Exploring The Usefulness Of Assessing ESM Data Using Dynamic Linear Regression

An N-of-1 Study Of The Association Between State Anxiety And State Depression

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August 4, 2023

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Abstract

In recent years the call for personalised mental healthcare has led researchers to attempt to understand individuals within their dynamic environments and characteristics by using methods other than traditional cross-sectional research. Experience sampling methods (ESM) make it possible to differentiate the individual from groups by looking at within-person associations instead of between persons on a group level, although this is often not utilized to its full extent. The aim of the study was to explore the usefulness of using dynamic linear regression modelling, a type of time series analysis, using ESM data. In addition the aim was to investigate intra-individual predictions of depressive mood (states) based on anxiety (states) over time. A secondary analysis was performed on a specific dataset of Hoppe (2019) containing ESM type data of state anxiety and state depression. The duration of the study was eight days. The first seven days state anxiety and state depression were measured four times a day using single item questions. First, on a group level the association was analysed using a linear mixed model. It was found that there was a significant, but weak, positive effect of lagged state anxiety on state depression (β = .13, *SE*= .046, *95%CI:* .04 to 22). Secondly, of the initial 26 participants, two participants were selected for dynamic linear regression analysis based on visual analysis of the variability of data, strength of the association, and factors that influence the association such as outliers. Dynamic linear regression showed that at the individual level for both participants no significant predictive association between anxiety hours prior and depressive state was present. Overall, it can be concluded that the usefulness of dynamic linear regression appeared limited. Although a weak significant positive association between lagged anxiety and state depression was found on a group level within-persons, within two individuals no association was found between state depression and lagged anxiety, since no significant association was found between lagged anxiety and state depression after accounting for autocorrelation. Several potential explanations are given for the difference on an individual level as opposed to the group level analysis. Furthermore, implications are given for future studies aiming to explore predictive associations between factors such as state anxiety and state depression using ESM-type data.

Content

Introduction

In the past decennia research on the association between anxiety and depression has led to the debate whether anxiety and depression are separate constructs or if they are part of a continuum (Tiller, 2013). The reason for this is, that it has been known for some time that anxiety and depression co-occur more times than not, with some research indicating the prevalence of a dual-diagnosis at 57 percent (Clark & Watson, 1991).

A well-known theory regarding the distinction and overlap between anxiety and depression based on emotions is the tripartite model of Anxiety and Depression as formulated by Clark and Watson (1991). This model consists of three components: General distress, Anhedonia vs Positive affect (PA), and physiological hyper arousal or somatic anxiety. General distress is argued to be part of both anxiety and depressive disorders and encompasses negative mood states such as distress, fear, and sadness, thus being non-specific symptoms for either anxiety or depression (Watson & Clark, 1991). Anhedonia vs. Positive affect (or PA), in contrast, is the reflection of pleasurable engagement with the environment, and lower levels of this component (indicating anhedonia) may be depression specific. Symptoms that are included in this component are for example feeling disinterested, lack of energy, and having no fun in life (Watson et al., 1995). The last construct, physiological hyperarousal, has been argued to play a key role in anxiety disorders and seems to be anxiety specific (Joiner et al., 1999). Example symptoms are shortness of breath, dizziness, trembling, and shaking (Watson et al., 1995). Recent reviews of this tripartite model have indicated that a bifactor structure, indicating one underlying general factor and three specific group factors, best explained the differences and overlap between anxiety and depression (Yeung et al., 2020). This finding, as opposed to the tripartite model, supports the notion that general distress is the main factor that underlies depression and anxiety.

Other views on the relation between anxiety and depression are more directly focused on the symptoms or cognitive factors that distinguish or show overlap between anxiety and depression. For example Hamilton (1983) indicates that to distinguish depressive mood, it is necessary to look at characteristic symptoms that are mostly present such as the triad of depression, guilt and suicidal ideation. Furthermore, Hamilton (1983) states that within anxiety one must look at positive symptoms (e.g., symptoms that are present such as muscle tension in anxiety) rather than use exclusion criteria to diagnose anxiety over depression.

Most of the research on the overlap and distinction between anxiety and depression as discussed in the previous paragraphs is based on cross-sectional or psychometric research. This kind of research focuses mainly on explaining the complex constructs of depression and anxiety as traits, where anxiety and depression are often seen as stable patterns of responding across multiple domains such as on the cognitive and behavioural level. For example, in the case of trait anxiety, high trait anxiety may drive cognitive biases often seen in anxiety disorders (Knowles & Olatunji, 2020).

In contrast to seeing complex constructs of anxiety and depression as traits, state anxiety and state depression can also be seen as the symptoms that are present at the moment of measurement. For example, in a study on assessing state depression, Chiappelli and colleagues looked at the current symptoms of depression in a sample of people with schizophrenia, differentiating from symptoms across lifetime (Chiappelli et al., 2014). Furthermore, as opposed to the conceptualization as trait anxiety in driving cognitive biases, state anxiety can also be seen as a momentary experience in a stressful situation which fluctuates over time (Gaudry et al., 1975). Recent studies on state anxiety have focused on analysing the differences or overlap between trait and state anxiety, which is reflected in the state-trait anxiety index (Spielberger et al, 1983). For example, a recent review of studies investigating the effect of nature walks on depression indicated that nature walks can reduce state anxiety but results on anxiety disorders were mixed (Kotera et al., 2021), indicating a difference between understanding anxiety as a state or trait.

Capturing these fluctuations or states of symptoms of depression and anxiety is thus important, because it provides further insight into the variety and duration of the symptoms on a daily basis within persons (Myin-Germeys et al., 2018). Whereas cross-sectional studies can give insight into associations between persons, these kind of studies cannot provide a basis for analysing associations between constructs within persons. Only intensive longitudinal studies can provide this perspective. Whereas cross-sectional research consists of observations at one moment, longitudinal studies use multiple observations within a specific timeframe, which thus also take into account environmental changes that may occur during the time of measurement (Myin-Germeys et al., 2018). In addition, longitudinal studies might help explain the temporal nature of complex relationships between feelings of anxiety and depression. For instance, in a longitudinal study (not experience sampling) on the directionality of the relationship between anxiety and depression, it was found that anxiety symptoms preceded symptoms of a depressive episode, but not the other way around

(Wetherell et al., 2001). Even though there is little known about the aetiology regarding this relationship, other studies have also shown that it is more likely to develop concurrent depressive symptoms after experiencing anxiety than the other way around (Wittchen et al., 2000; Merikangas et al., 2003; Kessler & Wang 2008). Lastly, cross-sectional studies that are based on the assumption that anxiety and depression are stable traits over time often measure anxiety and depression retrospectively. For example valid and reliable measures such as the Hospital anxiety and depression scale (HADS) or Beck inventory of depression ask respondents to indicate how they have felt during the past four weeks (HADS) to two weeks (Zigmond & Snaith, 1983; Beck et al., 1961). However, these retrospective methods are prone to retrospective bias in the recall of symptoms (Myin-Germeys et al., 2018).

Surprisingly enough, there is little to no research available that aims to analyse and predict intra-individual depressive states based on the supposedly longitudinal unilateral relationship between anxiety and depressive symptoms. Recently, in psychopathology and healthcare, there has been a shift of focus from between-person to within-person differences and associations. As a result, experience sampling methods (ESM) are gaining in popularity, which might be due to the need of clients and patients for more personalised healthcare and medicine (McDonald et al., 2017). This shift is important, because most theories explaining psychopathology are inherently focused on individual (within person) differences, mechanisms and associations, but often analysed on a group level between persons. These analyses, however, often do not generalise to the differences found in individuals (Conner et al., 2009) .

The principles of ESM are based on understanding daily life feelings and behavior in the changing context it occurs (Germeys & Kuppens, 2021). Within ESM data is gathered via a self-report technique assessing the variables of interest such as mood, affect, symptoms and physiological data multiple times a day (Myin-Germeys et al., 2018). Although ESM data allows to separate between-person from with-person associations, in most ESM studies this is not yet utilized to its full extent, and most ESM research still tests within-person associations on the group level. This means that only one mean association is tested for all participants, based on the group level, instead of individual mean associations for each individual. N-of-1 studies focus on some of the same principles of ESM, however analysing intensive repeated measurements from a single participant (Vieira et al., 2017). Whereas ESM studies are gaining in popularity, McDonald and colleagues argue that N-of-1 studies are often underused within behavioural studies and medicine (McDonald et al., 2017), even though they can give detailed insight into intra-individual behaviour (or feelings), which is key for personalised healthcare and the development of possible interventions (McDonald et al., 2017). Therefore, in this research ESM data will be utilized to conduct an N-of-1 study to gain more insight into the temporal relationship between anxiety and depression within individuals.

The differences between ESM and N-of-1 studies are small and, according to Myin-Germeys and Kuppens (2021), ESM can also contribute to a more personalised and patient-led personalized psychotherapy, indicating for example behavior patterns that impact their symptoms. An important difference is that, depending on the research questions, most of the time ESM focuses on within person associations on a group level, whereas N-of-1 studies focus on analysing, or zooming in on, one or a few individual persons. To analyse N-of-1 data, McDonald proposes to use a dynamic linear regression model (McDonald et al., 2020). According to Vieira and colleagues this approach has the advantage of being flexible and adaptable to the different challenges of statistical modelling of N-of-1 studies as opposed to other methods (Vieira et al., 2017). With this model it is possible to perform time series analysis (or forecasts) based on past data points (or lags), thus providing a possible picture of future symptoms. Based on repeated measurements in the past collected using ESM data, an individual dynamic regression model might be able to predict depressive mood states based on previous anxiety symptoms of an individual. However, since the usage of ESM data in N-of-1 studies is relatively new, it needs to become clear whether such analyses are feasible for ESM data. For instance, according to McDonald et al (2020) such analysis are feasible when there are at least 50 data points. It is unknown whether dynamic linear regression will prove useful when typical ESM data is used. Reasons for this are that due to the nature of ESM often less data points are available, and data consists mostly of subjective feelings/experiences scored by the respondents instead of behaviors which are highly fluctable. This study thus aims to explore the usefulness of using dynamic linear regression modelling as proposed by McDonald and colleagues (McDonald et al., 2020) using ESM data. Furthermore the aim is to investigate intra-individual predictions of depressive mood (states) based on anxiety (states) over time.

Method

The current study is a post-hoc analysis of ESM data gathered by Hassanabadi (2019) and Hoppe (2019) between the 23rd and 30th of April in 2019. In their intensive longitudinal quantitative study they measured, among other things, levels of state anxiousness and depressive feelings multiple times a day for one week. The participants were notified each day to complete self-report questionnaires on their mobile phone within the incredible intervention machine (TIIM) application (BMS Lab, 2020). This TIIM application was developed by the University of Twente, and has several functionalities such as the option to administer surveys at random or preselected time points.

In their study Hassanabadi (2019) and Hoppe (2019) analysed the concurrent associations between state anxiety and state depression on a group level and the overlap with trait measurements for these constructs, as well analyzing visually the development of state anxiety and state depression over time. They found that there were significant differences between the participants estimated means, with state anxiety and state depression being strongly correlated with each other in the moment as well as with trait anxiety and trait depression (Hoppe, 2019). Hoppe (2019) chose the ESM design to gain insight into feelings that were measured at the notified moment, instead of retrospectively. Furthermore the longitudinal nature of the study also allowed for an analysis on the variability of the levels of pleasure as well as energy over time (Hoppe, 2019).

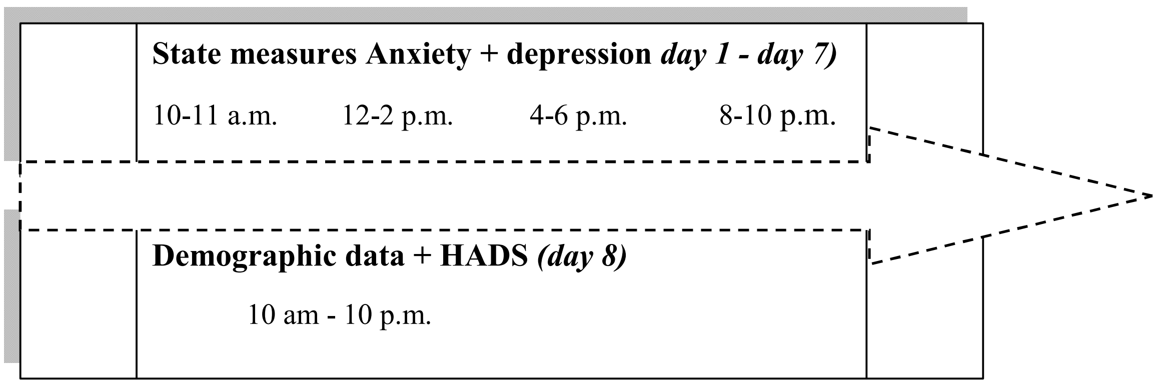
Design

The duration of the study was eight days, which was based on the recommendations of Hektner and colleagues (2007), who, at the time, advised that a minimum of one week is necessary to have a representative sample of people's activities or feelings. However, recent literature and studies focus on an extended period of time to assess feelings and emotions, such as the study conducted by Stieger and colleagues analysing the levels of loneliness and general levels of emotional wellbeing across a period of 21 days for 3 times a day (Stieger et al., 2021). In this light, Myin-Germeys and Kuppens (2021) additionally argue, regarding state emotions which are highly variable constructs, that a higher sampling frequency is appropriate with most studies having at least 10 assessments per day (Myin-Germeys & Kuppens, 2021). Furthermore, according to recent recommendations made by van Berkel and Kostakos (2021) this decision should be informed by several factors such as the frequency the variable is expected to occur or change, the effort that is needed to complete the questionnaires, and expected levels of motivation among the participant sample. Although Hassanabadi (2019) and Hoppe (2019) took the level of intrusiveness and motivation into account, they also recommended to extend the time window of measurement for future studies to better capture the state levels of depression and anxiety on daily life.

In the first seven days, starting on a Tuesday, the participants were prompted to fill in the state measures of anxiety and depression four times a day (see figure 1), resulting in a maximum of 28 data points for every participant. On the eighth day the participants were asked to complete demographic questions and the Hospital Anxiety and Depression scale (HADS) to capture trait anxiety and depression. To lessen the burden on the participants within this longitudinal ESM study, a signal contingent sampling method was chosen to gather data, using a semi-random sampling scheme. This has the advantage of being relatively high ecologically valid since the unpredictability increases, and therefore there is greater balance between predictability and unpredictability as opposed to other ESM sampling schemes (Germeys & Kuppens, 2021). Hoppe (2019), as mentioned earlier, divided the days into four timeframes and then decided the time of measurement within these intervals. On the eighth day participants were prompted to fill in demographic data and the hospital anxiety and depression scale (HADS) between 10 am and 10 pm.

Figure 1

Study's Timeline



Participants

To recruit participants, Hassanabadi (2019) and Hoppe (2019) used a convenience sampling method. Several selection criteria were relevant for this study: the participants had to be over 18 years old, they had to study at a university or university of applied science or be employed, they had to have access to an IOS or Android mobile phone, and finally they needed to have a basic understanding of the English language. Participants were excluded if they did not meet these criteria or they did not agree with the informed consent.

Participants were asked to partake in the study through social media, friends and family. In total, twenty-six participants agreed to partake. To determine the required sample size, Hassanabadi (2019) and Hoppe (2019) looked at previous ESM studies and partly based their decision on the systematic review of van Berkel and colleagues (2017), who found that a median of 19 participants were included in the reviewed studies.

Materials

Several questionnaires were used in the original study. Hoppe (2019) focused on measures related to state anxiety and depression, and trait anxiety and depression. Relevant to this study are the measures of state anxiety and state depression that were employed, as well as the measures of trait anxiety and depression and the demographic data that was gathered (as shown earlier in figure 1). For an overview of the other measures administered in the original study see the work of Hassanabadi (2019).

To measure state anxiety and state depression a single-item design was used. A single-item design is often used in ESM studies to reduce participant burden (Myin-Germeys & Kuppens, 2021) State anxiety was measured through asking the question: "How anxious do you feel right now?". Hoppe (2019) derived this question from a previous ESM study done by Cox and colleagues (2018). A similar question was formulated to measure state depression: "To what extent do you feel down right now?". Both questions could be answered on a scale from 0 (Not (..) at all) at all to 100 (extremely (..)) by using a slider.

On the last day, the participants completed demographic questions and the Hospital Anxiety and Depression Scale (HADS). The demographic questions were asked with the aim to gather data on age, gender, nationality, and occupational status. The HADS was used by

Hoppe (2019) to measure the trait anxiety and trait depression of the participants. The HADS is an extensively validated questionnaire that contains fourteen items, seven items contain the anxiety subscale, and the other seven measure the subscale depression. It is a retrospective measurement, with the instructions mentioning that the respondent should take into account the past weeks when answering the questions (Zigmond & Snaith, 1983). The respondents can indicate how they feel by answering on a four-point scale from 0 ("Not at all") to 3 ("Most of the time"). These answers can then be combined to calculate total scores on the subscales. Regarding the psychometric qualities of the HADS, Hoppe (2019) confirmed that the HADS demonstrated good internal consistency, which is in line with previous findings on the internal consistency of the HADS (Mykletun et al., 2001). Furthermore, when analysing the correlation between state and trait measurements, Hoppe (2019) found that the trait measurements were strongly correlated with their state counterparts, indicating a strong convergent validity.

Data analysis

Data analysis was conducted using IBM SPSS Statistics 27. To select individual cases from the ESM dataset for this current N-of-1 study, several steps were taken. First, eligible participants needed to have answered at least 50% of the momentary measurements to be included in the final analysis. Participants with less than 50% responses were excluded. Next, to explore the temporal association between anxiety and state depression within participants on a group level, as would be typical in an ESM analysis (Myin-Germeys et al., 2018), a mixed linear model was conducted using state depression ("To what extent do you feel down? ") as a dependent variable and one-period lagged (L1) anxiety as fixed effect using an AR(1) covariance matrix to model the correlations between repeated measurements.

Next, individual scatter graphs and regression lines were plotted to visualize the association between the outcome variable state depression and the lagged variable of state anxiety. One individual participant with a visually positive association, and one individual with a visually negative association, was selected for the N-of-1 analysis. Furthermore, variability in the state variables also was taken into account, as well as visually checking for potential outliers influencing the data. After selecting the cases, demographics of these selected cases were portrayed.

The next steps of the N-of-1 data analysis were performed following the steps described in the guide of McDonald et al. (2020). These steps included formatting the data set, identifying and imputing missing data, plotting the data and analysing variability, assessing the stationary of the data, analyzing time trends and periodicity patterns to adjust for possible non-stationary data, checking auto-correlation (lag) for the outcome and predictor variables and specifying autocorrelation by creating lagged variables, and finally conducting the dynamic linear regression using the final model.

The first steps that were important for an adequate analysis of the data were formatting the data set and identifying and imputing missing data. Hoppe (2019) extracted the data from TIIM and already transformed the existing data set into the long format that is required for dynamic linear regression modelling for an N-of-1 study specifically. The next step included identifying missing data. Hoppe (2019) indicated that for the ESM analysis no participants had to be excluded from the dataset, since the minimum of completed measurements was 13 out of 28 (46.43%). However, for this N-of-1 study the cut-off was set for at least 14 out of 28 (50%) completed measurements due the risk of overestimating (or underestimating) the dynamic linear regression model. In their guide McDonald et al. (2020) indicate that a missing percentage of less than ten percent only requires simple imputation to make up for missing data. Since in this post hoc analysis the proportion of missing data for all participants was 21.29% , imputing the data would require multiple imputation, which would have a significant impact on the outcomes of dynamic linear regression and the autocorrelation structure in this study (Velicer & Colby, 2005). For this reason no imputation method was used in this instance.

Next, for each selected individual case the standard deviation and mean were analysed for each variable to analyse the variability. In addition, time plot graphs were used to visually confirm that each case had sufficient variability in the outcome variable over time. Following this step, the data was analysed for non-stationarity. Stationarity is an assumption of dynamic regression, which assumes that the statistical properties (e.g. mean/variance) of the outcome variable (state depression) are constant over time and thus the time series is approximately stationary (McDonald et al., 2020). This assumption was checked by partitioning the data in two sections: the first section including data points up till 14, and the second partition including the rest of the data points. Non-stationary was analyzed by assessing time trends as well as periodic patterns within the data. Time trends were analysed by carrying out a standard linear regression using 'time points' as the independent variable and 'state anxiety' as the dependent variable or outcome variable. Since there was no prior indication of periodic patterns (e.g. state depression is not lower or higher on Saturday/Sunday) within the current literature, this was not modelled or included in the final model. Lastly, before carrying out the dynamic linear regression, an important step included checking for autocorrelation in the outcome variable (state anxiety), as well as possible indications of autocorrelation in the predictor variable (state depression). Autocorrelation was checked by plotting an autocorrelation correlogram and visually inspecting whether the coefficient exceeded the upper or lower confidence interval at lag number 1 or higher as indicated by the correlogram. Autocorrelation is present when the coefficient exceeds the confidence interval, and therefore needs to be taken into account by creating lagged variables and using those variables as independent variables within dynamic linear regression.

Finally, dynamic linear regression was conducted on both selected individuals using a standard fixed -effect model. The dynamic regression model included lagged state anxiety as the independent variable, and state depression as the outcome variable. Furthermore, possible lagged variables (either autocorrelation within the outcome or predictor variable) that were created in the model were included, as well as potential time trends. These potential time trends were analysed by assuming a linear relationship between time (timepoints) and the outcome variable of state depression. If time explains most of the variability in the data of a specific individual then a time trend is identified and was added to the dynamic linear regression model as an independent variable. Lastly, the estimated effect size (regression) coefficient was computed as well as the precision of the regression estimate at a confidence interval of 95%. To check if the assumptions for regression were valid, a post-model check included a histogram of the residuals, a normal probability plot and scatter plot of the residuals versus the predicted values as recommended by McDonald et al. (2020)

Results

Descriptives

26 participants took part in the study of Hoppe (2019) with 11 being male and 15 female. The age varied between 18 to 32 with 61.54 % of the sample being students and/or having a job besides their studies (42.31%). Furthermore, most participants where German

(88.46%) or Dutch (7.69%), and one participant was British. The average number of responses to the state measurement was 22.04 (*SD*=4.01). Two of the twenty-six respondents had a response rate of 13 out of 28 (46.43%) and therefore did not meet the inclusion criteria of 14 out of 28 (50%) measurements, these participants were excluded from the dataset before the linear mixed model was fitted.

Group level association between state anxiety and state depression

After converting the scores on the state variables to z-scores, a linear mixed model was performed to analyse the association between lagged state anxiety and state depression on a group level. Overall, there was a significant, but weak, positive effect of lagged state anxiety (β= .13,*SE*= .046, *95%CI:* .04 to .22) at the group level (see Table 1).

Table 1

Estimates of Fixed Effects Lagged Anxiety

Effect	β	*SE*	*p*	*95% CI*	
				Lower Bound	*Upper Bound*
Intercept	-.025	.060	.680	-.14	.09
Lagged Anxiety	.130	.046	.006	.04	.22

Selecting cases

In figure 1 the association between lagged anxiety and state depression is visualized within each participant for the first thirteen cases, where lagged state anxiety is used as the predictor of state depression for every participant. To select a case for performing dynamic linear regression, besides sufficient data points, another important criteria is variability within the data of the participant. Thus, to determine whether a participant was eligible for the N-of-1 analysis a visual inspection was performed looking the variability, strength of the association, and factors that influence the association such as the presence of outliers.

A visual inspection of figure 1 suggests that participant 2337 shows a moderate correlation between lagged state anxiety and state depression (*r*=.55, *n*=26). Furthermore there seems to be sufficient variability and there were no real outliers present. However participant 2337 only reported fourteen data points, therefore this positive association will not be included. Participant 2364, however, is interesting, showing a weak positive correlation (*r*=.26, *n*=20), but the variability seems to be sufficient and there are no real outliers. Therefore, participant 2364 will be considered for the analysis. Lastly, participant 2369 shows a weak negative correlation between lagged anxiety and state depression (*r*= .19, *n*=20), however the data shows some variability as opposed to other negative associations and will therefore be included for dynamic linear regression. The other cases were not considered for the analysis, since they were influenced by outliers or showed none existent correlation.

Figure 1

Scatterplot of the Association Between State Depression By Lagged State Anxiety of Participant 2337 through Participant 2372

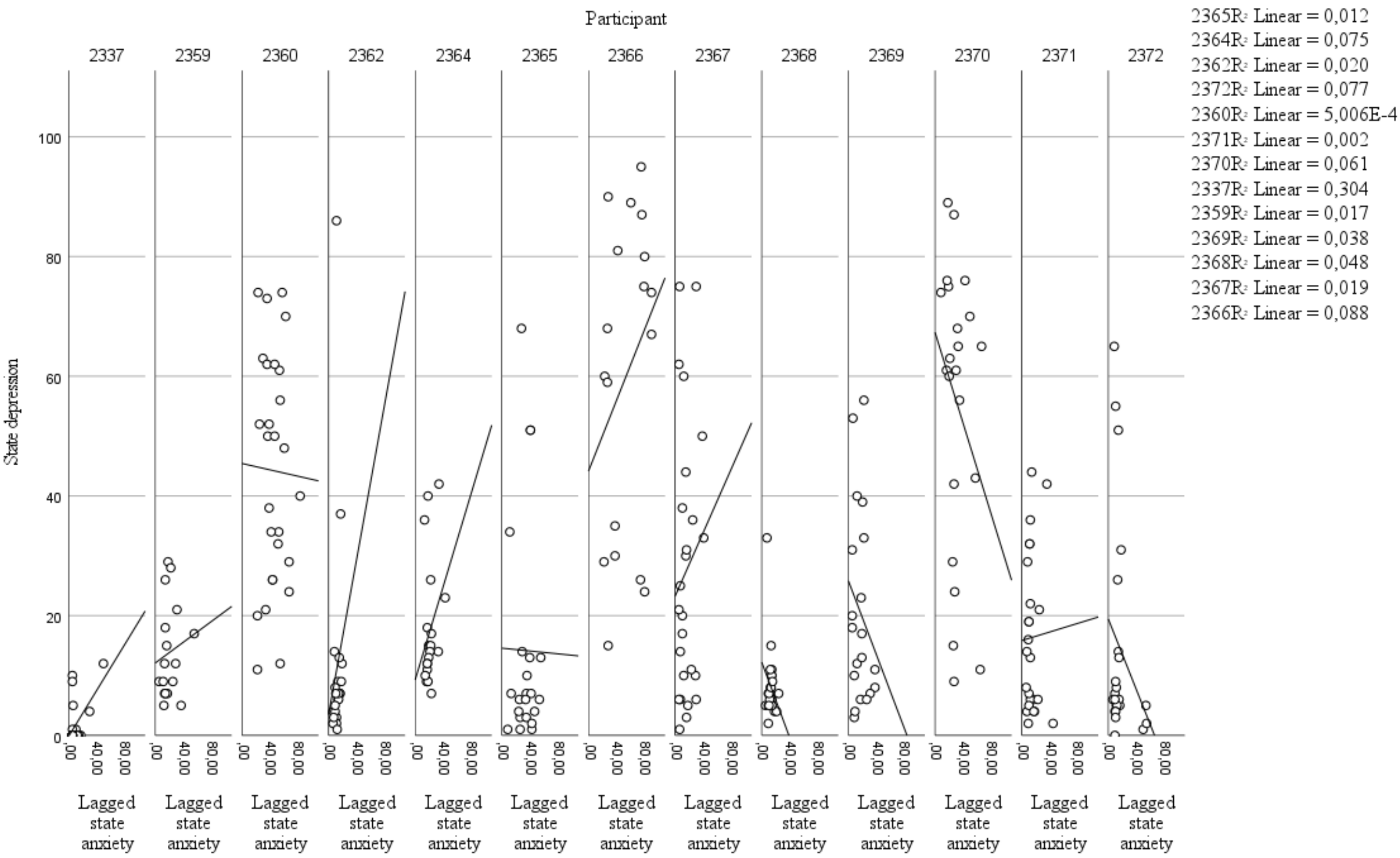
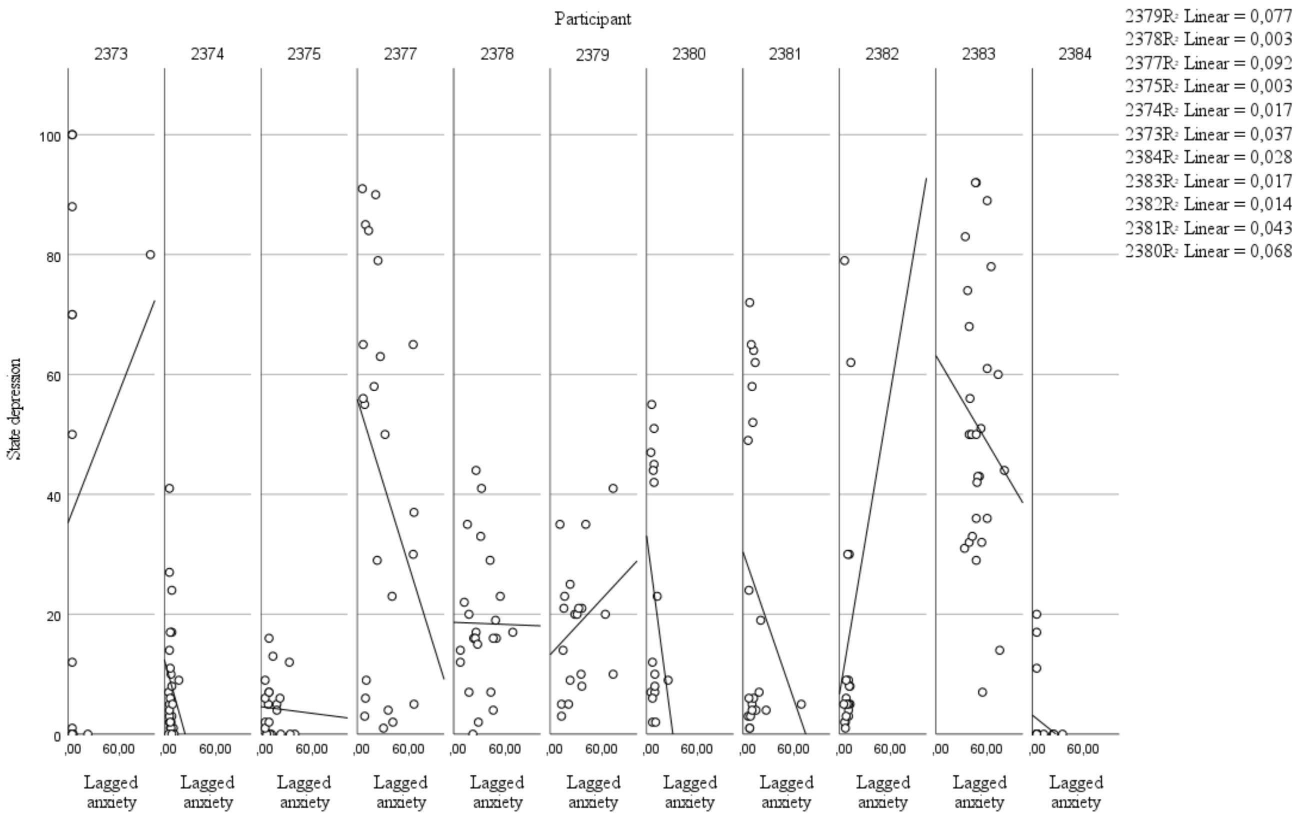


Figure 2 represents participant 2373 though 2384, however none of these cases were included for the analysis for varying reasons. For example: participant 2375 shows little variability and the correlation is also none existent. Participant 2377 through 2379 show sufficient variability, but all show weak correlation and there are some outliers present. Lastly, cases 2380 and 2382 are heavily influenced by outliers.

Figure 2

Scatterplot of the Association Between State Depression By Lagged State anxiety of Participant 2373 through Participant 2384



The cases that were finally selected for dynamic linear regression were participant 2364 and 2369. Participant 2364 is a 28 year old female from Germany who is currently employed, and participant 2369 is a 22 year old male from Germany, who was a student at the time of data gathering.

Visual inspection of variability within the variables-case 2364

No data was imputed as mentioned previously, and after cleaning the dataset 20 data points remained for case 2364. The first step before performing dynamic linear regression is visualising or plotting the individual data of state anxiety and state depression over time, to allow for visual inspection of the variability within the data. Figure 3 shows a time plot of lagged state anxiety and state depression over the study period including the 21 available data points. The variables seem to vary sufficiently over time, a further inspection of the descriptives of the variables (see table 2) supports this inspection, with a range of 30 on lagged state anxiety (*M*=16.15, *SD*= 7.44), and a range of 35 on state depression (*M*=18, *SD*=10.40). Conducting a preliminary inspection of the data, it seems as though through time point 1 to 4 as the score of state depression goes down, the score of state anxiety goes down a timepoint later. Furthermore, state anxiety seems to develop after state depression at timepoint four showing a possible momentary association.

Figure 3

Time plot Displaying Lagged State Anxiety and State Depression over the Study Period of Participant 2364

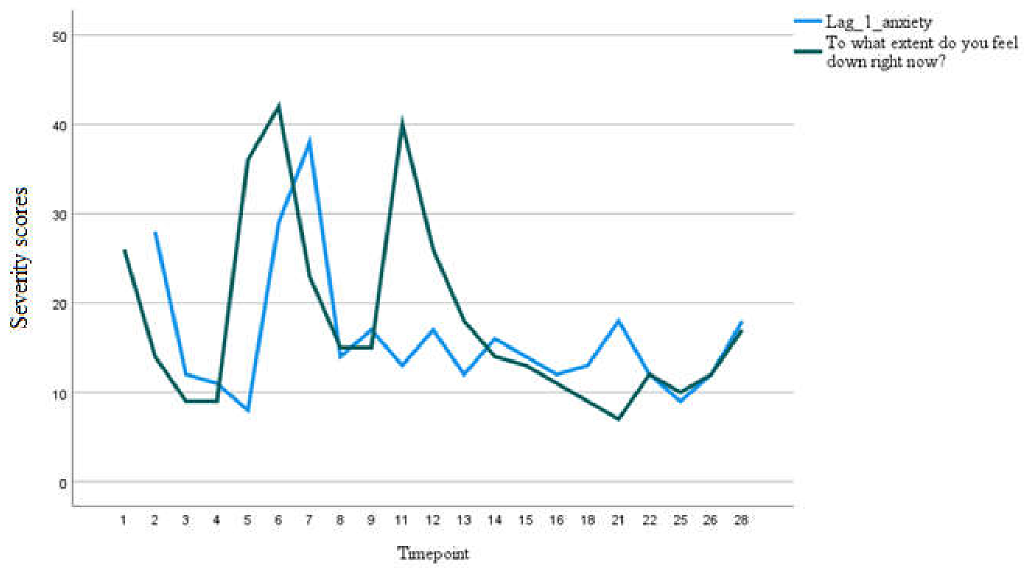


Table 2

Descriptives of Lagged State Anxiety And State Depression Participant 2364

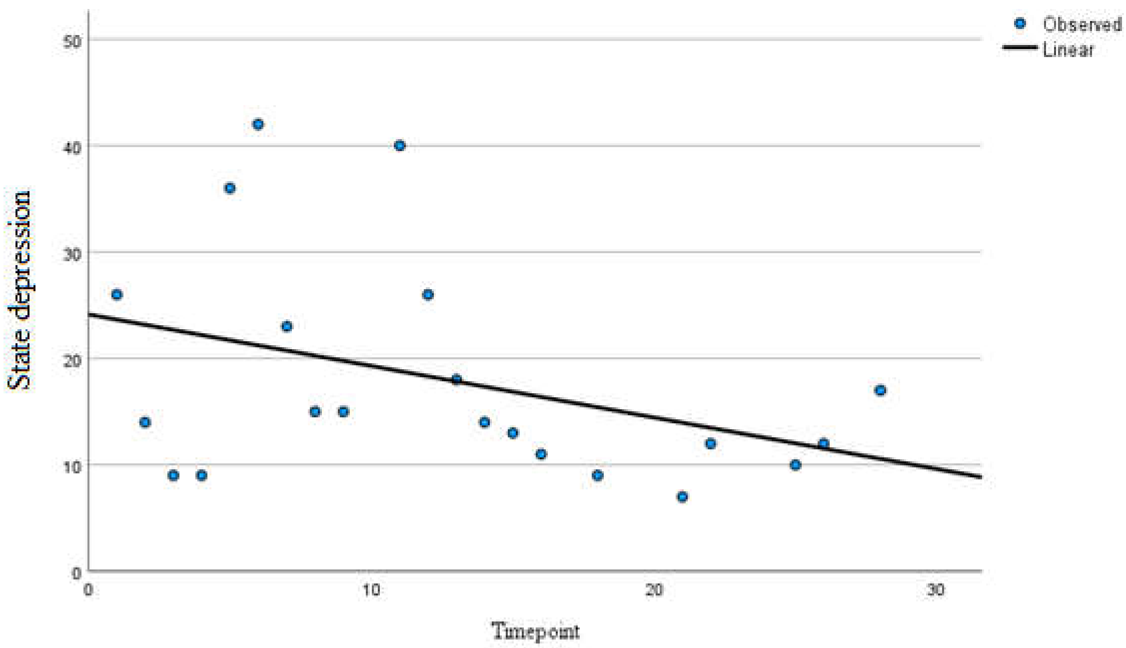
	N	*Range*	*M*	*SD*
Lagged state anxiety	20	30	16.15	7.44
State depression	21	35	18.00	10.40

Time trends & periodicity assumptions

To analyse if there are trends in the outcome variable over time a standard linear regression model was fitted in SPSS, where state depression was used as the dependent variable, and time points was added as an independent variable. The outcome can be seen in figure 4 below. The output in terms of explained variance assuming the relationship between state depression and timepoints (or duration of the study) is .148 (r=.38). This relationship is non-significant (p=.085) indicating that there was no significant time trend of state depression. Furthermore, since no prior literature about periodicity was found, it is assumed that periodicity does not influence the dynamic linear regression model of the association between state anxiety and state depression.

Figure 4

Linear Regression Model of State Depression By Timepoint of Participant 2364

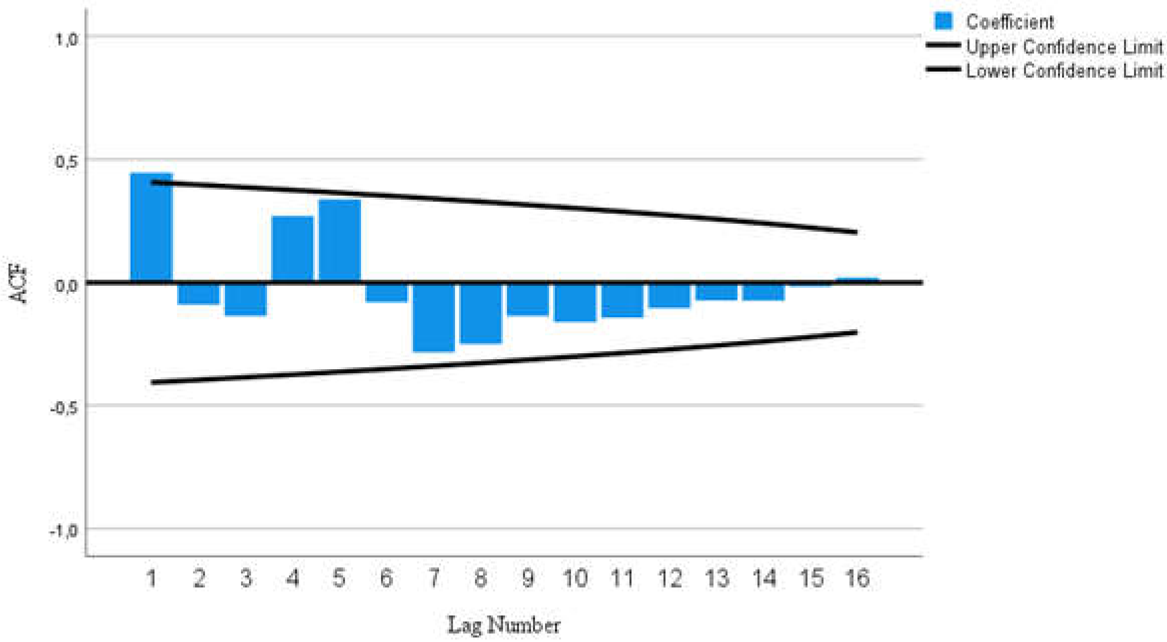


Autocorrelation in the outcome variable & creating lagged variables

To check for the presence autocorrelation two correlograms were plotted with SPSS to identify potential autocorrelation at a specific lag. Figure 5 shows the Autocorrelation Correlogram (ACF) for state depression, at lag 1 autocorrelation was identified since the ACF exceeded the upper confidence interval limit.

Figure 5

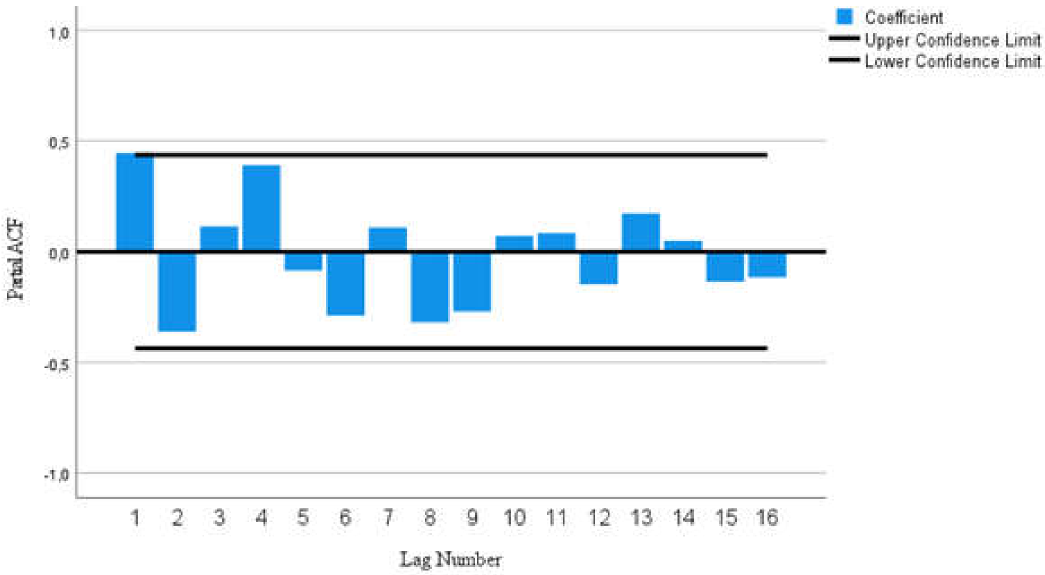
Autocorrelation Correlogram for the Outcome Variable State Depression of Participant 2364



To check whether a specific lag should be included in the model, a partial autocorrelation correlogram was plotted. Figure 6 shows that at lag 1 the upper CI limit is exceeded indicating remaining autocorrelation, thus an additional lagged variable of state depression was created by using the lag function in SPSS, before fitting the regression model.

Figure 6

Partial Autocorrelation Correlogram for the Outcome Variable State Depression of Participant 2364



Performing dynamic linear regression

Finally, a dynamic linear regression model was fitted using lagged state anxiety as a predictor, and state depression as the outcome variable. To account for autocorrelation, the lagged variables that were created at lag 1 were also included in the model. The regression coefficient of lagged anxiety was -0.20 (*95%CI*[-1.15, 0.75], p=.66), indicating that there was no significant lagged association between anxiety and state depression after accounting for autocorrelation in this participant.

Table 3

Dynamic Linear Regression Model of State Depression participant 2364

	Unstandardized Coefficients		Standardized Coefficients		95,0% Confidence Interval for B	
Model	*B*	*SE_B*	β	*p*	*Lower Bound*	*Upper Bound*
(Constant)	10.91	5.38		.059	-0.45	22.26
Lagged anxiety	-0.20	0.45	-.141	.660	-1.15	0.75
Lagged depression	0.55	0.31	.558	.099	-0.11	1.21

Conducting dynamic linear regression - case 2369

The procedure as described in the previous sections was also applied to case 2369 (see appendix 1). After cleaning the dataset 20 data points remained. First, the data was inspected visually to analyse the variability of lagged state anxiety and state depression. The data showed sufficient variability indicating a range of 33 for state anxiety (*Min*. = 0, *Max*. = 33), and 53 range for state depression (*Min*. = 3, *Max*.=56).

Following the first steps, it was found that there was a significant moderate time trend present in the data of participant 2369 (r= .56, p=.008), therefore time-point was added to the dynamic regression model. Periodicity was not accounted for in this model, since there was no theory found of periodicity between the variables as indicated in the previous case analysis. Lastly, autocorrelation was checked through plotting an autocorrelation correlogram, and a partial autocorrelation correlogram. It was found that there was autocorrelation remaining at lag 1 for state depression. After accounting for the autocorrelation by creating the lagged variable for state depression, dynamic linear regression was conducted.

The dynamic linear regression model for case 2369 (see table 4) included the lagged outcome variable state depression, accounting for autocorrelation. Lastly, the model included time points as the data showed significant time trends. As shown in the table below, after accounting for lagged state anxiety and lagged state depression, time point is not a significant predictor for state depression. Furthermore, after accounting for autocorrelation in the state variables both lagged state depression and state anxiety are not significant predictors for state depression.

Table 4

Dynamic Linear Regression Model of State Depression participant 2369

	Unstandardized Coefficients		*Standardized Coefficients*		*95% Confidence Interval for B*	
Model	*B*	*SE_B*	β	*p*	*Lower Bound*	*Upper Bound*
(Constant)	29.48	11.96		.025	4.14	54.83
Lagged anxiety	-0.28	0.29	-.18	.360	-0.90	0.34
Lagged depression	0.32	0.23	.32	.180	-0.17	0.81
Timepoint	-0.83	0.45	-.41	.085	-1.78	0.13

Discussion & conclusion

The current study was carried out with the goal to explore the usefulness of dynamic linear regression using ESM data, and to investigate intra-individual predictions of depressive mood states based on anxiety states over time. Overall, it can be concluded that the usefulness of dynamic linear regression appeared limited using the specific dataset of Hoppe (2019). In addition, although a weak significant positive effect of lagged anxiety was found on a group level within-persons, within two individuals no predictions of state depression could be made based on state anxiety as no significant association was found between lagged anxiety and state depression after accounting for autocorrelation(s).

Reasons for the limited usefulness of dynamic linear regression for this study may vary. First of all an important factor limiting the usefulness of dynamic linear regression was the amount of data points gathered for the ESM study. McDonald stated that when carrying out dynamic linear regression 50 data points makes the analysis feasible (McDonald et al., 2020). This study only included a maximum of 28 data points, which can simply be too little to have sufficient power to show weak significant associations within individuals. In addition, the individuals that were used in this study only filled in 20 momentary measurements. Although an imputation method could have been used, this might have led to an overestimation of the model (Velicer & Colby, 2005). Thus imputation methods should be considered in future studies. In this study, although it was expected to not have considerable effects, the current findings might have been more conservative because no imputation method was used.

Recent ESM studies often increase the amount of data points to analyse the associations within persons by increasing the frequency of sampling, increasing the duration of the study, and/or recruiting more participants (Myin-Germeys et al., 2018). Current standards for ESM are often 10 momentary measurements per day instead of the four used in this study, and studies range in duration mostly based on the constructs of interest (Germeys & Kuppens, 2021). Furthermore, a general rule should be that the study duration and sampling frequency make for enough data points (Germeys & Kuppens, 2021). For an N-of-1 methodology increasing the frequency of the sampling and increasing the duration of the study are measures that should be considered to gather sufficient data points. In regards to the frequency of the sampling, in this study four daily assessments were implemented to gather data, however, when assessing highly fluctuating variables such as feelings an argument can be made to increase the frequency (Myin-Germeys et al., 2018).

Another important finding in regard to the usefulness of this specific dataset is the presence of autocorrelation. For both individuals, significant autocorrelation was present at lag one for the outcome variable state depression, indicating that on average the data points in this time series are related to the preceding data points. In the longitudinal studies that were discussed, such as the study conducted by Wittchen and colleagues (2000), analysing autocorrelation was not taken into account in the models. Analysing the presence of autocorrelation is important, because it has important implications for future studies using ESM data within N-of-1 studies analysing the temporal relationship between state depression and state anxiety. For example, increasing the sampling frequency to improve the quality of the study as discussed previously might lead to more temporally closer observations which are often correlated (Fisher & To, 2012). Therefore, considering the general rule mentioned previously, when improving the quality of studies in the future for N-of-1 analysis, rather than increasing sampling frequency, the emphasis should lie on increasing the duration of the study to reduce the possibility of the presence of significant autocorrelation. As mentioned, the added effect of autocorrelation poses new challenges to ESM studies aiming to conduct time series analyses that were not considered previously.

When increasing the length of the study, another important aspect is the length of the questionnaire and reliable measurement of the state variables. The reliability of the single-item questionnaire was not examined in this study. For instance by using a test-retest procedure with the single items. According to Dejonckheere and colleagues (2022) a result of using a single item is that the measurement error of variance increases, therefore reliability should be assessed. In future ESM studies conducting time-series analyses, a test-retest procedure should be included to analyse the reliability of the single item questions. One method to implement this is to repeat the items within the same instance of momentary measurement and to evaluate the discrepancy between the test and re-test ratings to analyse the reliability (Dejonckheere et al., 2022). A more common method that can be implemented is based on split-half reliability, correlating the respondents mean and standard deviation of the individuals of the first half of the week with the means and standard deviations of the second half of the week (Csikszentmihalyi et al., 2014).

In regards to the intra-individual predictions, first a linear mixed model was performed to analyse the within person association between lagged state anxiety and state depression on a group level. Overall, there was a significant, but weak, positive effect of lagged state anxiety on state depression. This finding indicates that on a group level, anxiety experienced within an interval of one to four hours prior was weakly, but significantly, associated with increased state depression one to four hours later at the group level. Next, on an deeper level dynamic linear regression was used to investigate this possible association on an individual level in more detail. Using dynamic linear regression, it was found that for both subjects no significant lagged association between anxiety and state depression was present. This means that after accounting for autocorrelation, for the individual state anxiety experienced one to four hours earlier did not predict state depression an interval later. In addition, it was found that after accounting for autocorrelation for one individual there was also no significant association between state depression experienced one to four hours prior and state depression experienced at an interval later.

The findings of the association between state anxiety and state depression on a group level within individuals were in line with the literature as discussed previously. For example, some research indicated that symptoms of anxiety precede symptoms of depression and not the other way around (Wetherell et al., 2001; Wittchen et al., 2000; Merikangas et al., 2003; Kessler & Wang 2008). The finding that state anxiety hours prior was associated with increased state depression might indicate that the development of depressive and anxious state follows a similar development as their trait counterparts. Meaning that state anxiety develops prior to state depression, mirroring the development of their trait counterparts. However, the association found was weaker than for example in the study by Wetherell et al. (2001) who found standardized estimates between .28 and .30 of anxiety prior to depressive symptoms over a longer period of time. In addition, the mentioned analysis of the association on a group level did not take into account autocorrelation for state depression, it might be that the effect that was found is none existent after accounting for autocorrelation.

On an individual level, the association between state anxiety and state depression seem to be none existent after accounting for autocorrelation. The mentioned studies, however, although they were longitudinal in nature, used traditional methods to analyse between persons on a group level the association between anxiety and depression. As indicated earlier, these type of analyses often do not generalise to individuals (Conner et al., 2009), which might be a possible explanation for the difference in results on an individual level. Moreover, in intensive longitudinal studies like ESM, time series or lagged analyses are gaining popularity and are not used as often , therefore controlling for autocorrelation is often also not included. This study is one of the few studies that use a time-series analysis in an ESM context looking at predictive associations.

Besides the lack of times series analyses on an individual level in literature on state anxiety and state depression, there are other possible explanations for the difference in results on an individual level. Since every individual is different, it is possible that lagged state anxiety scores in these individuals are simply not significant predictors for state depression, whereas for other individuals this is the case, resulting in the positive association on a group level of lagged anxiety as a predictor. These results show the important difference between associations on a group level and the individual level using ESM data. Previous studies using ESM data have also shown the importance of distinguishing group models from the individual level using ESM data. For example, Kraiss and colleagues analysed the validity of the two-continua model in light of within person associations, since research focused mainly on between person associations on a group level, but the model is often used to infer within person associations (Kraiss et al., 2022). Interesting to note is that they found that for some persons the association between psychological distress and mental wellbeing was not present, whereas for some persons the assumption was stronger, although on a group level it showed that the association was similar to more traditional cross sectional research (Kraiss et al., 2022). This is in line with the findings of this study, where between-persons on a group level an association seemed to be present, but where the association was not present on an individual level. This issue presented is part of a larger issue in statistical work on psychological phenomena and is known as the term 'ecological fallacy' (Curran & Bauer, 2011). Furthermore, even though the individuals were selected through visual confirmation of the association between lagged state anxiety and depression, it is possible that this visual inspection led to errors in judgment, and future studies using this method should at least include another researcher to visually confirm possible positive or negative associations.

Important to note as well is that in this study only lagged anxiety and lagged depression were included in the final dynamic linear regression model. In a personalized machine learning approach using wearables, Shah and colleagues (2021) developed a personalized multimodal approach to examine predictors for depression in several individuals of which the most frequent predictor was anxiety. However, other frequent factors were physical activity, diet, levels of stress and breathing, sleep and neurocognition. Furthermore, In a meta-analysis amongst college students, Liu and colleagues (2019) analysed twenty-four articles which included longitudinal studies on predictors of depression. They found that positive predictors (meaning factors that increase depression) included among many factors: baseline depression, negative rumination, stressful life events (Liu et al., 2019). It can thus be concluded that using a reductionist approach of predicting state depression based only on anxiety hours prior to measurement does not do justice to the complex intra-individual dynamics of feelings of anxiety and depression. Although this is seen as one of the advantages of ESM, this could be further utilized when designing a future ESM study to assess possible predictor variables for state depression within individuals by including the most interesting aforementioned factors within the daily questionnaires.

Of the factors mentioned in the previous paragraph, the most interesting predictors that can be used within dynamic linear regression in an ESM context are physical activity (also used as a predictor in the example case of McDonald et al., (2020)), levels of stress or stressful events, and negative rumination. Physical activity has been shown to have beneficial effects on alleviating depressive symptoms (Dinas et al., 2011). Levels of stress and stressful events have also been linked to depression which is reflected in the general distress aspect of the model constructed by Clark and Watson (1991) as discussed previously. Lastly, negative rumination can be seen as a part of the cognitive perspective on depression such as the view by Hamilton (1983). Negative (self) rumination also has been shown to play an important role in developing higher levels of depressive symptoms over time after accounting for baseline depression (Nolen-Hoeksema , 2000). These predictors in these longitudinal studies are mostly focused on predicting trait depression. However, as there seems to be a strong overlap between the constructs of trait depression and state depression (Hoppe, 2019) it might be interesting to gather data in an ESM context and use these predictive factors (that are mostly used in cross-sectional research) in a time series analysis to investigate intra-individual predictions of state depression.

Finally, although the usefulness of dynamic linear regression for this specific dataset was found to be limited, and the results of this study cannot be generalized to other ESM studies investigating predictive associations, this study can be seen as a first step to grasp a basic understanding of the possibilities and impossibilities carrying out dynamic linear regression using ESM data. The limitations mentioned in the previous paragraphs, and the implications thereof should be taken into account when designing future ESM studies aiming to analyse intra-individual predictions of state depression. The most important implications being: increasing the length of the study to gather sufficient data points, and controlling for the possibility of autocorrelation. Understanding the possibilities of time series analysis in the context of ESM data can be a next step towards personalised mental healthcare.

Appendix 1: case 2369

Figure 7

Time Plot Displaying Lagged State Anxiety and State Depression over the Study Period of Case 2369

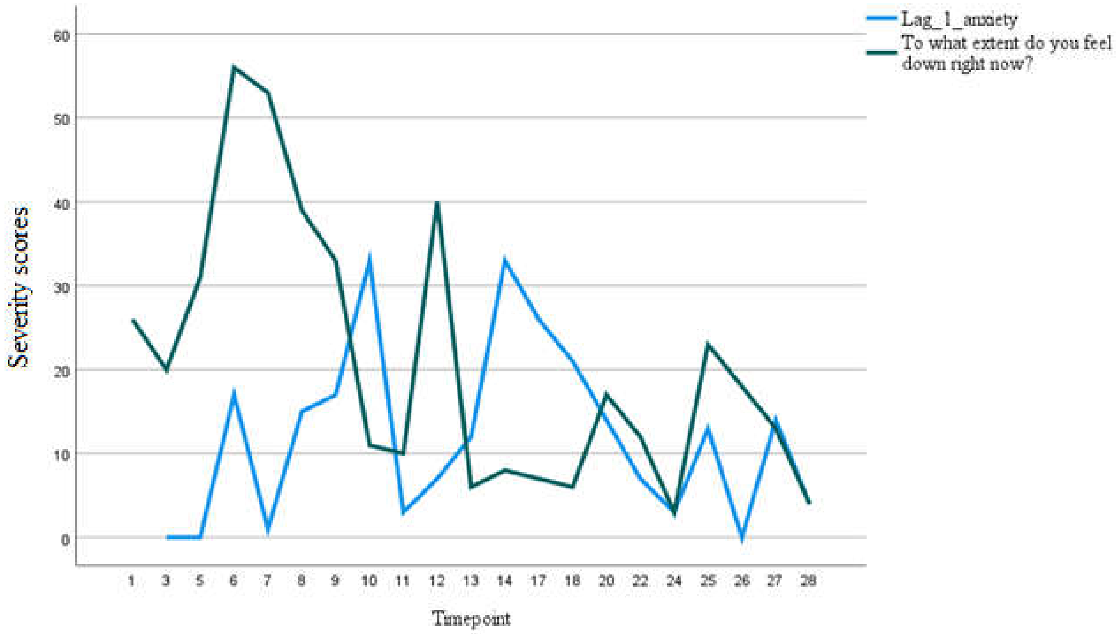


Table 5

Descriptive Statistics of Lagged State Anxiety and State Depression Case 2369

	N	*Range*	*M*	*SD*
Lagged anxiety	20	33	12.00	10.40
State depression	21	53	20.76	15.85

Table 6

Model of Timepoint By State Depression Case 2369

	Model Summary					Parameter Estimates	
Equation	*R Square*	*F*	*df1*	*df2*	*p*	*Constant*	*b1*
Linear	.31	8.67	1	19	.008	36.09	-1.05

Figure 8

Autocorrelation Correlogram for the Outcome Variable State Depression Case 2369

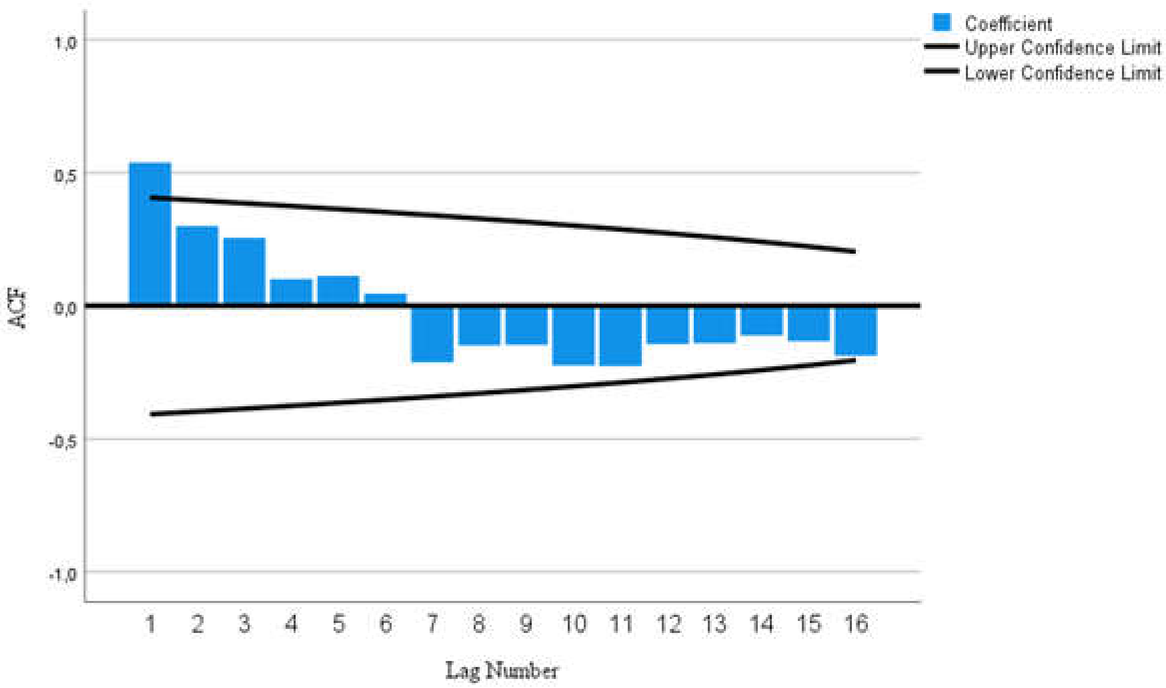
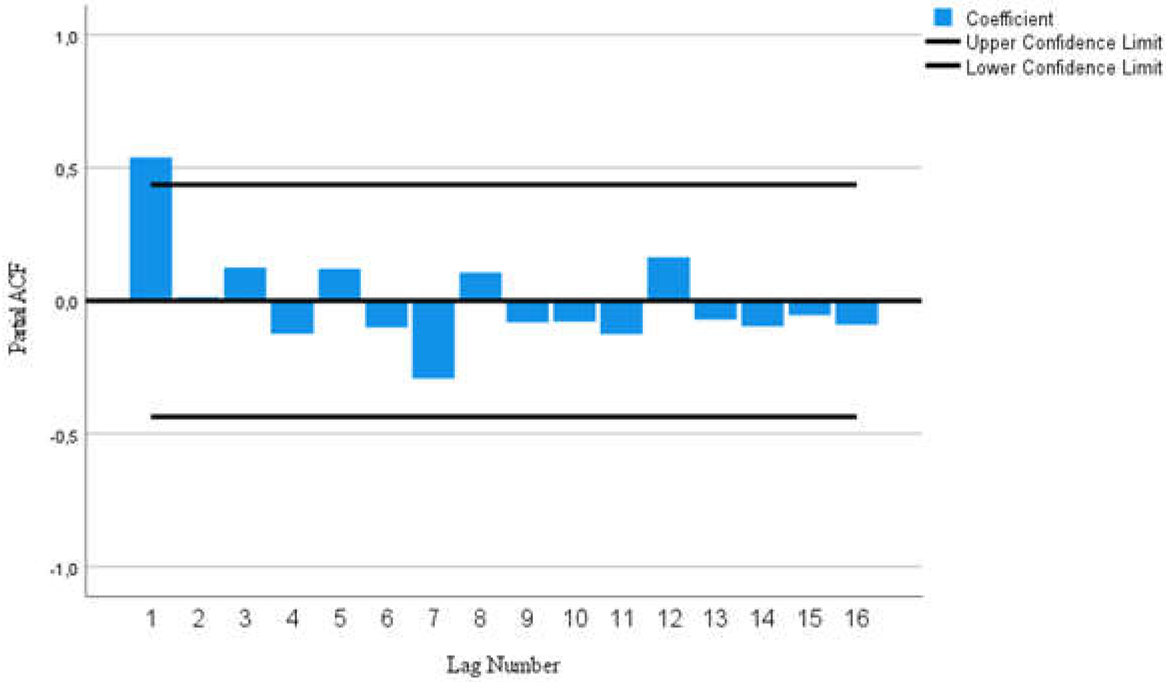


Figure 9

Partial Autocorrelation Correlogram for the Outcome Variable State Depression Case 2369



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