Changing networks

Bringmann, Laura f.; Ariens, Sigert; Ernst, Anja f.; Snippe, Evelien; Ceulemans, Eva

Published in:
Advances in Psychology

DOI:
10.56296/aip00014

advances.in/psychology

May 4, 2024
Doi: 10.56296/aip00014
ISSN: 2976-937X

METHODS

Changing networks: Moderated idiographic psychological networks

Laura F. Bringmann [1], Sigert Ariens [2], Anja F. Ernst [1], Evelien Snippe [3], & Eva Ceulemans [2]

Received: December 27, 2023| **Accepted:** April 15, 2024| **Published:** May 4, 2024| **Edited by:** Hudson Golino

[1]University of Groningen, [2]KU Leuven, [3]University Medical Center Groningen, University of Groningen.
* Please address correspondence to Laura F. Bringmann, University of Groningen, Faculty of Behavioural and Social Sciences, Department of Psychometrics and Statistics, Grote Kruisstraat 2/1, 9712 TS, Groningen, the Netherlands. E-mail: l.f.bringmann@rug.nl.

Idiographic psychological networks based on intensive longitudinal data are increasingly employed in clinical practice. However, these models mainly focus on the associations among psychological variables and changes in these associations, whereas the underlying factors for those changes are not taken into account. The factors contributing to change can be studied with moderation analyses, but although such analyses are standard in clinical research, they are hardly applied in the domain of idiographic networks. Therefore, we implement the fixed moderated time series model to study how networks change depending on context factors. Fixed moderated time series analysis is a vector autoregressive based model, in which all parameters of the model can be moderated, including the innovation structure. As the model is based on the state space framework, it can also directly estimate changes in the mean levels of the variables in the network. With two empirical examples, we demonstrate how the fixed moderated time series model can reveal changing network structures. We show that this idiographic moderation approach not only provides a new way to look at what parameters in a network change over time, but also offers tools to see which factors are associated with the change.

Keywords: personalized models; moderation analysis; networks; time series; vector autoregressive model

1. INTRODUCTION

Intensive longitudinal data (ILD) is increasingly used to study mental health, offering insights into emotional experiences and their fluctuations over time in the context of daily life (Mehl & Conner, 2012; Myin-Germeys & Kuppens, 2022; Trull & Ebner-Priemer, 2013). Such data are collected via techniques such as Ambulatory Assessment (AA), Experience Sampling Method (ESM), and Ecological Momentary Assessment (EMA; Delespaul & Devries, 1987; Kuppens et al., 2022; Palmier-Claus et al., 2011; Trull & Ebner-Priemer, 2020). Considering these opportunities, ILD is not only employed in research settings but is also making its way into clinical practice, including feedback based on ILD (Bartels et al., 2023). Most of this feedback is descriptive. For instance, it reveals how emotions develop over time, presented in a time series plot, and compares a patient's experienced happiness across different contexts, depicted through a bar graph (e.g., Bastiaansen et al., 2018; Kramer et al., 2014; Van der Krieke et al., 2016).

In addition to descriptive feedback, idiographic (i.e., person-specific) psychological networks are increasingly employed in clinical practice to illustrate associations among variables (e.g., symptoms, emotions, cognition, and behavior) over time (Bringmann et al., 2022; Klipstein et al., 2020; Lutz et al., 2018; Piccirillo & Rodebaugh, 2019). The expectation is that a personalized network can uncover risk factors, thus helping prevent mental disorders (Wright & Zimmermann, 2019). For example, identifying whether specific symptoms, such as sleep problems, can lead to other symptoms, such as feelings of sadness, helps reveal a potential vicious cycle between sleep and mood. Finding such interactions could guide interventions; if such dynamics are observed, improving sleep would be a good starting point to enhance mood (Borsboom, 2017a; Borsboom & Cramer, 2013; Cramer & Borsboom, 2015). This concept of not only focusing on the mean level of symptoms but also on how they influence each other (i.e., their temporal dynamics) aligns well with clinical practice (Robinaugh et al., 2020) and has therefore led to a surge in the use of idiographic networks (Bak et al., 2016; Bos et al., 2018; David et al., 2018; Epskamp et al., 2018a; Levinson et al., 2021; Reeves & Fisher, 2020; Tuin et al., 2022; Wichers et al., 2016).

Although therapists and patients express willingness to use idiographic networks, opinions in clinical practice and research are mixed (Bastiaansen et al., 2020; Blanchard & Heeren, 2022; Frumkin et al., 2020; Klipstein et al., 2020; Wichers et al., 2017). Some therapists, for example, have stated that these idiographic networks are challenging to interpret (Weermeijer et al., 2023), and concerns have been raised regarding the reliability of results due to a low number of time points relative to the number of variables in the network structure (Bulteel et al., 2018; Mansueto et al., 2022; Wright & Zimmermann, 2019).

More fundamentally, the gap from psychological network theory to the application of the right network model has been highlighted (Bringmann, 2021; Bringmann & Eronen, 2018; Burger et al., 2022a;

Fried, 2020; Wright & Woods, 2020). The current underlying model of personalized networks is a form of the vector autoregressive (VAR) model. This model captures the temporal dynamics between the elements of the network through lagged relationships: the predicted relationships between a variable at one time point and variables at the next time point (Bulteel et al., 2016; Epskamp et al., 2018b). While the network illustrates how variables, such as symptoms or emotions, are associated over time, it does not depict change in the network structure. In other words, the connections between the variables in the network and their mean level are assumed to be time-invariant (i.e., stationary; Bringmann et al., 2018; Lütkepohl, 2007).

However, change is often relevant for patients and therapists using such networks. Identifying which variable in the network leads to changes in the network, so that the network structure (the temporal dynamics) can develop into a healthier state, is frequently stated as a central goal in network theories (Borsboom, 2017a). For instance, improvements in sleep may lead to a change in the network that results in more positive mood (Borsboom, 2017b).[1] In general, as patients are studied for longer time periods—over the past decade, studies have extended to around 400 time points over periods exceeding four months in various patient groups—there is not only an anticipation to observe changes in mood, behavior, and cognition, but this change is of primary interest to be modeled for these patients (e.g., Bak et al., 2016; Bos et al., 2020; Bringmann et al., 2021; Burger et al., 2022b; Dejonckheere et al., 2021; Helmich et al., 2023; Smit et al., 2023; Wichers et al., 2016, 2020).

Recent developments in psychological networks, and the underlying models stemming from time series analyses more generally, have seen advancements in the form of time-varying versions of VAR models, where the mean and temporal dynamics are allowed to change over time (Albers & Bringmann, 2020; Bringmann et al., 2018; Cabrieto et al., 2019; Chen et al., 2021; Chow, 2019; Haslbeck et al., 2021a; Molenaar et al., 2016). However, researchers developing and using such models have primarily focused on when and where there is a change in the network structure, rather than the factors underlying this change (Haslbeck et al., 2022). In other words, with time-varying network models, researchers have only aimed to determine if certain connections are changing over time and when they do so (e.g., Bak et al., 2016; Wal et al., 2023; Wichers et al., 2020).

Nevertheless, interests in clinical research include not just when and where a change occurs, but also why the change occurs. Consequently, it is more in line with clinical thinking to investigate not just if a patient's mood and the connection between, for instance, feeling down and cheerfulness changes in the network, but also if certain (contextual) factors, such as being with others or alone, influence mood or connections in the network (Bringmann, in press; Piot et al., 2022). This in turn can not only provide insights into when a clinical intervention is needed, but also can give guidance on which factors can help in improving one's mood (Myin-Germeys et al., 2009; Wichers et al., 2011). For

[1] Note that there is a difference between changes and fluctuations (Bringmann et al., 2017). A standard VAR model cannot capture changes, but only fluctuations: For example, if a fluctuation of sleep in the positive direction happens after a positive fluctuation of mood, this is represented by a positive edge from sleep to mood.

example, by identifying individuals who can lift the patient's mood through offering social support (Fischer & Van Kleef, 2010; Stadel et al., 2023).

The most common way of studying whether certain factors contribute or are associated with change is by using a form of interaction analysis—identifying relevant moderators. Although moderation analyses are standard practice in clinical research (e.g., Bolger & Laurenceau, 2013; Chen et al., 2016) and have been developed for cross-sectional networks (Haslbeck, 2022; Haslbeck et al., 2021b), they are hardly applied in clinical feedback or idiographic networks in general.

Additionally, models currently available for fitting time-varying networks are not suitable to test the moderation of all parameters in a VAR model (Bringmann et al., 2018; Haslbeck et al., 2020, 2022). VAR models based on linear or additive regression allow for moderating the lagged connections within the network (i.e., the temporal dynamics), but not the innovation structure, in other words the error part of the network model (Bringmann et al., 2018; Swanson, 2023). However, it has been argued that all parts of a network should be studied and can be relevant for clinical research and practice (Epskamp et al., 2018a). For example, the innovation variance not only reflects the extent to which the process of interest (e.g., someone's cheerfulness) varies due to unobserved factors (e.g., the weather), but can also reflect reactivity to these factors (Jongerling et al., 2015; Koval et al., 2021). It may be, for example, that on stressful days unobserved factors, such as the weather or bad news, result in more variability in mood than similar unobserved factors on non-stressful days. Thus, relating changes in the innovation network structure to moderators (e.g., daily stress) is arguably informative for the patient and the therapist.

Furthermore, most idiographic networks do not take into account changes in the mean. This is partly due to the fact that mean changes can only be estimated indirectly, via the intercepts and temporal dynamics. Thus, a model that can immediately depict changes in the mean levels of variables could improve the clinical utility of idiographic networks. Therefore, we now turn to the fixed moderated time series model. This is a VAR-based model in which all parameters of the model can be moderated, including the innovation structure (Adolf et al., 2017). As the model is based on the state space framework, it can also directly estimate changes in the mean levels of the variables in the network.

In the following sections, we will first provide the necessary methodological background by introducing VAR-based networks in greater detail. Subsequently, we will explain the fixed moderated time series model, the model underlying this moderated idiographic network approach. We will then demonstrate how the fixed moderated time series model can be fitted to empirical data and reveal changing network structures with two examples. Specifically, we will test whether social interaction (binary moderator) and sleep quality (continuous moderator) have an impact on the emotion network of patients with depression. Furthermore, we will illustrate where in the network these changes due to the moderator manifest, such as in the connections between variables or solely in the mean levels.

The empirical data used to showcase the moderated idiographic network models come from two patients receiving treatment for depression in the TRANS-ID Recovery study, with over 400 time points collected for each individual (Helmich et al., 2023). While the data cannot be shared due to its sensitive nature (many observations within patients that cannot be fully anonymized), they are available on reasonable request. All code can be found on the Open Science Framework (OSF): https://osf.io/3aetv/?view_only=None.

2. METHODS BACKGROUND

2.1 VAR-based networks

The vector autoregressive (VAR) model is a variation of multiple regression where the independent variables are lagged forms of the dependent variables (Chatfield, 2003; Hamaker & Dolan, 2009; Lütkepohl, 2007; Stadnitski & Wild, 2019). There are as many equations in the model as dependent variables, and the dependent variable within each equation is a function of its own lagged value and the lagged values of all other dependent variables. The term 'lagged' refers to the fact that the values of the independent variables are the values of the dependent variables at previous time points. Lag-1 (i.e., one time point back) is the most common form of a VAR model (i.e., VAR (1); Bringmann, 2021). As the VAR(1) model is formulated in discrete time, it assumes that the time intervals between time points are equal across observations, for example, the time between successive time points is always three hours (Haan-Rietdijk et al., 2017).

A VAR(1) model can be written in matrix form as follows (Brandt & Williams, 2007):

$$y_t = \alpha + \Phi y_{t-1} + \epsilon_t. \tag{1}$$

with m variables measured at $t = 1, 2, 3, \dots, T$ different time points (i.e, occasions), where the values on the m variables at time point t are in a $(m \times 1)$ vector $y_t = (y_{1,t}, y_{2,t}, \dots, y_{m,t})'$, containing the dependent variables at time t. The values in y_t at time t depend on the lagged values, y_{t-1}, through autoregressive and cross-lagged effects, and these effects are captured by the matrix Φ, an $m \times m$ matrix. The intercept terms are contained in α, a column vector of dimensions $(m \times 1)$. The column vector ϵ_t, also of dimensions $(m \times 1)$, represents the innovation terms or random shocks.

In its simplest form, the VAR model consists of two variables (hence, $y_t = (y_{1,t}, y_{2,t})'$), such as cheerful ($Che$) and down ($Dow$), representing mood:

$$\begin{aligned} Che_t &= \alpha_1 + \phi_{11} Che_{t-1} + \phi_{12} Dow_{t-1} + \epsilon_{1,t} \\ Dow_t &= \alpha_2 + \phi_{21} Che_{t-1} + \phi_{22} Dow_{t-1} + \epsilon_{2,t}. \end{aligned} \tag{2}$$

In a VAR model, the focus lies on capturing the temporal dynamics and dependence among variables. The diagonal elements of the Φ matrix in Equation (1) contains the autoregressive effects, denoted as ϕ_{11} and ϕ_{22} in Equation (2). These autoregressive effects provide insights into the carryover effect of mood on itself over time, controlling for the cross-lagged effects (as they are analogous to partial coefficients in standard multiple regression). For instance, a positive autoregressive effect for the variable cheerfulness suggests that the cheerfulness value at a previous time point, $t-1$, predicts and is similar to its current time point, denoted as t (controlling for the cross-lagged effects). A positive autoregressive effect is commonly known as inertia (Kuppens et al., 2010; Suls et al., 1998). On the contrary, an autoregressive parameter of zero indicates the absence of a carryover effect from one time point to the next, and therefore, mood would not be predicted by its own previous values.

The off-diagonal elements of the Φ matrix in Equation (1) represent the cross-lagged effects (ϕ_{12} and ϕ_{21} in Equation (2)).[2] These effects indicate the direction and strength of the temporal dependence between the variables, controlling for the autoregressive effects and other cross-lagged effects (Bringmann et al., 2018). In this context, they represent the predictive or spillover effect of cheerful at time point $t-1$ on down at the subsequent time point t and the other way around (controlling for the autoregressive and other cross-lagged effects).

Apart from the temporal dynamics the model also has two intercepts (α_1 and α_2 in Equation (2) contained in α in Equation (1)) that together with the lagged effects (contained in Φ) can be used to determine the means of the process (μ_1 and μ_2 contained in μ):

$$\mu = (I - \Phi)^{-1}\alpha. \tag{3}$$

Here, I represents a $m \times m$ identity matrix. For our two variables we need a 2×2 identity matrix and thus the equation becomes

$$\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \right)^{-1} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \tag{4}$$

As the intercepts, α, often do not have a substantive interpretation, researchers prefer interpreting the means of the time series, μ. For example, to summarize how cheerful the person was on average over the whole time period. The mean is also interpreted as the equilibrium (or attractor) of a time series (De Haan-Rietdijk et al., 2016; Hamaker et al., 2018; Li et al., 2022; Oravecz et al., 2011).

In a VAR process, time series fluctuate around their means due to the innovations ($\epsilon_{1,t}$ and $\epsilon_{2,t}$). The innovations thus reflect random perturbations that affect the time series at every time point due to internal or external situations not being included in the model. Or in other words, they capture

[2] Also known as crossregressive effects.

the part of the current observations y_t that cannot be explained by the previous observations y_{t-1}. These innovations then carry over in time pushing the process away from its mean(s) and thus giving rise to the fluctuations around it. The rate at which an individual returns from these perturbations back to the mean or equilibrium is determined by the temporal dynamics (Φ; Ariens et al., 2020). Importantly, when measurement error is not separately modelled, as is the case in the models we discuss here, the innovations also include measurement error (Koval et al., 2021; Schuurman et al., 2015). The innovations are assumed to follow a multivariate normal distribution, with means of zero and a symmetric positive definite covariance matrix Σ.

Therefore, it is possible for correlations to occur between innovations. In such cases, the covariance matrix of the innovation matrix Σ contains non-zero values for symmetric elements σ_{12}^2 and σ_{21}^2. Correlated VAR innovations could arise for many reasons. For instance, they could arise when unobserved variables (variables not explicitly considered in the model), such as bad weather, simultaneously influence both feelings of cheerful and down, leading to an association between them (Schuurman & Hamaker, 2019). A second possibility is that there are contemporaneous relations (lag-0) between variables, which cannot be modeled directly in a standard vector autoregressive model (for an example of a model that specifies such relationships explicitly, see Beltz & Gates, 2017). Third, incorrect model specifications can also lead to correlations between innovations. For instance, using an incorrect time lag can contribute to these correlations, as the true relationship might occur at a different time scale than what is assumed in the model (Bringmann et al., 2022).

Given that there are numerous factors leading to correlations between innovations – unobserved variables, misspecified time lags, unmodeled contemporaneous effects or insufficient time lags – it is crucial to emphasize that contemporaneous effects and correlated innovations are not interchangeable terms (Brandt & Williams, 2007; Lütkepohl, 2007). This is why we will not call networks based on innovation correlations contemporaneous networks (for a different kind of interpretation, see Epskamp et al., 2018a). Although psychological network literature commonly focuses only on the parameters indicating the relationship between variables, we show how all parameters including the mean and innovation variances can be visualised as a network in Figure 1.

Finally, an important assumption in order to use the VAR model is that the data is covariance stationary (Bringmann et al., 2018; Chatfield, 2003; Hamilton, 1994). In the case of a Gaussian distribution, this means that the first two moments, the mean and the variance, do not change over time. Concretely, for the bivariate VAR(1) model, this entails that although the process is expected to fluctuate, the mean, autoregressive, cross-lagged effects, and (co)variances of the innovations are assumed to be time-invariant. There are several ways to relax the assumption of fixed parameters over time, such as using splines or kernel methods to allow for time-varying parameters (e.g., using Φ_t instead of Φ; see also Ariens et al., 2020; Bringmann et al., 2017; Haslbeck et al., 2020). We focus in the next section on relaxing the assumption of time-invariant parameters through the fixed moderated time series analysis approach (Adolf et al., 2017).

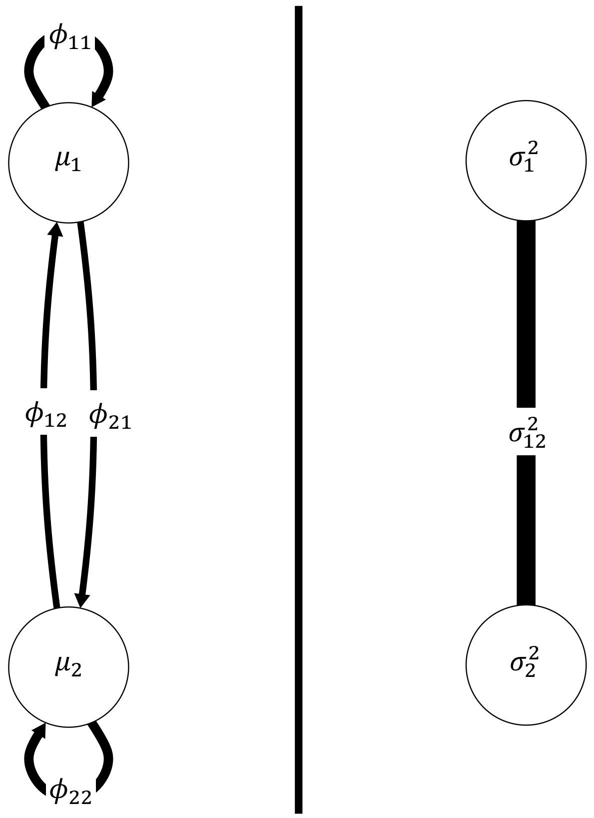
2.2 Fixed Moderated Time Series Analysis

2.2.1 Moderation analysis

In moderation analysis, interaction effects are used to examine how the relationship between the dependent and independent variables is influenced or altered by a third variable, the moderator (Cohen et al., 2003; Dawson, 2014). Extending this concept to the time series modeling domain, particularly in the context of the (vector) autoregressive model, we investigate, in the univariate case, the relationship between y_t and its lagged version (y_{t-1}), as well as whether this relationship is influenced by

Figure 1

Following the conventions in the psychological network literature, nodes and edges are used to represent the vector autoregressive (VAR) model (Borsboom et al., 2021). In this network representation, we illustrate the complete VAR model for two variables $y_{1,t}$ and $y_{2,t}$, in this case Cheerful and Down. On the left side, edges represent the autoregressive coefficients (ϕ_{11} and ϕ_{22}) and cross-lagged effects (ϕ_{12} and ϕ_{21}). The parameters μ_1 and μ_2 in the nodes represent the means of the two variables. On the right side of the figure, the innovation structure is represented, which includes the variances of the innovations (σ^2_ϵ), denoted as σ^2_1 and σ^2_2 in the nodes. Additionally, the edge represents the covariance between the innovations, denoted as σ^2_{12} (which is identical to σ^2_{21}, as the connection is undirected).



a moderator at the same time point (referred to here as x_t). As we focus on moderation in time series analysis, our moderator is also a covariate or variable that can vary over time. A time-varying covariate $X = (x_1, \ldots, x_T)$ could be, for instance, whether or not one is in the company of others. Following the standard multiple regression framework, moderation analysis includes both the main effect x_t, as well as its interaction effect with the independent variable of interest; in this case we multiply y_{t-1} by moderator x_t. In this way, potential changes in the intercept (α) and autoregressive effect (ϕ) due to the moderator can be captured. Since the moderator values are fixed and not estimated, we make the strong assumption that the moderator is error-free. This assumption implies that any measurement error in the moderator could result in inaccurate model estimations (Adolf et al., 2017). This approach to time series analysis, which utilizes a fixed moderator, is referred to as **fixed moderated time series analysis** (Adolf et al., 2017). In the univariate case, a fixed moderated autoregressive model can be formulated as follows:

$$y_t = \alpha + \phi y_{t-1} + \beta_\alpha x_t + \beta_\phi y_{t-1} x_t + \epsilon_t. \tag{5}$$

The main effect of x_t is indicated by β_α and the interaction effect of x_t with the lagged variable y_{t-1} by β_ϕ. Rewriting the formula as follows, it becomes clear that both the intercept and the autoregressive effect are moderated by x_t (see Ariens et al., 2022):

$$y_t = (\alpha + \beta_\alpha x_t) + (\phi + \beta_\phi x_t) y_{t-1} + \epsilon_t. \tag{6}$$

Therefore, we could also rewrite the formula as

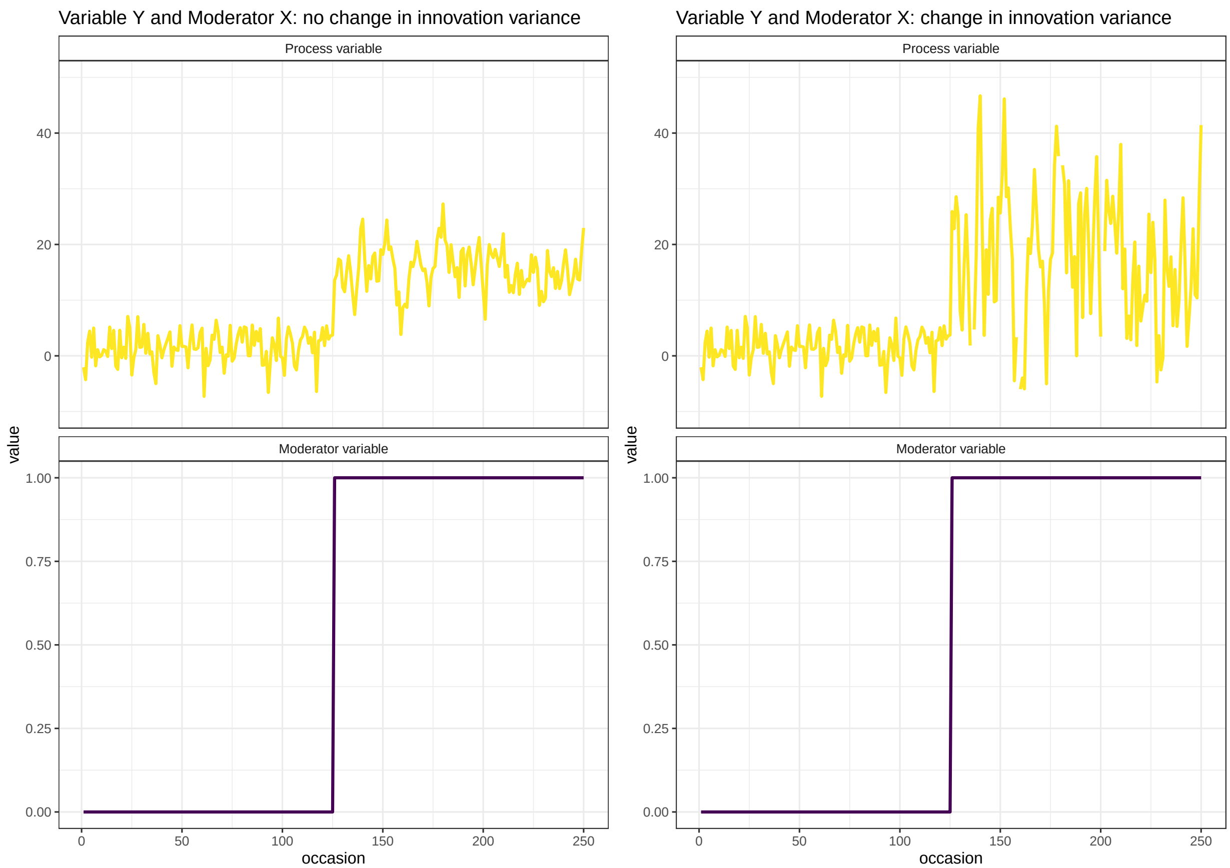
$$y_t = \alpha_t + \phi_t y_{t-1} + \epsilon_t \tag{7}$$

where both the intercept and the autoregressive effect now can vary over time (as indicated with t, added to both parameters) due to the moderator x_t, with α_t= $\alpha + \beta_\alpha x_t$ and $\phi_t = \phi + \beta_\phi x_t$. The intercept and autoregressive effect are thus specified to be linear functions of the moderator (x_t). For instance, in Equation (5), β_ϕ indicates how much the autoregressive effect of y_{t-1} on y_t changes as x_t increases or decreases by one unit (Hayes and Montoya, 2017). In addition, it does not have to be presumed that the moderator has a contemporaneous effect, instead it can also have a lagged effect, such as a lag-1 effect, where x_{t-1} is included in the equations above instead of x_t (Adolf et al., 2017; Ariens et al., 2022).

Furthermore, although not standard practice, moderation of the innovation variance can be of substantial interest. As before, the innovations (ϵ_t) in the AR model are normally distributed with a mean of zero and a variance of σ^2 ($\epsilon_t \sim N(0, \sigma^2)$). Moreover, as shown in Figure 2, the innovation variance

Figure 2

On the left, the innovation variance of variable $Y = (y_1, \ldots, y_T)$ is not moderated by variable $X = (x_1, \ldots, x_T)$. On the right, the innovation variance is moderated by variable X. As a result, when the binary moderator is 'on' after 125 time points, the innovation and overall variance is higher compared to the left-side figure. The code for this simulated example is available in the file Simulated_example_figure2.html.



is part of the overall variability of $Y = (y_1, \ldots, y_T)$, and therefore codetermines the variance (and thus standard deviation) of Y (ψ^2), which is equal to Chatfield, 2003; Jongerling et al., 2015:

$$\psi^2 = \frac{\sigma^2}{1 - \phi^2}. \tag{8}$$

The innovation variance can change as the process of interest (Y, e.g., someone's cheerfulness) varies due to shifting unobserved factors. For example, when someone is in the company of others, more unobserved factors may influence cheerfulness predictions compared to when they are alone, leading to a higher innovation variance and a higher overall variability (i.e., standard deviation of Y; see Figure; 2). A reason could be that, in a social context, additional factors like the mood of others may not be accounted for, but are relevant for predicting a person's cheerfulness. Notably, in the case where Y represents an emotion, the innovation variance can also reflect the variety in reactivity to these unobserved factors (Hamaker et al., 2018). For instance, it may be that on stressful days unobserved factors, such as the weather or bad news, result in more variation in affect than similar unobserved factors on non-stressful days, again increasing the innovation variance and overall variability (see Figure 2; Jongerling et al., 2015; Koval et al., 2021).

In all these cases, the innovation variance, denoted as σ^2, changes over time t (σ_t^2), and thus reflects heteroskedasticity (Cohen et al., 2003). By incorporating one or multiple moderator variables (X), it becomes possible to also model changes in the innovation variance (see again Figure 2; Adolf et al., 2017):

$$\sigma_t^2 = (\sigma^2 + \beta_{\sigma^2} x_t). \tag{9}$$

This enables the identification of changes over time in the variability of Y (e.g., cheerfulness) due to exposure and/or reactivity to unobserved factors that are not included in the model.

Moving the fixed moderated time series analysis to the multivariate and thus network realm, we would get, again in its simplest form, a two variable system with the following equations (the covariance matrix of the innovations being Σ_t):

$$\begin{aligned} Che_t &= \alpha_{1,t} + \phi_{11,t} Che_{t-1} + \phi_{12,t} Dow_{t-1} + \epsilon_{1,t} \\ Dow_t &= \alpha_{2,t} + \phi_{21,t} Che_{t-1} + \phi_{22,t} Dow_{t-1} + \epsilon_{2,t} \end{aligned} \tag{10}$$

In this vector autoregressive model, all parameters are again allowed to change (denoted by the lowercase $_t$) conditional on a moderator x_t:

$$\begin{aligned} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix}_t &= \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + x_t \begin{bmatrix} \beta_{\alpha,1} \\ \beta_{\alpha,2} \end{bmatrix} \\ \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}_t &= \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} + x_t \begin{bmatrix} \beta_{\phi,11} & \beta_{\phi,12} \\ \beta_{\phi,21} & \beta_{\phi,22} \end{bmatrix} \\ \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix}_t &= \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 \end{bmatrix} + x_t \begin{bmatrix} \beta_{\sigma^2,11} & \beta_{\sigma^2,12} \\ \beta_{\sigma^2,21} & \beta_{\sigma^2,22} \end{bmatrix}. \end{aligned} \tag{11}$$

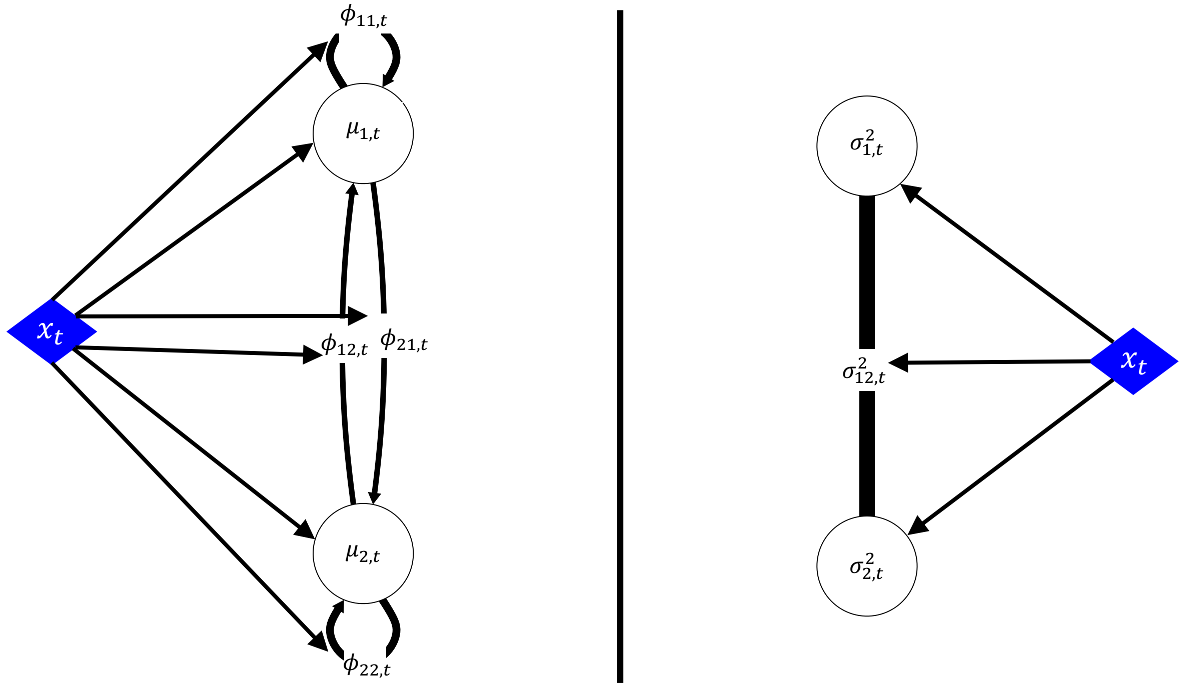
Furthermore, instead of the intercept α, the mean can be written, based on Equation (3), this time using the moderated Φ_t and α_t:

$$\mu_t = (I - \Phi_t)^{-1} \alpha_t. \tag{12}$$

This results in indirect estimation of the moderated μ_t. In the next section, an alternative method for directly inferring the mean is introduced. The fixed moderated time series model for two variables can again be visualized as a network (see Figure 3). Compared to Figure 1, the moderator x_t has now been included, with arrows indicating that all parameters are moderated.

Figure 3

Moderated network. In this network representation we illustrate the complete VAR model for two variables $y_{1,t}$ and $y_{2,t}$, in this case Cheerful and Down, conditioned on a moderator x_t (indicated by the blue diamond shape). On the left side, edges represent the changing autoregressive coefficients, ($\phi_{11,t}$ and $\phi_{22,t}$) and cross-lagged effects ($\phi_{12,t}$ and $\phi_{21,t}$). The parameters $\mu_{1,t}$ and $\mu_{2,t}$ in the nodes represent the means of the two variables. On the right side of the figure, the innovation structure is represented, which includes the changing variances of the innovations (denoted as $\sigma^2_{1,t}$ and $\sigma^2_{2,t}$ in the nodes. Additionally, the edge represents the changing covariance between the innovations, denoted as $\sigma^2_{12,t}$ (or $\sigma^2_{21,t}$ since the connection is undirected).



2.3 State space estimation

The estimation of a fixed-moderated time series analysis can, for the most part, be carried out using the standard multiple regression ordinary least squares approach. However, when the innovation variances are changing, the ordinary least squares approach becomes inadequate because it cannot accurately estimate the changing innovation variance. This inaccuracy cascades into the incorrect estimation of variability over time ψ_t (see also Equation (8)), as an accurate estimation requires the innovation variance to be able to change over time. Furthermore, while the estimates of the changing intercept α_t, autoregressive parameter ϕ_t (and in case of a multivariate process, also the cross-lagged parameters), and μ_t are still accurately estimated, the standard errors will be biased (see also Cohen et al., 2003; Hayes et al., 2007; Jongerling et al., 2015). Consequently, this can lead to erroneous conclusions about whether these parameters exhibit significant changes or not.

In this section, we therefore introduce the alternative state space framework.[3] More specifically, we will utilize the model developed by Adolf et al., 2017, which uses frequentist state space inference. State space modeling is a flexible framework that differs from standard ordinary least squares estimation, among other things, in that it allows for the modeling of latent variables. In this regard, it is similar to structural equation modeling. However, state space modelling was specifically developed for the time domain (see Chow et al., 2010 for similarities and differences between the two approaches).

According to the state space framework, two types of time series — latent and observed — describe the process that requires modeling. First there is the latent state of the process, aiming at capturing the true but not directly observable process η_t, for instance the precise value of feeling cheerful of an individual at time point t. It is assumed that the dependence or autocorrelation among the observations is induced by these latent states, the dependency in the latent affect process (Shumway & Stoffer, 2017). Second, there is the imperfectly measured observed time point y_t, such as the observed affect value that still contains measurement error. The observed measurement y_t is then related to the latent state η_t through Equations (13) and (14) (Auger-Méthé et al., 2021), commonly referred to as the measurement equation and the state equation respectively (Chua & Tripodis, 2022). This enables the distinction between process fluctuations due to dynamic error (i.e., innovations) and measurement error (Schuurman & Hamaker, 2019). The Appendix provides a comprehensive illustration of how the state and measurement equations can be broadly formulated to encompass various time series models, including those with time-varying parameters and measurement errors. It is important to note that, for the sake of simplicity, we have omitted measurement error in our model. We will revisit this point in the discussion section.

In our specific case, we can first write our standard VAR(1) model in state space form, with the one difference that now the mean can be estimated directly and does not need to be inferred from the intercept and autoregressive effects. This results in the measurement equation, where the mean is directly estimated (see also the Appendix and Schuurman et al., 2015)

$$\begin{aligned} y_{1,t} &= \mu_1 + \eta_{1,t} \\ y_{2,t} &= \mu_2 + \eta_{2,t}, \end{aligned} \tag{13}$$

and the state equation where there is no longer an intercept needed

[3] There are other methods available for estimating fixed moderated time series analyses, such as models using a Bayesian framework.

$$
\begin{aligned}
\eta_{1,t} &= \phi_{11}\eta_{1,t-1} + \phi_{12}\eta_{2,t-1} + \epsilon_{1,t} \\
\eta_{2,t} &= \phi_{21}\eta_{1,t-1} + \phi_{22}\eta_{2,t-1} + \epsilon_{2,t}.
\end{aligned} \tag{14}
$$

Building on our previous examples, both $y_{1,t}$ and $\eta_{1,t}$ represent the variable cheerful (the observed and latent value respectively), whereas $y_{2,t}$ and $\eta_{2,t}$ pertain to the variable down (the observed and latent value respectively). η_t indicates that these variables are no longer being modeled as observed but as latent states using the vector autoregressive process (see Figure 4).

The fixed moderated model estimated in the state space framework can then be written with the following measurement equation

$$
\begin{aligned}
y_{1,t} &= \mu_{t,1} + \eta_{1,t} \\
y_{2,t} &= \mu_{t,2} + \eta_{2,t},
\end{aligned} \tag{15}
$$

and state equation

$$
\begin{aligned}
\eta_{1,t} &= \phi_{11,t}\eta_{1,t-1} + \phi_{12,t}\eta_{2,t-1} + \epsilon_{1,t} \\
\eta_{2,t} &= \phi_{21,t}\eta_{1,t-1} + \phi_{22,t}\eta_{2,t-1} + \epsilon_{2,t}.
\end{aligned} \tag{16}
$$

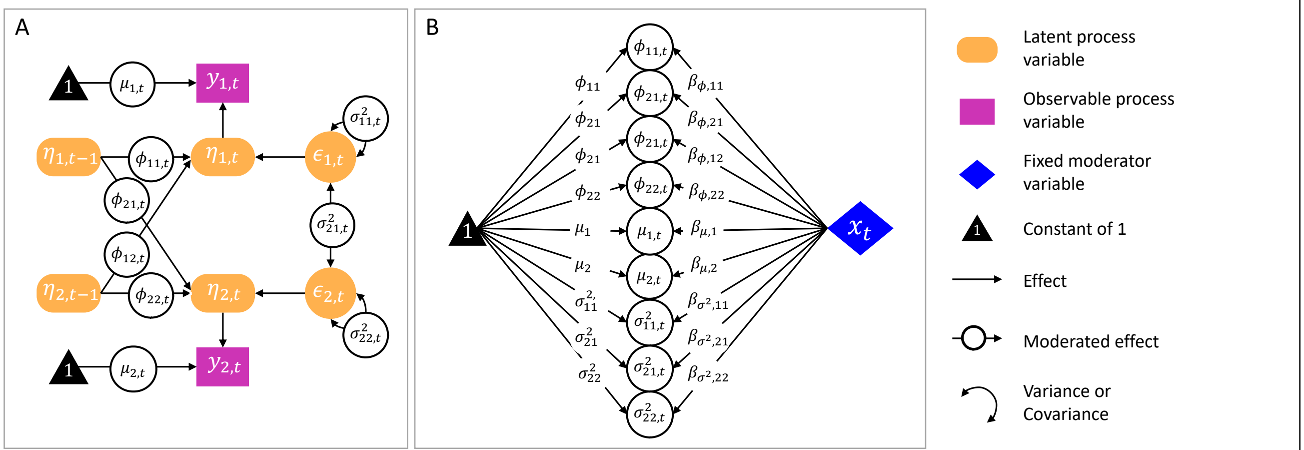
with the covariance matrix of the innovations Σ_t. Once more, all parameters (indicated by the subscript $_t$) can vary based on a moderator x_t:

$$
\begin{aligned}
\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}_t &= \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + x_t \begin{bmatrix} \beta_{\mu,1} \\ \beta_{\mu,2} \end{bmatrix} \\
\begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix}_t &= \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} + x_t \begin{bmatrix} \beta_{\phi,11} & \beta_{\phi,12} \\ \beta_{\phi,21} & \beta_{\phi,22} \end{bmatrix} \\
\begin{bmatrix} \sigma^2_{11} & \sigma^2_{12} \\ \sigma^2_{21} & \sigma^2_{22} \end{bmatrix}_t &= \begin{bmatrix} \sigma^2_{11} & \sigma^2_{12} \\ \sigma^2_{21} & \sigma^2_{22} \end{bmatrix} + x_t \begin{bmatrix} \beta_{\sigma^2,11} & \beta_{\sigma^2,12} \\ \beta_{\sigma^2,21} & \beta_{\sigma^2,22} \end{bmatrix}.
\end{aligned} \tag{17}
$$

which can be visualized as a path diagram (see Figure 4), illustrating the state space structure, or again as a more straightforward representation in the form of a simplified network, as shown in Figure 3.

Importantly, the way in which we estimate the mean has implications for interpreting the moderator's effect in the system. While the unmoderated mean remains the same whether it is indirectly inferred or directly estimated, the moderated mean takes on a different value and interpretation, depending on whether it is derived directly via Equation (3) or via Equation (13). This distinction arises because, as

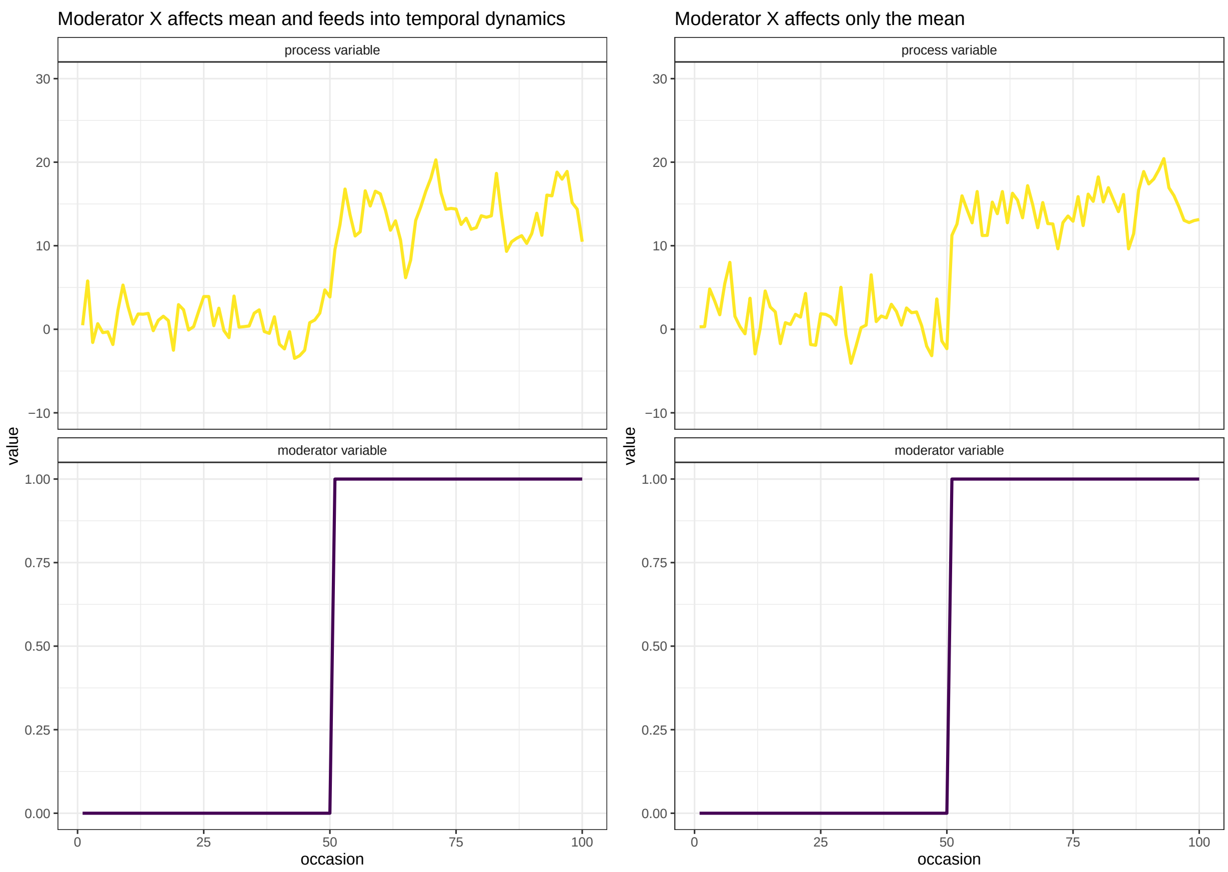
Figure 4
This path diagram represents the state space representation of a VAR model with two variables, $y_{1,t}$ and $y_{2,t}$. Panel A illustrates the direct modeling of the time-varying means ($\mu_{1,t}$ and $\mu_{2,t}$) instead of requiring inference from intercepts. Additionally, panel A highlights two distinct equations: the measurement equation, which models the observable process ($y_{1,t}$ and $y_{2,t}$), and the state or transition equation, which models the latent process ($\eta_{1,t}$ and $\eta_{2,t}$) following a VAR model. Panel B illustrates how the time-varying parameters depend on a moderator variable (i.e., the fixed moderator variable, x_t). Furthermore, it shows that all moderated parameters have an intercept when being modelled (i.e., constant of 1). For example $\mu_{1,t} = \mu_1 + \beta_{\mu,1} x_t$ where $\mu_{1,t}$ has the intercept μ_1. See also Equation (17).



seen in Equations (13) and (14), as well as Figure 3, the moderated effect on the means μ_t is estimated in a distinct equation, the measurement equation. Consequently, the moderation effect influences the means μ_t at time point t, but this moderated effect does not propagate further into the system, thereby not affecting future time points via autoregressive and cross-regressive effects (Ernst et al., 2023). This can be seen in seen in Figure 5: in the model where the mean is estimated directly (the right side of the figure), we see much less peaks and valleys after the moderator is introduced, and the change is more abrupt. In contrast, in the model where the mean is estimated indirectly (the left side of the figure), there are higher peaks and values, reflecting increase in the autocorrelation, and the change into the new mean is more gradual (Ernst et al., 2023).

The consequence of this is that, even though the moderated mean can be directly estimated, it neither holds the same value nor interpretation as when it is indirectly inferred (see Simulated_example_meanVSintercept_fig5.html): fitting the mean directly results in a mean of 12.9 instead of 15). However, within the state space model, one can opt to estimate the fixed moderated model not with the mean but simply with the intercept, as shown in Equation (10). We will compare both estimations in the empirical example.

Figure 5
A simulated example of two different effects of the moderator for one individual (for the code of the simulated example see Simulated_example_meanVSintercept_fig5.html*). Left we see that the mean, estimated indirectly (via Equation (10) and (12) estimating the intercept first), feeds into the temporal dynamics, leading to higher peaks and valleys after the moderator is introduced. On the right side, when the mean is estimated directly (via Equation (13)), the dynamic pattern stays the same before and after the moderator is introduced and merely the mean level changes.*



2.3.1 The Kalman filter

To estimate the parameters of the fixed moderated time series model, Adolf et al. (2017) proposed applying the Kalman filter, which is commonly used to estimate the parameters of state space models (Durbin & Koopman, 2012; Kalman, 1960).

The basic idea of a Kalman filter is that uncertainty or noise in our measurements is "filtered" by comparing these measurements to the scores that one would expect based on the dynamics of the process estimated from previous measurements (Rhudy et al., 2017). In other words, the filter generates predictions of future measurements and updates these based on the actual observations at the respective time points. These updates then allow to re-estimate the model parameters governing the process dynamics. In statistical terms, the Kalman filter algorithm operates recursively, continuously updating the estimate of the state vector η_t from the previous time point $t-1$ to the current time point t whenever new observations y_t become available (Song & Ferrer, 2009). The Kalman filter is used to estimate the latent variables η_t and gives maximum likelihood estimates for all parameters in the model (Hamaker & Grasman, 2012; Harvey, 1990).

To initiate the Kalman filter and calculate the maximum likelihood, it is necessary that the initial distribution, the latent means μ_0 and the associated covariance matrix Σ_0 is given for time point $t = 0$. Typically this initial distribution is unknown and therefore for the initial condition the mean and covariance of the observed variables are used (Gu et al., 2014; Song & Ferrer, 2009). Besides the initial distribution, all estimated parameters (the circles in Figure 4) need to be given starting values (Adolf et al., 2017). These initial condition and starting values tend to have a minimal impact on series of sufficient length as their effects decay exponentially over time (Durbin & Koopman, 2012).

One significant advantage of the Kalman filter and state space modeling is their ability to handle missing values seamlessly within time series data (Gu et al., 2014; Hamaker & Grasman, 2012). In the presence of missing data, the Kalman algorithm simply delays updates until new information becomes available, at which point it incorporates the observed values. This property also proves valuable in dealing with unevenly spaced measurements, as it can introduce missing values to align measurements at regular intervals Haan-Rietdijk et al., 2017; Hamaker et al., 2018. For instance, it can ensure a consistent three-hour gap between observations (similar to the approach in Dynamic Structural Equation Modeling, DSEM, within a Bayesian context McNeish & Hamaker, 2019. The Kalman filter makes a prediction of the next observation, based on the lagged predictors. This prediction is compared to the observation for that occasion and updated in light of it. If there is no observation, the Kalman filter simply continues with the prediction it had; if there is an observation, the Kalman filter continues with the updated prediction. In both cases, the filter moves forward to the next occasion and now makes a prediction based on the observations and predictions of the previous occasion. This method ensures that no observations are lost, even when many time points have missing values in the variables at hand.

In contrast to the process variables (Y) the moderator (X) is treated as fixed, and therefore missing values are not allowed in the moderator itself (Adolf et al., 2017). Therefore, missingness must be addressed, for instance, through imputation, before the moderator can be used in the model.

3. EMPIRICAL EXAMPLE

3.1 Research questions

In the analyses, we aimed to illustrate how moderation can be employed to test simple clinical network hypotheses. Given that, in network analyses, affect items are typically used separately instead of in sum scores or latent factors (Borsboom & Cramer, 2013; Cramer et al., 2010; Robinaugh et al., 2020), we opted to use two commonly used affect variables, *Cheerfulness* and *Down*, for constructing the network structure (e.g., Bringmann et al., 2013; Groen et al., 2020; Snippe et al., 2017; Stochl et al., 2019; Van Roekel et al., 2019). For the moderating variables, we selected both a dichotomous (*Alone*) and a continuous variable (*Sleep quality*). We chose these variables because they are known to have an influence on mood (Hawkley & Cacioppo, 2010; Konjarski et al., 2018; Park et al., 2020; Watling et al., 2017). Our objective was to investigate which aspects of the networks are influenced by these moderators at the concurrent time point t.

More specifically, the first research question (RQ1), with *Alone* as the moderator, was: On which aspect of the networks consisting of *Cheerfulness* and *Down* does the moderator *Alone* have an influence: the means and temporal dynamics network (i.e., autoregressive and cross-lagged effects) or the innovation network (i.e., innovation variances and covariance)? The second research question (RQ2), with *Sleep quality* as the moderator, was: On which aspect of the networks consisting of *Cheerfulness* and *Down* does the moderator *Sleep quality* have an influence: the means and temporal dynamics network (i.e., autoregressive and cross-lagged effects) or the innovation network (i.e., innovation variances and covariance)?

Furthermore, for both research questions, we explored whether a model estimating the mean directly using the measurement equation fits better than a model estimating the intercept directly using a state equation. See the files RQ1.html and RQ2.html at the OSF page for the code.

3.2 Data

We applied the fixed moderated time series analysis approach to time series data of individuals included in the TRANS-ID Recovery study (https://www.transid.nl/?lang=en). Participants of the TRANS-ID Recovery study were individuals with a current depressive episode of which most started psychological treatment for depression during the study period. Participants engaged in ecological momentary assessment (EMA) five times a day at fixed three-hour intervals for a period of four months. The EMA included questions on momentary mental states as well as context and behavior during the past three hour interval. Written informed consent was obtained from all participants. All procedures were approved on December 12, 2016, by the Medical Ethical Committee of the University Medical Center Groningen (Registration No. NL58848.04.16). A full description of the study design, EMA protocol, and inclusion and exclusion criteria can be found on the open science framework (https://osf.io/85ngu). A flowchart of the participants and description of the sample can be found in (Helmich et al., 2023).

We selected individuals from the TRANS-ID Recovery study because these individuals were likely to show change in emotions, behaviors, and cognitions (see Snippe et al., 2024) as they started treatment for depression during the study period. A second reason for sampling individuals from this data set is that a high number of observations was available for most individuals. Individuals received 620 EMA prompts over a four-month period with a mean compliance rate of 85 percent. The two participants for the analysis were chosen purely for the purpose of illustrating the fixed-moderated time series model. Both participants were female and had a major depressive episode at the start of the study period. They received weekly psychotherapy for depression during the study period.

Specifically, we selected these participants using simple linear regression based on either a significant difference between conditions *Alone* and *not Alone* in the variable *Cheerfulness*, or a strong correlation between *Cheerfulness* and *Sleep quality*. We chose the participants with the largest mean difference between conditions *Alone* and *not Alone*, or the strongest correlation between *Cheerfulness* and *Sleep quality*. This selection process can be likened to cherry-picking and was aimed at effectively showcasing the model. Therefore, it is important to limit the substantive conclusions drawn from these results, and to keep in mind that their generalizability will be restricted. We refrain from providing specific characteristics of the selected participants to safeguard their privacy.

The final item set was *Cheerfulness*, *Down*, *Alone*, and *Sleep quality*. *Cheerfulness*(formulated as 'I feel cheerful'), *Down* (formulated as 'I feel down'), and *Sleep Quality* (formulated as 'I have slept well last night'). All items were assessed using a visual analogue scale, ranging from 'not at all' (scored as 0) to 'very much' (scored as 100). For the item *Alone*, we selected the category 'Nobody' from the question 'Who am I with at the moment?' Other available categories included: 'Partner', 'Housemates', 'Family', 'Family (living elsewhere)', 'Friends', 'Colleagues or classmates', 'Caregiver', 'Acquaintances', and 'Strangers'.[4] The variable was scored in such a way that it assigned a score of 0 when the person was in company of others and a 1 when the person was alone (with nobody). In contrast to the other items, *Sleep quality* was measured only once a day.

3.3 Preprocessing steps

Before conducting the analyses, we had to perform several preprocessing steps. The first step involved creating a three-hour interval between all adjacent data points. This allowed for the interpretation of any lagged effect as a three-hour effect, which also and ensured that the last beep of the day would not predict the next morning's beep, as the interval there is more than three hours. To establish this three-hour interval, we included missing data values between data points that were adjacent in the data, but the actual time interval between them was more than three hours (e.g., 20:00 in the evening and 8:00 in the morning). In the second step, all continuous variables were standardized (*Cheerful*, *Down* and *Sleep quality*). This step was necessary for model convergence (Ketkar, 2017, Chapter 8).

As the fmTSA model assumes that the moderator values are known, the third step involved handling

[4] We also attempted to include two or more moderators, using dummy coding and multiple categories from this list. However, with more than two moderators, the model did not converge anymore.

missing data in the moderator variable. For RQ1, the *Alone* moderator and participant 1, we theoretically imputed missing values by assuming that when no data was available, the person was likely alone. Therefore, all missing values were imputed with a value of 1.

Regarding RQ2, the *Sleep quality* variable and participant 2, the imputation consisted of two parts: theoretical and multiple imputation. We began with the theoretical imputation, driven by the assumption that sleep quality likely influences mood throughout the entire day. Since we only measured sleep quality at the start of each day, and we needed the moderator to have a value throughout the day for examining its impact on mood, we simply used the sleep quality value from the first beep of the day and copied this same value for the rest of the day.[5]

However, on some occasions, participant 2 missed the first beep of the day, and as a result, we lacked a measurement of sleep quality for those days. Consequently, after the theoretical imputations, missing values still remained, for which we did not have a clear idea of what a plausible value could be. Therefore, the second part involved multiple imputation using the *R*-package *mice* (Buuren & Groothuis-Oudshoorn, 2011). Multiple imputation generates various alternative moderator values that are plausible based on the available information, including (lagged) observations of the other variables in the network (*Cheerful* and *Down*) and a lagged version of the moderator variable itself (i.e., *Sleep quality*; for further details, see section 3D in file RQ2.rmd). Subsequently, the analysis results are then pooled across these alternative datasets.

The process variables *Cheerful* and *Down* do not need to be imputed because missing values in these variables are handled by the Kalman filter. To study the effect of imputation, we also conducted sensitivity analyses. For RQ1, we filled in 0 instead of 1 for missing values, assuming the person was with somebody instead of alone. For RQ2, we filled in zeros everywhere instead of using multiple imputation. In the case of RQ1, this led to slightly different results (see Footnote 6), whereas for RQ2, the overall conclusions stayed the same.

3.4 Analyses

All analyses and visualizations were done in R (R Core Team, 2023). For model estimation we used the *R*-package *fmTSA* (Adolf et al., 2017) available on GitHub https://gitlab.kuleuven.be/ppw-okpiv/researchers/u0119417/published/fmTSA, which makes use of the *R*-package *OpenMx* (Neale et al., 2016). With the function *buildMTSAMxModel* we applied the Kalman filter for model estimation. In order to initialize the Kalman filter we used the mean and covariance of the standardized empirical data. We began with plausible starting values, such as a positive autocorrelation below 1. Then, we

[5] Alternatively, we explored a different hypothesis, specifically, the idea that sleep exclusively impacts mood in the morning and not during the rest of the day. Normally this could be achieved by having missing values for sleep during the rest of the day, but this was not possible in the fixed moderated time series model as it does not allow missing values in the moderator variable. Therefore, we retained only the data from the first beep of the day, discarding all other data. This resulted in a reduction of the dataset by approximately 80%. This model did not converge, probably due to the large data reduction. Non-convergence was almost always due to inadequate starting values.

employed the OpenMx function 'mxTryHard' to iteratively refine the starting values, utilizing prior parameter estimates. For visualization of the networks we used the *R*-package *qgraph* (Epskamp et al., 2012). See the supplemental code for the exact versions of R and its packages used in the analyses.

For the analyses we report both point estimates and the 95% confidence intervals (CI) of all parameters of interest. Our approach relies on likelihood-based CI calculations implemented in OpenMx. Likelihood-based CIs utilize the exact shape of the likelihood function, as opposed to the approximations used in Wald-type CIs. This method is particularly advantageous in situations with small sample sizes (Adolf et al., 2017; Pek & Wu, 2015). However, for the innovation (co)variances, we used Wald-based CI's based on the OpenMx-provided point and SE estimates, as calculating likelihood-based CIs was not possible for these three parameters. Note that for the multiple imputation the confidence intervals are based on the *mitml* package (Grund et al., 2023).

To explore whether a model that directly estimates the mean using the measurement equation fits better than a model that only estimates the intercept directly, we employed the Akaike Information Criterion (AIC) (Akaike, 1974) and Bayesian Information Criterion (BIC) (Schwarz, 1978). These criteria balance model fit against the number of model parameters, with lower values indicating a better fit. In the case of multiple imputation, we calculated the average AIC and BIC across all model solutions.

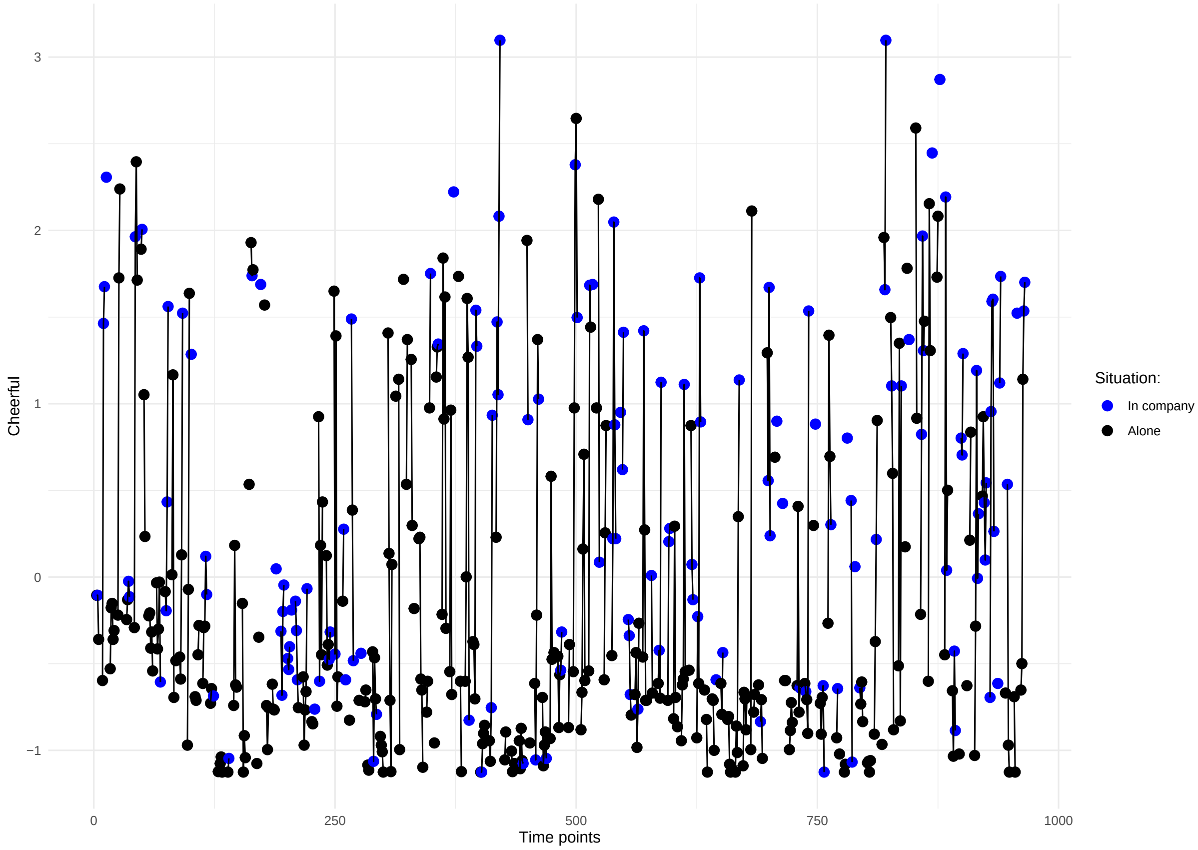
3.5 Results: RQ1

We will start with RQ1, whether being alone had an effect on the network of participant 1. Participant 1 was measured for 121 days, resulting in a total of 605 time points, with 21% of them being missing data. After making the data equidistant by introducing additional missing values, the time series now consists of 965 time points. She was alone 68% of the time (at 328 time points) and in company 32% of the time (at 151 time points). As is common practice we will look at the raw data first. We show here only the effect on *Cheerfulness*, while the result for *Down* can be found on the OSF page in the file RQ1.html. Figure 6 displays the time series of the raw data of participant 1. Although not a consistent pattern, when she is in company, she often reports feeling more cheerful than on average (indicated by the blue circles often being above 0) compared to when she is alone. In the boxplot depicted in Figure 7, the pattern becomes evident, with *being Alone* associated with lower levels of *Cheerfulness* compared to being in company.

While such descriptive statistics are an important initial step, they cannot provide us with precise information about which parameters in the network structure are affected by the moderator. Therefore, we will utilize the results of the fixed moderated time series model.

First, both the AIC and the BIC indicated that a model in which the mean was estimated directly had a slightly better fit than a model where the intercept was estimated directly (see Table 1). For example, the AIC of the model with the mean instead of the intercept directly estimated was lower:

Figure 6
The time series of participant 1 for the variable Cheerful with the moderator Alone. The time series represents the variable Cheerful. The blue circles indicate time points when she was in company and the black circles indicate when she was alone.



2126.370 versus 2151.195. This provides some evidence that the effect of *being Alone* for this specific participant primarily impacts the mean of *Cheerfulness* and *Down* at one time point but the effect does not necessarily feed forward into the rest of the process.

Furthermore, as indicated in Table 2, *being Alone* is associated with lower Cheerfulness (see, $\beta_{\mu,1}$) and higher levels of feeling *Down* (see, $\beta_{\mu,2}$). Concerning the temporal structure, the autoregressive effects (see $\beta_{\phi,11}$ and $\beta_{\phi,22}$) were not significantly affected by the moderator *being Alone*, with confidence intervals that include zero.

However, when the participant is alone, the cross-lagged effect from *Down* predicting *Cheerful* at the next time point weakens (see Figure 8 and $\beta_{\phi,12}$ in Table 2). In company, she had a negative cross-lagged effect from *Down* to *Cheerful* (i.e., ϕ_{12} in Table 2), which means that when she feels more *Down* at one time point, this predicts feeling less *Cheerful* at the next time point. Vice versa, feeling less *Down* at one time point leads to her feeling more *Cheerful* at the next time point, when in company (controlling for the other effects in the network). When she is *Alone*, on the other hand, the

Figure 7
A boxplot of the raw data indicating the effect of being Alone on Cheerfullness. The red dot is the mean as calculated with the fixed moderated time series model.

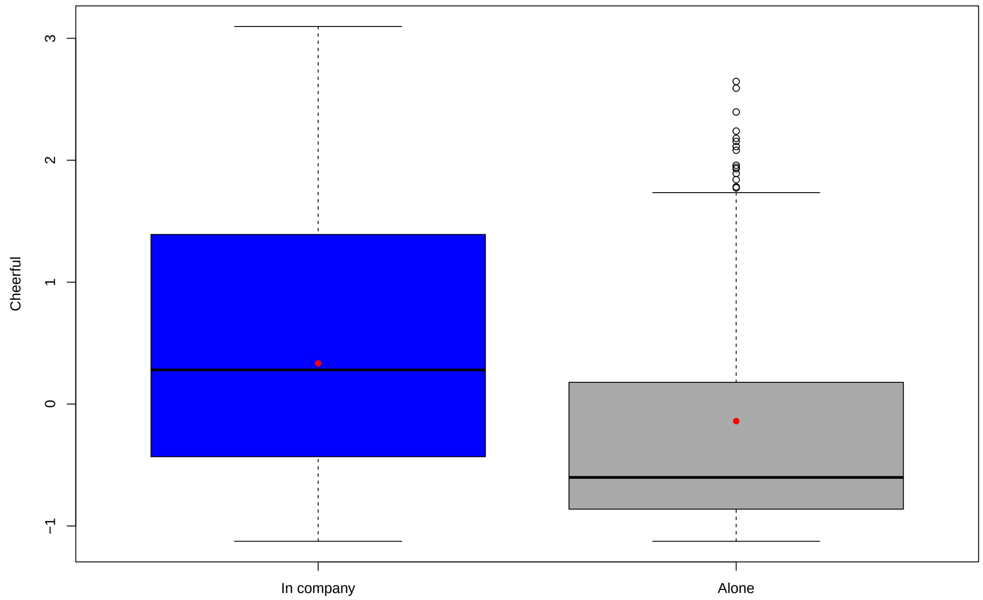


Table 1
AIC and BIC for the moderator Alone of participant 1. Alone (mean) refers to a model where the mean is directly estimated using the measurement equation, Alone (intercept) refers to a model where the intercept is estimated directly.

Model	AIC	BIC
Alone (mean)	2126.370	2214.068
Alone (intercept)	2151.195	2238.893

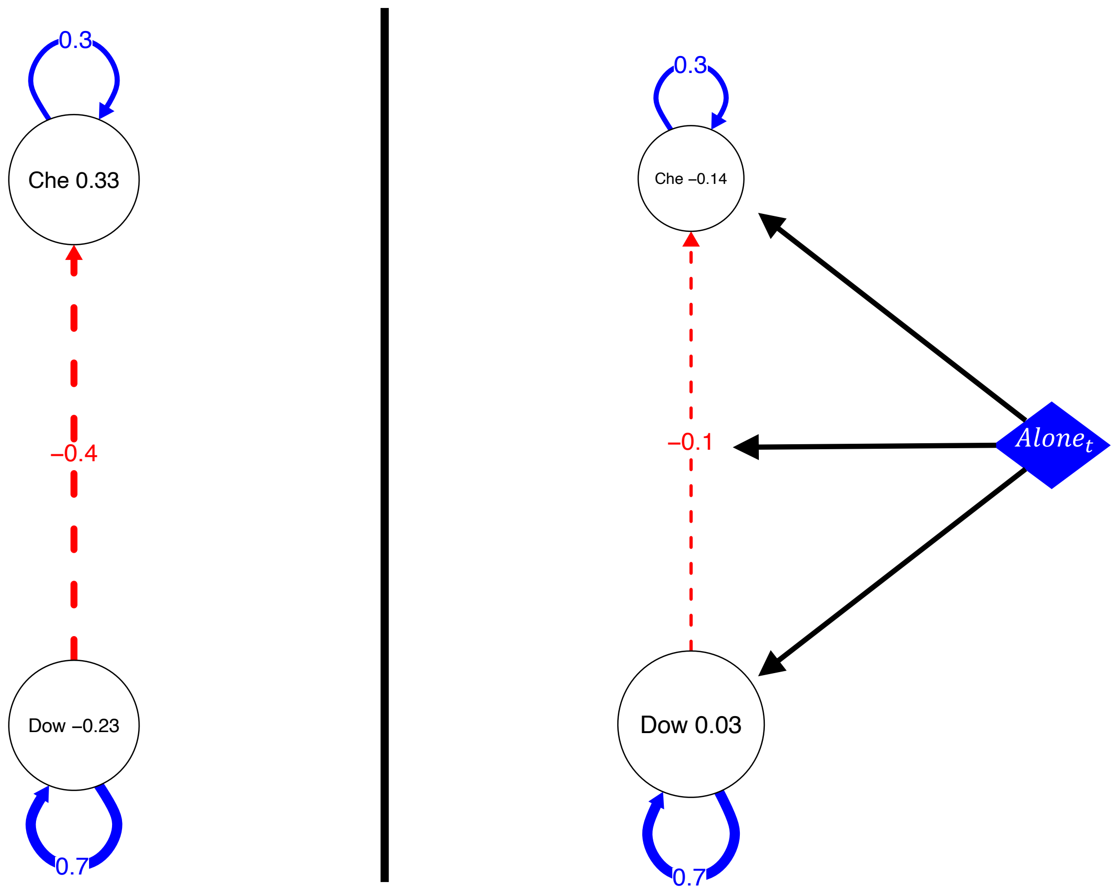
cross-lagged effect significantly decreases in magnitude ($\beta_{\phi,12}$ in Table 2), although the effect is still negative (see $\phi_{12,t} = -0.1$ in Figure 8). Thus, when she is *Alone*, feelings of *Down* have less influence on feelings of *Cheerful* at the next time point.[6]

Regarding the innovation network structure, *being Alone* only has an effect on the innovation of the variable *Down* (see Table 2 $\beta_{\sigma^2,22}$), leading to increase of this innovation. This indicates that either (1) there are more unobserved factors that are not being taken into account when predicting feeling *Down* and/or (2) the emotional reactivity to these unobserved factors is stronger when she is *Alone*.

[6]As can be seen on the OSF page in the file RQ1.html (section Sensitivity check), the effect of the moderator on $\beta_{\phi,12}$ is no longer significant in the sensitivity analysis. In clinical practice, it would therefore be important to ask the participant whether they were likely to be alone or not alone when there are missing values.

Figure 8

A psychological network illustrating the changes in temporal dynamics and average levels of Cheerful and Down when participant 1 is alone. To create this figure, we used Table 2 and Equation (17) to depict the time-varying effects conditional on the moderator Alone (also see Figure 3). We only show significant effects. From Table 2, it is evident that there is no significant effect from Cheerful to Down, as both ϕ_{21} and $\beta_{\phi,21}$ have confidence intervals that encompass zero. Furthermore, the changes in autoregressive effects, denoted as $\beta_{\phi,11}$ and $\beta_{\phi,22}$, have confidence intervals including zero, meaning that these effects remain constant over time. It is important to note that even though the time-varying mean of Down is specified as $\mu_{t,2} = 0.03$, the variables are standardized, and the scale ranges from -3 to 3. In this context, a value of 0 indicates a higher level than -.23. Therefore, when the participant is alone, she tends to experience higher levels of Down.



3.6 Results: RQ2

For our second research question, we turn to the continuous moderator *Sleep quality* to determine whether it had a moderating effect on the emotion dynamics networks of Participant 2. Participant 2 was measured for 123 days, resulting in a total of 615 time points, with 14% missing data. After making the data equidistant by including missing values, the time series consists of 981 time points. Figure 9 displays the time series of Participant 2, focusing on the impact of *Sleep quality* on *Cheerfulness*. When viewing the time series in Figure 9, there is no obvious pattern between sleeping well and

Table 2
Results of the fixed moderated time series analysis for participant 1, with Alone as the moderator.

	Alone with mean estimation		
	Estimate	95% CI	St.Error
μ_1	0.334	[0.126,0.531]	0.102
μ_2	-0.228	[-0.405,-0.044]	0.090
ϕ_{11}	0.290	[0.081,0.495]	0.104
ϕ_{21}	-0.018	[-0.159,0.121]	0.071
ϕ_{12}	-0.430	[-0.639,-0.221]	0.106
ϕ_{22}	0.680	[0.535,0.821]	0.072
σ^2_{11}	0.706	[0.539,0.874]	0.085
σ^2_{21}	-0.200	[-0.289,-0.111]	0.045
σ^2_{22}	0.310	[0.231,0.39]	0.041
$\beta_{\phi,11}$	0.162	[-0.08,0.399]	0.121
$\beta_{\phi,21}$	-0.055	[-0.231,0.123]	0.090
$\beta_{\phi,12}$	0.281	[0.047,0.514]	0.118
$\beta_{\phi,22}$	0.039	[-0.13,0.21]	0.086
$\beta_{\mu,1}$	-0.474	[-0.646,-0.299]	0.088
$\beta_{\mu,2}$	0.260	[0.137,0.384]	0.062
$\beta_{\sigma^2,11}$	-0.148	[-0.363,0.031]	0.098
$\beta_{\sigma^2,21}$	-0.019	[-0.129,0.102]	0.057
$\beta_{\sigma^2,22}$	0.147	[0.026,0.26]	0.058

Table 3
AIC and BIC for the moderator Sleep quality of participant 2. Sleep (mean) refers to a model where the mean is directly estimated using the measurement equation, Sleep (intercept) refers to a model where the intercept is estimated directly.

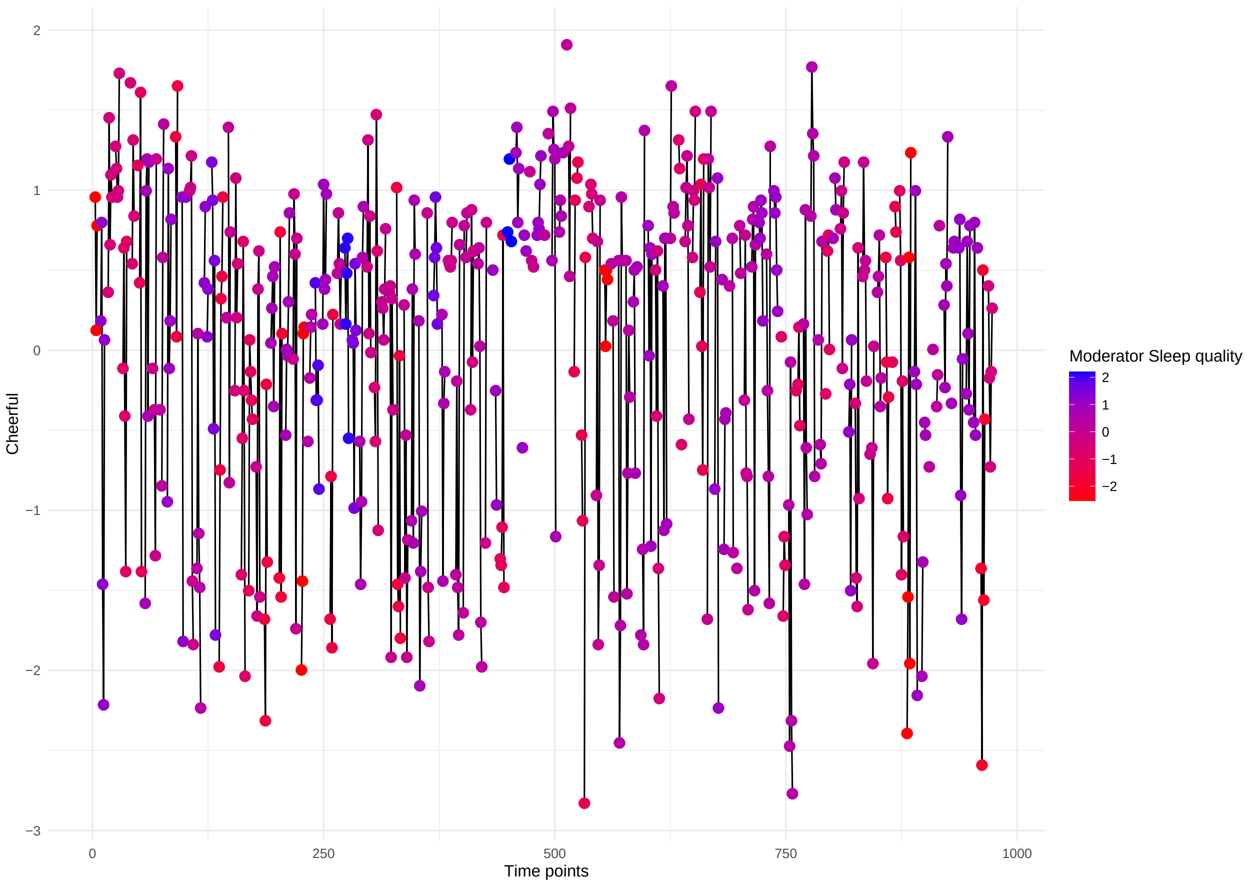
Model	AIC	BIC
Sleep (mean)	2485.375	2573.369
Sleep (intercept)	2486.032	2574.026

feeling more cheerful. In other words, the colour of the dots does not seem to be related to their position on the y-axis (i.e., *Cheerful*). For instance, both deep purple and blue-colored time points (the latter indicating when the participant has slept well) are observed when she is *Cheerful* (with values of zero and above) and when she is not *Cheerful* (with negative values for cheerfulness). Indeed, Pearson's correlation coefficient indicates only a minor significant effect of 0.15, with a 95% confidence interval of (0.06,0.23).

For this model, it becomes evident that the difference in AIC and BIC is negligible (see Table 3). Given that the difference between the mean and intercept models is so small, we assume that it is equally likely for the moderator, *Sleep quality*, to affect the mean at one point in time as it is for the effect of *Sleep quality* on the mean to influence the temporal dynamics and, consequently, impact the rest of the process over time. For simplicity, we focus on the model in which the mean is estimated directly.

Figure 9

The time series of Participant 2 for the variable Cheerful together with the moderator Sleep Quality. The gradient color from red to blue indicates the participant's sleep quality at different time points, with 2 (blue) representing high sleep quality and -2 (red) representing low sleep quality.



The results in Table 4 for this model indicate that *Sleep quality* does not lead to a change in the temporal dynamic network structure (i.e., $\beta_{\phi,11}$, $\beta_{\phi,12}$, $\beta_{\phi,21}$, and $\beta_{\phi,22}$; all encompassing zero in their confidence intervals, see Table 4). Thus, all autoregressive and cross-lagged effects are not influenced by sleep for this participant. *Sleep quality* does change the mean levels of *Cheerfulness* and *Down*. On average, a one-unit increase (of one standard deviation) in *Sleep Quality* is associated with a small increase of 0.12 in *Cheerfulness* and a small decrease of 0.15 in feeling *Down* at the same time point (see Table 4).

In contrast to Participant 1, the entire innovation network of Participant 2 is influenced by *Sleep quality* (see $\beta_{\sigma^2,11}$, $\beta_{\sigma^2,21}$ and $\beta_{\sigma^2,22}$ in Table 4). In Figure 10, it can be seen that the innovation variance becomes less pronounced when *Sleep quality* improves. Thus, when predicting *Cheerful* and *Down*, there is less noise when Participant 2 has slept well, possibly due to fewer unobserved factors and/or reduced emotional reactivity to these unobserved factors. Furthermore, the covariance (and cor-

Table 4
Results of the fixed moderated time series analysis for participant 2, with Sleep quality as the moderator.

	Sleep with mean estimation		
	Estimate	95% CI	St.Error
μ_1	0.008	[-0.091,0.108]	0.051
μ_2	-0.010	[-0.108,0.087]	0.050
ϕ_{11}	0.208	[0.04,0.376]	0.086
ϕ_{21}	-0.041	[-0.203,0.122]	0.083
ϕ_{12}	-0.045	[-0.208,0.117]	0.083
ϕ_{22}	0.172	[0.014,0.33]	0.081
σ^2_{11}	0.921	[0.807,1.036]	0.058
σ^2_{21}	-0.710	[-0.813,-0.607]	0.053
σ^2_{22}	0.924	[0.808,1.04]	0.059
$\beta_{\phi,11}$	0.043	[-0.124,0.211]	0.085
$\beta_{\phi,21}$	0.021	[-0.142,0.184]	0.083
$\beta_{\phi,12}$	0.034	[-0.128,0.195]	0.082
$\beta_{\phi,22}$	-0.014	[-0.173,0.145]	0.081
$\beta_{\mu,1}$	0.117	[0.017,0.217]	0.051
$\beta_{\mu,2}$	-0.145	[-0.245,-0.046]	0.051
$\beta_{\sigma^2,11}$	-0.189	[-0.311,-0.066]	0.063
$\beta_{\sigma^2,21}$	0.205	[0.098,0.312]	0.055
$\beta_{\sigma^2,22}$	-0.245	[-0.359,-0.13]	0.058

relation) of the innovations also becomes less pronounced (closer to zero) when her *Sleep quality* improves (for the exact correlation values, see section Calculating the correlations instead of covariances in the file RQ2.html).[7] The covariance of the innovations reflects unobserved factors, such as bad weather, that influence both feelings of *Cheerful* and *Down*. This can also be interpreted as there being less unobserved factors and/or the effect of unobserved factors decreasing when the participant sleeps better.

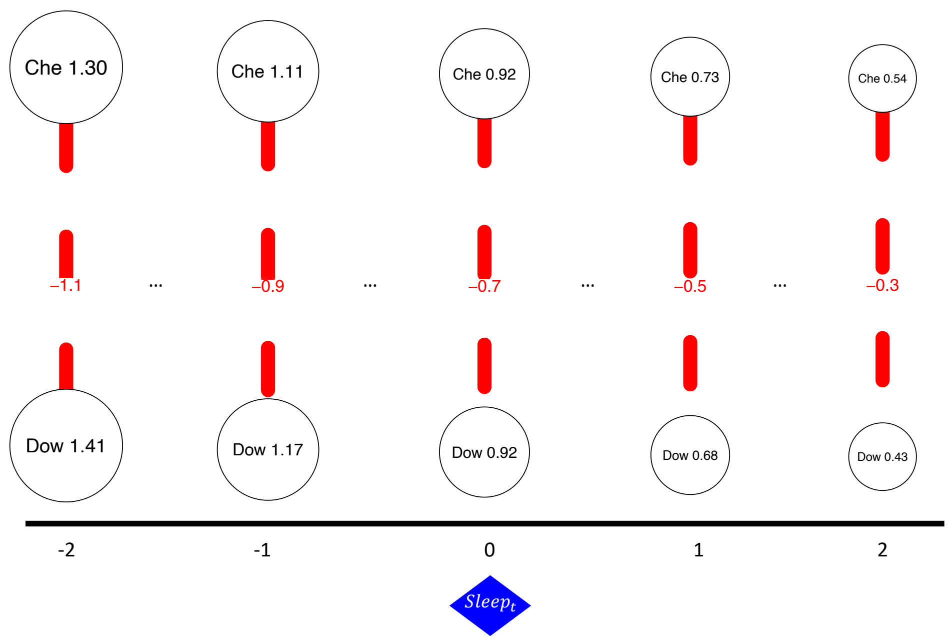
4. DISCUSSION

In this paper, we have illustrated moderated idiographic networks using intensive longitudinal data from two patients with current depression. We showed that in these two patients, different parts of the networks change due to the moderators *being Alone* and *Sleep quality*, where the networks consist of *Cheerfulness* and *Down*. We observed, for example, in participant one, that *being Alone* was associated with feeling more down and less cheerful than when she was in company. The relationship in the temporal dynamics network between feeling *Down* and feeling *Cheerfulness* at the next time point also decreased, meaning that the connection between the two became weaker when she was *Alone* compared to being in company. For the second participant, although only a small effect,

[7]We calculated also the correlation to make sure that the changes in the covariance were not just due to changes in the variance.

Figure 10

The effect of Sleep quality on the covariance structure of the innovation network. The circles represent the variances of the innovation and the edge represents the covariance. The moderator is represented as a blue diamond labeled Sleep. As Sleep quality is a continuous moderator, we show the networks for different values (in this case, standard deviations) of the moderator, with 0 representing no effect of the moderator. Furthermore, we indicate that these are not the only possible values by adding "…" between the networks.



higher *Sleep quality* for the participant was associated with increased *Cheerfulness* and decreased feelings of *Down*. Furthermore, *Sleep quality* also was associated with changes in the innovation network: factors not taken into account in the model, such as unobserved variables like bad weather, influenced feelings of *Cheerfulness* and *Down* less when she had slept well.

An important novel feature of the moderated idiographic network model approach is that it allows us to integrate context and other clinically relevant variables, which are often overlooked in existing clinical networks (Bak et al., 2016; David et al., 2018; Frumkin et al., 2020; Levinson et al., 2021; Reeves & Fisher, 2020), into the network, thereby enhancing its clinical utility. Currently, idiographic networks are data-driven, in which, for ease of analysis, often items with the same response and time scale are only included (Bastiaansen et al., 2020). In contrast, the analytic approach introduced here enables a hypothesis-driven form of idiographic network analysis, in which context variables, such as being in company of others or not, could be a part of the network (Bringmann, in press; Os et al., 2017). We furthermore showed how items that had a different time scale, such as sleep quality, could be incorporated into a network, using an explicit hypothesis about how sleep would affect mood over the day.

Taking this hypothesis-driven approach can encourage the development of even more person-specific items tailored to the patient (Klipstein et al., 2023). For example, instead of gathering information about being in the company of colleagues or friends, details about specific persons could be collected to understand which individuals influence a patient's mood, such as by helping regulate negative emotions (Stadel et al., 2023). Therefore, rather than solely focusing on emotions and symptoms, idiographic networks could enhance their clinical utility by incorporating personalized contextual items (Bringmann, 2021).

Furthermore, one of the advantages of using fixed moderated time series analysis is that it uses the state space framework, enabling effective handling of missing values, which are ubiquitous in ILD research (Rintala et al., 2019; Silvia et al., 2013). Additionally, the mean can be directly estimated, facilitating the straightforward inclusion of the mean level in networks. Considering that changes in the mean levels of variables, such as symptoms and mood, are almost always clinically relevant, we hope this encourages other researchers to also include mean levels in their network visualizations.[8]

We also discussed how the moderator can affect the mean of the process differently depending on whether the mean is estimated directly or indirectly via the intercepts (Ernst et al., 2023). The differentiation between these two effects is of substantial interest: does a moderator like stress persist in influencing the patient's emotions, or does it impact the mean level of the patient's emotions only at one time point? However, testing this with standard model selection proves difficult, given that the model differences are very subtle. In other words, the largest part of the model (variance and covariance of the innovation and the autoregressive and cross-lagged effects) remains the same. Thus, further research is needed to explore how well one can differentiate and perform model selection between these two different effects of the moderator on the mean level of the process of interest.

While the fixed moderated time series model, in contrast to other currently used VAR based network models, makes it possible to moderate all parameters of a VAR model, this flexibility also limits the scalability of the approach. There are 3 important sources of model dimensionality in the fixed moderated time series model. First, as in standard VAR approaches, increasing the *lag order, p* of the model will increase the number of free parameters by $dim(\Phi) * p$. For the fixed moderated VAR model, however, each lagged effect can also be made context dependent, further increasing the model dimensionality. Second, the number of process variables can be increased. Already in a VAR model increasing the number of process variables increases the number of free parameters dramatically (e.g., Loossens et al., 2021; Revol et al., in press). This is again exacerbated in the fixed moderated model, as each of these free parameters can in principle be made subject to moderation. Third, the number of moderators can be increased. With each included moderator, one could allow the estimation of that

[8] It is worth noting that, strictly speaking, within an ordinary least squares model, direct estimation of the mean is achievable through two-level equation estimation (for instance Ernst et al., 2020).

moderators' effects on all the process parameters.

In our application we fit the fixed moderated model on two process variables and one moderator. This model already has 18 parameters to estimate, and even this simplest case of a moderated idiographic network (using only lag-1), led to convergence issues. For example, when estimating the effect of *Sleep quality* on a reduced data set, convergence issues were encountered. Additionally, when attempting to estimate the influence of more than two moderator variables, the model also failed to converge.

The more time points a researcher has available, the less prone to convergence issues the model will typically be (keeping the overall model complexity constant). However, obtaining the approximately 500 time points in the current study is already burdensome for participants. making it unlikely that many more time points can be collected. Furthermore, other factors less within the power of the researchers also possibly influence convergence. For instance, Schuurman et al., 2015 pointed out that in the autoregressive model with measurement error, a nonzero autocorrelation is necessary for identification, with higher autocorrelation making empirical identification easier and thus reducing the likelihood of convergence problems (see also, Adolf & Ceulemans, 2023). Similar issues could play a role in the fixed moderated time series model, making it important that such factors, besides model dimensionality and the needed number of time points, are further studied with simulations.

It is clear from the above that careful thought should be placed on how to keep the dimensionality of the model as small as possible, while still being able to investigate meaningful relationships between context and the dynamics of affect variables. One option is to assess contextual dependence in only a subset of the fixed moderated VAR parameters and for specific processes of interest. For instance, a researcher might want to assess how the cross-lagged relationship from *Cheerfulness* to *Down* depends on social context, and might therefore only allow elements of the Φ matrix to be moderated. While one risks not capturing the full dynamical profile of change, it will be far easier to estimate those effects which are of prime interest to the researcher. Another option for reducing dimensionality involves utilizing data-driven techniques, such as regularization methods (e.g., Epskamp et al., 2018b), which can be used to shrink the model's dimensionality and thus mitigate convergence issues.

An additional limitation of the fixed moderated time series analysis is that there are more preprocessing steps compared to a linear regression approach, particularly involving the imputation of the moderator and the provision of initial values. While we have shown how this can be done, it requires careful consideration and familiarity with the model and data. In our empirical example, for instance, we found that the results were sensitive to differences in imputation. Therefore, we recommend relying on theory and qualitative information when selecting an appropriate imputation method. For instance, inquiring with the patient who provided the data about whether she was more likely to be alone or not when data was missing would be crucial. This implies that the model cannot be readily employed in clinical practice, especially when also considering the convergence issues that are more severe than in other contemporary network models based on ordinary least squares, kernels or generalized additive modeling.

Using a fixed moderated time series model also presents more general challenges that are not specifically tied to this model. One such challenge, as mentioned earlier, is measurement error. Due to the convergence issues already present, we did not explicitly model the measurement error, although it is technically simple to do so in a state space framework: one can model measurement error separately from the innovations. Failing to do this for the dependent variable(s) implies that the measurement error becomes part of the innovation. Research has shown that this can lead to severely distorted autoregressive and cross-lagged estimations (Schuurman & Hamaker, 2019; Schuurman et al., 2015). Additionally, it is possible that the moderators themselves are affected by measurement error (Adolf et al., 2017). In the fixed moderated time series model, we assume that the moderator is measured without error. This assumption implies that any measurement error in the moderator may introduce bias to the model estimations. Recognizing the probable presence of noise in the measurement of moderators, is important to study how measurement error behaves, for instance, whether it is continuous or only occasional in the process. Extending the model to explicitly account for measurement error in the moderator could be another potential solution (see for more information Ernst et al., 2024).

Another more general challenge pertains to what we include as moderators. In this paper, we did not explicitly distinguish between exogenous and endogenous variables (Arizmendi et al., 2021; Bringmann et al., 2022). While the weather is a typical example of an exogenous variable – we cannot influence the weather, but the weather can influence our mood – the process of sleeping well is more likely to be reciprocal and may be considered as an endogenous variable (Konjarski et al., 2018). In this case, perhaps we should not only consider sleep as a moderator of the emotion process but also explore the effect of emotions as a moderator of sleep quality. This topic requires further research, encompassing both theory and how this can be best implemented in the fixed moderated time series model.

In sum, this paper illustrates a new way of analyzing change in idiographic psychological networks using a more theory-driven approach, which not only looks at which parameters in a network change over time, but also offers tools to identify (context) factors associated with the change. We have shown that the use of fixed moderated time series analysis brought advantages in handling missing values and allowed for the direct estimation of mean levels, enhancing the clinical relevance of network visualizations. However, we have also emphasized several challenges, such as convergence issues and dealing with measurement error, urging the need for further research and exploration of alternative modeling techniques. We hope that the use of moderators in idiographic network models will help to give due importance to factors such as change, context, and hypothesis-driven investigation, and thereby play a role in increasing the clinical utility of network models in future research.

5. ACKNOWLEDGEMENTS

We are very grateful for Janne Adolf for thinking along on how to best execute the fixed moderated time series model, for helping with technical issues regarding modeling, and for providing Figure 5. We also thank Noemi Schuurman for helping with the notation in the Appendix and with the interpretation of the direct and indirect estimation for the mean. We are also grateful to Yong Zhang for providing very useful feedback on parts of the manuscript and figure code, to Sebastian Castro Alvarez for providing the code to make the data equidistant, and finally to Markus Eronen for giving feedback on several drafts of the manuscript. We furthermore thank Marieke Helmich for collecting the empirical data. The research presented in this article was supported by a grant of the European Research Council (ERC) under the European Union's Horizon 2020 research and innovative programme (ERC-CoG-2015; No 681466) awarded to Marieke Wichers. The research of Eva Ceulemans was supported by research grants from the Fund for Scientific Research-Flanders (FWO; Project No. G0C9821N) and the Research Council of KU Leuven (C14/23/062; iBOF/21/090). The research of Sigert Ariens was supported by the Research Council of KU Leuven (PDMT2/23/018). The research of Laura Bringmann was supported by the Dutch Research Council Veni Grant (NWO-Veni 191G.037), and by the 'Stress in Action' project (www.stress-in-action.nl), which is financially supported by the Dutch Research Council and the Dutch Ministry of Education, Culture and Science (NWO gravitation grant number 024.005.010).

REFERENCES

- Adolf, J., & Ceulemans, E. (2023). Improved estimation of autoregressive models through contextual impulses and robust modeling. https://doi.org/10.31234/osf.io/3qgse
- Adolf, J. K., Voelkle, M. C., Brose, A., & Schmiedek, F. (2017). Capturing Context-Related Change in Emotional Dynamics via Fixed Moderated Time Series Analysis. *Multivariate Behavioral Research*, *52*(4), 499–531. https://doi.org/10.1080/00273171.2017.1321978
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723.
- Albers, C. J., & Bringmann, L. F. (2020). Inspecting Gradual and Abrupt Changes in Emotion Dynamics With the Time-Varying Change Point Autoregressive Model. *European Journal of Psychological Assessment*, *36*(3), 492–499. https://doi.org/https://doi.org/10.1027/1015-5759/a000589
- Ariens, S., Adolf, J. K., & Ceulemans, E. (2022). Collinearity Issues in Autoregressive Models with Time-Varying Serially Dependent Covariates. *Multivariate Behavioral Research*, *58*(4), 687–705. https://doi.org/10.1080/00273171.2022.2095247
- Ariens, S., Ceulemans, E., & Adolf, J. K. (2020). Time series analysis of intensive longitudinal data in psychosomatic research: A methodological overview. *Journal of Psychosomatic*

Research, *137*, 110191. https://doi.org/10.1016/j.jpsychores.2020.110191

- Arizmendi, C., Gates, K., Fredrickson, B., & Wright, A. (2021). Specifying exogeneity and bilinear effects in data driven model searches. *Behavior research methods*, *53*(3), 1276–1288. https://doi.org/10.3758/s13428-020-01469-2
- Auger-Méthé, M., Newman, K., Cole, D., Empacher, F., Gryba, R., King, A. A., Leos-Barajas, V., Mills Flemming, J., Nielsen, A., Petris, G., & Thomas, L. (2021). A guide to state–space modeling of ecological time series. *Ecological Monographs*, *91*(4), e01470. https://doi.org/10.1002/ecm.1470
- Bak, M., Drukker, M., Hasmi, L., & Os, J. van. (2016). An n=1 Clinical Network Analysis of Symptoms and Treatment in Psychosis. *PLoS ONE*, *11*(9), e0162811. https://doi.org/10.1371/journal.pone.0162811
- Bartels, S. L., Van Zelst, C., Melo Moura, B., Daniëls, N. E., Simons, C. J., Marcelis, M., Bos, F. M., & Servaas, M. N. (2023). Feedback based on experience sampling data: Examples of current approaches and considerations for future research. *Heliyon*, *9*(9), e20084. https://doi.org/10.1016/j.heliyon.2023.e20084
- Bastiaansen, J. A., Kunkels, Y. K., Blaauw, F. J., Boker, S. M., Ceulemans, E., Chen, M., Chow, S.-M., Jonge, P. de, Emerencia, A. C., Epskamp, S., Fisher, A. J., Hamaker, E. L., Kuppens, P., Lutz, W., Meyer, M. J., Moulder, R., Oravecz, Z., Riese, H., Rubel, J., … Bringmann, L. F. (2020). Time to get personal? The impact of researchers choices on the selection of treatment targets using the experience sampling methodology. *Journal of Psychosomatic Research*, *137*, 110211. https://doi.org/10.1016/j.jpsychores.2020.110211
- Bastiaansen, J. A., Meurs, M., Stelwagen, R., Wunderink, L., Schoevers, R. A., Wichers, M., & Oldehinkel, A. J. (2018). Self-monitoring and personalized feedback based on the experiencing sampling method as a tool to boost depression treatment: A protocol of a pragmatic randomized controlled trial (ZELF-i). *BMC Psychiatry*, *18*(1), 276. https://doi.org/10.1186/s12888-018-1847-z
- Beltz, A. M., & Gates, K. M. (2017). Network Mapping with GIMME. *Multivariate behavioral research*, *52*(6), 789–804. https://doi.org/10.1080/00273171.2017.1373014
- Blanchard, M. A., & Heeren, A. (2022). Ongoing and Future Challenges of the Network Approach to Psychopathology: From Theoretical Conjectures to Clinical Translations. In G. Asmundson (Ed.), *Comprehensive Clinical Psychology - second edition* (pp. 32–46). Elsevier. https://doi.org/10.1016/B978-0-12-818697-8.00044-3
- Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. New York, NY: Guilford Press.
- Borsboom, D. (2017a). Mental disorders, network models, and dynamical systems. In *Philosophical Issues in Psychiatry IV: Psychiatric Nosology DSM-5 (International Perspectives in Philosophy and Psychiatry)* (pp. 80–97). Publisher: Oxford University Press New York.
- Borsboom, D. (2017b). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

- Borsboom, D., & Cramer, A. O. (2013). Network Analysis: An Integrative Approach to the Structure of Psychopathology. *Annual Review of Clinical Psychology*, *9*(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608
- Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., Borkulo, C. D. van, Bork, R. van, & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*, 58. https://doi.org/10.1038/s43586-021-00055-w
- Bos, F. M., Blaauw, F. J., Snippe, E., Krieke, L. van der, Jonge, P. de, & Wichers, M. (2018). Exploring the emotional dynamics of subclinically depressed individuals with and without anhedonia: An experience sampling study. *Journal of Affective Disorders*, *228*, 186–193. https://doi.org/10.1016/j.jad.2017.12.017
- Bos, F. M., Snippe, E., Bruggeman, R., Doornbos, B., Wichers, M., & Krieke, L. van der. (2020). Recommendations for the use of long-term experience sampling in bipolar disorder care: A qualitative study of patient and clinician experiences. *International Journal of Bipolar Disorders*, *8*(1), 38. https://doi.org/10.1186/s40345-020-00201-5
- Brandt, P. T., & Williams, J. T. (2007). *Multiple Time Series Models. Series: Quantitative Applications in the Social Sciences*. Thousand Oaks, CA: Sage Publications Inc.
- Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PLoS ONE*, *8*(4), e60188.
- Bringmann, L. F. (2021). Person-specific networks in psychopathology: Past, present, and future. *Current Opinion in Psychology*, *41*, 59–64. https://doi.org/10.1016/j.copsyc.2021.03.004
- Bringmann, L. F. (in press). The future of dynamic networks in clinical practice. *World Psychiatry*.
- Bringmann, L. F., Albers, C., Bockting, C., Borsboom, D., Ceulemans, E., Cramer, A., Epskamp, S., Eronen, M. I., Hamaker, E., Kuppens, P., Lutz, W., McNally, R. J., Molenaar, P., Tio, P., Voelkle, M. C., & Wichers, M. (2022). Psychopathological networks: Theory, methods and practice. *Behaviour Research and Therapy*, *149*, 104011. https://doi.org/10.1016/j.brat.2021.104011
- Bringmann, L. F., & Eronen, M. I. (2018). Don't Blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, *125*(4), 606–615. https://doi.org/10.1037/rev0000108
- Bringmann, L. F., Ferrer, E., Hamaker, E. L., Borsboom, D., & Tuerlinckx, F. (2018). Modeling Nonstationary Emotion Dynamics in Dyads using a Time-Varying Vector-Autoregressive Model. *Multivariate Behavioral Research*, *53*(3), 293–314. https://doi.org/10.1080/00273171.2018.1439722
- Bringmann, L. F., Hamaker, E. L., Vigo, D. E., Aubert, A., Borsboom, D., & Tuerlinckx, F. (2017). Changing dynamics: Time-varying autoregressive models using generalized addi-

tive modeling. *Psychological Methods*, *22*(3), 409–425. https://doi.org/10.1037/met0000085

- Bringmann, L. F., Veen, D. C. van der, Wichers, M., Riese, H., & Stulp, G. (2021). ESMvis: A tool for visualizing individual Experience Sampling Method (ESM) data. *Quality of Life Research*, *30*(11), 3179–3188. https://doi.org/10.1007/s11136-020-02701-4
- Bulteel, K., Tuerlinckx, F., Brose, A., & Ceulemans, E. (2016). Using Raw VAR Regression Coefficients to Build Networks can be Misleading. *Multivariate Behavioral Research*, *51*(2-3), 330–344. https://doi.org/10.1080/00273171.2016.1150151
- Bulteel, K., Tuerlinckx, F., Brose, A., & Ceulemans, E. (2018). Improved Insight into and Prediction of Network Dynamics by Combining VAR and Dimension Reduction. *Multivariate Behavioral Research*, *53*(6), 853–875. https://doi.org/10.1080/00273171.2018.1516540
- Burger, J., Epskamp, S., Veen, D. C. van der, Dablander, F., Schoevers, R. A., Fried, E. I., & Riese, H. (2022a). A clinical PREMISE for personalized models: Toward a formal integration of case formulations and statistical networks. *Journal of Psychopathology and Clinical Science*, *131*(8), 906–916. https://doi.org/10.1037/abn0000779
- Burger, J., Ralph-Nearman, C., & Levinson, C. A. (2022b). Integrating clinician and patient case conceptualization with momentary assessment data to construct idiographic networks: Moving toward personalized treatment for eating disorders. *Behaviour Research and Therapy*, *159*, 104221. https://doi.org/10.1016/j.brat.2022.104221
- Buuren, S. v., & Groothuis-Oudshoorn, K. (2011). Mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, *45*, 1–67. https://doi.org/10.18637/jss.v045.i03
- Cabrieto, J., Adolf, J., Tuerlinckx, F., Kuppens, P., Ceulemans, E., & Cabrieto, J. (2019). An Objective, Comprehensive and Flexible Statistical Framework for Detecting Early Warning Signs of Mental Health Problems. *Psychotherapy and psychosomatics*, *88*(3), 184–186. https://doi.org/10.1159/000494356
- Castro-Alvarez, S., Tendeiro, J. N., Jonge, P. de, Meijer, R. R., & Bringmann, L. F. (2022). Mixed-Effects Trait-State-Occasion Model: Studying the Psychometric Properties and the Person–Situation Interactions of Psychological Dynamics. *Structural Equation Modeling: A Multidisciplinary Journal*, *29*(3), 438–451. https://doi.org/10.1080/10705511.2021.1961587
- Chatfield, C. (2003). *The analysis of time series: An introduction*. Boca Raton, FL: Chapman; Hall/CRC.
- Chen, M., Chow, S.-M., Hammal, Z., Messinger, D. S., & Cohn, J. F. (2021). A Person- and Time-Varying Vector Autoregressive Model to Capture Interactive Infant-Mother Head Movement Dynamics. *Multivariate Behavioral Research*, *56*(5), 739–767. https://doi.org/10.1080/00273171.2020.1762065
- Chen, Y. W., Bundy, A., Cordier, R., Chien, Y. L., & Einfeld, S. (2016). The Experience of Social Participation in Everyday Contexts Among Individuals with Autism Spectrum Disorders: An Experience Sampling Study. *Journal of Autism and Developmental Disorders*, *46*(4),

1403–1414. https://doi.org/10.1007/s10803-015-2682-4

- Chow, S.-M. (2019). Practical Tools and Guidelines for Exploring and Fitting Linear and Nonlinear Dynamical Systems Models. *Multivariate Behavioral Research*, *54*(5), 690–718. https://doi.org/10.1080/00273171.2019.1566050
- Chow, S.-M., Ho, M.-h. R., Hamaker, E. L., & Dolan, C. V. (2010). Equivalence and Differences Between Structural Equation Modeling and State-Space Modeling Techniques. *Structural Equation Modeling: A Multidisciplinary Journal*, *17*(2), 303–332. https://doi.org/10.1080/10705511003661553
- Chua, A. S., & Tripodis, Y. (2022). A state-space approach for longitudinal outcomes: An application to neuropsychological outcomes. *Statistical Methods in Medical Research*, *31*(3), 520–533. https://doi.org/10.1177/09622802211055858
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences (3d ed.)* Lawrence Erlbaum Associates.
- Cramer, A. O. J., & Borsboom, D. (2015). Problems attract problems: A network perspective on mental disorders. In R. A. Scott & S. M. Kosslyn (Eds.), *Emerging Trends in the Social and Behavioral Sciences: An Interdisciplinary, Searchable, and Linkable Resource* (pp. 1–15). John Wiley & Sons.
- Cramer, A. O., Waldorp, L. J., Van Der Maas, H. L., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, *33*(2-3), 137–150. https://doi.org/10.1017/S0140525X09991567
- David, S. J., Marshall, A. J., Evanovich, E. K., & Mumma, G. H. (2018). Intraindividual Dynamic Network Analysis – Implications for Clinical Assessment. *Journal of Psychopathology and Behavioral Assessment*, *40*(2), 235–248. https://doi.org/10.1007/s10862-017-9632-8
- Dawson, J. F. (2014). Moderation in Management Research: What, Why, When, and How. *Journal of Business and Psychology*, *29*(1), 1–19. https://doi.org/10.1007/s10869-013-9308-7
- De Haan-Rietdijk, S., Gottman, J. M., Bergeman, C. S., & Hamaker, E. L. (2016). Get Over It! A Multilevel Threshold Autoregressive Model for State-Dependent Affect Regulation. *Psychometrika*, *81*(1). https://doi.org/10.1007/s11336-014-9417-x
- Dejonckheere, E., Houben, M., Schat, E., Ceulemans, E., & Kuppens, P. (2021). The short-term psychological impact of the COVID-19 pandemic in psychiatric patients: Evidence for differential emotion and symptom trajectories in Belgium. *Psychologica Belgica*, *61*(1), 163–172. https://doi.org/10.5334/pb.1028
- Delespaul, P. a. E. G., & Devries, M. W. (1987). The Daily Life of Ambulatory Chronic Mental Patients. *The Journal of Nervous and Mental Disease*, *175*(9), 537. https://doi.org/10.1097/00005053-198709000-00005
- Durbin, J., & Koopman, S. J. (2012). *Time series analysis by state space methods* (2nd ed). Oxford University Press.
- Epskamp, S., Borkulo, C. D. van, Veen, D. C. van der, Servaas, M. N., Isvoranu, A. M., Riese, H., & Cramer, A. O. (2018a). Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections. *Clinical Psychological Sci-*

ence, *6*(3), 416–427. https://doi.org/10.1177/2167702617744325

- Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). Qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04
- Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The Gaussian Graphical Model in Cross-Sectional and Time-Series Data. *Multivariate Behavioral Research*, *53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823
- Ernst, A. F., Albers, C. J., Jeronimus, B. F., & Timmerman, M. E. (2020). Inter-Individual Differences in Multivariate Time-Series: Latent Class Vector-Autoregressive Modeling. *European Journal of Psychological Assessment*, *36*(3), 482–491. https://doi.org/10.1027/1015-5759/a000578
- Ernst, A. F., Albers, C. J., & Timmerman, M. E. (2023). A comprehensive model framework for between-individual differences in longitudinal data. *Psychological Methods*. https://doi.org/10.1037/met0000585
- Ernst, A. F., Ceulemans, E., Bringmann, L. F., & Adolf, J. K. (2024). Evaluating contextual models for intensive longitudinal data in the presence of noise. https://osf.io/yxg72
- Fischer, A. H., & Van Kleef, G. A. (2010). Where have all the people gone? A plea for including social interaction in emotion research. *Emotion Review*, *2*(3), 208–211. https://doi.org/10.1177/1754073910361980
- Fried, E. I. (2020). Lack of Theory Building and Testing Impedes Progress in The Factor and Network Literature. *Psychological Inquiry*, *31*(4), 271–288. https://doi.org/10.1080/1047840X.2020.1853461
- Frumkin, M. R., Piccirillo, M. L., Beck, E. D., Grossman, J. T., & Rodebaugh, T. L. (2020). Feasibility and utility of idiographic models in the clinic: A pilot study. *Psychotherapy Research*, *31*(4), 520–534. https://doi.org/10.1080/10503307.2020.1805133
- Groen, R. N., Ryan, O., Wigman, J. T. W., Riese, H., Penninx, B. W. J. H., Giltay, E. J., Wichers, M., & Hartman, C. A. (2020). Comorbidity between depression and anxiety: Assessing the role of bridge mental states in dynamic psychological networks. *BMC Medicine*, *18*(1), 308. https://doi.org/10.1186/s12916-020-01738-z
- Grund, S., Robitzsch, A., & Luedtke, O. (2023). Mitml: Tools for Multiple Imputation in Multilevel Modeling. https://CRAN.R-project.org/package=mitml
- Gu, F., Preacher, K. J., & Ferrer, E. (2014). A State Space Modeling Approach to Mediation Analysis. *Journal of Educational and Behavioral Statistics*, *39*(2), 117–143. https://doi.org/10.3102/1076998614524823
- Haan-Rietdijk, S. de, Voelkle, M. C., Keijsers, L., & Hamaker, E. L. (2017). Discrete- vs. Continuous-Time Modeling of Unequally Spaced Experience Sampling Method Data. *Frontiers in Psychology*, *8*. https://www.frontiersin.org/articles/10.3389/fpsyg.2017.01849
- Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the Frontiers of Modeling Intensive Longitudinal Data: Dynamic Structural Equation Models for the Affective Measurements from the

COGITO Study. *Multivariate Behavioral Research*, *53*(6), 820–841. https://doi.org/10.1080/00273171.2018.1446819

- Hamaker, E. L., & Grasman, R. P. P. P. (2012). Regime Switching State-Space Models Applied to Psychological Processes: Handling Missing Data and Making Inferences. *Psychometrika*, *77*(2), 400–422. https://doi.org/10.1007/s11336-012-9254-8
- Hamaker, E. L., & Dolan, C. V. (2009). Idiographic Data Analysis: Quantitative Methodsâ From Simple to Advanced. In J. Valsiner, P. C. M. Molenaar, M. Lyra, & N. Chaudhary (Eds.), *Dynamic Process Methodology in the Social and Developmental Sciences* (pp. 191–216). New York, NY: Springer-Verlag.
- Hamilton, J. D. (1994). *Time series analysis*. Princeton, NJ: Princeton university press.
- Harvey, A. C. (1990). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press.
- Haslbeck, J., Ryan, O., Robinaugh, D., Waldorp, L., & Borsboom, D. (2021a). *Modeling Psychopathology: From Data Models to Formal Theories* (tech. rep.). https://doi.org/10.31234/osf.io/jgm7f
- Haslbeck, J. M. B. (2022). Estimating group differences in network models using moderation analysis. *Behavior Research Methods*, *54*(1), 522–540. https://doi.org/10.3758/s13428-021-01637-y
- Haslbeck, J. M. B., Borsboom, D., & Waldorp, L. J. (2021b). Moderated Network Models. *Multivariate Behavioral Research*, *56*(2), 256–287. https://doi.org/10.1080/00273171.2019.1677207
- Haslbeck, J. M. B., Bringmann, L. F., & Waldorp, L. J. (2020). A Tutorial on Estimating Time-Varying Vector Autoregressive Models. *Multivariate Behavioral Research*, *56*(1), 120–149. https://doi.org/10.1080/00273171.2020.1743630
- Haslbeck, J. M., Ryan, O., Maas, H. L. van der, & Waldorp, L. J. (2022). Modeling Change in Networks. In *Network Psychometrics with R* (pp. 193–209). Routledge.
- Hawkley, L. C., & Cacioppo, J. T. (2010). Loneliness Matters: A Theoretical and Empirical Review of Consequences and Mechanisms. *Annals of Behavioral Medicine*, *40*(2), 218–227. https://doi.org/10.1007/s12160-010-9210-8
- Hayes, A. M., Laurenceau, J.-P., Feldman, G., Strauss, J. L., & Cardaciotto, L. (2007). Change is not always linear: The study of nonlinear and discontinuous patterns of change in psychotherapy. *Clinical Psychology Review*, *27*(6), 715–723. https://doi.org/10.1016/j.cpr.2007.01.008
- Hayes, A. F., & Montoya, A. K. (2017). A Tutorial on Testing, Visualizing, and Probing an Interaction Involving a Multicategorical Variable in Linear Regression Analysis. *Communication Methods and Measures*, *11*(1), 1–30. https://doi.org/10.1080/19312458.2016.1271116
- Helmich, M. A., Smit, A. C., Bringmann, L. F., Schreuder, M. J., Oldehinkel, A. J., Wichers, M., & Snippe, E. (2023). Detecting Impending Symptom Transitions Using Early-Warning Signals in Individuals Receiving Treatment for Depression. *Clinical Psychological Science*, *11*(6), 994–1010. https://doi.org/10.1177/21677026221137006

- Jongerling, J., Laurenceau, J.-P., & Hamaker, E. L. (2015). A Multilevel AR(1) Model: Allowing for Inter-Individual Differences in Trait-Scores, Inertia, and Innovation Variance. *Multivariate Behavioral Research*, *50*(3), 334–349. https://doi.org/10.1080/00273171.2014.1003772
- Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, *82*(1), 35–45. https://doi.org/10.1115/1.3662552
- Ketkar, N. (2017). *Deep Learning with Python*. Apress. https://doi.org/10.1007/978-1-4842-2766-4
- Klipstein, L. von, Riese, H., Veen, D. C. van der, Servaas, M. N., & Schoevers, R. A. (2020). Using person-specific networks in psychotherapy: Challenges, limitations, and how we could use them anyway. *BMC Medicine*, *18*(1), 1–8. https://doi.org/10.1186/s12916-020-01818-0
- Klipstein, L. von, Servaas, M. N., Schoevers, R. A., Veen, D. C. van der, & Riese, H. (2023). Integrating personalized experience sampling in psychotherapy: A case illustration of the Therap-i module. *Heliyon*, *9*(3), e14507. https://doi.org/10.1016/j.heliyon.2023.e14507
- Konjarski, M., Murray, G., Lee, V. V., & Jackson, M. L. (2018). Reciprocal relationships between daily sleep and mood: A systematic review of naturalistic prospective studies. *Sleep Medicine Reviews*, *42*, 47–58. https://doi.org/10.1016/j.smrv.2018.05.005
- Koval, P., Burnett, P. T., & Zheng, Y. (2021). Emotional inertia: On the conservation of emotional momentum. In C. E. Waugh & P. Kuppens (Eds.), *Affect dynamics* (pp. 63–94). Springer Nature Switzerland AG.
- Kramer, I., Simons, C. J., Hartmann, J. A., Menne-Lothmann, C., Viechtbauer, W., Peeters, F., Schruers, K., Van Bemmel, A. L., Inez, M., Delespaul, P., Van Os, J., & Wichers, M. (2014). A therapeutic application of the experience sampling method in the treatment of depression: A randomized controlled trial. *World Psychiatry*, *13*(1), 68–77. https://doi.org/10.1002/wps.20090
- Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science*, *21*(7), 984–991. https://doi.org/10.1177/0956797610372634
- Kuppens, P., Dejonckheere, E., Kalokerinos, E. K., & Koval, P. (2022). Some Recommendations on the Use of Daily Life Methods in Affective Science. *Affective Science*, *3*(2), 505–515. https://doi.org/10.1007/s42761-022-00101-0
- Levinson, C. A., Hunt, R. A., Keshishian, A. C., Brown, M. L., Vanzhula, I., Christian, C., Brosof, L. C., & Williams, B. M. (2021). Using individual networks to identify treatment targets for eating disorder treatment: A proof-of-concept study and initial data. *Journal of Eating Disorders*, *9*(1), 147. https://doi.org/10.1186/s40337-021-00504-7
- Li, Y., Wood, J., Ji, L., Chow, S.-M., & Oravecz, Z. (2022). Fitting Multilevel Vector Autoregressive Models in Stan, JAGS, and Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *29*(3), 452–475. https://doi.org/10.1080/10705511.2021.1911657
- Loossens, T., Dejonckheere, E., Tuerlinckx, F., & Verdonck, S. (2021). Informing VAR(1) with qualitative dynamical features improves predictive accuracy. *Psychological Methods*,

26(6), 635–659. https://doi.org/10.1037/met0000401
- Lütkepohl, H. (2007). *New introduction to multiple time series analysis*. New York: Springer.
- Lutz, W., Schwartz, B., Hofmann, S. G., Fisher, A. J., Husen, K., & Rubel, J. A. (2018). Using network analysis for the prediction of treatment dropout in patients with mood and anxiety disorders: A methodological proof-of-concept study. *Scientific Reports*, *8*(1), 1–9. https://doi.org/10.1038/s41598-018-25953-0
- Mansueto, A. C., Wiers, R. W., Weert, J. C. M. van, Schouten, B. C., & Epskamp, S. (2022). Investigating the feasibility of idiographic network models. *Psychological Methods*. https://doi.org/10.1037/MET0000466
- McNeish, D., & Hamaker, E. L. (2019). A Primer on Two-Level Dynamic Structural Equation Models for. *Psychological Methods*, *25*(5), 610–635. https://doi.org/10.1037/met0000250
- Mehl, M. R., & Conner, T. S. (Eds.). (2012). *Handbook of research methods for studying daily life*. New York, NY: Guilford Press.
- Molenaar, P. C. M., Beltz, A. M., Gates, K. M., & Wilson, S. J. (2016). State Space Modeling of Time-Varying Contemporaneous and Lagged Relations in Connectivity Maps. *NeuroImage*, *125*, 791–802. https://doi.org/10.1016/j.neuroimage.2015.10.088
- Myin-Germeys, I., & Kuppens, P. (Eds.). (2022). *The open handbook of experience sampling methodology: A step-by-step guide to designing, conducting, and analyzing ESM studies* (2nd). Leuven: Center for Research on Experience Sampling and Ambulatory Methods Leuven.
- Myin-Germeys, I., Oorschot, M., Collip, D., Lataster, J., Delespaul, P., & Van Os, J. (2009). Experience sampling research in psychopathology: Opening the black box of daily life. *Psychological medicine*, *39*(9), 1533–1547. https://doi.org/10.1017/S0033291708004947
- Neale, M. C., Hunter, M. D., Pritikin, J. N., Zahery, M., Brick, T. R., Kirkpatrick, R. M., Estabrook, R., Bates, T. C., Maes, H. H., & Boker, S. M. (2016). OpenMx 2.0: Extended Structural Equation and Statistical Modeling. *Psychometrika*, *81*(2), 535–549. https://doi.org/10.1007/s11336-014-9435-8
- Oravecz, Z., Tuerlinckx, F., & Vandekerckhove, J. (2011). A hierarchical latent stochastic differential equation model for affective dynamics. *Psychological Methods*, *16*(4), 468–490. https://doi.org/https://doi.org/10.1037/a0024375
- Os, J. van, Verhagen, S., Marsman, A., Peeters, F., Bak, M., Marcelis, M., Drukker, M., Reininghaus, U., Jacobs, N., Lataster, T., Simons, C., Lousberg, R., Gülöksüz, S., Leue, C., Groot, P. C., Viechtbauer, W., & Delespaul, P. (2017). The experience sampling method as an mHealth tool to support self-monitoring, self-insight, and personalized health care in clinical practice. *Depression and Anxiety*, *34*(6), 481–493. https://doi.org/10.1002/DA.22647
- Palmier-Claus, J. E., Myin-Germeys, I., Barkus, E., Bentley, L., Udachina, A., Delespaul, P. A., Lewis, S. W., & Dunn, G. (2011). Experience sampling research in individuals with mental illness: Reflections and guidance. *Acta Psychiatrica Scandinavica*, *123*(1), 12–20. https://doi.org/10.1111/j.1600-0447.2010.01596.x
- Park, C., Majeed, A., Gill, H., Tamura, J., Ho, R. C., Mansur, R. B., Nasri, F., Lee, Y., Rosenblat, J. D.,

Wong, E., & McIntyre, R. S. (2020). The Effect of Loneliness on Distinct Health Outcomes: A Comprehensive Review and Meta-Analysis. *Psychiatry Research*, *294*, 113514. https://doi.org/10.1016/j.psychres.2020.113514

- Pek, J., & Wu, H. (2015). Profile Likelihood-Based Confidence Intervals and Regions for Structural Equation Models. *Psychometrika*, *80*(4), 1123–1145. https://doi.org/10.1007/s11336-015-9461-1
- Piccirillo, M. L., & Rodebaugh, T. L. (2019). Foundations of idiographic methods in psychology and applications for psychotherapy. *Clinical Psychology Review*, *71*, 90–100. https://doi.org/10.1016/j.cpr.2019.01.002
- Piot, M., Mestdagh, M., Riese, H., Weermeijer, J., Brouwer, J. M., Kuppens, P., Dejonckheere, E., & Bos, F. M. (2022). Practitioner and researcher perspectives on the utility of ecological momentary assessment in mental health care: A survey study. *Internet Interventions*, *30*, 100575. https://doi.org/10.1016/j.invent.2022.100575
- R Core Team. (2023). R: A Language and Environment for Statistical Computing. https://www.R-project.org/
- Reeves, J. W., & Fisher, A. J. (2020). An Examination of Idiographic Networks of Posttraumatic Stress Disorder Symptoms. *Journal of Traumatic Stress*, *33*(1), 84–95. https://doi.org/10.1002/jts.22491
- Revol, J., Lafit, G., & Ceulemans, E. (in press). A new sample size planning approach for the VAR(1) model: Predictive Accuracy Analysis. *Behavior Research Methods*. https://doi.org/10.31234/osf.io/2geh4
- Rhudy, M. B., Salguero, R. A., & Holappa, K. (2017). A Kalman Filtering Tutorial for Undergraduate Students. *International Journal of Computer Science & Engineering Survey*, *08*(01), 01–18. https://doi.org/10.5121/ijcses.2017.8101
- Rintala, A., Wampers, M., Myin-Germeys, I., & Viechtbauer, W. (2019). Response compliance and predictors thereof in studies using the experience sampling method. *Psychological Assessment*, *31*(2), 226–235. https://doi.org/10.1037/pas0000662
- Robinaugh, D. J., Hoekstra, R. H., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008-2018 and an agenda for future research. *Psychological Medicine*, *50*(3), 353–366. https://doi.org/10.1017/S0033291719003404
- Schuurman, N. K., & Hamaker, E. L. (2019). Measurement error and person-specific reliability in multilevel autoregressive modeling. *Psychological Methods*, *24*(1), 70–91. https://doi.org/10.1037/met0000188
- Schuurman, N. K., Houtveen, J. H., & Hamaker, E. L. (2015). Incorporating measurement error in n=1 psychological autoregressive modeling. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01038
- Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464.
- Shumway, R. H., & Stoffer, D. S. (2017). *Time Series Analysis and Its Applications: With R Examples*. Springer International Publishing. https://doi.org/10.1007/978-3-319-52452-8
- Silvia, P. J., Kwapil, T. R., Eddington, K. M., & Brown, L. H. (2013). Missed Beeps and Miss-

ing Data: Dispositional and Situational Predictors of Nonresponse in Experience Sampling Research. *Social Science Computer Review*, *31*(4), 471–481. https://doi.org/10.1177/0894439313479902

- Smit, A. C., Snippe, E., Bringmann, L. F., Hoenders, H. J. R., & Wichers, M. (2023). Transitions in depression: If, how, and when depressive symptoms return during and after discontinuing antidepressants. *Quality of Life Research*, *32*(5), 1295–1306. https://doi.org/10.1007/s11136-022-03301-0
- Snippe, E., Elmer, T., Ceulemans, E., Smit, A. C., Lutz, W., & Helmich, M. A. (2024). The Temporal Order of Emotional, Cognitive, and Behavioral Gains in Daily Life during Treatment of Depression. *Journal of Consulting and Clinical Psychology*.
- Snippe, E., Viechtbauer, W., Geschwind, N., Klippel, A., Jonge, P. de, & Wichers, M. (2017). The Impact of Treatments for Depression on the Dynamic Network Structure of Mental States: Two Randomized Controlled Trials. *Scientific Reports*, *7*(1), 46523. https://doi.org/10.1038/srep46523
- Song, H., & Ferrer, E. (2009). State-Space Modeling of Dynamic Psychological Processes via the Kalman Smoother Algorithm: Rationale, Finite Sample Properties, and Applications. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(2), 338–363. https://doi.org/10.1080/10705510902751432
- Stadel, M., Stulp, G., Langener, A. M., Elmer, T., Duijn, M. A. J. van, & Bringmann, L. F. (2023). Feedback About a Person's Social Context - Personal Networks and Daily Social Interactions. *Administration and Policy in Mental Health and Mental Health Services Research*. https://doi.org/10.1007/s10488-023-01293-8
- Stadnitski, T., & Wild, B. (2019). How to Deal With Temporal Relationships Between Biopsychosocial Variables: A Practical Guide to Time Series Analysis. *Psychosomatic Medicine*, *81*(3), 289–304. https://doi.org/10.1097/PSY.0000000000000680
- Stochl, J., Soneson, E., Wagner, A. P., Khandaker, G. M., Goodyer, I., & Jones, P. B. (2019). Identifying key targets for interventions to improve psychological wellbeing: Replicable results from four UK cohorts. *Psychological Medicine*, *49*(14), 2389–2396. https://doi.org/10.1017/S0033291718003288
- Suls, J., Green, P., & Hillis, S. (1998). Emotional reactivity to everyday problems, affective inertia, and neuroticism. *Personality and Social Psychology Bulletin*, *24*(2), 127–136. https://doi.org/10.1177/0146167298242002
- Swanson, T., James. (2023). *Modeling Moderators in Psychological Networks* [Doctoral dissertation]. Retrieved November 14, 2023, from https://www.proquest.com/openview/d151ab6b93ad47e3f0d5e59d7b6fd3d3
- Trull, T. J., & Ebner-Priemer, U. (2013). Ambulatory assessment. *Annual Review of Clinical Psychology*, *9*, 151–176. https://doi.org/10.1146/annurev-clinpsy-050212-185510
- Trull, T. J., & Ebner-Priemer, U. W. (2020). Ambulatory assessment in psychopathology research: A review of recommended reporting guidelines and current practices. *Journal of Abnormal Psychology*, *129*(1), 56–63. https://doi.org/10.1037/abn0000473
- Tuin, S. van der, Balafas, S. E., Oldehinkel, A. J., Wit, E. C., Booij, S. H., & Wigman, J. T. W. (2022).

Dynamic symptom networks across different at-risk stages for psychosis: An individual and transdiagnostic perspective. *Schizophrenia Research*, *239*, 95–102. https://doi.org/10.1016/j.schres.2021.11.018

- Van der Krieke, L., Jeronimus, B. F., Blaauw, F. J., Wanders, R. B., Emerencia, A. C., Schenk, H. M., Vos, S. D., Snippe, E., Wichers, M., Wigman, J. T., Bos, E. H., Wardenaar, K. J., & De Jonge, P. (2016). HowNutsAreTheDutch (HoeGekIsNL): A crowdsourcing study of mental symptoms and strengths. *International Journal of Methods in Psychiatric Research*, *25*(2), 123–144. https://doi.org/10.1002/mpr.1495
- Van Roekel, E., Heininga, V. E., Vrijen, C., Snippe, E., & Oldehinkel, A. J. (2019). Reciprocal associations between positive emotions and motivation in daily life: Network analyses in anhedonic individuals and healthy controls. *Emotion*, *19*(2), 292–300. https://doi.org/10.1037/emo0000424
- Wal, J. M. v. d., Borkulo, C. D. v., Haslbeck, J. M. B., Slofstra, C., Klein, N. S., Blanken, T. F., Deserno, M. K., Lok, A., Nauta, M. H., & Bockting, C. L. (2023). Differential impact of preventive cognitive therapy while tapering antidepressants versus maintenance antidepressant treatment on affect fluctuations and individual affect networks and impact on relapse: A secondary analysis of a randomised controlled trial. *eClinicalMedicine*, *66*. https://doi.org/10.1016/j.eclinm.2023.102329
- Watling, J., Pawlik, B., Scott, K., Booth, S., & Short, M. A. (2017). Sleep Loss and Affective Functioning: More Than Just Mood. *Behavioral Sleep Medicine*, *15*(5), 394–409. https://doi.org/10.1080/15402002.2016.1141770
- Weermeijer, J., Kiekens, G., Wampers, M., Kuppens, P., & Myin-Germeys, I. (2023). Practitioner perspectives on the use of the experience sampling software in counseling and clinical psychology. *Behaviour & Information Technology*, 1–11. https://doi.org/10.1080/0144929X.2023.2178235
- Wichers, M., Hartmann, J. A., Kramer, I. M., Lothmann, C., Peeters, F., Bemmel, L. van, Myin-Germeys, I., Delespaul, P. H., Os, J. van, & Simons, C. J. (2011). Translating assessments of the film of daily life into person-tailored feedback interventions in depression. *Acta Psychiatrica Scandinavica*, *123*(5), 402–403. https://doi.org/10.1111/j.1600-0447.2011.01684.x
- Wichers, M., Groot, P. C., & Psychosystems. (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression [Publisher: Karger Publishers]. *Psychotherapy and Psychosomatics*, *85*(2), 114–116.
- Wichers, M., Smit, A. C., & Snippe, E. (2020). Early warning signals based on momentary affect dynamics can expose nearby transitions in depression: A confirmatory single-subject time-series study. *Journal for Person-Oriented Research*, *6*(1), 1–15. https://doi.org/10.17505/jpor.2020.22042
- Wichers, M., Wigman, H., Bringmann, L., & Jonge, P. de. (2017). Mental disorders as networks: Some cautionary reflections on a promising approach. *Social Psychiatry and Psychiatric Epidemiology*, *52*(2), 143–145.
- Wright, A. G., & Woods, W. C. (2020). Personalized Models of Psychopathology. *Annual Review of Clinical Psychology.*, *7*(16), 49–74.

https://doi.org/10.1146/annurev-clinpsy-102419-125032

- Wright, A. G., & Zimmermann, J. (2019). Applied ambulatory assessment: Integrating idiographic and nomothetic principles of measurement. *Psychological Assessment*, *31*(12), 1467–1480. https://doi.org/10.1037/pas0000685

A. APPENDIX: STATE SPACE FORMULATION OF ME-VAR(1) MODEL

We will now give a general formulation of the state space model for a VAR(1) model with measurement error (ME-VAR(1)). Note that the state space framework allows for more general formulations, such as allowing for time-varying parameters (Chen et al., 2021) or dynamic factor analysis (Song & Ferrer, 2009). The measurement equation can be formulated as follows, with m representing the number of observed or manifest variables and q representing the number of latent variables.[9]

$$\begin{aligned} y_t &= d + F\eta_t + \omega_t \\ \omega_t &\sim MvN(0, \Sigma_\omega), \end{aligned} \tag{18}$$

where y_t again contains the observed variables in a $m \times 1$ vector, η_t is a q-dimensional vector of latent variables, also known as the states in the state space framework. Furthermore, d is a vector of $m \times 1$ containing the intercepts of the observed variables and the matrix F of $m \times q$ that entails the factor loadings. The $m \times 1$ vector ω_t represents the measurement residuals, which represent a mix of a true, occasion-specific fluctuation in mood due to contextual effects (Castro-Alvarez et al., 2022) and measurement error, but are often referred to as just measurement error (see for more information Schuurman & Hamaker, 2019). The measurement residuals are assumed to be multivariate normally distributed with a covariance matrix Σ_ω of $m \times m$ and means of zero.

The measurement model links the observational variables to the latent or state variables. The state or transition equation can be formulated as follows

$$\begin{aligned} \eta_t &= c + \Phi\eta_{t-1} + \epsilon_t \\ \epsilon_t &\sim MvN(0, \Sigma_\epsilon), \end{aligned} \tag{19}$$

in this case, the latent intercepts are represented in a $q \times 1$ vector, and η_t represents a vector of latent variables (denoted by $q \times 1$) known as states. These states are regressed on their own values at the previous time point η_{t-1}.[10] Respectively, Φ is the transition matrix of $q \times q$ linking the state from one time point to the next via the auto- and cross-lagged regression effects it entails. The $q \times 1$ vector ϵ_t representing the dynamic residuals at time t and are also assumed to be multivariate normally distributed with a covariance matrix Σ_ϵ of $q \times q$ and means of zero.

The VAR model where we estimate the mean instead of the intercept directly is a special case of the two state space equations (18) and (19). To do so we set the factor loadings of the matrix F to 1, we leave out the measurement residuals ω_t, so we do not allow for separating the dynamic error from measurement error and we set the latent intercept c to zero. This leaves the intercept vector d as the

[9] We follow here the formulation and equations based on (Jongerling et al., 2015; Schuurman et al., 2015; Song & Ferrer, 2009).
[10] Note that also other lags can be incorporated into this term, such as a lag-2 effect. However, for simplicity, we only focus on the lag-1 case (see Song and Ferrer, 2009).

only constant in the equations and with the dynamic residuals ϵ_t having a mean of zero, this results in d becoming the mean μ of the process. This leads to Equations (13) and (14).