The non-existent average individual
Blaauw, Frank

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Chapter 6

Personalized improvement of well-being: Automated Impulse Response Analysis

The attention for personalized mental health care is thriving. Research data specific to the individual, such as time series sensor data or data from ecological momentary assessment (EMA) studies, is relevant from a research perspective, as analyses on these data can reveal the heterogeneity among the participants and provide precise and individualized results, often more precise than with group-based methods. However, using this data for self-management and to help the individual to improve his or her mental health has proved challenging.

In this chapter, we present a novel approach to automatically generate personalized advice for the improvement of the well-being of individuals by using time series data from intensive longitudinal studies: Automated Impulse Response Analysis (AIRA). AIRA analyzes vector autoregression (VAR) models of well-being by generating impulse response functions (IRFs). These IRFs are used in simulations to determine which variables in the model have the largest influence on the other variables and thus on the well-being of the participant. The effects found can be used to support self-management and a more personal medicine.

We demonstrate the practical usefulness of AIRA by performing an analysis on longitudinal self-reported data about psychological variables. To evaluate its effectiveness and efficacy, we ran its algorithms on two data sets \((n = 4\) and \(n = 5\)), and discuss the results. We compare AIRA’s output to the results of a previously published study and show that the results are comparable. Moreover, we used AIRA for investigating the relation between depression and anhedonia (i.e., the inability to experience interest in or pleasure from activities) in the HowNutsAreTheDutch (HND) data set, using \(n = 40\) participants from HND in the analysis. By automating...
IRF Analysis, AIRA fulfills the need for accurate individualized models of health outcomes at a low resource cost with the potential for upscaling. Throughout this chapter, we adhere to a simple running example using six variables that could be related to well-being: (i) ‘rumination’, (ii) ‘self-esteem’, (iii) ‘concentration’, (iv) ‘cheerfulness’, (v) ‘agitation’, and (vi) ‘eating candy’.

6.1 Automated Diary Study Data Analysis

When questionnaires are filled out in sequence, the data is a time series. A popular technique for analyzing multivariate, equally spaced time series data is vector autoregression (VAR; Sims, 1980). VAR can be used to fit a multivariate regression model; a model in which the outcome of one variable (e.g., ‘concentration’) is regressed on the outcomes of several other variables (e.g., ‘self-esteem’ and ‘agitation’). The VAR model itself is a set of such multivariate regression equations for a system of two or more variables, where each variable in the system is regressed on its own time-lagged values and the time-lagged values of all other variables in the system (Brandt & Williams, 2007). That is, a variable \( x \) at time \( t \) is predicted by the same variable \( x \) at time \( t - 1, t - 2, \ldots, t - p \) and by other variables at time \( t - 1, t - 2, \ldots, t - p \). The number of measurements used to look back in time (\( p \)) are called lags in time series parlance.

VAR models allow for determining Granger causality, which can be depicted by means of a weighted directed graph (Granger, 1969). Figure 6.1 gives an example of such a graph related to our running example. In this figure, for example, an increase in the variable ‘agitation’ at time \( t - 1 \) Granger causes an increase in ‘rumination’ and a decrease in ‘self-esteem’, ‘concentration’, ‘cheerfulness’, and ‘eating candy’ at time \( t \). The figure only shows relations present at lag 1. A description of these networks and their nodes is provided in Section 2.3.1.

Graphs like these encompass relevant information regarding the interactions in a VAR model that could be of interest to the participant. However, they also lack several important features to serve as a means to provide advice on how to improve the participant’s well-being. Firstly, participants may have a hard time understanding these graphs (van der Krieke, Blaauw, et al., 2016). This can be attributed to the conceptual complexity of the different edge and node types in the graph. Secondly, these graphs give a general overview of the coefficients in a VAR model by providing an edge-focused representation. Although such a representation gives information about the individual relations between nodes, it remains complicated to interpret the model as a whole, especially with respect to the temporal interplay between the nodes in the model. The VAR coefficients are meaningless when interpreted in-
6.1. Automated Diary Study Data Analysis

Figure 6.1: An example of a Granger causality graph.

dividually, as it is the VAR model as a whole that describes the complete dynamic behavior of the variables in the system (Brandt & Williams, 2007).

In this chapter, we describe AIRA, an approach to automatically generate advice for improving a participant’s well-being using VAR models derived from EMA data. AIRA creates advice by simulating the interactions between variables in a VAR model (i.e., showing what would happen to $y$ when variable $x$ increases). The technique AIRA uses is called IRF analysis. IRF analysis allows to shock (i.e., give an instantaneous exogenous impulse to) certain variables to see how this shock propagates through the various (time-lagged) relations in the VAR model. In other words, IRF shows how variables respond to an impulse applied to other variables (Brandt & Williams, 2007). AIRA generates the IRFs for each of the equations in a VAR model, and analyzes these IRFs to automatically generate personalized advice. AIRA uses and partly extends some of our previous work; the automatic creation of VAR models (Emerencia et al., 2016). The fact that AIRA analyzes the VAR model as a whole enables AIRA to be a more appropriate and more precise technique for analyzing a VAR model than a mere manual inspection of said model. A second novelty of the present work is an implementation of VAR and IRF analysis in the JavaScript-language. To the best of our knowledge, this is the first openly available cross-platform Web-based implementation of its kind. The JavaScript implementation can be useful for calculating VAR models or IRFs in the browser, or on a server running for example NodeJS\(^1\), which can aid upscaling.

AIRA generates several types of advice answering questions similar to the following: (i) Which of the modeled variables has the largest effect on my well-being?, (ii) How long is $Y$ affected by an increase in $X$?, and (iii) What can I do to change a certain $Y$ variable? Firstly, AIRA shows how well each of the modeled variables can be used to

\(^1\text{Website: http://nodejs.org.}\)
improve all other variables in the network, by summing over the effects variables have on the other variables. For this type of advice, we consider an improvement of the complete network an improvement of the participant’s well-being in general. Secondly, AIRA provides insight into the duration of an effect, giving insight in the persistence of a perceived relation. Thirdly, AIRA allows the participant to select a variable he or she would like to improve and by how much, after which AIRA will try to find a suitable solution to achieve this improvement. AIRA iterates over all other variables and estimate for each of these variables how large a change is needed to achieve the desired effect.

This chapter is organized as follows. Section 6.2 gives an overview of related work. Section 6.3 illustrates the concept of AIRA presenting its mathematical foundation. Section 6.4 describes AIRA by presenting pseudo code of the algorithms. Section 6.5 describes the experimental results acquired when evaluating AIRA. We also evaluate the implementation of AIRA by comparing its analysis with a manually performed analysis. Finally, we applied AIRA to answer questions related to anhedonia and major depressive disorder (MDD). This real-world application of AIRA to research is provided in Section 6.6.

6.2 Impulse Response Function Analysis and Ecological Momentary Assessment Advice

IRF is a technique used in several fields, including digital and analog signal processing (Bellanger, 1984), control theory (Hespanha, 2009), psychiatry (Hoenders, Bos, de Jong, & de Jonge, 2011), econometrics (Pesaran & Shin, 1998), and even for the quality assurance of fruit (Diezma-Iglesias, Ruiz-Altisent, & Barreiro, 2004). Each field applies IRF differently, but all applications revolve around a comparable principle; IRFs are used to determine how a model or system, or part of that model or system, responds to a sudden large change or shock.

Several applications exist that have functionality to provide users with feedback based on diary studies or other longitudinal health data collected by them. The feedback and advice provided in EMA studies can roughly be split into two categories: real-time advice and post-hoc advice. The type of advice chosen for a study depends on the goal of the study.

Real-time advice can be used to intervene directly in the EMA study. For example, Hareva, Okada, Kitawaki, and Oka (2009) present advice to a participant by means of applying a severity threshold to the EMA results. They describe a use case of their system for smoking cessation in which an email is automatically sent whenever a participant has smoked fewer cigarettes than a set threshold in order to encourage
the behavior of smoking less. Real-time advice triggered by diary data has also been applied in treating childhood overweight. In a study by Bauer, de Niet, Timman, and Kordy (2010), juvenile participants sent weekly text messages (SMS) describing various parameters (such as emotion and eating behavior), after which an algorithm would automatically compare these results to the preceding week and create advice. Post-hoc advice is offered after completing the study. One of the advantages of this method is that elaborate statistical analysis can be performed, since all collected data can be used (instead of a small window of data). Furthermore, post-hoc feedback can be used in cases where the goal is to map the baseline behavior of a participant, not affected by interventions. To the best of our knowledge, only a few studies exist to date that provide personalized, post-hoc advice based on the dynamic relations between the variables in an EMA study. In an electronic diary study performed by Booij et al. (2015) participants received a post-hoc personal report on their daily activity and mood patterns. Van Roekel et al. (2016) provided participants of their electronic diary study with a written report and gave them lifestyle advice based on VAR models and the variables most promising for inducing a change in pleasure. Our two platforms, described in Chapter 3 (i.e., HND and Leefplezier), also provide post-hoc feedback. Both platforms provide feedback based on VAR models, but merely present Granger causality networks as-is, without performing analysis on the VAR models. Furthermore, the feedback provided in these studies is mainly descriptive and does not provide concrete examples on how participants can enhance their well-being, unlike AIRA.

6.3 From Variable Selection to Advice Generation

AIRA uses IRF analysis to determine the effect each variable has on the other variables in the VAR model for generating advice. The outcome of this analysis is then converted by AIRA into several types of advice for the participant. The advice describes in several ways which of the variables can best be adjusted in order to achieve the desired effect. The advice generation process of AIRA can be subdivided into four phases: (a) initialization, (b) simulation, (c) variable selection, and (d) advice generation. The AIRA process is illustrated in Figure 6.2.

6.3.1 Initialization

In the first phase, AIRA converts the VAR model into its VMA representation. This VMA representation shows how the model responds to changes in the residuals or to exogenous shocks on the model (i.e., shocks from outside of the model; Brandt & Williams, 2007). As an example, we show a basic var($p$) model (a VAR model with
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Figure 6.2: Overview of the AIRA advice generation process.
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$p$ lags) as

\[ Y_t = c + B^1 Y_{t-1} + \cdots + B^p Y_{t-p} + \xi X + \tilde{e}_t, \]  

(6.1)

in which we define $Y_t$ as a vector containing $m$ variables ($\tilde{v}$) at time $t$, $p$ as the number of lags in the model, $c$ as a vector containing $m$ constant terms, $X$ as the exogenous variables (i.e., variables that can influence the model, but cannot be influenced by the model, such as the day of the week or the weather), $\xi$ as the coefficient matrix for the exogenous variables, $\tilde{e}_t$ as a vector containing the error in the model (i.e., all variance left in the data not explained by the model), and each $B^1, B^2, \ldots, B^p$ as a coefficient matrix for a specific lag in time. Each entry ($\beta$) of one of the matrices $B^p$ is a coefficient for one variable predicting another value at a specific lag. Each matrix in $B^p$ has the order variable coefficients. That is, each row of a $B^p$ matrix represents the coefficients of lag $p$ for the variable in that row (e.g., $\beta^p_{i,j}$ is the scalar coefficient for predicting variable $i$ using variable $j$, at lag $p$). From this VAR model, we can then define the vma representation as

\[ Y_t - d = \tilde{e}_t \cdot (I_m + \sum_{i=1}^{k} C_{1,i})L + \left( \sum_{i=1}^{k} C_{2,i} \right)L^2 + \cdots, \]  

(6.2)

which is the same model as in Equation (6.1), but centered around its equilibrium values and converted to a function of the error term in the model (Brandt & Williams, 2007). The VMA representation allows one to investigate the standardized impact of a shock on the model. For more information on the VAR to VMA model conversion, see Brandt and Williams (2007). In Equation (6.2), $L^k$ is the lag operator which shifts the variable that it is multiplied by with $k$ steps, that is, $L^k x_t = x_{t-k}$. $C_1, C_2, \ldots, C_p$ are the VMA coefficient matrices of the model. Each $C_i$ represents the $i^{th}$ row of $C$, each $C_{i,j}$ a specific element from that row. $C$ itself is a block lower triangular matrix, defined as

\[
C = \begin{bmatrix}
B^1 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\
B^1 C_1 & B^2 & 0 & 0 & 0 & 0 & 0 & \cdots \\
B^1 C_2 & B^2 C_1 & B^3 & 0 & 0 & 0 & 0 & \cdots \\
B^1 C_3 & B^2 C_2 & B^3 C_1 & B^4 & 0 & 0 & 0 & \cdots \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\
B^1 C_{p-1} & B^2 C_{p-2} & B^3 C_{p-3} & \cdots & B^{p-1} C_1 & B^p & 0 & 0 & \cdots \\
\vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\
B^1 C_{p-1} & B^2 C_{p-2} & B^3 C_{p-3} & \cdots & B^{p-1} C_{p-(p-1)} & B^p C_{p-p} & 0 & C_{p-(p+1)} & \cdots \\
\end{bmatrix}
\]

Note that $C$ is contained in itself, as each row of $C_i$ contains all preceding entries in $C$ (i.e., $C_{i-1}, C_{i-2}, \ldots, C_0$). The reason for this recursion is that an effect at time $t$ is also affected by all of the preceding effects ($t-1, t-2, \ldots$). Theoretically, the
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A matrix can contain an infinite number of rows. However, when using a stable VAR model, a property Autovar tests for, the responses will eventually converge to zero (Brandt & Williams, 2007). This number of rows can be limited to a certain number of steps \((k)\), also known as horizon. The horizon is the total number of steps the IRF model will predict. The \(\vec{e}_t\) vector \((m \times 1)\) originates from an \(m \times k\) matrix \(E\) that contains the error terms for each variable corresponding to a variable at the same location in \(\vec{v}\). When performing IRF analysis, the \(\vec{e}_t\) term is replaced by a vector of shocks \(\vec{s}\), which is a not-lagged vector of structural shocks to the model. In this work, we assume shocks of unit size, that is, each entry in this vector is either 1 (if a variable receives a shock) or 0 (if a variable does not receive a shock). Because of the standardized effects, this corresponds to an standard deviation (SD) increase.

Equation (6.2) does not take into account the contemporaneous effects, and captures these effects in the error term. It is often problematic to determine the direction of the effect for the contemporaneous effects, as they merely show the correlation, and therefore the direction remains unclear. If one has a hypothesis regarding the directionality of these contemporaneous effects they could be implemented by using a technique named orthogonalized impulse response functions (OIRFs; Brandt & Williams, 2007). In that case, \(I_m\) (the \(m \times m\) identity matrix) should be changed to a matrix representing the contemporaneous effects, for example, by computing the first matrix from the Cholesky decomposition of the error covariance matrix and possibly testing all directions for the effects, or by using theoretical domain knowledge for the directions (Brandt & Williams, 2007; Pesaran & Shin, 1998). The \(d\) term is the VAR constant term divided by the vector autoregressive lag polynomial.

6.3.2 Simulation

In the second phase, AIRA runs IRF calculations for each of the variables in the model. AIRA simulates an impulse on one variable \((x)\) in the model and registers how all other variables respond. The response of each variable is used to determine the effect of a variable on the other variables in the model. Besides using all responses caused by an impulse, AIRA can also be configured to consider only the effects which have a certainty of at least 95\%, by bootstrapping the model (Lütkepohl, 2005). The methods in this phase allow for determining the variables most suitable for influencing other variables and serves as a preprocessing step for generating advice.

An example of an IRF of the network model used in Figure 6.1 is shown in Figure 6.3. The figure shows how a shock on ‘agitation’ (the green line) affects the other variables in the model. The shock is an SD increase of the variable ‘agitation’ (at time \(t = 0\)). The other variables respond from \(t = 1\) onwards (as contemporaneous rela-
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Figure 6.3: An example of the responses of six variables from a VAR(1) model after a shock on the variable ‘agitation’, corresponding to the network shown in Figure 6.1.

The shock on ‘agitation’ has an effect on most of the variables in the model: a negative effect on ‘eating candy’, ‘cheerfulness’, ‘self-esteem’, and ‘concentration’, and a positive effect on ‘rumination’. The effect converges to zero after about 7 time steps.

The response of one variable to changes in another variable can be calculated using the IRF function,

\[
\text{irf}(x, y, k) = [(\zeta_0 \odot \bar{\alpha}(x))_y, \ldots, (\zeta_k \odot \bar{\alpha}(x))_y]_T,
\]

\[
\zeta_i = \begin{cases} 
1_m & \text{if } i = 0, \\
\sum_{j=1}^{i} C_{i,j} & \text{if } i \geq 1,
\end{cases}
\]

in which \(x\) is the index of the variable receiving the shock and \(y\) the index of the variable for which the response is analyzed. The outcome of this equation is a vector with the response of \(y\), where each entry is a response on the horizon \(k\). The remainder of the equation is similar to Equation (6.2). However, in this equation, \(\bar{\alpha}\) is a vector of zeros, with a 1 on the index of the variable to shock (\(x\)). Additionally, AIRA applies a form of cumulative IRF analysis to determine the total response a variable has on another variable. In cumulative IRF analysis, the response of a variable is summed to a total value, as

\[
\text{irf}_c(x, y, k) = \sum_{j=0}^{k} \text{irf}(x, y, k)_j,
\]

where \(x\) is the variable that is shocked and \(y\) is the variable the response is analyzed on. It sums all responses on the horizon \(k\). The cumulative IRF is equivalent to the
net area under the curve (AUC), where areas corresponding to a response less than zero are subtracted from areas corresponding to responses higher than zero. Using the example IRF in Figure 6.4, the cumulative response is the green areas minus the red areas. The definition of the IRF as shown in Equation (6.3) takes all responses into account, which might be too optimistic and cause inaccuracies. These inaccuracies may cause small insignificant effects to add up to a large, seemingly significant effect. To circumvent this, AIRA can be configured so that it only considers significant effects by bootstrapping the results (Brandt & Williams, 2007; Lütkepohl, 2005; Sims & Zha, 1999) and only use effects significantly different from 0. In Figure 6.4 the darker areas depict the significant areas. The dashed lines indicate the 95% confidence interval (CI). The advantage of using this cumulative approach is that we obtain a single value representing the total effect of a single variable on another variable in the model, whilst taking into account all other interrelated variables.

![Figure 6.4: Artificial example of the area under the curve to demonstrate the response to an impulse.](image)

### 6.3.3 Variable Selection

In the third phase, AIRA selects the variable that is most suitable for adjusting the other variables in the model. AIRA determines the net effect one variable has on all other variables. By using the total AUC, including the negative effects, AIRA gives an estimate of the net effect a variable has. We define the function for calculating
this net effect of a single variable \((x)\) as follows

\[
\text{irf}_t(x, k) = \sum_{i=1}^{m} \text{irf}_c(x, i, k),
\]

in which \(k\) is the horizon over which the effect is calculated, and \(m\) is the number of variables in the model. The result of this equation is the net effect variable \(x\) has on the other variables. This result is contained in a vector of size \(m - 1\). The \(\text{irf}_c\) function uses a \(\text{VAR}\) model that handles ‘positive’ and ‘negative’ variables differently. Whether a variable is ‘positive’ or ‘negative’ is defined by its interpretation, that is, variables are considered positive or negative with respect to the well-being of a participant. For instance, a model might include two variables: ‘agitation’ and ‘cheerfulness’, in which ‘Agitation’ is considered a negative variable and ‘cheerfulness’ is interpreted as a positive one. A variable deemed positive (‘cheerfulness’) is presumably preferred to be increased, while a negative variable (‘agitation’) is preferred to be decreased. To deal with this dichotomy, a transformation is performed on the negative variables using the \(\Gamma\) and \(E\) matrices; two matrices that convert the variables of a \(\text{VAR}\) model so that they are always positive. That is, negative variables change sign so their interpretation switches from an increase to a decrease of said variable. These matrices are defined as

\[
\begin{align*}
\vec{v}_l &= [-1, 1, -1, 1, -1, 1]^T, \\
\Gamma &= \vec{v}_l \cdot \vec{v}_l^T, \\
E &= \vec{v}_l \cdot \vec{1}_l^T.
\end{align*}
\]

Each entry of the \(\Gamma\) matrix is \(\in \{1, -1\}\) and is created using \(\vec{v}_l\), a vector representing the interpretation of a variable. That is, \(\vec{v}_{l,i} = 1\) if the variable at position \(i\) in \(\vec{v}\) (a vector containing the variables in the model) is positive, and \(\vec{v}_{l,i} = -1\) if \(\vec{v}_i\) is negative. The \(E\) matrix is a matrix of which the rows of a negative endogenous variable are negative. This equation shows how \(\vec{v}_l\) built using a \(\vec{v}\) with our six variables: \(\vec{v} = [\text{’eating candy (negative)’, ‘cheerfulness (positive)’, ‘agitation (negative)’, ‘concentration (positive)’, ‘rumination (negative)’, ‘self-esteem (positive)’}]^T\). The \(l\) variable denotes the number of exogenous variables in the model. After the transformation the \(\vec{v}_l\) can be considered a vector of all ones.

These \(\Gamma\) and \(E\) matrices are used to calculate the Hadamard product of \(\Gamma\) and the \(B\) matrices (\(\Gamma \circ B^p\)) and \(E\) and the \(\xi\) matrices (\(E \circ \xi\) of Equation (6.1), and is then used as input for the \(\text{irf}_c\) function. AIRA can use this equation to determine the total effect of each variable on other variables, and therewith calculate the effect of a variable on the network as a whole.
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6.3.4 Advice Generation

In the last phase, AIRA generates the actual advice for the participant. The procedures of the previous phases are combined and personalized advice is constructed. AIRA currently generates three types of advice: (i) most influential node in network, (ii) percentage effect, and (iii) length of an effect.

Most influential node in network.

AIRA identifies the variable with the largest net positive effect that can best be used for changing other variables. The advice describes how a participant can have the largest positive influence on his or her well-being. For example, if we determine that overall an increase in activity has a positive effect on the network, the advice is: ‘If you were to increase your amount of activity, this seems to positively affect your well-being’. The well-being of a participant is in this case expressed by all variables in the network model. An increase in the network as a whole is considered an increase in the well-being of the participant. The generated advice consists of a sorted list of all variables and the extent to which they positively (i.e., increase one’s well-being), negatively (i.e., decrease one’s well-being), or neutrally (i.e., do not affect one’s well-being) impact the network. The net effect of a variable is calculated by summing the cumulative IRFs. By using the net effect approach, we deal with the issue where the signs of coefficients for different lags of variables are conflicting. For example, a variable can have a positive coefficient for a variable on the first lag, but a negative effect in the second one. AIRA balances these effects by using the net effect.

Length of effect.

AIRA shows the participant how long an impulse is estimated to have an effect on the other variables in the model. For calculating the length of an effect AIRA uses the (bootstrapped) IRF as input, and determines how long, in minutes, a response of a variable remains (significantly) different from zero. The length is calculated by multiplying the EMA measurement interval with the number of steps on the horizon for which the effect is (significantly) greater or less than zero. For example, if an impulse on ‘activity’ has an effect smaller than zero on ‘depression’ for two time-steps and the measurement interval is six hours, AIRA would state that a one standard deviation increase on ‘activity’ has a negative effect on ‘depression’ for approximately 720 minutes (or twelve hours). Furthermore, it determines how long the effective horizon is with respect to the given impulse. That is, after how many steps all the (significant) effects have converged to zero.
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Percentage effect.

AIRA generates specific advice showing what a participant could do in order to improve a single specific variable in the network by a specified percentage. For example, imagine a participant that would like to increase his or her ‘cheerfulness’ variable by 10%. AIRA can determine how to achieve this increase by advising the participant to either increase or decrease certain other variables in the model. Advice could then be generated as follows: ‘In order to increase your cheerfulness by 10%, you can either increase your concentration by 20% or decrease your agitation by 33%’. This advice calculation is defined as follows. Provided that $\text{irf}_{c}(y, x) \neq 0$, $\hat{y} \neq 0$, and $\sigma_{x} \neq 0$ (the SD of $x$), then $\forall y \mid \vec{v}_{y} \in \vec{v}, y \neq x$,

\[
\Delta_{y} = \frac{(\hat{k} \cdot \hat{x}) \cdot \Delta \cdot \sigma_{y}}{\hat{y} \cdot \text{irf}_{c}(y, x, k) \cdot \sigma_{x}},
\]

in which $\Delta \cdot 100$ is the desired percentage for increasing ($\Delta > 0$) or decreasing ($\Delta < 0$) variable $x$. $\Delta_{y} \cdot 100$ is the calculated percentage effect $y$ has on $x$. $\hat{x}$ and $\hat{y}$ represent the average scores for the variables $x$ and $y$ of a participant respectively, $\sigma_{x}$ and $\sigma_{y}$ are the SDs of respectively variables $x$ and $y$, and $k$ is the effective horizon over which the effect is calculated. The effective horizon is the number of steps on the horizon when the response of a shock has not yet converged to zero. The calculation is performed for all variables in the model ($\vec{v}_{y} \in \vec{v}$) not equal to the variable to improve ($y \neq x$), and the advice is established from the outcomes for each variable. The total effect $y$ has on $x$ is used in the calculation.

As an example, assume a person that has a variable $x$ (the variable this person would like to change) with a mean value of 50, and $\sigma_{x} = 15$. Assuming normality, an increase of one standard deviation would mean an increase of 15, i.e., an increase of $\frac{\sigma_{x}}{\sigma_{x}} \cdot 100 = 30\%$. Assume this person would like to increase the value of $x$ by 10%, we would require an increase of $\frac{0.10 \cdot \sigma_{x}}{\sigma_{x}} = \frac{1}{10}$, i.e., a $\frac{1}{10}$ SD increase causes an increase of 10% with respect to the mean of $x$. Secondly, assume this person also has the variables $\{w, y, z\}$ that affect $x$ (so $\vec{v} = \{w, x, y, z\}$). For now, we only consider one of these variables, namely $y$. Assume that we have calculated that a unit (one SD) impulse in $y$ has a unit increase in $x$ over an arbitrary horizon of 10 steps, i.e., $\text{irf}_{c}(y, x, 10) = 1$. Since the IRF are standardized, this corresponds to a one SD response. For each step, the effect of $y$ on $x$ is therefore on average $\frac{\text{effect}_{\text{horizon}}}{\text{horizon}}$. Recalling that the person would like an increase in $x$ of 10%, equal to a $\frac{1}{10}$ SD increase on a single step. As $y$ has an average effect of $\frac{1}{10}$ SD on $x$ per step, we require a difference of $\frac{10}{10^{10}} = 10$ SDs in $y$. Because the impulse is standardized, we can determine the exact percentage of change needed in $y$ with respect to the average of $y$, $\hat{y}$. Thus, the required change was $\frac{10}{10} \sigma_{y}$, which is a $\frac{10 \cdot 3 \cdot \sigma_{y}}{\hat{y}} \cdot 100\%$ required change in $y$. 

6.4 Algorithms

AIRA is freely available (open source)\(^2\). We implemented two versions of the proof-of-concept algorithm, one version in JavaScript\(^3\), a language designed to run client-side in a Web browser, and one version in the R-language\(^4\), a software environment for statistical computing (R Development Core Team, 2008). We created two implementations because of the purposes the two languages generally serve. JavaScript has the advantage that the calculations can be performed in a client’s Web browser and do not require any computation on the server or any specialized software. JavaScript also provides interactivity in the Web browser; it allows for live updating the document object model (DOM) of the Web page, enabling animations and interactivity. Furthermore, the JavaScript implementation could aid the use of AIRA on a large scale, as the implementation can be used on a back-end server (for example using NodeJS) or in the browser. The R-language requires the R statistical environment to run and is generally used for research purposes. Our AIRA implementation in the R-language mainly focuses on this scientific audience.

Each of the algorithms used for generating advice in AIRA is elaborated in the following sections. The algorithms used for performing the IRF calculations and for converting the VAR model to a VMA representation are provided in Appendix B.1. In all examples, we use \( m \) to denote the number of variables in the model and \( p \) to denote the number of lags.

6.4.1 Selecting Variables and Determining Advice

The advice generation of AIRA is split up into three parts: (i) ‘most influential node in network’ (determining the net effect of a variable on well-being), (ii) ‘length of effect’ (presenting the duration of a significant effect), and (iii) ‘percentage effect’ (giving advice on how each of these variables can actually be changed). The pseudo code of the algorithm used for the first type of advice is provided in Algorithm 6.1. The result of this function is an associative array (\( r \)) of cumulative effects (positive or negative) for each variable, sorted by descending absolute value. The algorithm iterates over all variables in the model (Lines 3 to 16). From Lines 6 to 14 it determines the net cumulative IRF effect a variable has on each other variable, and stores summed effect per variable in \( r \).

Besides showing the net effect a variable has on well-being, AIRA shows how long an impulse has a (significant) response. AIRA makes it insightful what the effect duration would be when an impulse is given to another variable. Algorithm 6.2

\(^2\)Website: http://frbl.eu/aira.
\(^3\)Source available at https://github.com/frbl/aira.
\(^4\)Source available at https://github.com/frbl/airaR.
Algorithm 6.1 Determines the most influential variable.

1: function DETERMINEMOSTINFLUENTIALNODE(C, k)
2: arguments C are the VMA coefficients as returned by Algorithm B.1, k is the horizon to forecast.
3:    r ← associative array
4:    for x ← 1, x ≤ m do
5:        r_x ← 0
6:        eff ← CALCULATEIRF(\bar{\alpha}(x), C, k)
7:        for y ← 1, y ≤ m do
8:            if x ≠ y then
9:                for l ← 1, l ≤ k do
10:                    r_x ← r_x + (eff_y)l
11:                    l ← l + 1
12:            end if
13:        end for
14:    end for
15:    x ← x + 1
16:    y ← y + 1
17:    r ← Sort r based on the absolute values
18:    return r
19: end function

The algorithm iterates over all steps on the horizon (Lines 7 to 22). For each step it then checks whether the effect differs (significantly) from zero (Line 8). It does so until an effect has been found. When this first effect has been found, a flag (effect_started) is toggled (Line 12), and the start and direction of the effect are estimated. The direction is either positive or negative, and is determined in Line 9. If the effect does not start in the first step, the effect is linearly interpolated to the expected moment it passed a threshold (Line 11). This continues until the effect converges or exceeds the threshold. If this is the case, the algorithm linearly interpolates the point where it exceeded the threshold (Line 16). This result is stored, in terms of the total duration of the effect (Line 18) and the total time the effect took to converge to zero (Line 19).

In case the chosen horizon was too small, and the effect did not have enough time to converge, the total effect and effective horizon are determined in Lines 23 to 26. The algorithm returns several values on Line 27. Firstly it returns the total time of the effect, that is, the length of the effect multiplied by the interval between measurements, yielding the total length of the effect in minutes. Secondly it returns the
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total length of the effect, that is, the number of steps where the (significant) effect is non-zero. Lastly it returns the total effective horizon. That is, the total horizon over which the effect is non-zero (i.e., the last step where there is a (significant) effect. It defaults to the horizon if the effect does not converge within the given horizon).

Algorithm 6.2 Determines the actual effect length.

1: function DETERMINELENGTHOFEFFECT(x, y, inter, k)
   arguments x is the variable that receives the shock, y is the variable we measure the response on, inter is the interval with which the data was sampled, and k the horizon to forecast.
2:   $\gamma \leftarrow \text{IRF}(x, y, k)$
3:   start, end $\leftarrow 0$
4:   effect_started $\leftarrow FALSE$
5:   total, effective_horizon, d $\leftarrow 0$
6:   threshold $\leftarrow 1e^{-4}$
7:   for $i \leftarrow 1, i \leq k$ do
8:     if $|\gamma_i| > \text{threshold}$ then
9:       $d \leftarrow \left( (\gamma_i > \text{threshold}) ? -1 : 1 \right)$
10:      if $i > 1 \land \neg \text{effect_started}$ then
11:         start $\leftarrow i \left( (\gamma_i + d \times \text{threshold}) \right)$
12:        effect_started $\leftarrow TRUE$
13:      end if
14:     else
15:       if effect_started then
16:         end $\leftarrow i - 1 + \left( 1 - \left( (\gamma_i + d \times \text{threshold}) \right) \right)$
17:         effect_started $\leftarrow FALSE$
18:         total $\leftarrow \text{total} + (\text{end} - \text{start})$
19:         effective_horizon $\leftarrow \text{end}$
20:       end if
21:     end if
22:   end for
23:   if effect_started then
24:     total $\leftarrow \text{total} + (k - \text{start})$
25:     effective_horizon $\leftarrow k$
26:   end if
27: return [total \cdot \text{inter}, \text{total}, \text{effective_horizon}]
28: end function

Lastly, AIRA shows what a participant can do to adjust said variables. Algo-
Algorithm 6.3 shows the pseudo code designed for generating this advice. The `AVG` and `SD` functions used in the algorithm give respectively the average and the standard deviation of the values of the answers, as measured during the diary study. The algorithm iterates over all variables in the model (Lines 3 to 15), and for each variable the algorithm determines the length of the effect, and the net effect the current variable \(y\) has on the variable to be changed \(x\) (Line 5 and Line 6). In Lines 7 to 12, this net effect is converted to a percentage of the average value of the variable and stored, according to Equation (6.7). The algorithm allows to filter out effects lower than a threshold \(\theta\) (expressed in terms of standard deviations, Line 7), as the percentage needed for a change with a low effect might become unrealistically large.

Algorithm 6.3 Determines the percentage of change needed per variable in order to induce a change of a certain percentage in another variable.

```
1: function DETERMINEPERCENTAGEFFECT(perc, x, \(\theta\), k)
2: arguments
3: perc is the percentage with which the variable to change \((x)\) needs to be changed. \(\theta\) is a threshold of minimal effect needed in the variables, and \(k\) the horizon to forecast.
4: results <- associative array
5: for \(y \leftarrow 1, y \leq m\) do
6: if \(y \neq x\) then
7: \(\hat{k} \leftarrow \text{DETERMINELENGTHOF EFFECT}(y, x, 0, k)\)
8: \(\text{eff}_c \leftarrow \text{IRF}_c(y, x, \hat{k})\)
9: if \(\text{eff}_c > \theta\) then
10: \(\Delta \leftarrow \text{perc} \cdot 100^{-1}\)
11: \(\zeta \leftarrow \text{AVG}(x) \cdot \hat{k} \cdot \Delta \cdot \text{SD}(y)\)
12: \(\zeta \leftarrow \zeta \cdot (\text{eff}_c^{-1} \cdot \text{AVG}(y)^{-1} \cdot \text{SD}(x)^{-1})\)
13: results\(_y \leftarrow \zeta \cdot 100\)
14: end if
15: end if
16: \(y \leftarrow y + 1\)
17: end for
18: return results
19: end function
```

### 6.4.2 Time Complexity

We determined the time complexity of each of the algorithms presented in Section 6.4 using the Big-O notation technique (denoted using \(O\)). These time com-
plexities describe the upper bound of the processing time of the algorithm when the input size grows infinitely large. The time complexity of the algorithms for generating the IRF functions are provided Appendix B.2.

For determining the most influential node in the model (Algorithm 6.1), the algorithm calculates the total effect each variable has on all other variables and therefore loops over all \( m \) variables in the model \( m \) times. For each of these variables, it determines the IRF once. Finally, it iterates over each calculated response on the horizon of length \( k \). The total time complexity of determining the advice is therefore \( O(m \cdot (O(CALCULATEIRF) + mk)) \) or \( O(m \cdot (k^2 m^2 + mk)) \), which reduces to \( O(k^2 m^3) \), where \( m \) is the number of variables in the model and \( k \) is the horizon of the IRF.

For determining the length of the effect a variable \( x \) has on a variable \( y \) (Algorithm 6.2), the algorithm first calculates the IRF of this effect \( (O(IRF)) \). The algorithm itself then loops over each of the \( k \) steps on the horizon \( (O(k)) \). As calculating the IRF has a higher complexity than \( O(k) \), the upper bound for the complexity of this algorithm is \( O(IRF) = O(k^2 m^2) \).

Determining the percentage advice as listed in Algorithm 6.3 considers the effect all variables have on a single variable. Hence, for this algorithm we do not need to loop over all variables more than once, making the time complexity \( O(m \cdot (O(DETERMINELENGTHOFEFFECT) + O(IRF_c))) = O(m \cdot (k^2 m^2 + k^3 m^3)) \). When one would apply dynamic programming to cache the IRF calculation, the time complexity could be reduced to \( O(2mk + k^2 m^2) = O(k^2 m^2) \), as the IRF then only has to be calculated once for all variables.

We can now use these previous calculations to define the total time complexity of AIRA as the maximum complexity of its algorithms. The algorithm with the highest complexity is the algorithm for calculating Algorithm 6.3. This results in the time complexity of AIRA being \( O(m^3 k^3) \).

The algorithms presented in this section do allow for parallelization on several levels. For example, the most complex algorithm (Algorithm 6.3) can be optimized by parallelizing its outer loop, in which it iterates over the \( m \) variables in the model. This reduces the complexity of AIRA by a factor \( m \), resulting in a time complexity of \( O(m^2 k^3) \) for AIRA on systems with at least \( m \) threads available for parallel execution. The practical performance of AIRA is acceptable and usable for general use. For instance, calculating advice for a model of six variables and a horizon of twenty steps took less than a second, as measured on both a modern laptop and a tablet.
6.5 Experimental Results

We performed several experiments to evaluate the performance of AIRA, first by showing the actual forms of advice AIRA can generate and then by comparing part of the results to previous research. These experiments show possible use cases of AIRA and give an impression of the three advice types AIRA can generate.

We ran each of the aforementioned algorithms on data sets from two studies. The first dataset we used originated from the HND, from which we randomly selected five participants having more than 85% or 77 completed measurements \( n = 164 \), henceforth referred to as the HND data set, see Part I). For these five participants, we fitted \( \text{VAR} \) models using the AutovarCore procedure (Emerencia, 2016). AutovarCore is a faster and more efficient version of the original Autovar procedure (Emerencia, 2016; Emerencia et al., 2016). Both Autovar and AutovarCore automatically check assumptions for a \( \text{VAR} \) model of stationarity, serial independence, homoscedasticity, and normality of the residuals (Brandt & Williams, 2007; Emerencia et al., 2016). We used three variables recorded in this study: (i) feeling gloomy, (ii) relaxation, and (iii) feeling inadequate. These variables were selected so that our experiment would contain both positive and negative variables.

The second data set was retrieved from the study performed by Rosmalen, Wenting, Roest, de Jonge, and Bos (2012), henceforth referred to as the Rosmalen data set. Rosmalen et al. investigate the relation between depression and activity using \( \text{VAR} \) and IRF analysis. In their work, they describe for one subject how long significant effects on activity and depression remain by inspecting the IRF.

6.5.1 Most Influential Node

We ran Algorithm 6.1 on the HND data set to demonstrate a particular use case of AIRA. We loaded each model in AIRA and applied the procedure as described in Algorithm 6.1, DETERMINEMOSTINFLUENTIALNODE. We marked ‘feeling gloomy’ and ‘feeling inadequate’ as negative variables and only used effects having a confidence of at least 95% by bootstrapping the results 200 times. The results are shown in Table 6.1. Note that the ‘feeling gloomy’ and ‘feeling inadequate’ variables have been converted their inverse counterparts, and can as such be considered to be positive variables (resp. ‘feeling less gloomy’ and ‘feeling less inadequate’).

These results show several interesting findings. First of all, they emphasize the apparent heterogeneity between the participants. Some participants show similar responses, but some participants are rather deviant or even have opposite responses. For Person B and Person E, ‘feeling less gloomy’ seems to have a positive effect on ‘well-being’, whereas the effect is neutral for the other participants. For Person A,
Table 6.1: Effects of feeling less gloomy, relaxation and feeling less inadequate on well-being, in terms of standard deviations.

<table>
<thead>
<tr>
<th>Person</th>
<th>Feeling less gloomy</th>
<th>Relaxation</th>
<th>Feeling less inadequate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Person A</td>
<td>0.000</td>
<td>-0.061</td>
<td>0.045</td>
</tr>
<tr>
<td>Person B</td>
<td>0.230</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Person C</td>
<td>0.000</td>
<td>0.000</td>
<td>0.057</td>
</tr>
<tr>
<td>Person D</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Person E</td>
<td>0.015</td>
<td>0.410</td>
<td>0.000</td>
</tr>
</tbody>
</table>

‘relaxation’ seems to have a negative effect on ‘well-being’ whereas this effect is positive for Person E. ‘Feeling less inadequate’ seems to have a small positive effect for Person A and Person C. The variables do not seem to have an effect on the well-being of Person D.

6.5.2 Length of the Effect

In the second evaluation, we used AIRA on the Rosmalen data set and we compared AIRA’s method for determining the length of an effect to the results of the manual analysis performed by Rosmalen et al. (2012). In this experiment, AIRA was configured to use orthogonalized IRF similar to Rosmalen et al. we compared the contemporary effects where activity is assumed to precede depression with those of Rosmalen et al.

During the experiment, we noticed differences between the outcomes of Rosmalen et al. and our outcomes. These differences mainly originate from the two distinct statistical packages used. Firstly, the VAR coefficients as generated for AIRA (in R using the vars package; Pfaff, 2008) and the VAR models used by Rosmalen et al. (as generated using Stata 11.0; StataCorp, 2009) are similar, but unequal. Secondly, the CIs for IRF as calculated in Stata compared to the CIs calculated using the R VARS package deviate. The deviations in both the VAR coefficients and CIs seem to originate from the different methods used by Stata and R to calculate the VAR models and error bands for IRF (for details, see the Stata Time series Manual and Pfaff, 2008). Lastly, the method for calculating the CIs uses bootstrapping, which depends on a random component that also contributes to the differences.

To remove the bias introduced by the statistical packages, we refitted each of the VAR models from the Rosmalen et al. using the R VARS package and compared AIRA with these models. The IRF time plots of these models are shown in Figure 6.5. In these figures, each PP represents a participant, the horizontal axis depicts the
6.5. Experimental Results

Figure 6.5: The IRF output of the models from Rosmalen et al. (2012), recalculated using the R VARS package (Pfaff, 2008). The red dashed lines indicate the 95% CI, the black line the IRF curve. Each of the examples has been bootstrapped 200 times. The area under the 95% CIs correspond to values presented in Table 6.2.

horizon of the IRF, and the vertical axis shows the variable from which the response is recorded (this is ‘depression’ if a shock is given to ‘activity’, and ‘activity’ if a shock is given to ‘depression’). These figures are nearly identical to the results of Rosmalen et al. (as shown in Figure 2 on page 7 of Rosmalen et al., 2012).

Table 6.2 shows the outcome of AIRA. The second and third columns show the predictions of AIRA, the fourth and fifth column show the predictions based on the VAR models in the work of Rosmalen et al., and the last two columns show the results of a manual inspection of the VAR models from Rosmalen et al. refitted using the VARS package. The results between AIRA and the refitted models are very similar, and it can be argued that the results of AIRA are in fact more precise as AIRA applies linear interpolation to estimate the exact length of the effect.

6.5.3 Percentage Effect

In the third evaluation, we apply Algorithm 6.3 to the HND data set. For each of the modeled variables, we determined how well each of the other variables in the model could be used to increase the positive variables or decrease the negative variables by 10%. That is to say, we estimated how well ‘activity’ and ‘relaxation’ can be used
Table 6.2: Comparison between the outcomes of AIRA (i) and results from the study by Rosmalen et al. (ii, iii). The table shows both the results from their paper (ii) and from the VAR models refitted using the VARS package (iii).

<table>
<thead>
<tr>
<th></th>
<th>(i) AIRA</th>
<th>(ii) Rosmalen</th>
<th>(iii) Rosmalen using VARS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A → D</td>
<td>D → A</td>
<td>A → D</td>
</tr>
<tr>
<td>pp1</td>
<td>1746.2 minutes (1.2 days)</td>
<td>0 minutes (0 days)</td>
<td>5 days</td>
</tr>
<tr>
<td>pp2</td>
<td>639.4 minutes (0.4 days)</td>
<td>0 minutes (0 days)</td>
<td>3 days</td>
</tr>
<tr>
<td>pp4</td>
<td>0 minutes (0 days)</td>
<td>11,081.5 minutes (7.7 days)</td>
<td>2 days</td>
</tr>
<tr>
<td>pp5</td>
<td>0 minutes (0 days)</td>
<td>0 minutes (0 days)</td>
<td>0 days</td>
</tr>
</tbody>
</table>

6.6 Real-world Application of Automated Impulse Response Analysis

In our final practical evaluation of AIRA, we applied AIRA to research the relation between MDD and anhedonia. It has been suggested that anhedonia, one of the two Diagnostic and Statistical Manual of Mental Disorders (DSM) core symptoms of MDD\(^5\), constitutes a distinct endophenotype of MDD (American Psychiatric Association, 2013; Pizzagalli, 2014; Vrieze & Claes, 2009). Anhedonia is the inability to experience interest in or pleasure from activities usually found enjoyable and is reported by roughly one third of MDD patients (Pelizza & Ferrari, 2009). It has been linked to poorer prognosis of MDD (Moos & Cronkite, 1999; Wardenaar, Giltay, van Veen, 2001). (i) depressed mood and (ii) loss of interest or pleasure. See Section 1.1 for an overview of the DSM criteria for MDD.

\(^5\)
Zitman, & Penninx, 2012), poorer treatment response (Vrieze et al., 2014; Wichers, Barge-Schaapveld, et al., 2009; Yee et al., 2015), and increased risk of suicide (Damen et al., 2013). Despite its debilitating influence, relatively little is known about underlying mechanisms of anhedonia. In order to bridge this gap, we need to find better and more direct ways to study the differences between depressed individuals with and without anhedonia. This requires a translation from abstract measures of anhedonia (e.g., in the laboratory) to specific emotional responses to situations in daily life. These micro-level dynamics may offer insight into the underlying mechanisms of anhedonia and elucidate how they may build up to poorer outcomes. Such knowledge potentially helps in targeting anhedonia more directly and effectively. The hypothesis that anhedonia is a distinct MDD endophenotype (Pizzagalli, 2014) suggests that different daily life dynamics underlie depressive symptoms in individuals with anhedonic symptoms versus those without. Given that anhedonia is characterized by less enjoyment of activities, depressed individuals with anhedonic symptoms might benefit less from pleasurable behaviors, as indicated by smaller increases in positive affect (PA) and smaller reductions in negative affect (NA). Physical activity might be such a pleasurable behavior, since it is generally viewed as a behavior that increases PA and is often advised to depressed patients by clinicians (Backhouse, Ekkekakis, Biddle, Foskett, & Williams, 2007). In anhedonic individuals, we would expect that the favorable impact of physical activity on affect is diminished. Further, anhedonia has been related to higher perceived stress (Horan, Brown, & Blanchard, 2007) and the experience of stress has been found to worsen hedonic capacity and responsiveness to positive events (Pizzagalli, 2014). We would therefore expect that the experience of stress exerts a stronger unfavorable impact on affect (i.e., in reducing PA and increasing NA) for individuals with anhedonia.

Research so far mainly focused on group-level results and may thereby have overlooked important heterogeneity in emotional dynamics (Hamaker, 2012; Molenaar, 2004). MDD is highly heterogeneous (Fried & Nesse, 2015) and the effects of physical activity have been found to vary widely across individuals (Rosmalen et al., 2012; Snippe et al., 2016; Stavrakakis et al., 2015). Thus, in contrast to previous research, we examine mechanisms of anhedonia in daily life on a case by case basis so as to account for and gain insight into this heterogeneity. Based on individual models generated using AIRA, we discern more general patterns. Such a personalized approach may also have relevance for clinical practice in understanding emotional dynamics of individual patients.
6. Personalized improvement of well-being: Automated Impulse Response Analysis

6.6.1 Aims of the Study

In this practical application of AIRA, we aim to examine emotional dynamics in the flow of daily life in subclinically depressed individuals with versus without anhedonia. Specifically, we study the possibly differential (i.e., positive or negative, specific to the individual) impact of physical activity and stress experience on positive and negative affect in subclinically depressed individuals with versus without anhedonic symptoms. These micro-level dynamics can be optimally measured through the ecologically valid EMA or experience sampling method (ESM; Reis, 2012). We perform IRF analysis using AIRA to compare the impact of a hypothetical increase in physical activity or stress experience on affect for both subgroups. We apply AIRA to estimate network models for each individual, after which these models are combined into aggregated models to compare the two groups. This approach accounts for and offers insight into individual differences in daily dynamics and depressogenic mechanisms.

6.6.2 Methods

Participants are 629 individuals from HND (see Chapter 3). We selected individuals who (i) were at least mildly depressed, as indicated by a Quick Inventory of Depressive Symptoms (QIDS; A. Rush et al., 2003) score of 6 or higher, and (ii) completed at least 67 (75%) of the diary assessments (see Figure 6.6 for a flow-chart).

Given that anhedonia is defined as loss of interest or pleasure, we used the QIDS item on loss of interest (‘I notice that I am less interested in people or activities’) as a proxy for anhedonia. Participants who endorsed this item (scored at least ‘1’) are henceforth referred to as ‘anhedonic’, participants who reported no loss of interest as ‘non-anhedonic’. All anhedonic individuals were matched to non-anhedonic individuals based on their QIDS score, sex, and education level, respectively. This resulted in 50 matched individuals, 25 in each group.

Measures.

Depressive symptoms at the time of study entry were assessed through the QIDS, which covers all depressive symptoms as described by the DSM and shows adequate validity and reliability (A. Rush et al., 2003). To accommodate the two dimensions of affect, valence and arousal (Watson & Tellegen, 1985), four affective variables were constructed using the items defined in Table A.2. The mean score of the emotional items ‘energetic’, ‘enthusiastic’, and ‘cheerful’ was taken to reflect PA high-arousal. PA low-arousal was assessed by ‘relaxed’, ‘content’, and ‘calm’. Likewise, NA high-arousal was assessed by ‘anxious’, ‘nervous’, and ‘irritable’, and NA low-arousal by
6.6. Real-world Application of Automated Impulse Response Analysis

Full HND diary sample (n = 629)

Participants with QIDS-SR data (n = 459)

No anhedonia

- Participants with ≥ 67 measurements (n = 151)
- Participants with QIDS-SR ≥ 6 (n = 43)
- Matched participants (n = 25)
- Participants with valid models (n = 22)
- Final sample after matching (n = 20)

Anhedonia

- Participants with ≥ 67 measurements (n = 53)
- Participants with QIDS-SR ≥ 6 (n = 44)
- Matched participants (n = 25)
- Participants with valid models (n = 20)
- Final sample after matching (n = 20)

Figure 6.6: Overview of participant selection.

‘gloomy’, ‘dull’, and ‘tired’. Participants further indicated their level of physical activity over the last six hours (‘since the last measurement I was physically active’, item number 41) and subjective experience of stress (‘I am upset’, item number 25, see Table A.2 on page 202).

Analysis.

We estimated personalized models of the dynamics between physical activity, stress experience, and affect in individuals with versus without anhedonia. Based on these models, we first examined our hypotheses on the potentially differential impact of activity and stress experience on the affective variables in anhedonic versus non-anhedonic individuals. Next, we explored other relevant differences in emotional dynamics between the two groups. Finally, we illustrated the individual differences in emotional dynamics.

First, we fitted a VAR model for every participant. A lag of 1 or 2 was chosen dependent on the most optimal model for the participant. The VAR models were fit using the R-package AutovarCore (Emerencia, 2016; Emerencia et al., 2016). In these
VAR models, we included six endogenous variables: PA high and low arousal, NA high and low arousal, physical activity, and stress experience. Measurement moment was included as an exogenous variable, weekday and study day were modeled if they improved the model for an individual, as well as linear and quadratic trends. Missing data was imputed using the R-package Amelia-II, which is a well-validated approach to missing data handling (Honaker & King, 2010). The automatic assumption checking of AutovarCore (stationarity, serial independence, homoscedasticity, and normality of the residuals) resulted in 42 valid VAR models (no anhedonia: 22; anhedonia: 20). Two individuals could no longer be matched, resulting in a final sample of 40 individuals; 20 in each group.

Second, we used AIRA to automatically analyze our VAR models. For every person and every association between variables, we calculated cumulative IRFs (Rosmalen et al., 2012). These individual cumulative IRFs reflect the impact of all variables on each other over time, which was then visualized in 40 individual network models, one for each participant. Next, we constructed group cumulative IRFs by summing all individual cumulative IRFs for each association, to enable us to compare the non-anhedonic versus the anhedonic group. This was done separately for individual positive cumulative IRFs and individual negative cumulative IRFs, because combining both could possibly cancel out present associations. Thus, the higher the positive or negative group cumulative IRF, the stronger the impact of one variable on another.

We used three approaches to compare emotional dynamics between the non-anhedonic group and the anhedonic group as described above. First, we compared the group cumulative IRFs for each association. Such a comparison would indicate whether the impact of physical activity and stress experience is stronger in one of the two groups. Second, we compared the number of individuals who showed a given IRF association by examining the individual models. Third, we compared the importance of the variables in the network by comparing network centrality (node strength) indices between the two groups for each variable. Strength centrality is the sum of the connection strength values (based on the cumulative IRF scores) of all IRF associations that a given variable has within the network (Opsahl, Agneessens, & Skvoretz, 2010). Thus, a high strength centrality of a variable indicates that this variable has a strong impact on other variables or is impacted by many variables. We focused on ‘outstrength’ centrality, which is the total impact of a given variable on all other variables in the network (sum of outgoing cumulative IRF associations). We further examined whether each variable impacted other variables in a favorable manner (resulting in an increase of PA and activity or decrease of NA and stress) or unfavorable manner (resulting in a decrease in PA and activity or an increase in NA and stress).
6.6. Real-world Application of Automated Impulse Response Analysis

Finally, we explored individual differences in emotional dynamics displayed in the individual network models. We depict two of these individual models to illustrate existing individual emotional dynamics and how the use of such personalized networks may possibly inform on choice of intervention type.

### 6.6.3 Study Results

Multilevel analyses indicated no significant differences in mean levels of affect, physical activity, and stress experience between the anhedonic group and the non-anhedonic group over the thirty day study period (for the means, SDs, and \( p \)-values, see Table 6.3). As the groups were matched, level of depression was the same in both groups (mean QIDS score = 9.1; range 6 to 17), as well as the distribution of gender (19 female and 1 male), and education level (non-anhedonic group: \( n = 17 \) with higher education; anhedonic group: \( n = 18 \) with higher education). Groups were of similar age (non-anhedonic: mean = 43.6, SD = 13.2; anhedonic: mean = 39.5, SD = 11.7, \( p \)-value of difference = 0.302).

Table 6.3: Mean levels of affect, physical activity, and stress experience of the two groups.

<table>
<thead>
<tr>
<th>Variable</th>
<th>No anhedonia (( n = 20 ))</th>
<th>Anhedonia (( n = 20 ))</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA high arousal</td>
<td>46.6</td>
<td>52.3</td>
<td>0.155</td>
</tr>
<tr>
<td>PA low arousal</td>
<td>52.0</td>
<td>57.5</td>
<td>0.166</td>
</tr>
<tr>
<td>NA high arousal</td>
<td>29.5</td>
<td>27.2</td>
<td>0.607</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>40.8</td>
<td>37.8</td>
<td>0.479</td>
</tr>
<tr>
<td>Physical activity</td>
<td>33.4</td>
<td>39.1</td>
<td>0.057</td>
</tr>
<tr>
<td>Stress experience</td>
<td>32.4</td>
<td>26.0</td>
<td>0.217</td>
</tr>
</tbody>
</table>

Note: Scores could range between 0 to 100. Multilevel analyses were conducted to test for significant differences in mean levels of the two groups.

**Impact of physical activity and stress experience.**

Table 6.4 and Figure 6.7 show the strength of the IRF associations through the group cumulative IRFs, which are composed of the individual cumulative IRFs, split into positive and negative associations for each possible association within the network. It also shows the range in individual cumulative IRFs. Further, it shows the number of individuals who showed a particular significant IRF association. Table 6.5 shows
the importance of each of the variables in the network. Each association shown in Figure 6.7 reflects the total impact one variable has on another over time for the individuals in that group (group cumulative IRF). Green / solid arrows indicate positive relationships between variables, red / dashed arrows negative ones. The stronger a particular relationship, the brighter the color of the arrow.

In both groups, the impact of physical activity on affect was weak, as shown by the small positive and negative group cumulative IRFs and the small number of individuals with significant IRFs (see Table 6.4). Further, the groups did not differ on the importance of physical activity in the network (non-anhedonic: outstrength = 0.98; anhedonic: outstrength = 1.04). In both groups, physical activity seemed to have a more unfavorable (non-anhedonic: unfavorable outstrength = 0.83; anhedonic: unfavorable outstrength = 0.61) than favorable impact (non-anhedonic: favorable outstrength = 0.15; anhedonic: unfavorable outstrength = 0.43) on affect and stress experience (see Table 6.5).

Table 6.4: group cumulative (GC) IRF associations per group (strength) and the range in individual cumulative IRFs, and the number of individuals showing a given association significantly.

<table>
<thead>
<tr>
<th>Effect of</th>
<th>On</th>
<th>Range</th>
<th>Non-anhedonic</th>
<th>Anhedonic</th>
<th>Range</th>
<th>Non-anhedonic</th>
<th>Anhedonic</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>NA high arousal</td>
<td>NA low arousal</td>
<td>0.11</td>
<td>5</td>
<td>0.07 to 0.21</td>
<td>0.46</td>
<td>3</td>
<td>0.14 to 0.53</td>
<td>0.05</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>NA</td>
<td>0.00</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
<td>0.01 to 0.04</td>
<td>0.02</td>
<td>0.01 to 0.02</td>
</tr>
<tr>
<td>Physical activity</td>
<td>Physical activity</td>
<td>0.47</td>
<td>2</td>
<td>0.21 to 0.66</td>
<td>0.53</td>
<td>3</td>
<td>0.14 to 0.43</td>
<td>0.30</td>
</tr>
<tr>
<td>Stress experience</td>
<td>Stress experience</td>
<td>0.01</td>
<td>1</td>
<td>0.05 to 0.07</td>
<td>0.30</td>
<td>1</td>
<td>0.01 to 0.03</td>
<td>0.40</td>
</tr>
<tr>
<td>NA high arousal</td>
<td>NA low arousal</td>
<td>0.19</td>
<td>2</td>
<td>0.10 to 0.58</td>
<td>0.43</td>
<td>3</td>
<td>0.36 to 0.68</td>
<td>0.60</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>NA</td>
<td>0.18</td>
<td>2</td>
<td>0.05 to 0.64</td>
<td>0.32</td>
<td>1</td>
<td>0.03 to 0.34</td>
<td>0.16</td>
</tr>
<tr>
<td>Physical activity</td>
<td>Physical activity</td>
<td>0.51</td>
<td>1</td>
<td>0.32 to 0.67</td>
<td>0.64</td>
<td>2</td>
<td>0.38 to 0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>Stress experience</td>
<td>Stress experience</td>
<td>0.06</td>
<td>0</td>
<td>0</td>
<td>0.32</td>
<td>0.40</td>
<td>1</td>
<td>0.01 to 0.03</td>
</tr>
<tr>
<td>NA high arousal</td>
<td>NA low arousal</td>
<td>0.19</td>
<td>2</td>
<td>0.10 to 0.58</td>
<td>0.43</td>
<td>3</td>
<td>0.36 to 0.68</td>
<td>0.60</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>NA</td>
<td>0.18</td>
<td>2</td>
<td>0.05 to 0.64</td>
<td>0.32</td>
<td>1</td>
<td>0.03 to 0.34</td>
<td>0.16</td>
</tr>
<tr>
<td>Physical activity</td>
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<td>0.51</td>
<td>1</td>
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<td>0.64</td>
<td>2</td>
<td>0.38 to 0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>Stress experience</td>
<td>Stress experience</td>
<td>0.06</td>
<td>0</td>
<td>0</td>
<td>0.32</td>
<td>0.40</td>
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<td>0.01 to 0.03</td>
</tr>
<tr>
<td>NA high arousal</td>
<td>NA low arousal</td>
<td>0.19</td>
<td>2</td>
<td>0.10 to 0.58</td>
<td>0.43</td>
<td>3</td>
<td>0.36 to 0.68</td>
<td>0.60</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>NA</td>
<td>0.18</td>
<td>2</td>
<td>0.05 to 0.64</td>
<td>0.32</td>
<td>1</td>
<td>0.03 to 0.34</td>
<td>0.16</td>
</tr>
<tr>
<td>Physical activity</td>
<td>Physical activity</td>
<td>0.51</td>
<td>1</td>
<td>0.32 to 0.67</td>
<td>0.64</td>
<td>2</td>
<td>0.38 to 0.70</td>
<td>0.71</td>
</tr>
<tr>
<td>Stress experience</td>
<td>Stress experience</td>
<td>0.06</td>
<td>0</td>
<td>0</td>
<td>0.32</td>
<td>0.40</td>
<td>1</td>
<td>0.01 to 0.03</td>
</tr>
</tbody>
</table>

The unfavorable impact of stress experience on affect was more profound among non-anhedonic individuals compared to anhedonic individuals. For non-anhedonic individuals, an increase in stress experience resulted in more NA high arousal (non-
6.6. Real-world Application of Automated Impulse Response Analysis

Figure 6.7: Networks per group showing the strength of the IRF associations, by displaying the group cumulative IRFs, i.e., the sum of all positive and negative individual IRF associations of all participants of each group. The plots were created using the qgraph R-package (Epskamp et al., 2012).

anhedonic: group cumulative IRF = 0.24; anhedonic: group cumulative IRF = 0.01)
and more NA low arousal (non-anhedonic: group cumulative IRF = 0.94; anhedo-
nic: group cumulative IRF = 0.19) than for anhedonic individuals. Further, for non-anhedonic individuals, stress experience more strongly decreased PA high arousal (non-anhedonic: group cumulative IRF = −0.44; anhedonic: group cumulative IRF = −0.18) and PA low arousal (non-anhedonic: group cumulative IRF = −0.66; anhedonic: group cumulative IRF = −0.18) than for anhedonic individuals. However, the individual models show that the number of individuals demonstrating an unfavorable impact of stress (i.e., these individuals showed at least one unfavorable IRF association of stress) was similar for both groups (non-anhedonic: n = 7; anhedonic: n = 5). The strong negative impact of stress experience for non-anhedonic individuals is further reflected by their high unfavorable outstrength centrality (see Table 6.5), which was doubled for anhedonic individuals (non-anhedonic: unfavorable outstrength centrality = 2.28; anhedonic: unfavorable outstrength centrality = 1.02).

Table 6.5: Centrality estimates per group showing the importance of a variable in the network.

<table>
<thead>
<tr>
<th>Variable</th>
<th>No anhedonia (n = 20)</th>
<th>Anhedonia (n = 20)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Favorable</td>
</tr>
<tr>
<td>PA high arousal</td>
<td>3.75</td>
<td>3.58</td>
</tr>
<tr>
<td>PA low arousal</td>
<td>1.99</td>
<td>0.97</td>
</tr>
<tr>
<td>NA high arousal</td>
<td>1.51</td>
<td>0.64</td>
</tr>
<tr>
<td>NA low arousal</td>
<td>2.97</td>
<td>1.03</td>
</tr>
<tr>
<td>Physical activity</td>
<td>0.98</td>
<td>0.15</td>
</tr>
<tr>
<td>Stress experience</td>
<td>2.64</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Note: Numbers in bold reflect the highest estimate per group, indicating that this variable has the strongest impact on all other variables (outstrength). Outstrength was split into favorable and unfavorable impact of the variables. For example, the favorable outstrength of PA high arousal for the non-anhedonic group was constructed by summing all positive group cumulative IRFs for positive variables and all negative group cumulative IRFs for negative variables (0.51 + 0.47 + 0.89 + 1.06 + 0.65 = 3.58, see Table 6.4).

* indicates the variables considered positive variables.

Network dynamics: role of other variables.

As the other dynamic IRF associations may provide additional insight in the mechanisms underlying anhedonia, we also conducted exploratory analysis to examine the roles of other variables in the network. For non-anhedonic individuals, PA high arousal showed a favorable impact on the other variables, which was evident in the strength as well as the number and the importance of the impact of PA high arousal. Regarding strength, for non-anhedonic individuals, PA high arousal resulted in less NA high arousal (non-anhedonic: group cumulative IRF = −0.89;
anhedonic: group cumulative IRF = −0.29), less NA low arousal (non-anhedonic: group cumulative IRF = −1.06; anhedonic: group cumulative IRF = −0.01), and less stress (non-anhedonic: group cumulative IRF = −0.65; anhedonic: group cumulative IRF = −0.33). Further, the individual models show that the number of individuals with IRF associations originating from PA high arousal was larger in the non-anhedonic group (non-anhedonic: \( n = 13 \), anhedonic: \( n = 8 \)). Finally, in terms of centrality measures, the favorable outstrength of PA high arousal was more than twice as high for non-anhedonic individuals (non-anhedonic: favorable outstrength = 3.58; anhedonic: favorable outstrength = 1.74) and was by far the most important variable in the network. For anhedonic individuals, rather than PA low arousal, PA high arousal showed a favorable impact on the other variables, as indicated in the strength, the number, and the importance of PA low arousal in the network. This indicates that certain positive emotions have a very different role in the network of anhedonic compared to non-anhedonic individuals with depressive symptoms. Further, NA high arousal showed a stronger unfavorable impact on the other variables for anhedonic individuals relative to non-anhedonic individuals. This was reflected in the strength, the number, and the importance of NA high arousal in the network. The strong unfavorable impact of NA high arousal mainly seemed to stem from six individuals showing a strong impact of NA high arousal on stress experience (see Table 6.4). No other important and consistent patterns emerged from the data.

Exploration of individual networks of emotional dynamics.

The individual models reveal large individual differences in the dynamic associations between physical activity, stress experience, and affect within the groups of people with and without anhedonia. Three individuals (non-anhedonic: \( n = 1 \); anhedonic: \( n = 2 \)) had no IRF associations, indicating that their physical activity, stress experience and affect did not have a dynamic impact on each other in these individuals. Nine individuals (non-anhedonic: \( n = 4 \); anhedonic: \( n = 5 \)) only showed one or two IRF associations. Seven individuals (non-anhedonic: \( n = 3 \); anhedonic: \( n = 4 \)) showed ten or more IRF associations. Figure 6.8 illustrates an example of two participants who differ in their emotional dynamics. Each association shown in the individual networks reflects the total impact one variable has on another over time (individual cumulative IRF). The stronger a particular relationship, the thicker the color of the arrow. Both individual A (Figure 6.8a) and B (Figure 6.8b) were non-anhedonic and had equal levels of depression severity (QIDS = 6). However, for individual A, PA high arousal had a strong favorable impact on the other variables in the network (i.e., it decreased NA high and low arousal and stress, and increased
6. Personalized improvement of well-being: Automated Impulse Response Analysis

PA low arousal). For individual B, stress experience had a strong unfavorable impact on the other variables (i.e., it increased NA high and low arousal, and decreased PA high and low arousal), further showing the apparent heterogeneity amongst seemingly similar people.

![Diagram of Individual IRF networks for two non-anhedonic individuals with equal levels of depression (QIDS = 6), female, who both received higher education. This figure illustrates that although clinical characteristics are highly similar, emotional dynamics can show very different patterns, warranting a personalized approach to treatment.](image)

6.6.4 Discussion

With the practical application of AIRA we investigated the impact of physical activity and stress experience on affect in daily life, and explored other relevant differences in emotional dynamics, in subclinically depressed individuals with anhedonia versus without anhedonia. To the best of our knowledge, this is the first study that maps individual models of the dynamic relationships between physical activity, stress, and affect to understand the mechanisms of anhedonia.

Contrary to our hypotheses, the impact of physical activity on affect was low for both anhedonic and non-anhedonic individuals. Thus, when a sudden increase in physical activity was simulated, the other variables only marginally changed in re-
In addition, the exploratory analysis revealed that PA states played a very different role in the network dynamics of depressed people with versus without anhedonic symptoms: PA high arousal showed a much stronger favorable impact on affect, physical activity and stress experience for non-anhedonic individuals. The finding that PA, although present to the same extent in both groups, had a different dynamic impact in daily life in the context of anhedonia shines a new light on what anhedonia may represent. Finally, this study reveals the presence of large heterogeneity in emotional dynamics within the anhedonic and non-anhedonic group.

We know of no other study that examined the effects of physical activity in subclinically depressed individuals with versus without anhedonia. In depressed individuals, ESM studies have generally shown a favorable effect of physical activity on PA (Mata et al., 2012; Snippe et al., 2016; Wichers et al., 2012). In the present study, the impact of physical activity was surprisingly small for all participants and did not differ between anhedonic versus non-anhedonic individuals. However, in line with a previous ESM study, we detected large individual differences in whether this impact was favorable or unfavorable (Stavrakakis et al., 2013). The small impact of physical activity might partially be due to the relatively large time window of six hours between measurements; studies reporting larger effects had less time in between measurements (Mata et al., 2012; Wichers et al., 2012).

Contrary to our expectations, stress showed a more profound unfavorable effect for non-anhedonic individuals: stress more strongly decreased PA and increased NA in this group than in the anhedonic group. In the anhedonic group, this was the other way around: NA high arousal demonstrated a more profound unfavorable impact on stress experience. Thus, in non-anhedonic individuals, stress experience seems to generate NA; whereas in anhedonic individuals, NA seems to generate stress experience. Previous ESM studies have consistently shown that MDD is associated with increased reactivity to stress (Myin-Germeys et al., 2003; Wichers, Geschwind, et al., 2009). The current study builds on these findings by showing that increased stress reactivity is especially profound in depressed individuals without anhedonia. Further, our findings show even though anhedonic individuals experienced PA high arousal to similar extent, its impact on subsequent emotional and behavioral states was considerably lower.

Research suggests that specifically the high arousal component of PA is associated with readiness for action, motivation, and goal-directed behavior (Bradley & Lang, 2007; Harmon-Jones, Gable, & Price, 2013). The finding that PA high arousal does not have a favorable impact on NA and stress experience may help explain why
anhedonic individuals in general tend to show poorer prognosis (Moos & Cronkite, 1999; Wardenaar et al., 2012). By reducing the impact of daily stressors and NA, PA high arousal may constitute a resilience factor that buffers against depressive symptoms. In line with this proposition, previous research has shown that PA may buffer against stress sensitivity (van Winkel et al., 2014). Together with a close inspection of the individual models, these results may give rise to the hypothesis that different pathways underlie depressive symptoms. The individual models demonstrated that these pathways may be present to different extent in subclinically depressed individuals with and without anhedonia. For some individuals, this pathway may be heightened reactivity to stress or NA, for others, this may be diminished favorable impact of PA. Interestingly, the extent to which these pathways were present differed for the anhedonic group versus the non-anhedonic group. Where more individuals in the anhedonic group showed diminished favorable impact of PA and heightened reactivity to NA, individuals in the non-anhedonic group showed heightened reactivity to stress.

The large heterogeneity in the extent to which these pathways of emotional dynamics were present in individuals suggest that interventions need to be personalized in order to adequately target the relevant pathway for each patient. If specific pathways of emotional dynamics can be linked to different courses of MDD, and if intervening on central nodes is found to be effective, these individual models might guide the clinician towards a more informed choice for effective interventions. For example, for individuals demonstrating deficient PA high arousal dynamics, interventions may focus on enhancing the favorable effects of PA high arousal to render the individual more resilient (Figure 6.8). For individuals exhibiting strong unfavorable effects of stress experience (or NA high arousal), the clinician may concentrate on strategies to prevent or reduce stress experience, such as through mindfulness techniques. This call for personalized medicine is underscored by studies demonstrating large heterogeneity of MDD (Fried & Nesse, 2015) and strong indications that group-level findings may not generalize to individual patients (Molenaar, 2004). Future studies should reveal whether targeting the most central element of a personalized dynamic network indeed optimizes treatment outcomes.

In order for clinicians to be able to implement this personalized approach to treatment, it is paramount that these complex statistical analysis are automated, so the clinician can easily produce personalized models of emotional dynamics. AIRA automatically generates such personalized models, and facilitates implementation of these analysis in clinical practice. Although the implementation of personalized networks in clinical practice is yet to receive empirical support, this approach shows promise in making more informed decisions on the focus of treatment.
6.7 Discussion and Concluding Remarks

We presented AIRA, an algorithm and related implementations on two platforms that can automatically provide feedback and advice on time series data such as diary data collected using EMAs. We described the basis and theoretical foundation of AIRA and created a method to give specific advice on which variables require change, and with what percentage, in order to have the desired adjustment in other variables. Furthermore, we provided a proof-of-concept implementation of this algorithm for use in e-mental health platforms. AIRA provides an automated method to deal with the previously unsolved problem where the lags of a variable have conflicting effects (e.g., a positive effect on one lag and a negative effect on another lag). Such mixed effects make it difficult to determine whether the overall effect of a variable is a net gain or a net loss. Using AIRA, these effects can be summarized, revealing the net effect.

Future versions of AIRA could include algorithms to determine which sequence of impulses over time, rather than which single impulse, has the desired effect. Moreover, the percentages currently provided could be converted to an easier to understand format, such as time investment required to effectuate a change. In its current form, AIRA can be used by participants to find out how best to self-manage their well-being. This can be improved by allowing the individual to personally assign importance to the variables under study. We currently apply a general, binary approach to determining whether a variable is considered positive or negative. This self-management can be improved further by allowing users to provide a relative importance for each variable.