the independent variable and depression and anxiety as the respective outcome variable. Additionally, for the anxiety model, the time variable and the first lag of the outcome variable were entered as independent variables. All three measures of the post-model check, i.e., the histogram and normal probability plot of the residuals as well as the scatterplot of the residuals versus the predicted values, indicated that the usual assumptions of ordinary least squares regression (linearity, normality, heteroskedasticity) did apply for the data of this participant for both the anxiety and the depression model (see Figure 5). The analyses yielded an unstandardized regression coefficient of $B_A = 0.92$ and a 95% CI_A of -0.44 to 2.29 in the anxiety model, and $B_D = 0.95$ and 95% CI_D -0.74 to 2.64 in the depression model (c.f. Table 3). Accordingly, the confidence intervals contained 0 in both models, indicating that previous well-being was not a significant independent predictor of anxiety and depression, respectively, in the subsequent measurement point for this individual when controlling for autocorrelation and / or time trend.

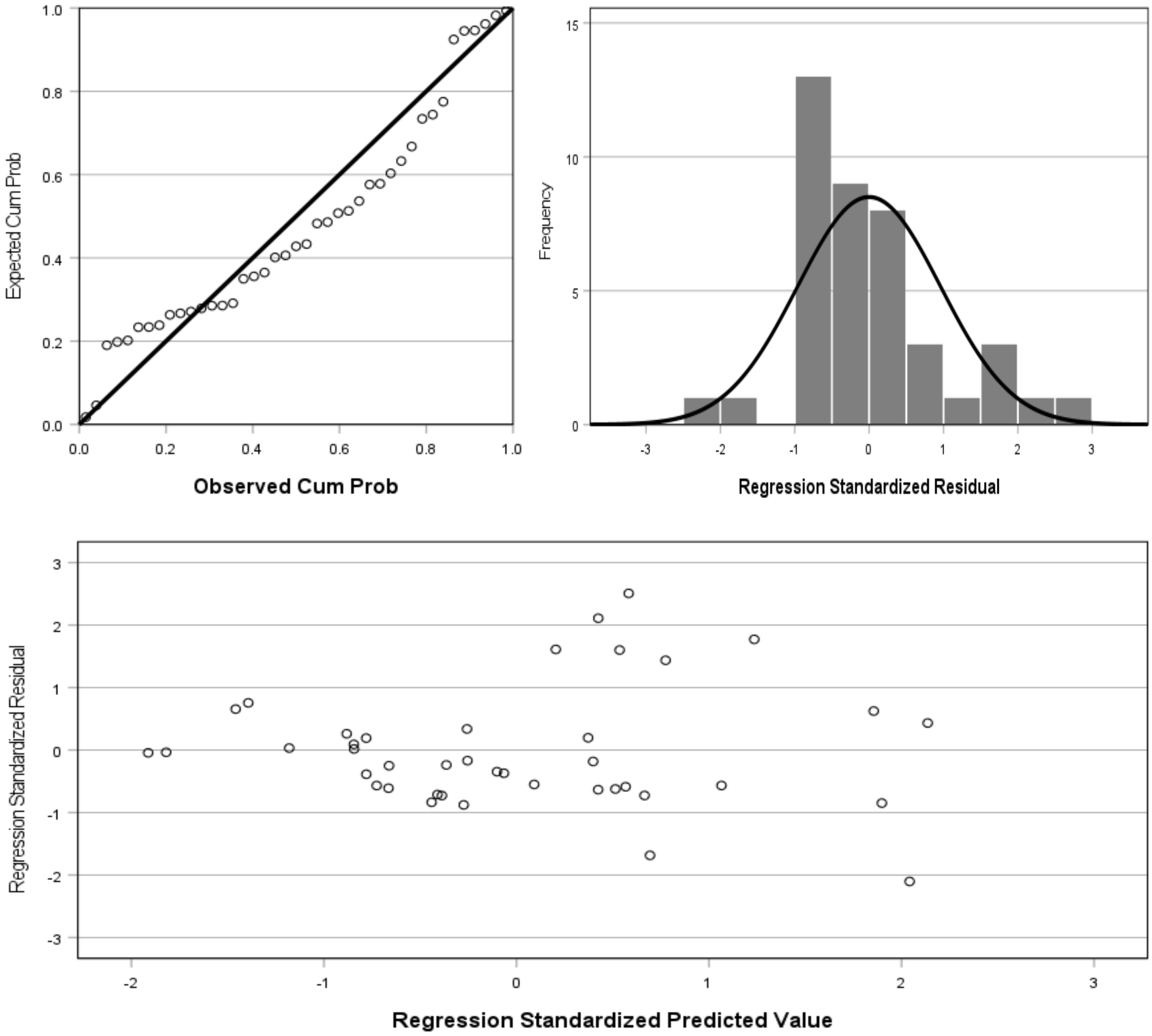

Figure 5

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the anxiety variable for Respondent I

Table 3

Results of the Dynamic Regression Models for all four participants

Participant	Variable	B (95% CI)	β	t	p
I	Dependent Variable: Anxiety				
	(Constant)	12.01 (-33.78, 57.79)		0.53	.598
	Lag1_SWEMWBS	0.92 (-.44, 2.29)	.19	1.37	.179
	Lag1_Anxiety	0.24 (-.09, .58)	.25	1.47	.150
	Time	-0.52 (-.98, -.07)	-.38	-3.30	.025
	Dependent Variable: Depression				
	(Constant)	9.82 (-35.07, 54.70)		0.44	.661
	Lag1_SWEMWBS	0.95 (-0.74, 2.64)	.18	1.13	.264
II	Dependent Variable: Anxiety				
	(Constant)	-4.36 (-25.66, 16.94)		-0.42	.680
	Lag1_SWEMWBS	0.46 (-0.41, 1.33)	.17	1.07	.291
	Lag2_Anxiety	0.340 (-0.413, 1.34)	.33	2.13	.040
	Dependent Variable: Depression				
	(Constant)	-5.16 (-32.37, 22.05)		-0.38	.704
	Lag1_SWEMWBS	0.98 (-0.09, 2.05)	.28	1.84	.073
III	Dependent Variable: Anxiety				
	(Constant)	26.30 (-9.41, 62.00)		1.50	.144
	Lag1_SWEMWBS	-0.75 (-1.95, 0.46)	-.23	-1.26	.216
	Lag1_Anxiety	0.14 (-0.25, 0.52)	.14	0.72	.477
	Lag3_Anxiety	0.40 (0.10, 0.70)	.41	2.73	.010
	Dependent Variable: Depression				
	(Constant)	18.26 (-25.41, 61.93)		0.85	.402
	Lag1_SWEMWBS	-0.46 (-1.91, 1.00)	-.12	-0.64	.528
	Lag1_Depression	0.20 (-0.15, 0.54)	.22	1.16	.255
	Lag3_Depression	0.37 (0.11, 0.64)	.41	2.86	.007
IV	Dependent Variable: Anxiety				
	(Constant)	14.45 (-15.97, 44.87)		0.97	.341
	Lag1_SWEMWBS	-0.39 (-1.51, 0.71)	-.11	-0.73	.471
	Time	0.23 (-0.14, 0.60)	.20	1.26	.215
	Lag6_Anxiety	0.44 (0.12, 0.75)	.44	2.81	.008
	Dependent Variable: Depression				
	(Constant)	-8.66 (-52.85, 35.52)		-0.40	.693
	Lag1_SWEMWBS	-0.28 (-1.34, 1.91)	.05	0.35	.725
	Time	1.17 (0.66, 1.68)	.69	4.63	<.001
	Lag1_Depression	0.11 (-0.24, 0.45)	.11	0.62	.538

Note. B = unstandardized coefficient; β = standardized coefficient.

Participants II to IV

Assessment of Variability and Stationarity

Descriptive statistics (mean, standard deviation, and range) of the outcome variables for the entire measurement period as well as each week of measurement are provided for all participants in Table 1. Participants II and IV had substantially higher means and standard deviations for depression than for anxiety, suggesting that these two persons experienced depression symptoms that were more severe and varied than their anxiety symptoms. Comparing the ranges between the two outcome variables, for participant II, the maximum for depression was considerably higher than for anxiety, while all other maxima and minima were relatively similar among the three participants. For all three participants, visual inspection of the time series plots displayed sufficient variability in the variables of interest while no clear temporal patterns could be recognized (see Figures 8, 13, and 18 in the Appendices B, C, and D, respectively).

Regarding time trends, for participant II both outcome variables appeared relatively stationary in terms of mean, SD, minimum, and maximum across the two measurement weeks, whereas for participants III and IV both outcome variables increased substantially (see Table 1). Linear regression modelling revealed a significant time trend only for participant IV, for anxiety and depression (see Table 2). Accordingly, the time variable was included in the final dynamic regression models for participant IV for both outcome measures, while it was disregarded for participants II and III. The ANOVAs yielded no significant evidence of periodicity for any participant in relation to the time of day when the measurements were taken (see Table 2).

Autocorrelation Analysis

Because the autocorrelation analyses yielded relatively different results across the three participants and were thus difficult to summarize, they are presented separately for participants II, III and IV. The ACF and PACF correlograms of the outcome variables are provided in the Appendices B, C, and D for each of the participants.

Participant II

Regarding the anxiety variable of participant II, the bars for the second ($\rho_{2, A} = .38$, $p_{2, A} = .020$) and 13th lag ($\rho_{13, A} = .32$, $p_{13, A} = .133$) of the ACF plot exceeded the bounds of the 95% CI. In the PACF, a similar pattern was found ($\rho_{2, A} = .36$, $\rho_{13, A} = .33$), while the first and third lag had a small negative value. Even though the 13th lag displayed high autocorrelation, this was neglected because it does not make sense from a theoretical point of view and there are not enough data points to conduct statistically sound analyses using lag 13. Accordingly, autocorrelation was controlled only for the second lag in the dynamic regression model of anxiety. After incorporating lag 2 into the regression model, no significant autocorrelation remained in the residuals, except for lag 13, as this lag was not controlled for. Concerning depression, ACF and PACF revealed autocorrelation values which were all inside the 95% CI, so no lag was included for this outcome measure in the dynamic regression model.

Participant III

Autocorrelation analysis for participant III for the anxiety variable revealed autocorrelation values in the ACF for lag 1 ($\rho_{1, A} = .38$, $p_{1, A} = .010$) and lag 3 ($\rho_{3, A} = .42$, $p_{3, A} < .001$) which were not within the 95% CI. The sample PACF also exhibited high autocorrelation values for lags 1 and 3, while lags 2 and 4 converged to zero. These findings suggest the need to control for autocorrelation at lag 1 and lag 3 when analysing the anxiety variable with dynamic regression. After incorporating lags 1 and 3 in the regression analysis, the residuals showed no remaining significant autocorrelation. For the depression variable of participant III, the ACF revealed autocorrelation values also for lag 1 ($\rho_{1, D}$ = .29, $p_{1, D}$ = .050) and lag 3 ($\rho_{3, D}$ = .36, $p_{3, D}$ = .018) to be out of the bounds of the 95%. In the PACF, lags 1 and 3 were rather high ($\rho_{1, D}$ = .29, $\rho_{3, D}$ = .41), while lags 2 and 4 converged to 0. Therefore, the first and third lags were incorporated in the dynamic regression analysis of state depression as well. After accounting for lags 1 and 3, there was no autocorrelation left in the residuals.

Participant IV

Autocorrelation analysis for participant IV yielded significant autocorrelation for the sixth and tenth lag in the ACF of the anxiety variable. In the PACF, the sixth lag was out of the bounds of the 95% CI, while all other lags were relatively low. Only lag 6 was thus included in the dynamic regression model. With regard to depression, the ACF was significant for lags 1, 2, 3, 5, and 6. The PACF was significant only for the first lag, after which it converged to zero, so lag 1 was incorporated in the final model. The correlograms of the residuals, with the appropriate lag incorporated, confirmed that the autocorrelation structures were adequately specified for both models.

Dynamic Regression Analysis

The plots of the post-model checks of the dynamic regression models of anxiety and depression for participants II to IV are shown in the respective Appendices B to D. These plots confirmed that assumptions of linearity, normality, heteroskedasticity sufficiently applied for all six models. The 95% confidence intervals for the depression and anxiety models did not include zero for any of the participants (see Table 3), suggesting that state well-being is neither a statistically significant short-term predictor of state anxiety nor of state depression for each of the individuals. The direction and strength of the relationship between one-lagged well-being and the two outcome variables varied considerably among the participants. Negative associations were found for participants III and IV, whereas distress was positively predicted in participant II. In the case of participant II, well-being was nearly significantly predictive of depression, as the value of 0 was at the extreme end of the 95% confidence interval.

Discussion

Research Objective

The objective of this study was to investigate the short-term predictive relationship between mental well-being and psychological distress at the individual level using intensive longitudinal data collected through the Experience Sampling Method (ESM). This study adopted an idiographic approach, treating each participant as a unique case, and utilized time series analysis to model the predictability of well-being on distress separately for four participants. Thereby, this research aimed to address two key research gaps: (1) the lack of studies examining the short-term predictability of well-being on distress within the same day, and (2) the limited understanding of individual variations in the relationship between well-being and distress, which is often erroneously assumed to be consistent across all individuals in nomothetic studies.

Summary & Interpretation of Findings

The dynamic regression analyses conducted indicate that previous well-being was not a statistically significant short-term predictor of anxiety or depression for any of the participants when controlling for time trends and autocorrelation. The absence of any significant outcome may principally have two reasons: either there really exists no (linear) short-term predictive relationship of well-being on psychological distress within individuals, or the current study was unable to detect it (type II error).

Even though previous longitudinal research has demonstrated a predictive relationship between high levels of well-being and reduced distress in the long term, spanning months or even years (Grant et al., 2013; Keyes et al., 2010; Lamers et al., 2015; Schotanus-Dijkstra et al., 2016; Wood & Joseph, 2010), it remains uncertain whether this relationship holds true for shorter time intervals within the same day. From existing theory and research, it is not yet possible to deduce whether this relationship is also typically manifested in short-term state changes within the same day.

Moreover, it is possible that this relationship is generally observed at a group level, but may not be consistent at the individual level. This is supported by the findings of Kraiss et al. (2022), which already revealed considerable individual variation in the concurrent relationship between well-being and distress. Accordingly, it is possible that the lack of a significant short-term predictive relationship observed is specific to the four participants selected for this study, and, because of the small number of participants selected, it is plausible that a significant relationship of well-being and distress can exist for other people. Yet, it should be noted that the most promising participants were already selected from the original sample, so it is unlikely that significant results would be obtained from any of the 35 respondents. Nevertheless, it is important to emphasize that due to the non-representative nature of the participant sample, the current study does not allow conclusions to be drawn at the group level as this could lead to an atomistic fallacy (Leong, 2006). Further research is needed to assess whether there exists a meaningful predictive relationship between well-being and distress for some people.

Methodological Factors Affecting the Findings

Besides the possibility that in the selected participants simply no short-term predictive relationship exists between wellbeing and distress, the inability to identify potential significant relationships could be attributed to methodological limitations concerning the data characteristics and analysis approach. Notably, this study constitutes a post-hoc analysis of the ESM data obtained for Kraiss et al. (2022), thus the data was not primarily collected for the purpose of the N-of-1 analyses of the current study.

Number of Measurements

One significant limitation of the current study resulting from the use of this ESM dataset is the relatively low number of data points measured per participant. Dynamic regression models typically require a minimum of 50 data points for reliable estimations (Keele & Kelly, 2006), and it is generally recommended to have even more data points (Jebb et al., 2015). In the context of investigating dynamic relationships between affective processes within individuals, researchers often collect dozens to thousands of measurement points (Ariens et al., 2020). Unfortunately, the ESM study from which the data were drawn included a maximum of only 42 data points per participant, leading to relatively low statistical power for the current analyses.

Experience Sampling Method

The utilization of the Experience Sampling Method (ESM) as the data collection approach in the current study introduces several common issues that need to be considered. In conflict with a need for high amounts of measurement points, the burden imposed on participants should always be taken into account in ESM studies (Myin-Germeys & Kuppens, 2021). In the current study, participants were prompted to respond to multiple question three times per day for two consecutive weeks. High measurement frequency may lead to participant fatigue or attrition, which can compromise the quality and quantity of the collected data (Eisele et al., 2022). Notably, participant selection for this study was based on the criterion of high compliance, meaning only highly engaged participants were included.

Moreover, Csikszentmihalyi and Larson (2014) proposed that the pattern of self-reported responses can change over time due to the nature of the measurement process. This could be responsible for the observed decrease in variance over the measurement period, as observed in the anxiety variable of participant I (see Figure 3). Such a phenomenon can be attributed to habituation to the measurement process or a “more precise self-anchoring on the response scales” (Csikszentmihalyi & Larson, 2014, p. 44). Additionally, the act of repeatedly self-reporting one’s affective states may actually influence participants' feelings, as their emotional awareness may increase over time, known as measurement reactivity (Eisele et al., 2023; Widdershoven et al., 2019). This further diminishes measurement reliability and stationarity of the data. One potential approach to enhance reliability and stationarity would be to disregard the first few measurement points as a habituation period as has been suggested for analysis of ESM studies (Myin-Germeys & Kuppens, 2021). However, this would in turn reduce the amount of measurement points, which was already rather low for N-of-1 analysis.

Types of Variables

Regarding what kind of variables were being measured in the current study, especially the two outcome variables, anxiety and depression, directly relate to affective states. Affective states are inherently dynamic and volatile (Kuppens, 2015), making them challenging to measure accurately (Wilhelm & Schoebi, 2007). Accordingly, distinguishing between measurement error and meaningful fluctuations becomes difficult (Dejonckheere et al., 2022).

The high volatility of affective states also gives rise to the "lag problem," which involves determining the optimal time interval for the time-series prediction model (Surakhi et al., 2021). It is possible that the chosen time interval for assessing predictability in the current study does not align with the speed at which the variables change in reality. For instance, if mental well-being were to predict psychological distress within minutes or hours, the current study would be unable to detect it due to the relatively long measurement interval. Similarly, if the optimal lag value were three instead of one, meaning that especially well-being in the morning predicted distress the following morning, the current analysis would also fail to identify it since the analysis was only conducted with a lag value of one. Exploring all possible lag values comprehensively was not feasible due to both time and statistical constraints. The presence of varying autocorrelation structures found in the current study, including significant partial autocorrelation at lag values as high as 13, may suggest such an inadequate measurement frequency, as emotions are typically expected to be contingent on prior states (Wood & Brown, 1994). The observed autocorrelation structures contradict theoretical expectations, because such high lag values are uncommon (McDonald et al., 2020), and autocorrelation is presumed to weaken as the lag length increases (Jebb et al., 2015). Consequently, future research is needed to determine the rate at which meaningful fluctuations in the variables of interest occur and the time intervals over which the potential predictive relationship may unfold.

Moreover, the valid measurement of momentary affect relies strongly on participants' willingness and ability to access and report their affective states (Schimmack, 2003). For example, participants are not likely to report their affective states while in highly emotional situations (e.g., during an argument). Additionally, their reports may be subject to social desirability bias (Dejonckheere et al., 2022). Furthermore, affective states can be influenced by a wide range of factors, including both external and internal events, and are determined by what the individual pays attention to (Csikszentmihalyi, 2014).

Taken together, the volatile nature of affective constructs, the multitude of possible factors contributing to fluctuations, the challenge of identifying the appropriate lag, and the difficulties participants may face in validly reporting their affective states all make it potentially challenging to establish significant predictability of anxiety and depression by well-being.

Measurement Instruments

The measurement of anxiety and depression in the current study utilized single-item scales, a common practice in ESM research to minimize participant burden, but potentially compromising the reliability of each measurement point (Dejonckheere et al., 2022). However, a statistical compensation for individual measurement errors can be achieved with a high number of measurement points overall (Csikszentmihalyi, 2014). Nevertheless, it remains questionable whether the 42 data points per participant in the current study are sufficient to achieve the desired level of reliability.

In contrast, well-being was assessed using seven items, each rated on a five-point Likert scale, meaning potentially higher reliability for each measurement point. However, it is important to note that the SWEMWBS primarily focuses on eudaimonic well-being rather than hedonic well-being (Ng Fat et al., 2017). It raises the question of whether eudaimonic well-being can truly be measured in the moment, as it requires reflection on one's overall functioning in life. In addition, the act of contemplation when responding to the seven questions may hinder a genuine momentary assessment. These aspects make this variable structurally different from the two outcome variables, as evidenced by considerably less variability in the well-being scores than in anxiety and depression.

To improve the study, it could be beneficial to shift the focus to hedonic well-being, specifically emphasizing the emotional components (Kahneman et al., 1999). Utilizing brief measures of positive and negative affect could be more suitable for capturing emotion dynamics with relatively high measurement frequencies. This adjustment would address the potential limitations associated with the current measurement of the relationship between well-being and distress.

Stationarity

Another notable issue in the current study is the lack of stationarity observed in the data of some participants. While some participants' anxiety and depression scores exhibited relative stability in mean, standard deviation, and range of their measurements across the two-week period, linear regression analysis revealed significant time trends in anxiety twice and depression once. However, in the context of affective states, these variables are generally expected to be relatively stationary (Jebb et al., 2015).

The absence of stationarity may be attributed to the nature of ESM data collection, as discussed earlier, or it could be due to the presence of special circumstances or events during the measurement period that are not representative of the person's typical experiences. In the current study, even a few relatively high or low scores could disrupt stationarity. One potential solution to this issue would be to conduct longer measurement periods where outliers are statistically compensated by a larger number of data points.

Stationarity is crucial for accurate prediction in time series analyses (Hamaker et al., 2005). Furthermore, to address time trends, they should either be explicitly modelled or, if irrelevant to the theory, eliminated through mathematical transformations, such as detrending

(Jebb et al., 2015). Since there were no known theoretical reasons for non-stationarity in this study, it may have been more appropriate to mathematically remove the time trends rather than modelling them in the dynamic regressions.

Implications

These considerations highlight the importance of meticulous research design and data collection methods in future N-of-1 investigations into the topic. Irrespective of its possible methodological limitations, this study may have important implications for the dual-continua model of mental health, which holds that well-being and distress are distinct constructs which are only moderately interrelated (Huppert & Whittington, 2003; Keyes, 2005, 2007; Westerhof & Keyes, 2010). Kraiss et al. (2022) validated this model by examining the relationship between psychological distress and mental well-being within individuals at the group level. Their findings generally confirmed the applicability and universality of the dual continua model, but also highlighted considerable variation in the concurrent association between distress and well-being among individuals. The current study sought to further understand the relationship between the two constructs by examining their short-term predictive relationship at the individual level, and yielded preliminary findings suggesting the absence of such a relationship. This could have significant implications for the theory and application of the model. The growing evidence from cross-sectional and longitudinal research suggests a negative association between well-being and distress, yet the nature and mechanisms of their relationship remain poorly understood (Trompetter et al., 2017). The potential absence of a short-term predictive relationship may imply that both well-being and distress are oppositely influenced by similar factors, leading to negative associations, while there may be little interaction between the two phenomena over time. This would contradict the typical assumptions of positive psychology interventions (PPIs), which are based on the idea that enhancing well-being can bolster resilience against distress (Trompetter et al., 2017). Previous research has shown that PPIs effectively increase well-being and reduce distress, particularly in the context of depression (Bolier et al., 2013; Sin & Lyubomirsky, 2009). However, there is limited understanding regarding the mechanisms and reasons behind the effectiveness of PPIs (Wellenzohn et al., 2016). It is possible that these interventions impact both well-being and distress independently, rather than well-being mediating the alleviation of distress. For example, PPIs have been proposed to enhance emotion regulation strategies (Quoidbach et al., 2015), which may simultaneously foster well-being and alleviate depression (Kraiss et al., 2020), instead of improved well-being enabling adaptive emotion regulation strategies that subsequently ameliorate depression, as proposed by (Trompetter et al., 2017). Further research is warranted to gain a more comprehensive understanding of the short-term predictive relationship between well-being and distress, taking into account individual variations and addressing the methodological constraints identified in this study. This will help deepen our understanding of how these constructs interact over time and provide valuable insights into their dynamic nature.

Significance

Psychological research has been primarily dominated by the nomothetic approach, which assumes that psychological phenomena, including cognitions, emotions, and actions, function similarly in all humans (De Luca Picione, 2015). Accordingly, this approach treats individuals as interchangeable by calculating average values at the group level (Curran & Bauer, 2011). However, it thereby disregards the uniqueness of the human psyche, which cannot be adequately captured by population means (Salvatore & Valsiner, 2010). Yet, (clinical) psychological practice predominantly deals with individual people, who are virtually never accurately represented by the average patterns found at the group level (Estes & Todd Maddox, 2005; Fisher et al., 2018; Hamaker et al., 2005; Molenaar, 2004; Molenaar & Campbell, 2009). Indeed, to enable personalised psychological practice, person-specific psychological research is indispensable.

Moreover, psychological phenomena are inherently bound by time, and temporal factors are integral to understanding psychological processes, necessitating the inclusion of time in their analysis (Hamaker et al., 2005). However, the application of time series methods in the field is still limited. A survey conducted by Jebb et al. (2015) across 15 prominent psychology journals revealed that only a small number of empirical papers (36 in total) utilized time series methods. Moreover, the majority of research in psychology has predominantly employed descriptive or causal explanatory models when analysing time series data, overlooking the potential of predictive models (Shmueli, 2010).

In conclusion, the utilization of predictive models in the idiographic analysis of observational time series data in clinical psychology is crucial from both theoretical and practical perspectives. By doing so, the current study provides valuable insights into the required data characteristics and the applicability of N-of-1 statistical methods in the field. Thereby, this study encourages further exploration and application of N-of-1 analyses in clinical psychology.

Future Directions

The use of N-of-1 analyses and intensive longitudinal data provides researchers with a powerful approach to investigate the dynamic relationships between affective processes (Ariens et al., 2020). This methodology allows for a detailed examination of how psychopathology and well-being are linked to specific patterns of short-term emotion dynamics, such as variability, instability, and inertia of emotions (Houben et al., 2015; Kuppens, 2015).

As the field moves towards more personalized mental health care, there is a growing recognition of the importance of capturing and analysing mood states over time (Zuidersma et al., 2020). Process-based psychotherapy, for example, emphasizes the assessment and understanding of ongoing psychological processes and their dynamics throughout therapy (Moskow et al., 2023). By monitoring mood states and analysing their temporal patterns, clinicians can gain valuable insights into an individual's psychological well-being and tailor interventions accordingly.

Technological advancements, particularly the widespread use of smartphones, have facilitated the collection of large amounts of time series data in real-world settings (Berkel et al., 2017; Raento et al., 2009). With the availability of mobile applications and wearable devices, individuals can easily track their mood, behaviour, and other relevant variables over time. This proliferation of time series data opens up new opportunities for both research and clinical practice (Jebb et al., 2015), allowing for a deeper understanding of individual differences in affective processes and the development of personalized interventions (Kwasnicka et al., 2019; McDonald et al., 2017).

Conclusion

To the author's knowledge, this is the first study to investigate the short-term predictive relationship between mental well-being and psychological distress using N-of-1 analyses. The results showed that previous well-being was not a statistically significant short-term predictor of anxiety or depression for any of the four participants. Accordingly, this study provides tentative evidence for the absence of a short-term predictability of distress by well-being at the individual level, which may have relevant implications for the theory of the dual continua model and its applications. For example, it implies a different mechanism of action for positive psychology interventions, which are often assumed to enhance well-being as a means of reducing distress. This study highlights the need for further research to understand the potential temporal precedence of well-being over distress and emphasizes the importance of using time series analysis methods in clinical psychology.

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Appendices

Appendix A: Supplementary Figures for Participant I

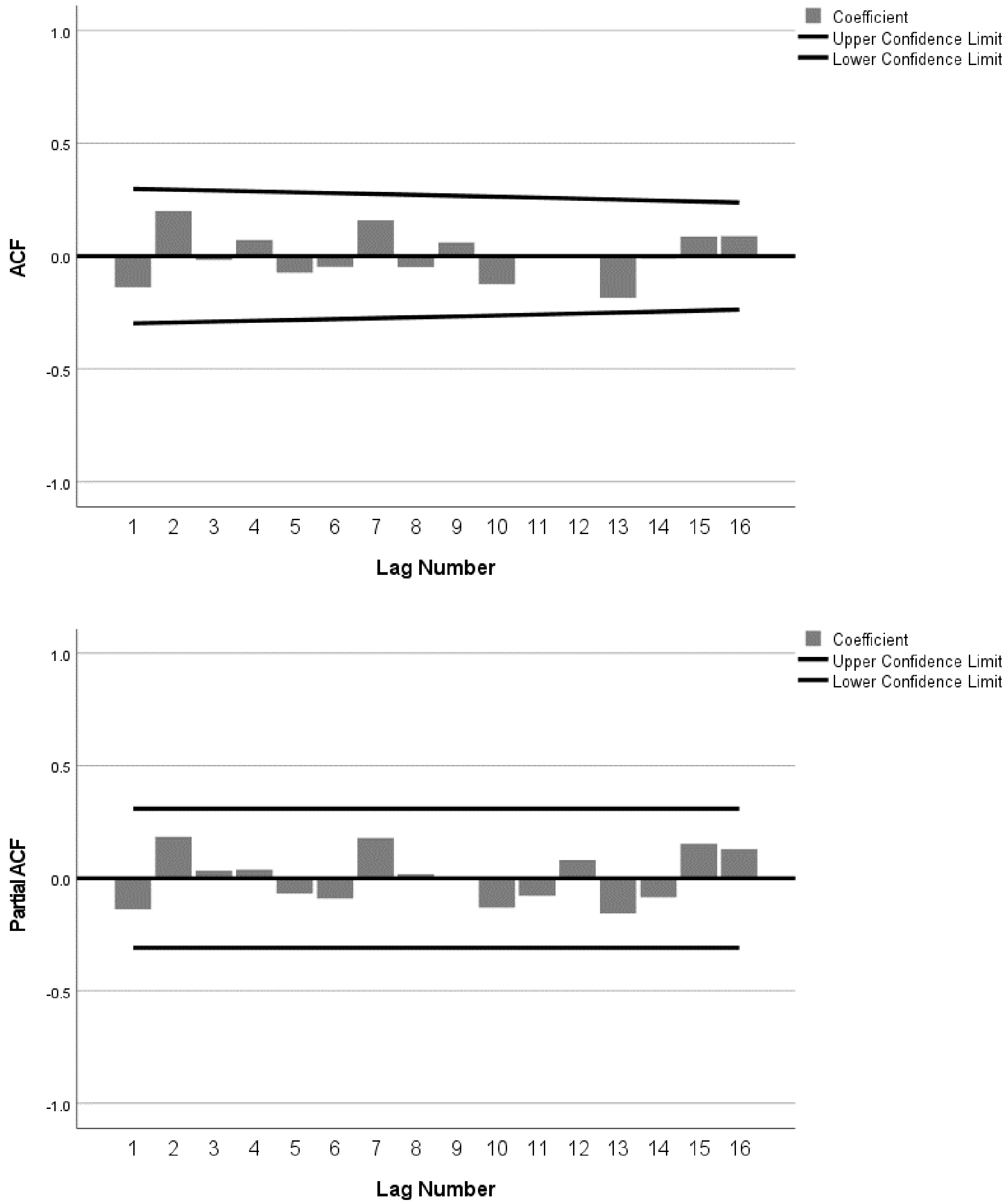


Figure 6

ACF (top) and PACF (bottom) plot of the depression variable for Respondent I

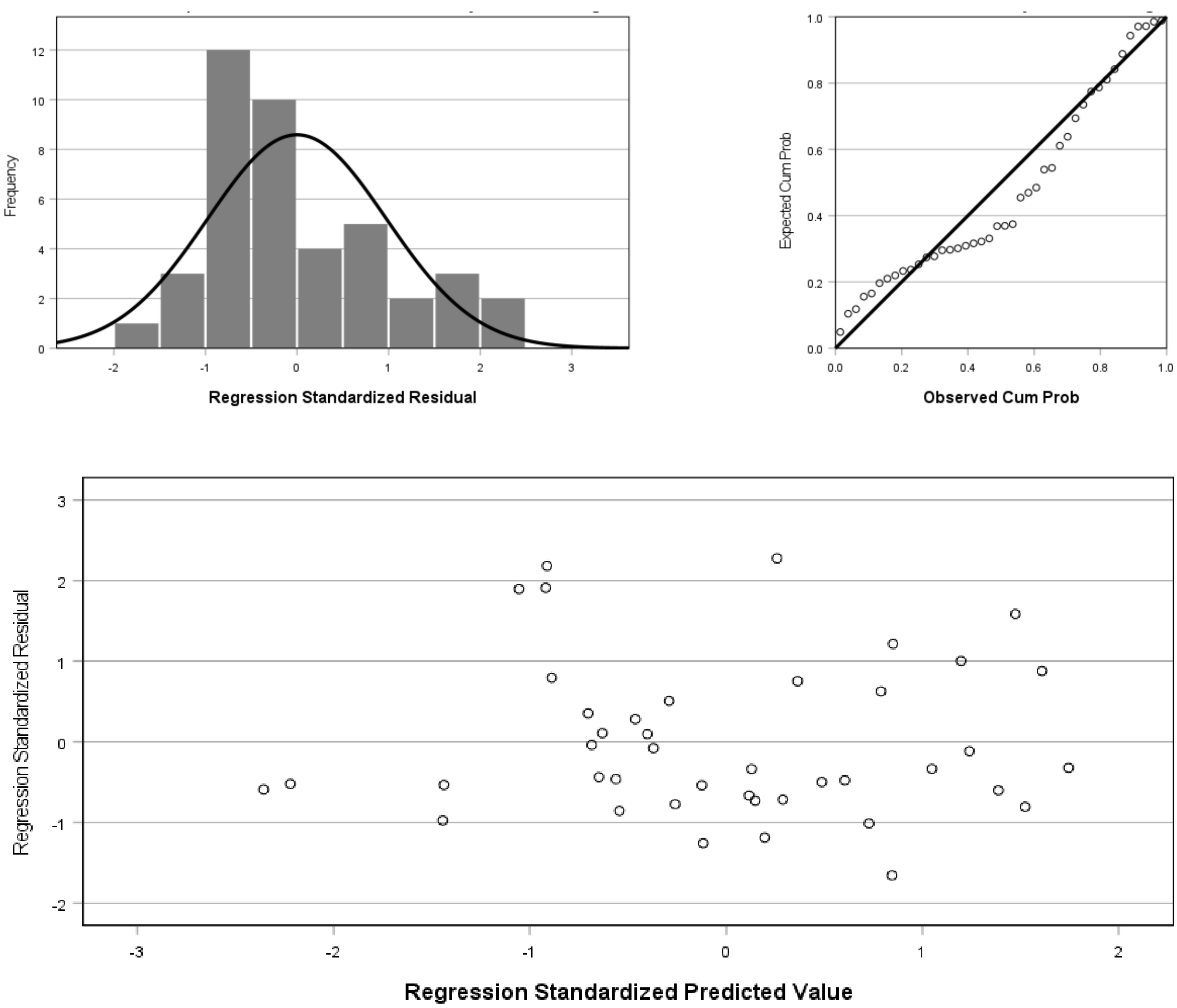


Figure 7

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the depresssion variable for Respondent I

Appendix B: Supplementary Figures for Participant II

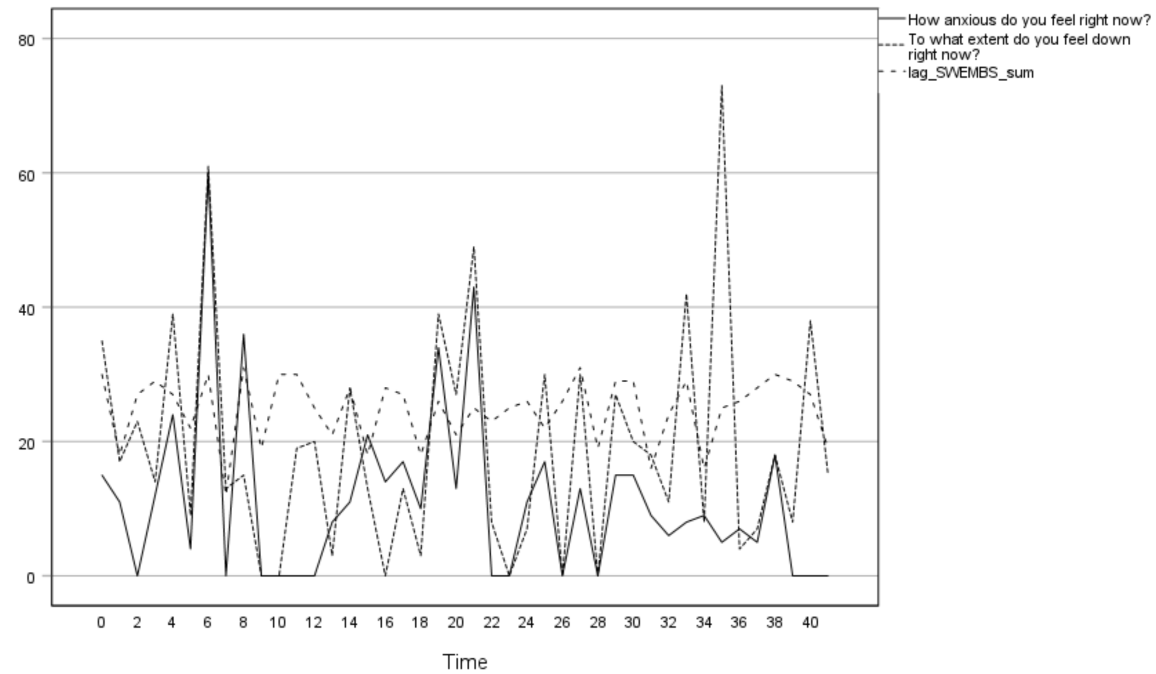
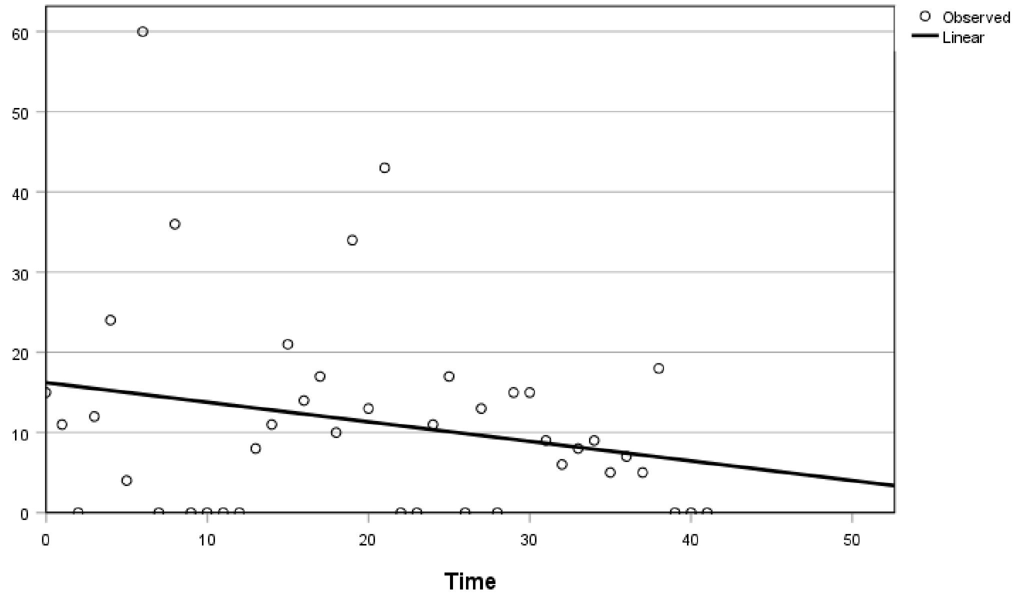


Figure 8

Time Series Plot for Anxiety, Depression and Well-being for Participant II

How anxious do you feel right now?



To what extent do you feel down right now?

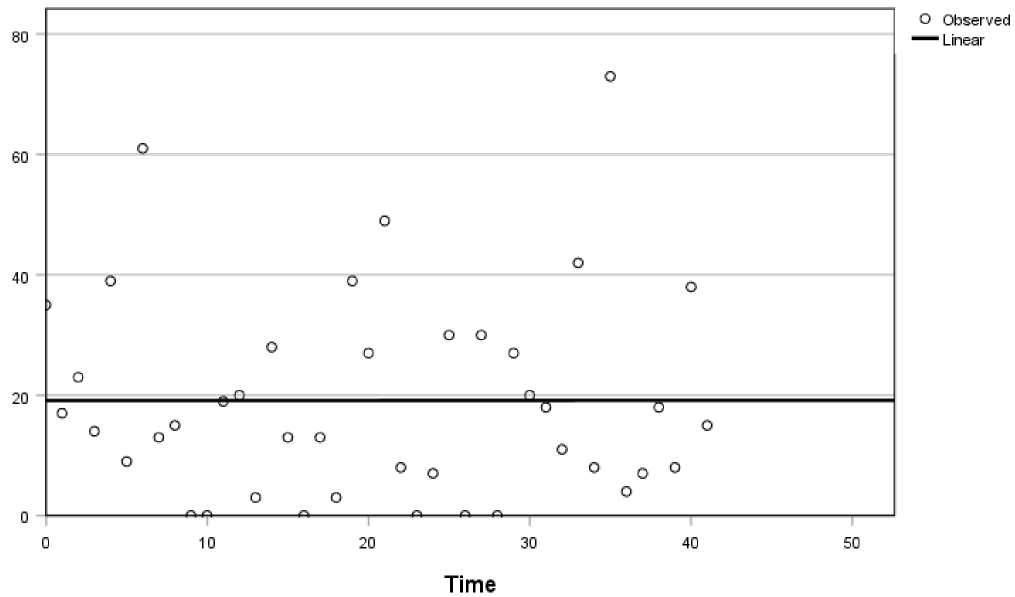


Figure 9

Time Plots for Anxiety (top) and Depression (bottom) for Participant II

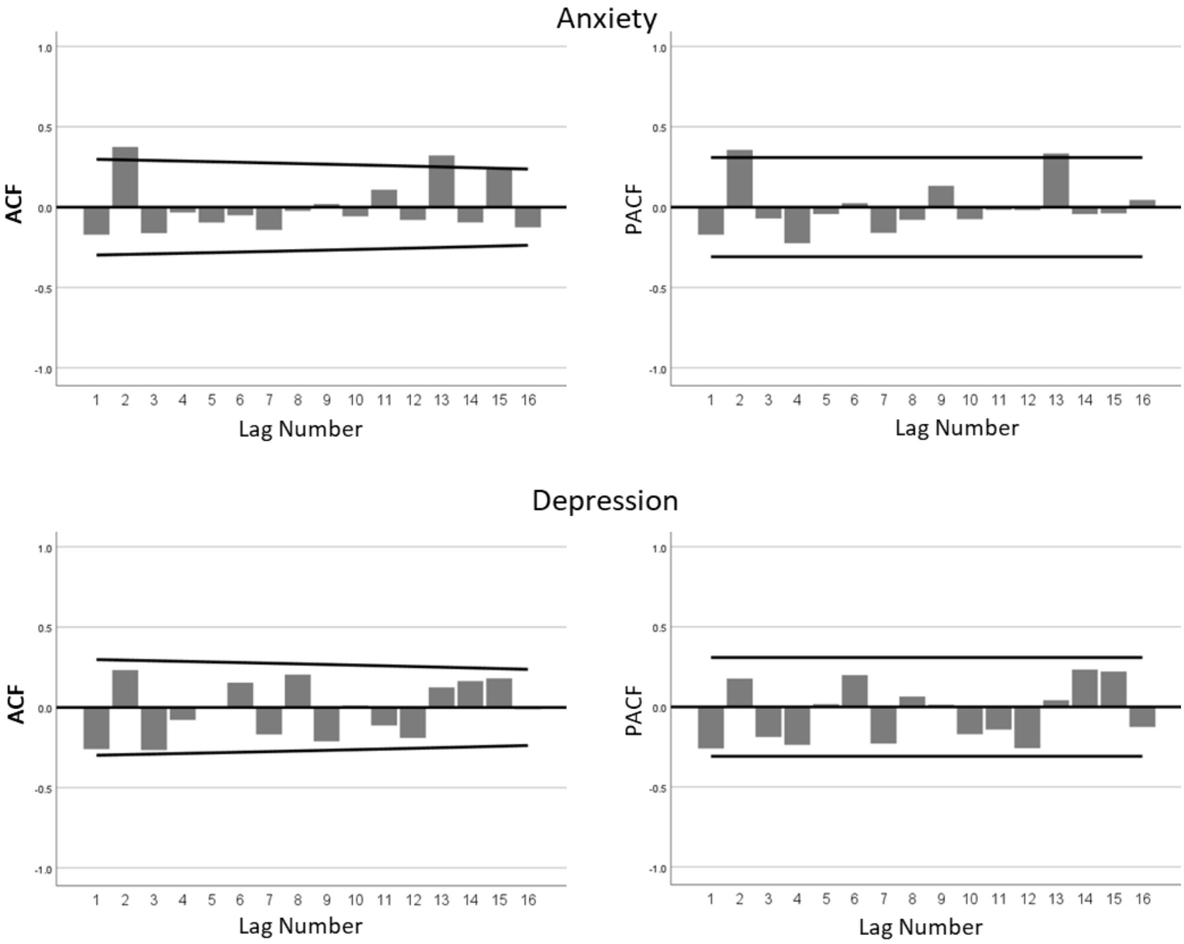
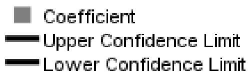


Figure 10

ACF (left) and PACF (right) plots of the anxiety variable (top) and depression variable (bottom) for Respondent II



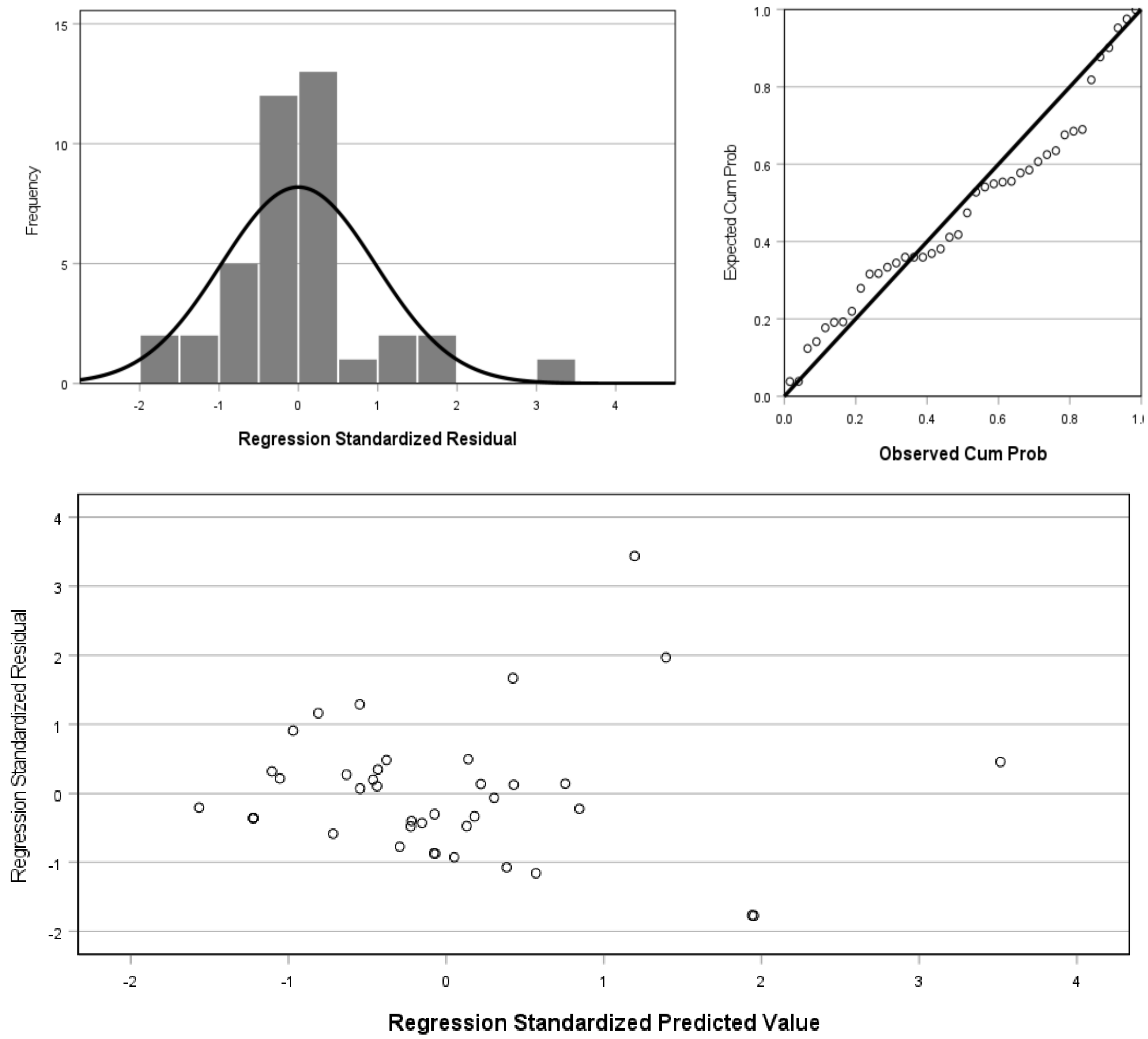


Figure 11

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the anxiety variable for Respondent II

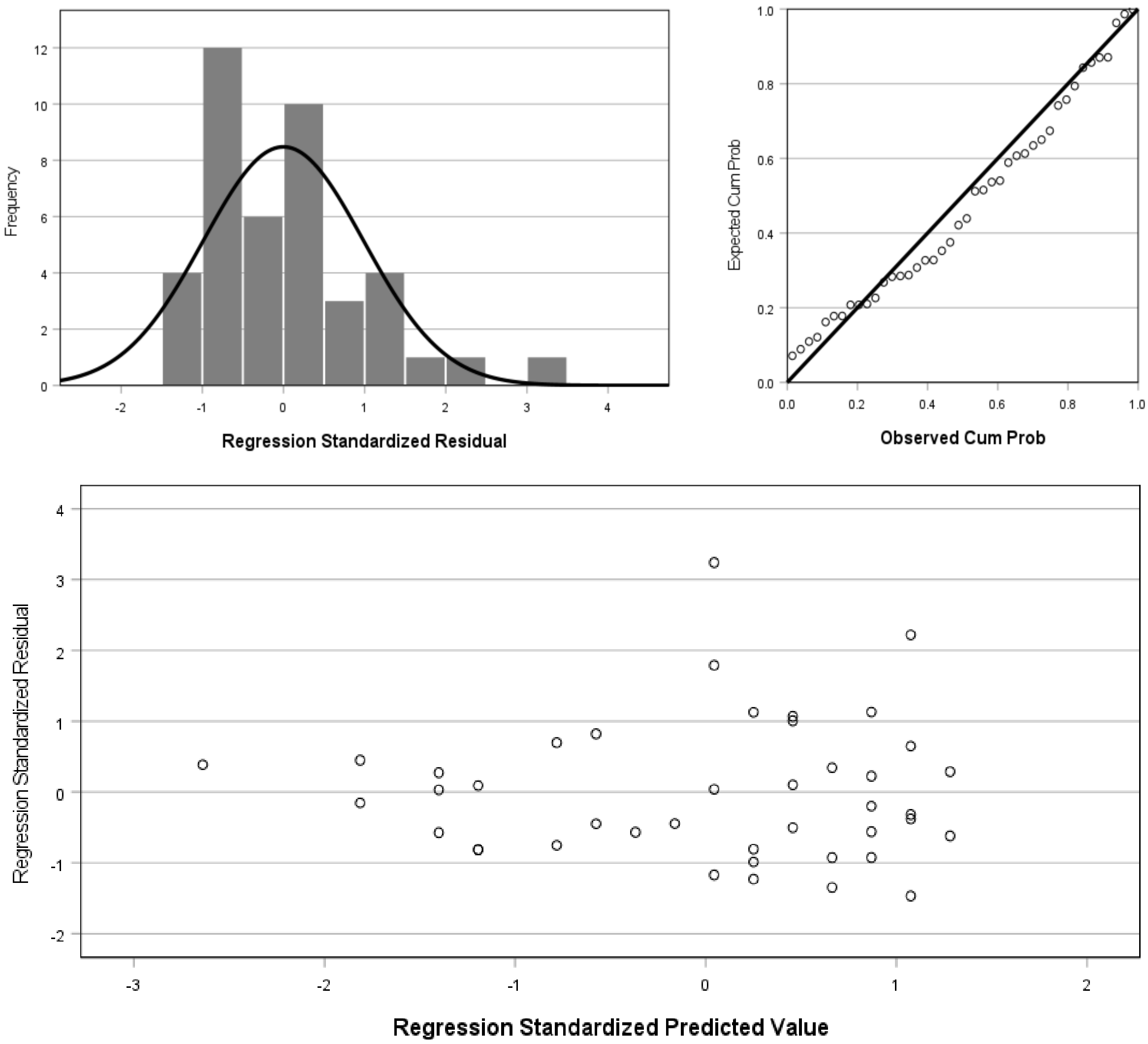


Figure 12

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the depression variable for Respondent II

Appendix C: Supplementary Figures for Participant III

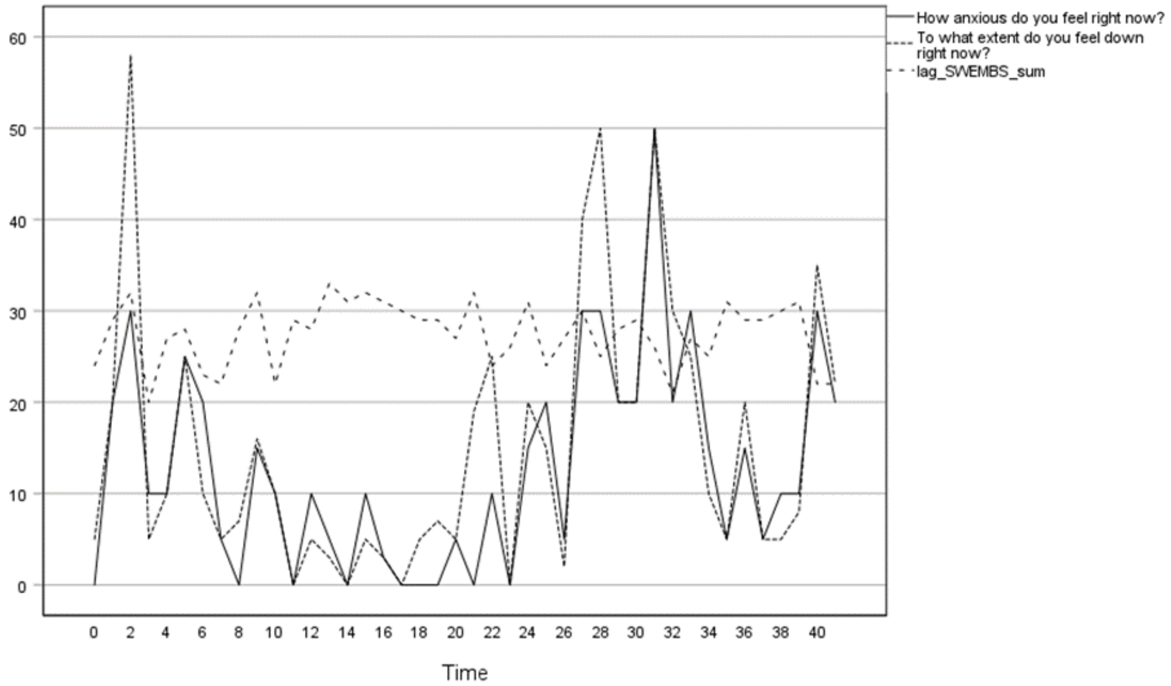
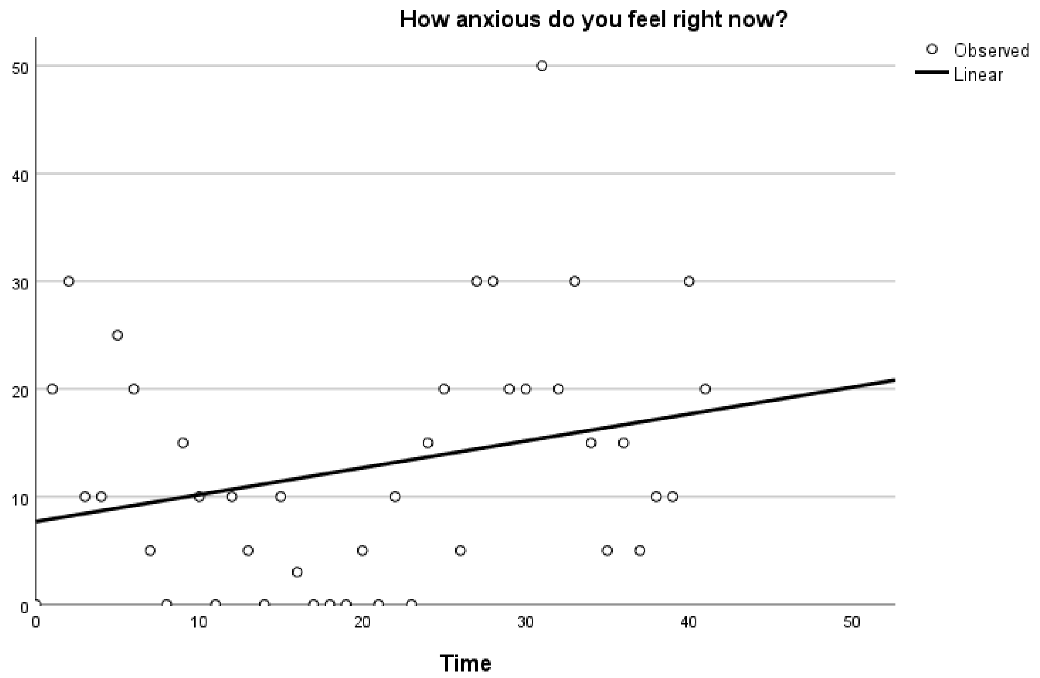


Figure 13

Time Series Plot for Anxiety, Depression and Well-being for Participant III



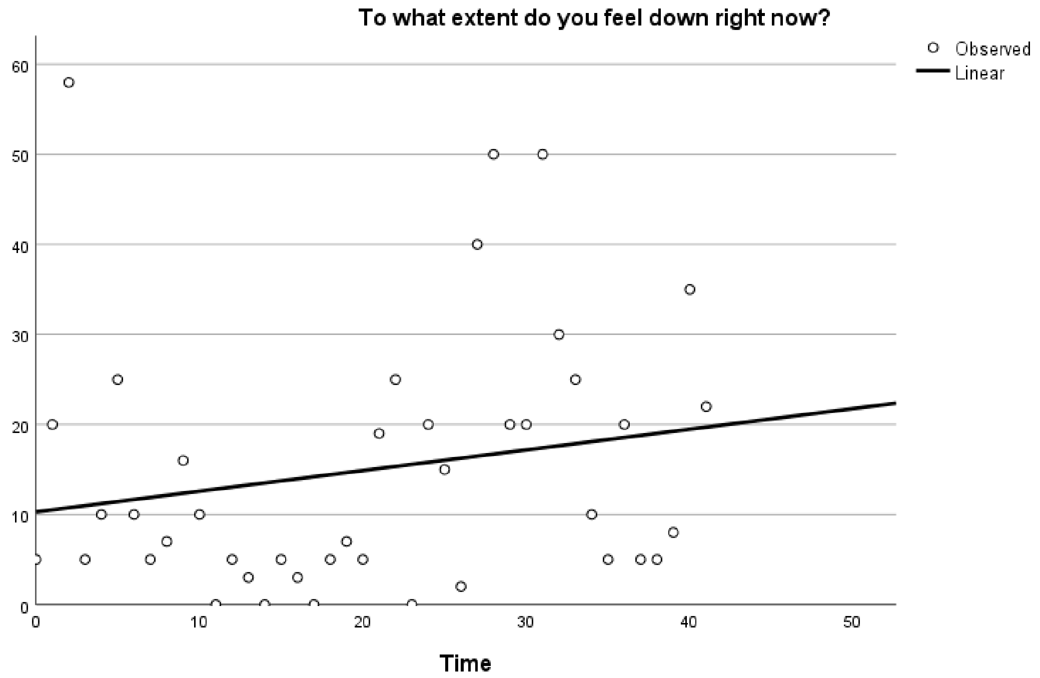


Figure 14
Time Plots for Anxiety (top) and Depression (bottom) for Participant III

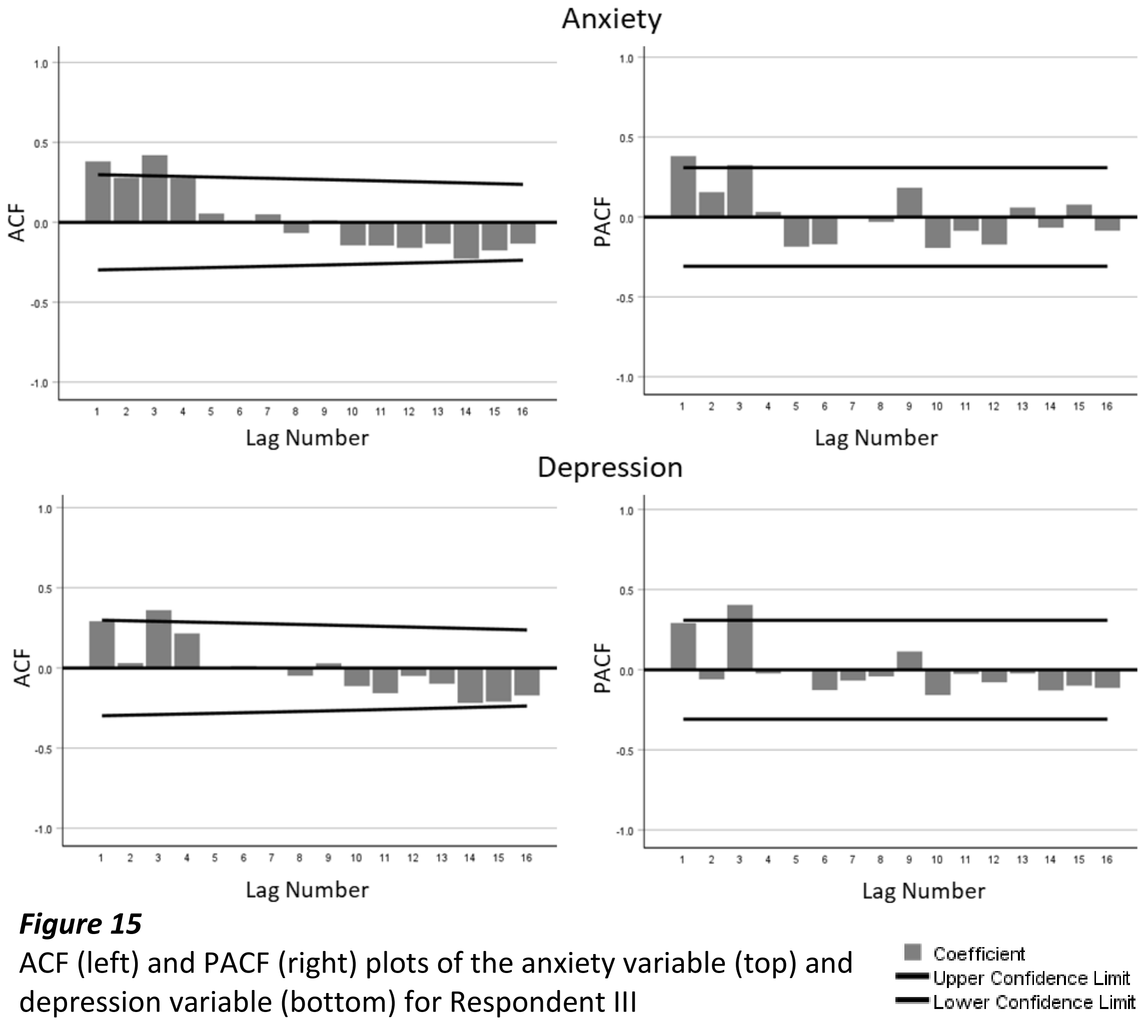


Figure 15

ACF (left) and PACF (right) plots of the anxiety variable (top) and depression variable (bottom) for Respondent III

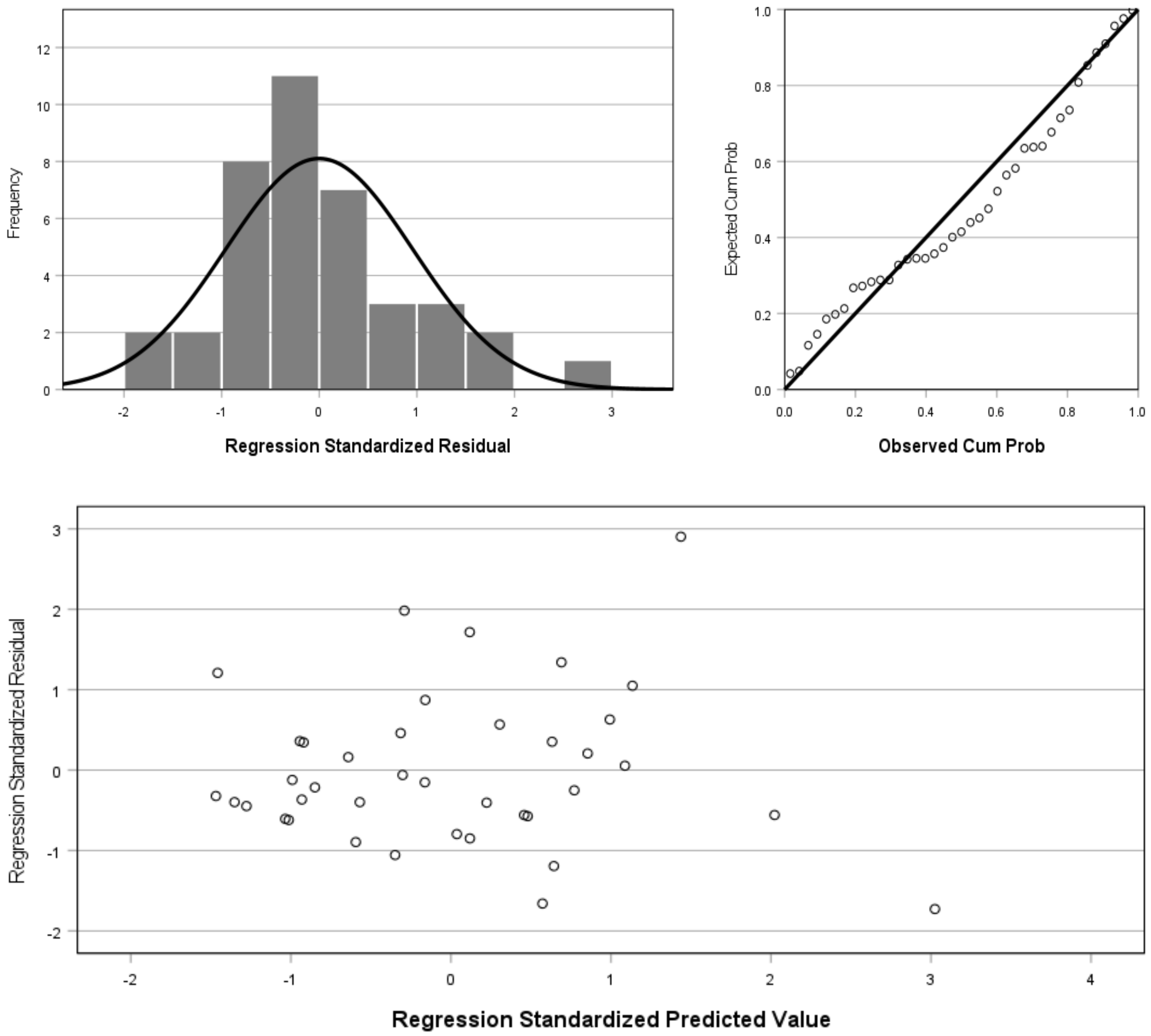


Figure 16

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the anxiety variable for Respondent III

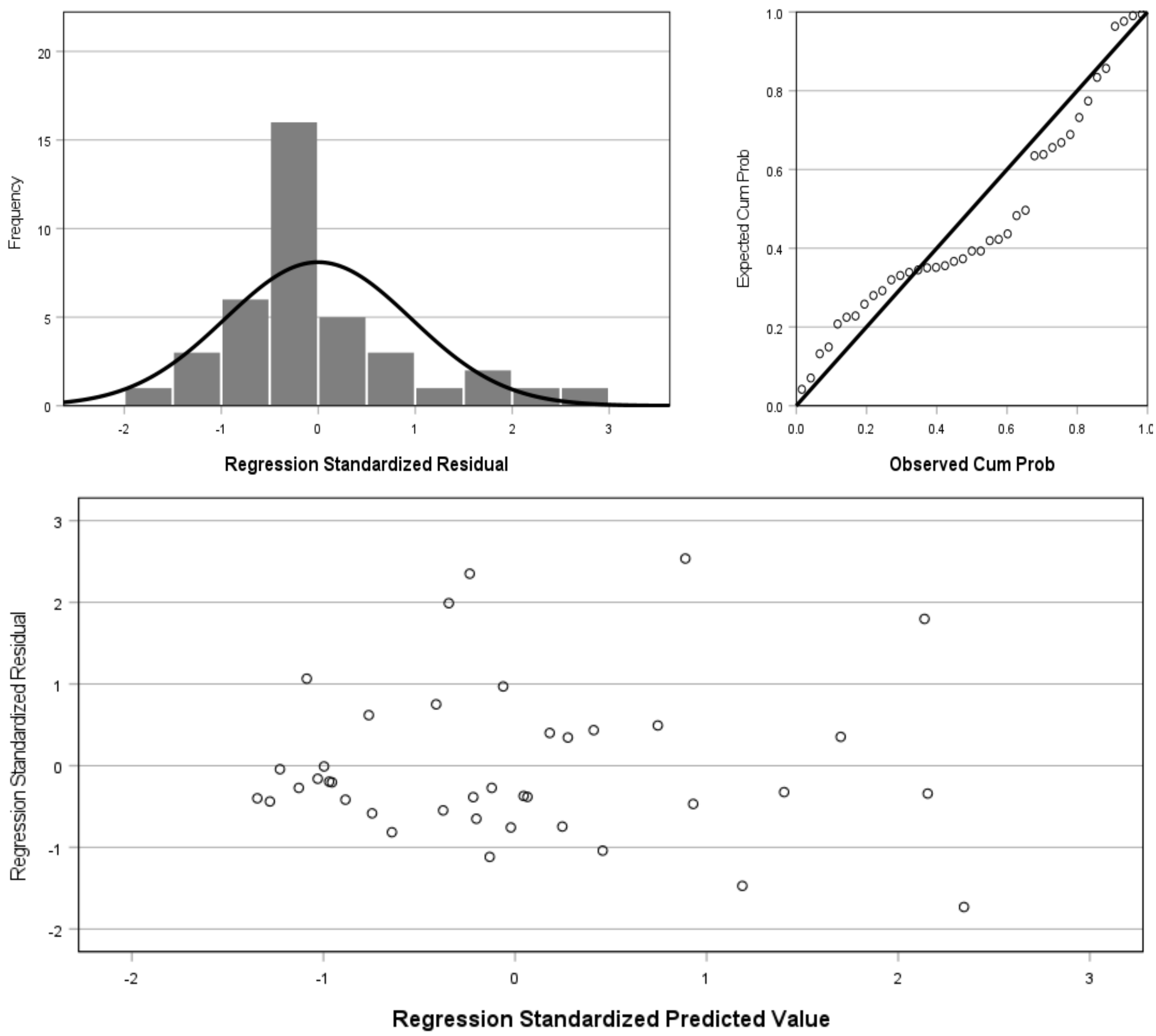


Figure 17

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the depression variable for Respondent III

Appendix D: Supplementary Figures for Participant IV

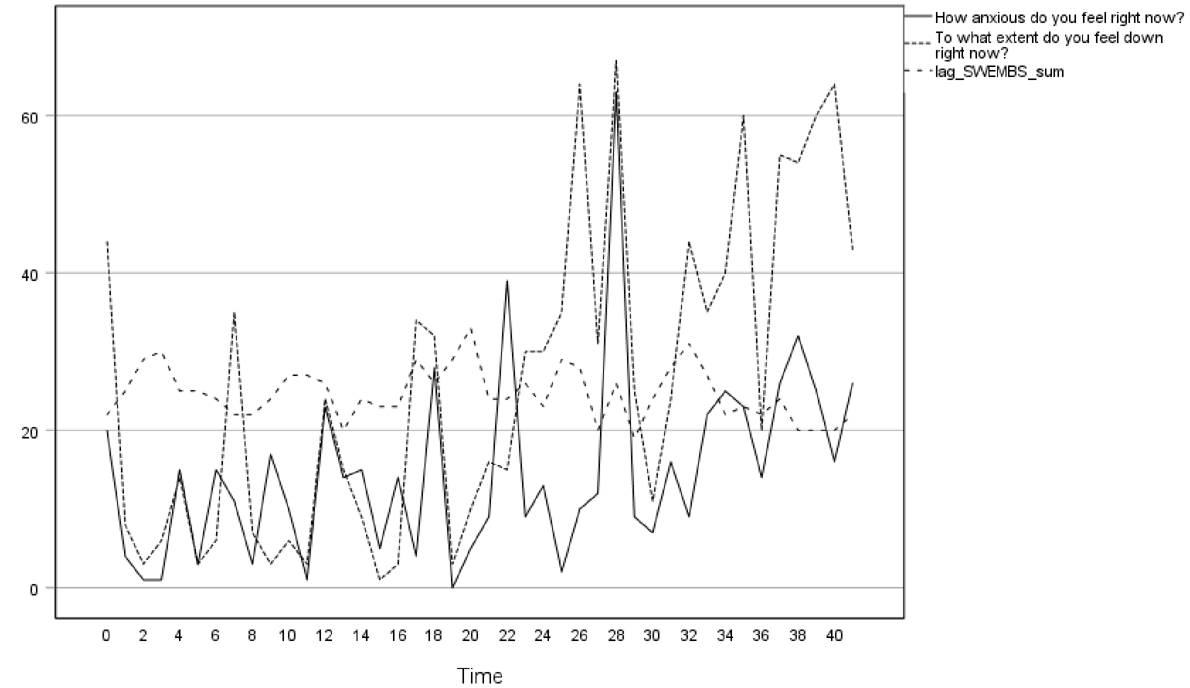
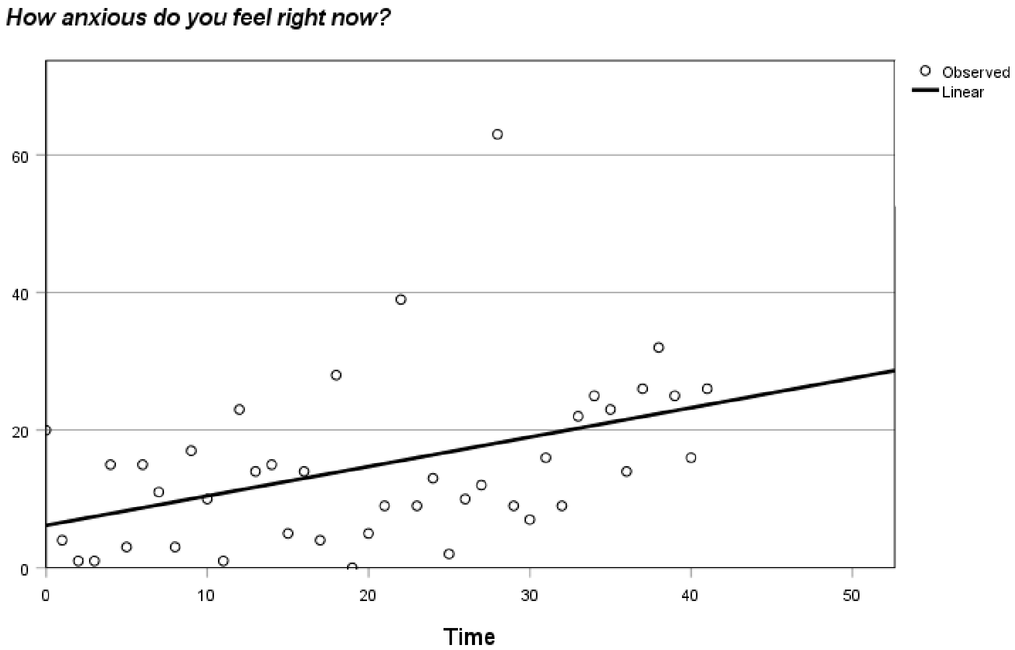


Figure 18

Time Series Plot for Anxiety, Depression and Well-being for Participant IV



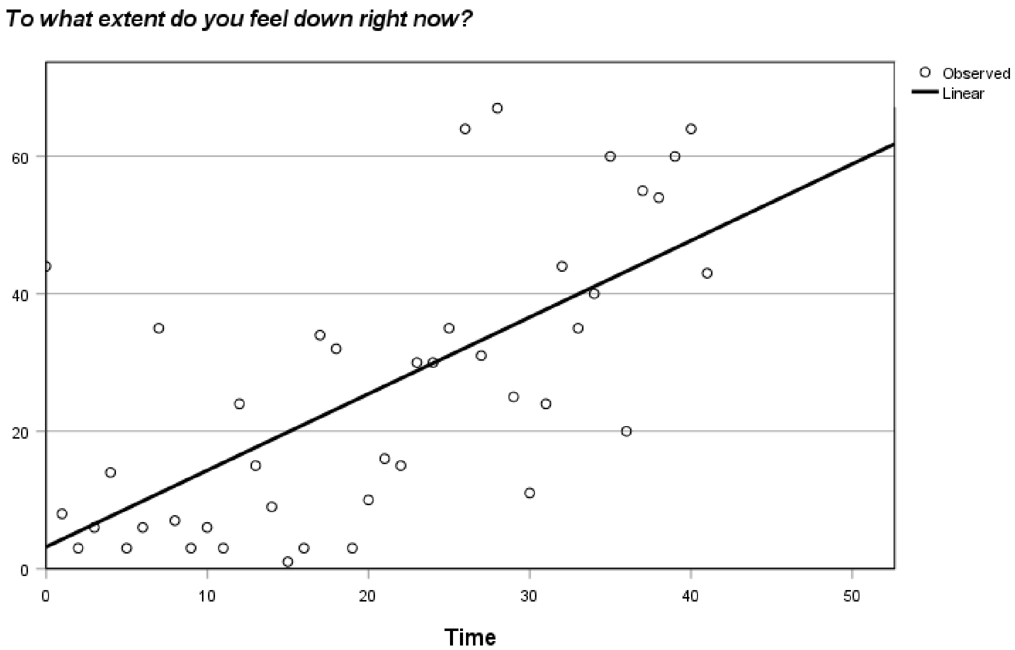


Figure 19

Time Plots for Anxiety (top) and Depression (bottom) for Participant IV

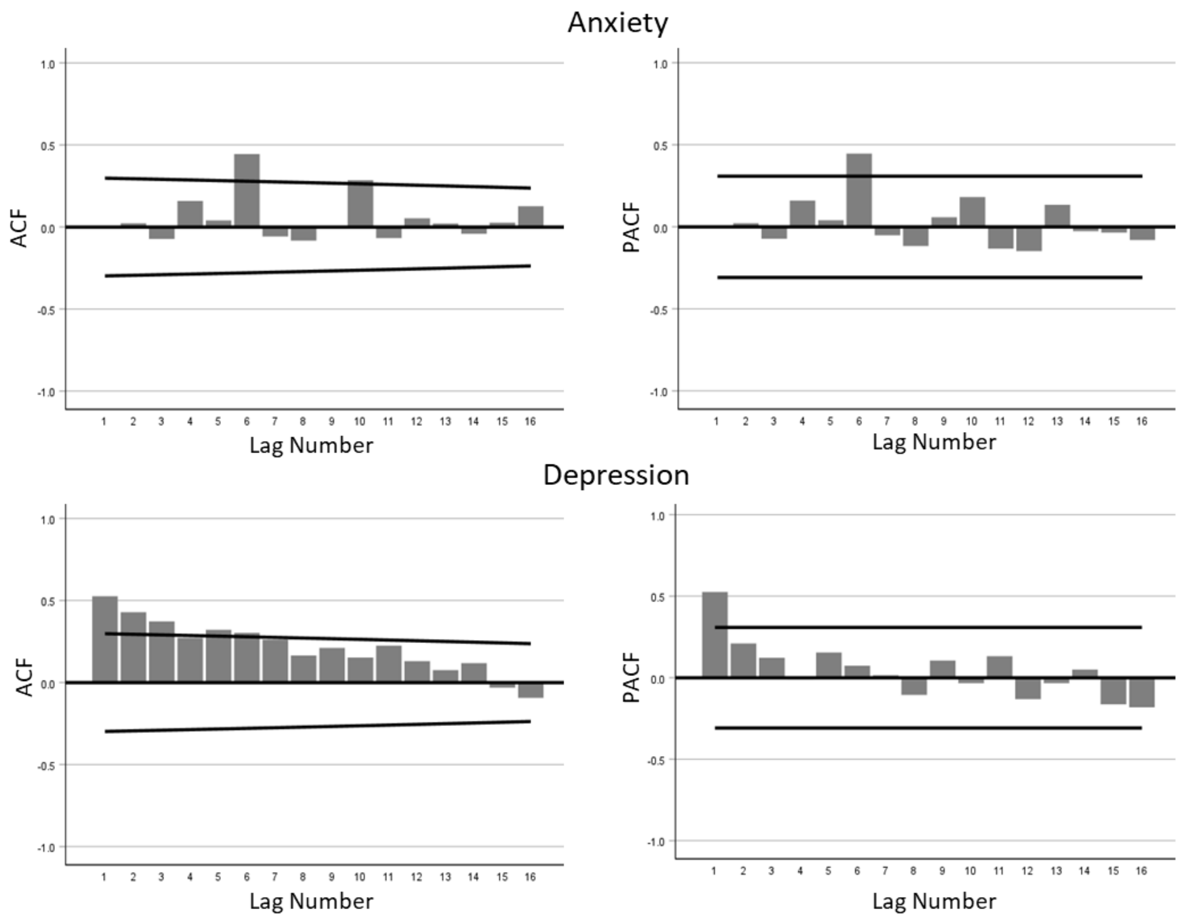


Figure 20

ACF (left) and PACF (right) plots of the anxiety variable (top) and depression variable (bottom) for Respondent IV

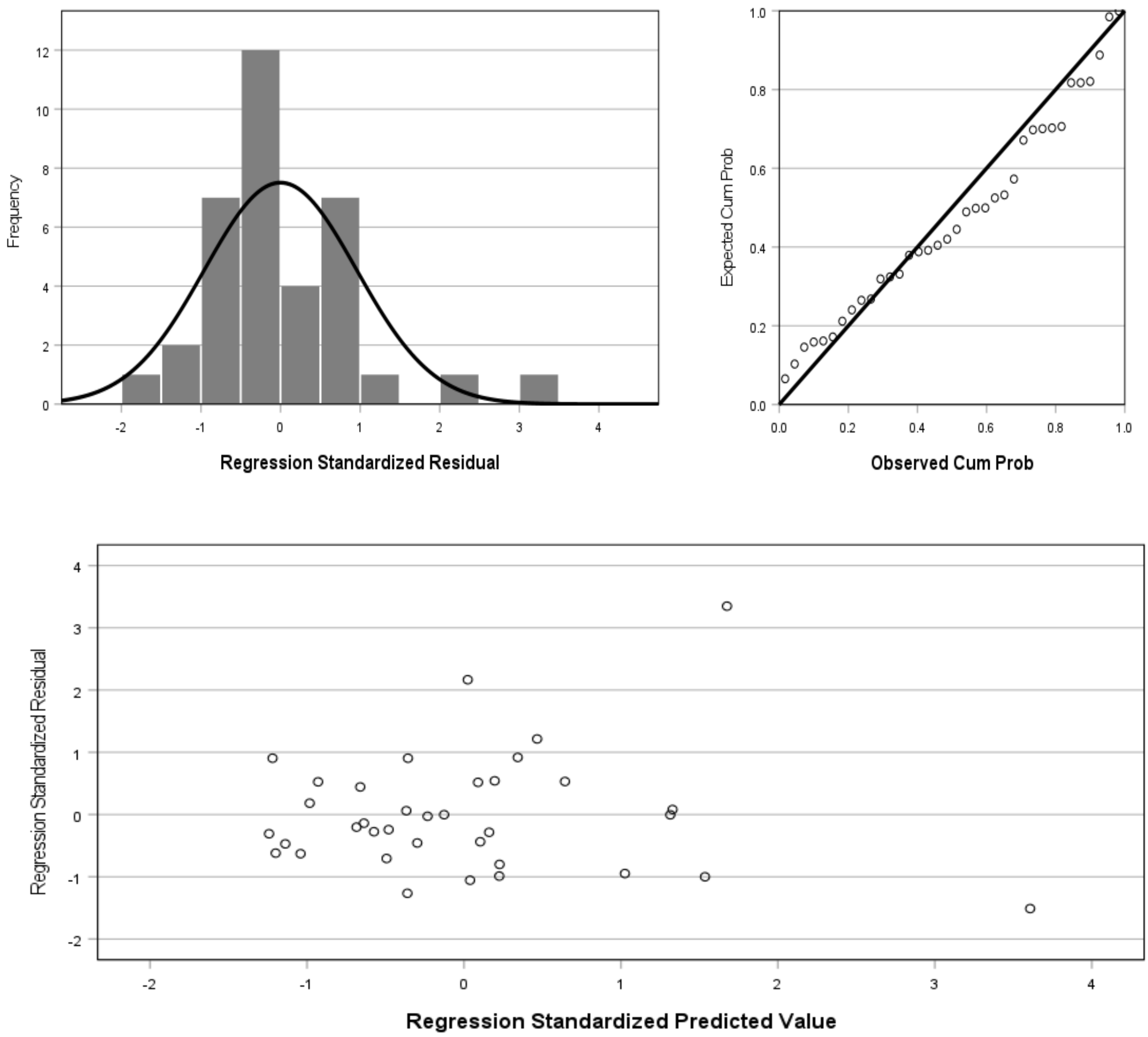


Figure 21

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the anxiety variable for Respondent IV

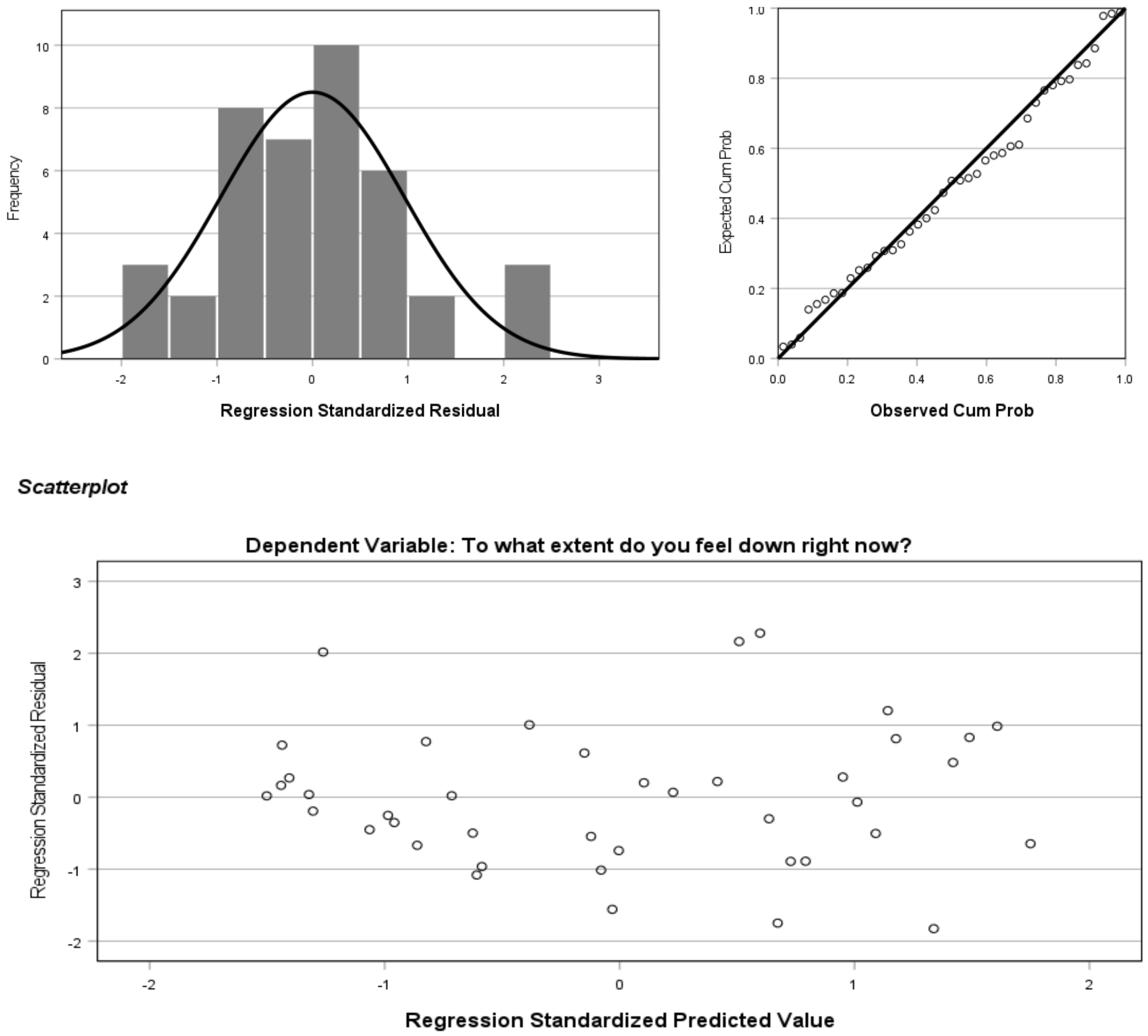


Figure 22

Histogram of the residuals (top left), normal probability plot of the residuals (top right), and scatterplot of the residuals versus predicted values (bottom) for the dynamic regression model of the depression variable for Respondent IV