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A Single Subject Time Series Analysis of the Dynamic Interplay between Sleep and Physical Activity during Cognitive Behavioral Treatment for Insomnia

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Master's Thesis in Psychology
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Åbo 2020

Subject: Psychology	
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Title: A Single Subject Time Series Analysis of the Bidirectional Effects between Sleep and Physical Activity during Cognitive Behavioral Treatment for Insomnia	
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Abstract: The association between sleep and physical activity has on a group-level been well-documented but seems to vary between individuals. Research addressing the problems of group-to-individual generalizability and temporal aspects within-individuals has been called for. The aim of the present study was therefore to investigate sleep and physical activity as a unique dynamic system, through utilizing novel time series analysis to explore the person-specific changes occurring in an insomnia-prone participant undergoing a CBT-I treatment. Intensive longitudinal data were gathered from a single participant carrying an activity tracker and were investigated with time-varying vector autoregressive modeling (TV-VAR). The hypotheses were that changes would be identified in the autoregressive and cross-lagged parameters of the two variables over time. The autoregressive parameter of total sleep time (TST) was expected to decrease from positive to zero or negative. A positive cross-lagged effect of daytime physical activity on TST the following night was expected to appear over the course of the intervention, and finally, if a positive cross-lagged effect of TST on physical activity the following day was identified in the beginning of the intervention, this effect was expected to decrease over time. For this participant, a slight decrease in the autoregression of TST during the time of the intervention could be observed, but the change seen was statistically insignificant. A significant decrease in the intercept of TST was identified, and the positive association between daytime physical activity and TST of the following night disappeared over time. TST could significantly predict physical activity of the following day, but in a pattern opposite of the expected; less sleep predicted more physical activity the following day and vice versa. In conclusion, the results highlight the benefits of using intensive longitudinal data to identify unique, patient-specific processes that would have been overseen in group-level data.	
Keywords: Total Sleep Time, Physical Activity, Insomnia, Psychological Treatment, CBT-I, Intensive Longitudinal Data, Ecological Momentary Assessment, Time-varying Time Series Design, Time-varying Vector Autoregressive Analysis	
Date: 14.10.2020	**Pages**: 44

Ämne: Psykologi	
Författare: Matilda Thors	
Arbetets titel: En fallstudie som genom tidsserieanalys undersöker sambandet mellan sömn och fysisk aktivitet under en kognitiv-beteendeterapeutisk behandling för insomni	
Handledare: Marianne Källström, Patrik Jern	

Svenskt abstrakt:
Associationen mellan fysisk aktivitet och sömn är väldokumenterad, men sambandet verkar variera individer emellan. Studier som beaktar problemet med variation på individnivå och intraindividuell variation över tid har av forskningsfältet önskats. Syftet med denna studie var därför att undersöka sömn och fysisk aktivitet som ett dynamiskt system, genom att använda tidsserieanalys för att utforska personspecifika förändringar hos en person med insomnibenägenhet som genomgår en KBT-I-behandling. Intensiva longitudinella data insamlades från en enskild deltagare som fick bära en aktivitetsklocka, och data undersöktes sedan med en tidsvarierande vektor-autoregressiv modell (TV-VAR).

Hypoteserna var att förändringar skulle kunna identifieras i de autoregressiva parametrarna och i de tidsfördröjda statistiska relationerna mellan variablerna. Den autoregressiva parametern för total sömnmängd förväntades minska från positiv till noll eller negativ. Ett positivt samband mellan fysisk aktivitet på dagen och total sömnmängd följande natt förväntades träda fram under interventionen. Ifall total sömnmängd i början av interventionen kan konstateras vara associerat till fysisk aktivitet följande dag förväntades denna effekt minska över tid.

För denna deltagare kunde en minskning i den autoregressiva effekten av total sömnmängd identifieras visuellt, men parametern uppnådde inte signifikans. En signifikant minskning i interceptet för total sömnmängd kunde hittas, och den positiva associationen mellan fysisk aktivitet på dagen och total sömnmängd följande natt verkade avta och försvinna under interventionen. Total sömnmängd kunde signifikant predicera fysisk aktivitet följande dag, men riktningen var motsatt mot vad som förväntats; mindre sömn predicerade mer fysisk aktivitet följande dag och vice versa. Sammanfattningsvis lyfter resultaten fram fördelen med användningen av intensiva longitudinella data för att identifiera unika, patientspecifika processer, vilka på gruppnivå skulle ha förbisetts.

Nyckelord: Total sömnmängd, fysisk aktivitet, insomni, psykologisk behandling, KBT-I, intensiva longitudinella data, ekologisk momentan skattning, tidsvarierande tidsseriedesign, tidsvarierande vektor-autoregressiv analys

Datum: 14.10.2020	**Sidantal**: 44

Acknowledgements

I would like to thank my supervisor Marianne Källström, who patiently helped me figure out my way through the jungle of time series methodology. Patrick Jern, my second supervisor, provided with useful ideas and well-grounded feedback. I also want to thank the seminar group who helped me look at both the findings and the text with fresh eyes when I got lost in my own writing process, and Martin Lagerström, who used his spare time to help me out with exploring my data. My friends kept me company during long days in "gula huset" and made sure to remind me of taking long (long!) coffee breaks every once in a while. A final thank you to my dear family who are always there for me.

Table of Contents

1 Introduction

Sleep is a complex, multidimensional phenomenon, and an essential part of mental well-being. Problems with sleep have broad implications both on psychosocial and somatic health (Roth, 2007). In addition to personal distress, insomnia-related consequences place a high economic burden on society (Daley, Morin, LeBlanc, Grégoire, & Savard, 2009). Sleep has a well-documented association with physical activity, a connection that on a group-level commonly has been considered bidirectional (Kline, 2014). Still, the association between the two seems to vary in both strength and direction between individuals (Armstrong, Covington, Unick, & Black, 2019). Such interindividual variation has, in recent years, led researchers to question the suitability of applying results from group-level studies on, for instance, the individual patient (Fisher, 2015; Fisher & Boswell, 2016; Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2004). In addition to the concern of interindividual variation, temporal dynamics within the single individual are often collapsed and disregarded, partly as a result of the limited capacity of former research methodology to take such factors in consideration (Hamaker & Wichers, 2017). Thus, research addressing both the problem of group-to-individual generalizability and temporal aspects within-individuals has been called for (Barlow & Nock, 2009; Molenaar, 2004).

In the context of sleep and insomnia treatment, these concerns can be taken into consideration by not only exploring the general association between sleep and physical activity across individuals at one point in time, but also, by having research encompass questions about the strength and direction of the association for the specific patient at hand and examine how this association might change over time due to, for instance, psychological treatment. To determine the causal pathways in the dynamic system of sleep and physical activity for a specific patient at a specific time, new approaches are needed. Recent advances in the field of time series methodology offer novel explorative $N = 1$ techniques to address the temporal dynamic interplay between symptoms or behaviors in psychological disorders (Bringmann, Ferrer, Hamaker, Borsboom, & Tuerlinckx, 2018; Haslbeck, Bringmann, & Waldorp, 2020). These explorative analyses of clinical intensive longitudinal data introduce new opportunities to improve the understanding of the individual patient and could eventually provide clinicians with much-needed data-driven tools for guiding clinical decision-making. These methods increase the possibility of applying a personalized medicine approach in psychological treatment (Fisher, 2015). To my knowledge, the present study was the first to investigate physical activity and sleep as a person-specific dynamic system. The aim of the study was to investigate the interplay between total sleep time (TST) and physical activity for a single patient undergoing Cognitive Behavioral Therapy for insomnia (CBT-I), with a time series cross-lagged design utilizing intensive longitudinal data.

1.1 Insomnia

Insomnia, as defined in The International Classification of Diseases (ICD-11, World Health Organization, 2018), is characterized by enduring difficulties with sleep initiation, duration, consolidation or quality that persist even though the opportunities and circumstances for sleep are adequate. Daytime symptoms typically include fatigue, decreased mood or irritability, general malaise, and cognitive impairment. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Assosication, 2013) states similar criteria, where symptoms from two areas are demanded for diagnosis; negative day- and nighttime consequences. Insomnia is not diagnosed based on the number of hours slept or the duration of sleep initiation, but rather, by the qualitative experience of sleep and the distress caused by perceived sleep difficulties. In fact, in a study by Perlis (2001), it was concluded that people suffering from insomnia generally tend to underestimate the number of hours slept, and overestimate the time it takes to fall asleep. Individuals with insomnia slept only 25 minutes less on an average compared to people without insomnia, and with a time of sleep initiation only 12 minutes longer. This rather minimal difference in terms of sleep duration between the groups is in stark contrast to the levels of distress experienced by clinical populations (Ohayon & Roth, 2003). The results highlight the importance of the individual’s subjective experience of sleep.

Insomnia is common, affecting approximately 10 % of Finnish adults (Ohayon & Partinen, 2002), a number rather consistent with other global estimates varying between 6 - 18 % depending on the restrictiveness regarding diagnostic criteria (Ohayon, 2002). In addition to clinical insomnia, a group of individuals with subthreshold or short-term problems with falling asleep (insomnia proneness) can be identified (World Health Organization, 2018). There are data suggesting that occasional self-reported insomnia-related symptoms affect close to half of the Finnish population (Kronholm et al., 2016). Insomnia is known to affect women more often than men and is generally more prevalent among the elderly (Ohayon, 2002). Insomnia is related to a wide array of psychiatric and medical conditions, such as depression (Baglioni et al., 2011; Ohayon & Roth, 2003), anxiety (Ohayon & Roth, 2003), pain conditions (Sivertsen, Krokstad, Øverland, & Mykletun, 2009), as well as substance related problems (Wong, Robertson, & Dyson, 2015).

Cognitive Behavioral Therapy for insomnia (CBT-I) is considered a first-line treatment for insomnia, recommended ahead of pharmacotherapy (Insomnia: Current Care Guidelines, 2019). Significant treatment effects have been found also for internet-based versions of CBT-I treatment (Blom et al., 2015). CBT-I encompasses both behavioral techniques, such as stimulus control and sleep restriction, and other cognitive and affective techniques for managing worry and the dysfunctional beliefs often accompanying insomnia (see Manber and Carney, 2016). The effect of using CBT-I components in treatment has been evaluated in a recent meta-analysis by van Straten et al. (2017) and has been shown to produce beneficial effects on sleep. More specifically, the study showed significant medium to large effects on insomnia severity ($g = 0.98$), sleep effectivity, sleep quality, wake after sleep onset (WASO), sleep onset latency (SOL) as well as on the number of awakenings per night. The effect on total sleep time (TST) was small ($g = 0.16$). The abbreviation TST refers to the total amount of sleep when excluding the time of awakenings during the night. Sleep effectivity refers to the ratio between time in bed (TIB) and TST. The term WASO refers to the total time of all awakenings for one night, and SOL is a measurement for the time it takes for a person to fall asleep at night when being in bed and attempting to sleep.

1.2 The Interplay between Sleep and Physical Activity

Previous research has studied the association between physical activity and a variety of sleep factors. A meta-analysis of 66 experimental studies ($N = 670$) showed beneficial effects of physical activity on sleep (Kredlow, Capozzoli, Hearon, Calkins, & Ott, 2015). Overall, engaging in exercise for one week or less had a small, beneficial effect on TST ($d = 0.22$) across 41 studies, and a small effect on SOL ($d = 0.17$) across 35 studies. The effect of regular exercise (exercise for one week or more) on TST was small ($d = 0.25$) and on SOL small-to-moderate ($d = 0.35$), across 10 studies. The overall results were in line with previous meta-analyses on the topic (Kubitz, Landers, Petruzzello, & Han, 1996; Youngstedt, O'Connor, & Dishman, 1997). Sleep complaints were not included as a moderating factor in the meta-analyses, due to the sparse amount of studies investigating this subgroup. Another recent meta-analysis of nine randomized controlled trials ($N = 557$) focused specifically on the association between sleep and physical activity in clinical populations diagnosed with insomnia. The study found that exercise interventions improved perceived sleep quality, but no significant effects were found for SOL, TST or sleep effectivity. The authors indicated the need for studies of higher quality, since bias (e.g., lack of blinding and allocation concealment, attrition bias and report bias) was identified in some of the studies included (Banno et al., 2018).

Based on the research presented above, lack of physical activity could be considered as a risk factor for developing sleep problems (Yang, Shin, Li, & An, 2017). Still, there are studies suggesting that an even stronger reversed association is possible. Apart from physical activity influencing sleep, lack of sleep also predicts less exercise and physical activity (Baron, Reid, & Zee, 2013; Haario, Rahkonen, Laaksonen, Lahelma, & Lallukka, 2013; Schmid et al., 2009). A time series study on the association between sleep and sedentary behavior among toddlers (Armstrong, Covington, Unick & Black, 2019) showed that on group-level. sleep predicted sedentary behavior better than sedentary behavior predicted sleep. However, when investigating individual-level coefficients, both the strength and the direction of the associations differed between individuals. Group-level data have overall been found not to generalize well to the context of a single individual within the realm of psychological research (Molenaar, 2004). Although interindividual variation has long been recognized in the clinical field, this concern is only beginning to emerge in a research context (Fisher & Boswell, 2016). Fisher et al. (2018) found the variance around the expected value to generally be around two or four times larger in individuals than in groups. The findings of Armstrong et al., (2019) indicate that variation between individuals seem to be present also when it comes to the association between sleep and physical activity levels. Thus, based on the group-level research presented above, the interplay between sleep and physical activity cannot with certainty determined in the case of a single individual. New idiographic methods for determining the person-specific interplay between the two factors in a treatment context has yet to be tested.

1.3 Time Series Design in Psychological Research

The time series design originates from econometrics (Dahlhaus, 1997) but has recently entered the research field of psychology (Bringmann et al., 2013). Time series data have previously been used for analyzing time-relations between a variety of psychological variables on a group-level (e.g., Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015; Groen et al., 2019; Kramer et al., 2014; Lutz et al., 2018; Snippe et al., 2017) and at the level of the single individual, where person-specific models are created (e.g., Bak, Drukker, Hasmi, & Van Jim, 2016; Fisher, 2015; Kroeze et al., 2017; van der Krieke et al., 2015; Wichers & Groot, 2016). Some studies have also used time series designs where both group-level and individual level data are analyzed (e.g., De Vos et al., 2017; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017; Hartmann et al., 2015). The personalized models have the benefit of higher accuracy in clinical application, since they are derived from the person at hand and not merely from group-level data (Fisher, 2015). Time series models are based on intensive longitudinal data nested within individuals, allowing in-detail investigation of temporal effects or unique person-specific dynamics. Information about these temporal patterns could, for example, be used as an aid in planning and tailoring interventions (Bak et al., 2016) or for forecasting treatment dropout (Lutz et al., 2018), but not for making generalizations to a larger group of individuals (Schuurman, Ferrer, de Boer-Sonnenschein, & Hamaker, 2016).

For gathering the intensive longitudinal data needed for time series analysis, Ecological Momentary Assessment (EMA) is frequently used (Shiffman, Stone, & Hufford, 2008). EMA data are collected in real-time, and in the participant's natural environment. Data are generally collected multiple times a day using – for example – wearable technology, smartphone applications or electronic diaries, with the advantages of attaining high ecological validity and accuracy, compared to retrospective estimates (Fisher, 2015; Shiffman et al., 2008). By analyzing the dynamics of EMA data (i.e., analyzing temporal associations) predictive relations between the variables can be identified (Bringmann et al., 2013). If a variable at an earlier time point (e.g., $t - 1$) is related to another variable (or itself) at a later time point *(t),* causality between the variables can be inferred, since t - 1 evidently precedes t in time. This type of reasoning, where temporal precedence is assumed to be indicative of causality, is referred to as Granger causality (Granger, 1969).

When estimating time series models, multiple repeated measures are fitted into one model, with the aim of being able to explain how the variable(s) in the model predict themselves and each other over time. Each variable is regressed on a time-lagged version of itself (e.g., on its own state at $t - 1$), a so-called autoregression. The autoregressive coefficient describes how well a variable tends to predict itself over time. An autoregression close to zero would indicate that when the system is perturbated by a high or low score (for example, by a night of excessive sleep or no sleep) it rapidly recovers and returns to its typical state, its equilibrium (e.g., the typical amount of sleep). A value close to 1 would indicate major carry-over from one time-point to the next (i.e., high inertia), implying a regulatory weakness of the system. A negative autoregression indicates antipersistence of the system, a zigzag pattern where relatively low amounts of sleep one night predicts relatively high amounts of sleep the following night, and vice versa. (Armstrong et al., 2019; De Haan-Rietdijk, Gottman, Bergeman, & Hamaker, 2016). In bivariate or multivariate time series models, cross-lagged associations between variables can be analyzed to investigate how variables interact over time, when the internal relations and the strength of the associations between variables are unknown. When modeling cross-lagged effects the variable is regressed on the other variable(s) at an earlier time-point, while accounting for the autoregressive effects (Hamilton, 1994; Schuurman et al., 2016). The results indicate the predominating cause-effect relations and the relative strengths of the effects between variables, without utilizing experimental design.

To date, the majority of time series research within psychology has focused on statistical analyses where temporal stationarity is assumed, meaning that all variables in the model are assumed to have means that are constant over the whole measurement period. Bringmann and colleagues (2018) state that it is daring to assume stationarity of parameters in psychological phenomena where emotional processes are present, since psychological dynamics are likely to shift over time, both over shorter and longer time-intervals. Armstrong and colleagues (2019) also point out that the assumption of stationarity might not hold in place for behaviors with cyclic tendencies such as the potential seasonal, developmental, hormonal or weekday-weekend patterns highly probable for sleep and activity. Instead, it would be of great importance to begin utilizing new methods, allowing detection of time-variant processes.

Time-varying time series models have gained substantial interest due to their potential of detecting both univariate temporal dependencies (Bringmann et al., 2017) and temporal dynamics in bivariate systems (Armstrong et al., 2019; Bringmann et al., 2018) without assuming that the process or the relationships observed are stationary over time. These novel non-stationary methods of analyzing psychological data are currently in constant development. Since the purpose of psychological treatment is to facilitate change (such as decreasing overall distress), the assumption of stationarity is likely to be violated in these contexts. Consequently, when modeling the relationship between physical activity and sleep over the course of a CBT-I treatment, the use of a time-varying time series model is the most appropriate. Studying the temporal dynamics of a system during psychological treatment can yield important information about what types of changes occur, and when.

1.4 Aims and Hypotheses of the Present Study

The aim of the present study was to investigate the unique, dynamic interplay between total sleep time (TST) and physical activity in a case study involving one insomnia-prone participant undergoing a CBT-I treatment. This was achieved by explorative analysis of time series data gathered throughout the intervention period. Introducing a psychological intervention, such as CBT-I, is an external element that has the potential to not only alter the mean level of sleep and activity in the participant, but also affect the temporal dynamics of the system. My research collaborators and I were specifically interested in detecting any potential changes in the extent to which sleep and physical activity predicted themselves over time, or, changes in the degree to which the two variables predict each other over time. The following research questions were formed:

- Does the extent to which TST predicts itself over time change over the course of the treatment?
- Does the extent to which TST predicts physical activity the following day change over the course of the treatment?
- Does the extent to which physical activity predicts itself over time change over the course of the treatment?
- Does the extent to which physical activity predicts TST the following night change over the course of the treatment?

I expected the autoregressive effects of TST to be positive at the beginning of treatment, indicating high carry-over (Armstrong et al., 2019). A single night of less sleep might not alarm a person with no difficulties with sleep, while a person with proneness to insomnia might enter a counterproductive state of hyperarousal and worry about sleep (Riemann et al., 2010), potentially leading to a pattern of several consecutive nights of disrupted sleep. Towards the end of the treatment period I expected the autoregression of TST to diminish from positive to zero or negative, due to increased flexibility of the system and increased influence of natural sleep processes such as sleep pressure and the circadian rhythm (Borbely, 1982). No change was expected in the intercept or autoregression of physical activity, since no treatment intervention targeted a change of physical activity levels. Also, I expected the cross-lagged effect of physical activity on TST to be time-variant. Since the participant had tendencies of cognitive hyperarousal, possibly masking the sleepiness (Riemann et al., 2010), it is possible that physical activity does not predict TST at the beginning of treatment, but that a cross-lagged effect of physical activity on sleep would appear towards the end of the treatment, if the cognitive hyperarousal is (as expected) mitigated by treatment. Finally, if a positive cross-lagged effect of TST on physical activity can be identified, I expected to observe decrements in this effect over the course of the treatment, since the intervention would be expected to make the participant less likely to cancel activities solely due to little sleep.

2 Method

2.1 Participant

The participant was a Finnish 23-year-old female student, who announced interest in a free psychotherapeutic intervention for sleeping problems, offered by a Masters-level student (the author) as a part of the course Internet-based Treatment of Disordered Sleep at the Department of Psychology at Åbo Akademi University. The participant reported subjective difficulties with falling asleep at night, caused by sleep interfering thoughts, and light and sound sensitivity before sleep onset. These difficulties were hypothesized to be triggered by a general proneness towards insomnia, sustained by cognitive hyperarousal conditioned to the bed over time (Riemann et al., 2010). The participant had an overall active lifestyle, containing for example studies, office work, physical exercise at the gym and social activities. Overall, she had few tendencies to cancel activities due to lack of sleep, and she did not perceive her sleep problems to be interfering with her everyday performance, but she described herself as being constantly tired, leading to negative effects on her mood, such as irritability. Her problems were described as fluctuating regarding severity, and at the time of the treatment she perceived the problems to be at an easy-to-medium level, in comparison to other, previous time periods of worse symptoms. Insomnia Severity Index-scores (Bastien, Vallières, & Morin, 2001) obtained before the intervention indicated clinically significant insomnia of medium severity (17 points). The participant was not using any sleep medication and had not previously participated in any treatment for sleep problems. She did not report any other medical or psychiatric conditions nor any comorbid sleep disorders.

2.2 Procedure

The data collection for the present study was given a positive evaluation by the Board for Research Ethics at Åbo Akademi University on January 8, 2019. The participant was initially screened by a licensed psychologist to ensure suitability for the study and the intervention. Written informed consent was collected from the participant. The data collection period was composed by three parts: A pre-intervention phase, an intervention phase and a post-intervention phase. During all three phases, data on total sleep time and activity levels were gathered through an activity tracker (Fitbit Charge 3), regularly synchronized to an online platform (www.fitbit.com). The pre- and post-intervention period lasted 21 and 14 days, respectively, based on a recommended minimum baseline period of 1-3 weeks for persons prone to insomnia, in order to obtain stable and representative estimations of the current sleep patterns (Wohlgemuth, Edinger, Fins, & Sullivan, 1999). During the intervention phase, additional self-reported data on sleep, mood and activity levels were gathered through a sleep diary (Jernelöv, 2008). Both before and after the intervention, the participant completed two online questionnaires about sleep, Insomnia Severity Index (ISI; Bastien et al., 2001) and Dysfunctional Beliefs and Attitudes Scale (DBAS-16; Morin, Vallières, & Ivers, 2007). The complete period of data gathering lasted approximately 18 weeks (127 days and 128 nights) between January and May 2019.

2.2.1 Content of Intervention Sessions

The intervention was carried out as a part of the course Internet-based Treatment of Disordered Sleep at the teaching clinic at Åbo Akademi University. The student counsellor was regularly supervised by a licensed psychologist between each treatment session over the entire course of the intervention. An individual case conceptualization was made based on a CBT-I protocol and instructions by Manber and Carney (2016), and treatment elements were modified with respect to the participant's wishes and premises. The intervention consisted of six internet-delivered video sessions lasting 30-60 minutes, over a period of 13 weeks in total. The sessions were conducted through a secure online internet therapy platform (www.minduu.fi).

The participant's overall goals for the treatment were to feel less tired, to fall asleep faster (to have a shorter sleep onset latency) and to have a longer TST. The main therapeutic interventions chosen were based on the individual case conceptualization, and included tools such as psychoeducation, stimulus control, and a less demanding alternative to sleep restriction, sleep compression (Manber & Carney, 2016). The participant was also introduced to techniques addressing stress management and the cognitive components of her problems with sleep, such as scheduled worry time (Borkovec, Wilkinson, Folensbee, & Lerman, 1983), relaxation and visualization (Jernelöv, 2008). One session incorporated techniques from Motivational Interviewing (MI) (see e.g., Miller & Rollnick, 2012) in order to increase treatment adherence and motivation based on observations from previous sessions, and entries in the sleep diary. Between each session, the participant was assigned homework, such as trying out the new techniques introduced, doing readings in an evidence-based self-help book authored by a clinical psychologist specializing in disordered sleep (Jernelöv, 2008), and completing the sleep diary.

2.3 Measures

The instruments presented below were used for measuring variables included in the analyses. Data from the wearable activity tracker can be considered objective and were thus used for the time-series analyses. All other instruments are based on self-reported subjective data and were mainly used for reviewing treatment effects.

2.3.1 Wearable Activity Tracker

A consumer-grade, wrist-worn activity tracker equipped with a heart-rate monitor (Fitbit Charge 3, Fitbit, 2018) was used to measure physical activity and sleep. More specifically, the activity tracker gathered objective data such as daily averages TST, time awake during the night, and data for physical activity (measured as number of footsteps, energy expenditure and time in activity). TST and steps were the variables used for time series analysis. TST is identified via heart-rate patterns in combination with movements indicative of sleep behavior. Steps are measured by a 3-axis accelerometer detecting movements, together with an algorithm determining motion patterns indicative of steps or walking (Fitbit, 2019).

In a systematic review of wearables in the Fitbit category of products, it was concluded that the devices generally have a higher validity for steps and a lower validity for energy expenditure and sleep (Evenson, Goto, & Furberg, 2015). In a systematic review by Feehan and colleagues (2018), literature on the accuracy of a variety of Fitbit models was reviewed, with similar results. For operationalizing physical activity, only the measurements of steps were included in the analyses. Only a few studies in the review studied the accuracy of measuring sleep variables in a free-living setting, but these studies indicated relatively similar results between Fitbit and research-graded devices. To my knowledge, no studies have yet investigated the accuracy for the newly released Fitbit Charge 3 (Fitbit, 2018). Further studies on the reliability and validity of this device are warranted. To date, the device was chosen because of the relatively low cost and because of measuring the parameters of interest. The wearable data gathered was compared to sleep diary measures in order to investigate the correspondence between the objective and the subjective measures of sleep and physical activity.

2.3.2 Sleep Diary

A sleep diary was used to gather subjective estimations of sleep, mood and activity levels. The sleep diary was mainly used for guiding the intervention and for investigating the level of agreement with the activity tracker data gathered. Sleep diaries have frequently been used in CBT treatments and are often considered as the gold-standard subjective assessment tool for sleep (Buysse, Ancoli-Israel, Edinger, Lichstein, & Morin, 2006). In addition, sleep diaries are both practical and cost-effective. The sleep diary used in the present study was retrieved from the self-help book by Jernelöv (2007) and corresponds well with a standardized consensus sleep diary developed by Carney and colleagues (2012). Diary entries were recorded once in the morning and once in the evening by the participant throughout the treatment.

The participant recorded the following measures every morning: bedtime hour; time of falling asleep; length of nighttime awakenings; time of waking up; and time of getting out of bed. Based on this input, mean values for sleep onset latency (SOL), wake after sleep onset (WASO), total sleep time (TST) and sleep effectivity (SE) were calculated. Subjective sleep quality was also rated on a 1 (very poor) – 5 (very good) Likert scale. In the evenings, the participant recorded relevant daytime variables such as activity level and mood.

2.3.3 Insomnia Severity

The Insomnia Severity Index (ISI), developed by Morin (1993), is a brief self-report questionnaire measuring subjective symptoms of insomnia. ISI was administered to measure pre- and post-intervention severity of sleep problems (Bastien et al., 2001). The questionnaire is based on DSM-IV diagnostic criteria (APA, 1994) and consists of seven items measuring the severity of problems with sleep onset, maintenance or early morning awakenings, the level of satisfaction or distress concerning sleep, the effects on daily functioning, and the noticeability of the problem by others. All items were rated on a Likert scale (0-4) and were summed up to a total score between 0-28, where a higher score corresponds to insomnia with higher severity. In a study by Morin and colleagues (2009), it was suggested that patients who had undergone treatment and who had a relative ISI change score of higher than 7 were responding to treatment, and that patients with absolute ISI-scores lower than 8 were remitting. ISI has shown good psychometric qualities. For example, ISI shows both high internal consistency (Cronbach $\alpha = 0.91$) and item-total correlations (0.5-0.85) in a clinical sample, and good convergent validity to related instruments, such as the Pittsburgh Sleep Quality Index ($r = .8$, $p < .05$) (Morin, Belleville, Bélanger, & Ivers, 2011). Psychometric properties have also been shown to be acceptable when, as in the present study, the questionnaire is administered online (Thorndike et al., 2011).

2.3.4 Dysfunctional Beliefs and Attitudes about Sleep

The Dysfunctional Beliefs and Attitudes about Sleep Scale, DBAS-16 (Morin, Vallières, & Ivers, 2007), was used to evaluate the strength and quality of endorsed maladaptive beliefs about sleep. DBAS-16 consists of 16 self-report items, measuring perceived consequences of insomnia, helplessness/worry about insomnia, sleep expectations and medication. Each item is rated on a Likert scale of 0 (*"strongly disagree"*) to 10 (*"strongly agree"*), where higher scores indicate stronger dysfunctional beliefs. The DBAS-16 has adequate psychometric properties. Internal consistency (Cronbach's alpha = 0.77 for clinical and 0.79 for research samples) and temporal stability (r = 0.83) are satisfactory. Convergent validity is acceptable; scores correlate significantly with ISI (r = 0.33-0.45) and other measures of conceptually related constructs, such as depression (r = 0.42) and anxiety (r = 0.41). (Morin et al., 2007).

2.4 Statistical Analyses

2.4.1 Data Preparation

From the activity tracker data from 128 time points were gathered, and from the sleep diary 80 (night variables) and 81 (day variables) time points were gathered in total (see Figure 1). First, data were prepared for the analyses with Microsoft Excel 16 and IBM SPSS statistics 24. All variables measuring time were converted into minutes for the sake of uniformity. Pre- and post-intervention data were in total gathered for 21 and 16 days, respectively. Means and standard deviations for the pre- and post-intervention periods were calculated. No pre- and post-intervention data were gathered through the sleep diary, to minimize the burden on the participant. For the sleep diary, means and standard deviations were instead calculated for the time period between the first and the second session (early intervention) and for the fifth and the sixth session (late intervention) in order to compare the beginning of the intervention to the end. Correlations were then calculated between activity tracker variables and sleep diary variables measuring sleep and activity, to identify the level of agreement between the

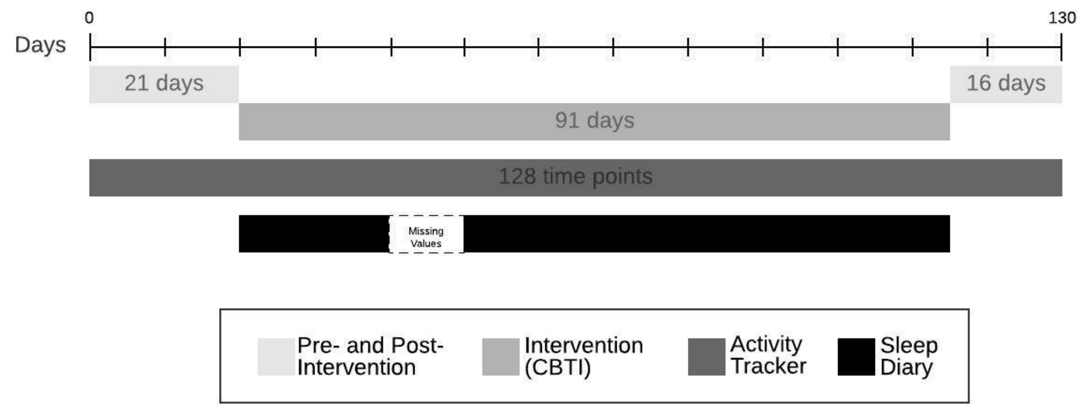


Figure 1. Illustration of the complete period of data collection.

objective and the subjective measurement tools. From the activity tracker, there were no missing values. In the sleep diary, 12 - 13 % of values were missing for the night- and day-entries, due to the participant being on holidays. The variables used for the time-varying vector autoregressive analyzes were standardized to make it possible to compare cross-lagged effects. To explore the raw data of sleep, a linear regression line and two polynomial regression lines were also fitted to the raw data with the R-package ggplot2 (Wickham, 2016).

2.4.2 Time-Varying Vector Autoregressive Models

The software environment R 3.5.3 was used for carrying out the time series analyses. In the present study, the semi-parametric time-varying vector autoregressive model (TV-VAR), proposed by Bringmann and colleagues (2018), was used to create a bivariate lag-1 model. TV-VAR is an extended version of the temporally stationary vector autoregressive model, VAR (Brandt & Williams, 2007) but uses additional time-varying parameters to enable modeling of the dynamic aspects of temporal relationships between variables in a system. Bringmann and colleagues (2018) advocate the use of a TV-VAR model if one is analyzing intensive longitudinal data which is likely to involve time-varying dynamics, and if data includes 100 or more observations from different time points, which was the case in this study. The TV-VAR model does not assume stationarity, meaning that statistical parameters such as intercepts, autoregressive effects and cross-lagged effects are allowed to vary over time. Thus, changes in the dynamics of the system can be identified (Bringmann et al., 2018). Still, TV-VAR model assumes local stationarity and is therefore unable to model abrupt changes. Any changes occurring in the data are assumed to be gradual (Dahlhaus, 1997).

The TV-VAR model uses a Generalized Additive Modeling framework for estimating the relationship between variables. Each time-varying parameter in the model is estimated though selecting a certain amount of basis functions, defining the extent to which the parameters are allowed to vary. The more basis functions, the more curvature and complexity in the estimated function, but the higher the likelihood of overfitting (for a detailed description, see Keele, 2008). The curvature of the function was here regulated by adding a "wiggliness" penalty through generalized cross-validation (GCV; Golub, Heath, & Wahba, 1979), a technique carried out using the *mgcv* package in R (Wood, 2006). Here, the standard of 10 regression spline basis functions were used, as in Bringmann and colleagues (2018). Since the model allows time-variation, the direction of the autoregressive and cross-lagged relationships between variables are inspected visually and cannot be effectively summarized in a numeric manner. The time-varying relationship could be aggregated by a linear relationship for the whole time period, to allow extraction of numeric parameters for the overall relationship, but with the cost of great information loss regarding potential changes in the relationship over time. Visually inspected plots where the functions are allowed to vary as a sine are more informative when analyzing time-varying data (Bringmann et al., 2018).

Since nighttime and daytime activity are inherently lagged with one another, it is essential to clarify how the variables were coded and regressed upon each other in the analyzes. When sleep is lagged on itself, the present night at time t (e.g., sleep between Sunday to Monday), is regressed upon the previous night at t - 1 (e.g., sleep between Saturday to Sunday; lag 1). But, when estimating cross-lagged effects of nighttime sleep on the activity of the following day, the lagged relationship was modeled so that the present daytime activity (e.g., values registered for Sunday day) was regressed upon what seems to be the present nighttime sleep (TST also registered on Sunday, when waking up; lag 0). In reality these are inherently lagged variables, since the nighttime sleep from Saturday to Sunday naturally foregoes daytime activity on Sunday. To estimate the reversed cross-lagged effect of daytime activity on the following nighttime sleep, present nighttime sleep at time *t* was regressed upon previous daytime activity at $t - 1$ (lag 1).

In total, 8 different models were estimated for each dependent variable, and the models were compared by how well they fit the data. The standard TV-VAR model where all parameters where allowed to vary over time (model 1) was compared to other more parsimonious models where one, two or all three of the parameters were stationary (see Table 1). For all models, *F*- and *p*-values were calculated. The *F*-value describes the variance of group means, while the *p*-value indicates whether the difference is significantly different from zero. For the statistically significant effects, the effective degrees of freedom (*edf*) should also be inspected. The *edf* indicates the number of values of a statistic that in the final calculation are free to vary. If the *edf* is higher than one, a dynamic process is indicated. But importantly, since both a stationary process and a linear increase has an *edf* of around 2, the *edf* cannot in these cases discriminate between stationarity or a linear increase (Bringmann et al., 2017).

Table 1

The 8 Models Estimated for both Sleep and Physical activity (16 models in total). Each Model has a Different Combination of Time-variant and Stationary Parameters

	Intercept	Autoregressive Parameter	Cross-lagged Parameter
Model 1	tv	tv	tv
Model 2	tv	tv	s
Model 3	s	tv	tv
Model 4	tv	s	tv
Model 5	tv	s	s
Model 6	s	tv	s
Model 7	s	s	tv
Model 8	s	s	s

Note. tv = Time-variant parameter, s = Stationary parameter.

Model comparison was carried out by (1) comparing the Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC) fit indices, (2) by inspecting the significance and the effective degrees of freedom of the smooth parameters and (3) by visually inspecting whether the Bayesian confidence intervals of the parameters overlapped with zero (Bringmann et al., 2017). As stated by Bringmann and colleagues (2018, 2017), in TV-VAR models containing fewer than 100 time points both BIC and AIC fit indices perform poorly, but when data includes more than 100 time points (as in the analyzes of the present study) the BIC is sufficient and performs fairly well. For the sake of comparison, both BIC and AIC will be reported. The model with the lowest BIC and AIC is indicated as having the best fit. The BIC suggests whether a standard VAR or one of the time-varying models are a better fit to the data, but cannot reliably distinguish which one among the time-varying models that are the best fit for the data (Bringmann et al., 2017). The fit indices were simply used as an indication for whether a time-varying model should be used or not. Thus, additional criteria are required.

3 Results

3.1 Summary of Descriptive Statistics and Correlations between Measures

The participant's pre- and post-intervention total scores for ISI were 17 and 14, respectively (score range of 0-28). The pre-intervention score indicates insomnia of moderate severity, and the post-intervention score has decreased to the score range of subthreshold insomnia (Morin 1993), even though the score does not indicate complete remission (Morin et al., 2009). For DBAS-16, the pre-intervention mean score was 5 and decreased to a post-intervention mean score of 3. A DBAS-16 mean score of more than 3.8 is generally indicating that the person may have unrealistic expectations on their sleep (Carney et al., 2010). The subjective score of effectiveness for the intervention provided was 70 and the alliance was rated at 90 (out of 100). Descriptive statistics for pre- and post-intervention data of the activity tracker can be found in Table 2 and sleep diary data is summarized in Table 3.

Table 2
Descriptive Statistics for Pre- and Post-Intervention Data Gathered through the Activity Tracker

	Pre-intervention (n = 21 days)	Post-intervention (n = 16 days)
	M (SD) [min-max]	*M (SD) [min-max]*
TST[a]	445.81 (44.00) [391-558]	395.19 (34.88) [338-475]
Total Time Awake	65.81 (12.82) [49-94]	57.44 (8.85) [46-76]
Steps[a]	704.70 (169.34) [313-1096]	612.62 (120.53) [441-859]
Total Minutes Active	301.14 (66.20) [232-489]	304.53 (42.70) [220-365]
Activity Calories	1030.14 (258.20) [768-1880]	983.00 (149.00) [703-1177]

Note. M = mean; *SD* = standard deviation; TST = total sleep time in minutes; Total time awake in minutes; Steps = total amount of steps taken per hour; Total minutes active = activity minutes for one day; Activity Calories = kCal burned during activity.
[a]Variable included in TV-VAR analyses.

Table 3

Descriptive Statistics for Sleep Diary Data from the 1st – 2nd Session and the 5th – 6th Session

	1st - 2nd Session (*n* = 19 days)	5th - 6th Session (*n* = 29 days)
	M (SD) [min-max]	*M (SD) [min-max]*
Sleep Diary TST	444.53 (74.49) [200-530]	431.48 (43.04) [310-520]
Sleep Diary TIB	543.16 (44.30) [420-600]	502.14 (54.41) [340-590]
Sleep Diary SE	82.09 (13.17) [35.7-92.1]	86.00 (4.65) [76.3-94.8]
Sleep Diary Time Awake	35.26 (52.77) [0-240]	19.21 (13.21) [0-50]
Sleep Diary SOL	47.94 (31.56) [1-120]	29.482 (19.57) [10-105]
Sleep Diary Sleep Quality	3.00 (0.87) [0-4]	2.90 (0.48) [2-4]
Sleep Diary Activity Level	2.89 (0.81) [1-4]	2.72 (0.80) [0-4]

Note. *M* = mean; *SD* = standard deviation; TST = total sleep time, in minutes; TIB = Time in Bed during the night, in minutes; SE = Sleep Effectivity (%); SOL = Sleep Onset Latency, in minutes; Sleep Quality, Activity Level, Alertness, Happiness, Level of functioning, Tiredness, Irritation and Stress = all measured on self-reported Likert scales from 0 (low) – 5 (high).

The TST of the activity tracker and the sleep diary were strongly correlated ($r = .83$, $p < .001$). Activity tracker and sleep diary measurements of Total Minutes Awake were moderately correlated ($r = .67$, $p < .001$). The activity tracker measurements of Steps had a weak positive correlation with sleep diary reports of activity level ($r = .25$, $p = .023$) but no significant correlation was found between activity tracker measurements of Total Minutes Active and sleep diary reports of activity level ($r = -.08$, $p = .490$) or Activity Calories and sleep diary reports of Activity Level ($r = -.04$, $p = .736$).

3.2 Model Estimation and Selection: Fit Indices and Significance Testing

First, I investigated whether a model indicating a time-varying process should be used, or if a stationary VAR model (model 8) is a better fit for the data. The BIC and AIC values of the models created for physical activity (steps) and sleep (TST) are summarized in Table 4. Here, AIC suggested model 5 (a time-varying intercept with stationary autoregressive and cross-lagged parameters) as the best fitting model for both physical activity and sleep, while BIC suggested the stationary model 8 for physical activity, and model 5 for sleep. For sleep, both the BIC and the AIC suggest a model from the class of time-varying models, and thus we can assume that the process is, to some extent, time-varying. For physical activity, it is less clear whether the process is time-varying or not based on simply the BIC and AIC values.

To gain additional information about if the process was time-varying or not, the smooth parameters of model 1 were investigated, where all parameters were allowed to vary. For physical activity the parameters of the intercept ($F = 2.47$, $p = .02$, *edf* = 5.99, *ref.df* = 7.17) and the cross-lagged effect ($F = 3.50$, $p = .03$, *edf* = 2.00, *ref.df* = 2.00) were statistically significant at a .05 level in predicting activity, while the autoregression was not ($F = 0.63$, $p = .54$, *edf* = 2.00, *ref.df* = 2.00). The same pattern was apparent for sleep, where the intercept ($F = 10.18$, $p = .002$, *edf* = 1.00, *ref.df* = 1.00) and the cross-lagged effect ($F = 4.80$, $p = .01$, *edf* = 2.00, *ref.df* = 2.00) were statistically significant at a .01 level, while the autoregression was not ($F = 1.05$, $p = .37$, *edf* = 3.91, *ref.df* = 4.63). Based on the results above, we can be confident that at least the intercepts for both physical activity and sleep were dynamic over time, and that at time-varying model thus is needed. If the autoregressive or the cross-lagged parameters are significant, it does not indicate that the parameter in question is indeed time-varying, but rather, that this parameter is needed in the model (Bringmann et al., 2017). According to the results, both of the cross-lagged parameters of sleep and physical activity had predictive value, while the autoregressions did not have any added value, meaning that the autoregressions could not significantly predict themselves at the following time point. The *edf* for both cross-lagged parameters were 2. Thus, the *edf* cannot indicate whether the process is time-variant or not. Since we cannot reliably differentiate between the time-varying models based on fit indices and significance testing, visual inspection of a model where all parameters were allowed to vary (model 1) was required.

Table 4

Summary of the BIC and AIC Values for the Eight Models Estimated

	Physical Activity (Steps)		Sleep (TST)	
	BIC	AIC	BIC	AIC
Model 1	384.95	350.94	368.52	343.17
Model 2	380.69	349.59	360.72	343.65
Model 3	381.86	357.38	374.51	351.11
Model 4	381.72	350.10	361.14	344.08
Model 5	378.13	**349.36**	**357.31**	**343.09**
Model 6	372.75	358.57	370.31	351.32
Model 7	377.74	355.87	369.05	354.83
Model 8	**368.60**	357.25	364.52	353.15

Note. Lowest BIC and AIC indices are marked in **bold** typeface.

3.3 Visual Representation of Results

For giving an overview of the variation over time in variables used for the TV-VAR analyses, raw data gathered from the participant is presented in Figure 2. By visual inspection, the average amount of physical activity (steps) showed random variation, where no apparent trends or sudden shifts could be observed (upper panel). Regarding sleep, it seems that the TST had a slight trend downwards, indicating that the participant appeared to sleep slightly less over the course of the treatment (even though sleep effectivity increased and SOL decreased, indicating that the treatment had a positive effect). No sudden shifts could be identified in the raw data (lower panel).

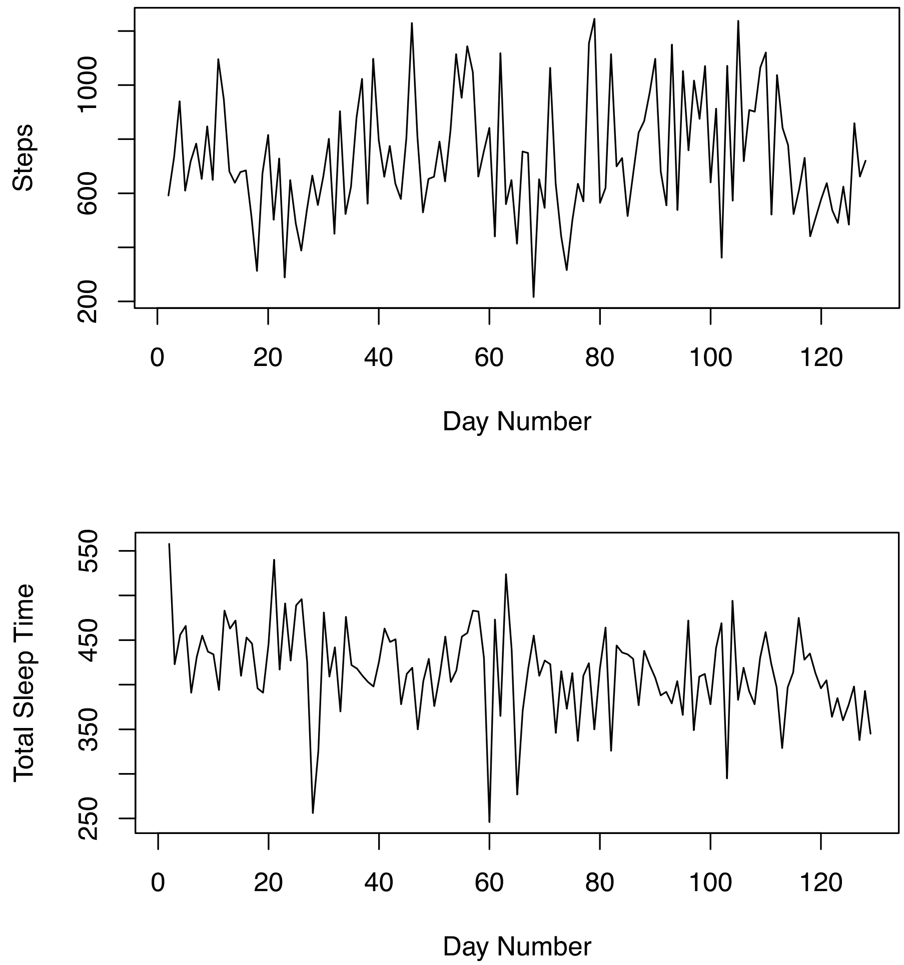


Figure 2. Graphs depicting the participant's average amount of steps taken per hour each day (upper panel), and the total amount of sleep per night in minutes (lower panel), during the time period of the study (127 days and 128 nights).

To better visualize the overall trend in TST not evident solely by inspection of raw data, a linear regression line was fitted to the data. For explorative purposes only, two supplementary polynomial regression lines were also added, in order to aid visual inspection and detection of any potential non-linear trends or shifts occurring during the time period (see Figure 3). For the sake of comparison, I fitted both a lower and a higher degree polynomial regression line to the data. A polynomial regression fits a nonlinear model to the data, allowing curvature in the function (a higher degree polynomial allows

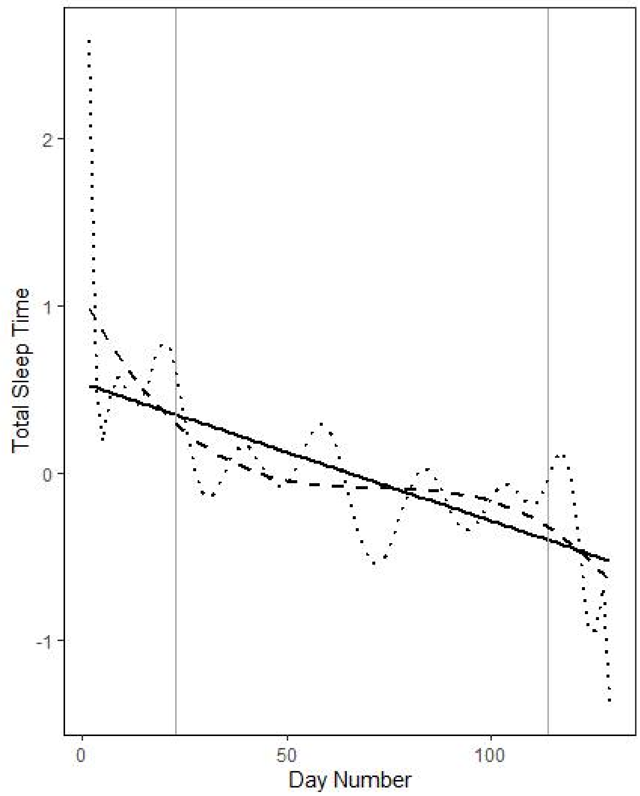


Figure 3. Explorative linear and polynomial regression lines fitted to the raw data of sleep. The solid line indicates a linear regression, the dashed line shows a third-degree polynomial regression, and the dotted line shows a twentieth-degree polynomial regression. The two vertical gray bars indicate the beginning and the end of the intervention.

more curvature, and a lower degree polynomial allows less curvature). Based on visual inspection, a third degree and a twentieth-degree polynomial function were chosen, as these lines were sufficiently different to create better understanding of the data, even though BIC values indicated that the linear line had the best overall fit. All three regression lines confirm the presence of a downward trend. Additionally, when inspecting both of the polynomial functions, it seems as if TST is somewhat more stable during the intervention period but drops markedly after the end of the intervention.

Time-varying parameters as smooth terms are presented in Figure 4. The functions of a TV-VAR analysis can be time-invariant, vary as a linear function or as a sine (Bringmann et al., 2018). From left to right, on both the upper row (steps) and the lower (sleep), the panels indicate: (1) the functions of the intercepts, (2) the functions of the autoregressions, and (3) the functions of the cross-lagged effects. Regarding the cross-lagged effects, the upper right panel represents the effect TST had on steps taken the following day, and the lower right panel represents the effect steps taken during the day had on TST the following night.

Physical activity (steps) had a time-variant dynamic intercept, a sine function with tendencies of cyclic variation but no clear overall trend upwards or downwards. The sine seemed to rise and fall, reaching a peak or a bottom approximately every 20^{th} to 30^{th} day. The autoregression of physical activity showed a slight linear decrease over the whole time-period. It can also be observed that the Bayesian confidence interval (dashed line) for the autoregression contains zero during the whole time period, a visual cue for statistical non-significance. The cross-lagged effect of TST on physical activity showed a linear negative regression, slightly decreasing over time (from -.1 to -.3). The effect was regardless small across the whole time period. These results show that when the participant slept less, she tended to be slightly more physically active the following day, and when she slept more, she tended to be slightly less active the following day. Numerically, the effect was significant, and visually it can be seen that the confidence interval was excluding zero between day 50-100.

The intercept of sleep (TST) was time-variant and linear, and decreased significantly over time. Interestingly, even though statistically insignificant, the autoregressive effect of TST lessened during the majority of the intervention, even though it seemed to be on the increase both before and after the intervention phase. In the beginning, the autoregression is weakly positive, and is slightly increasing over time (.02 at its highest point). Over the intervention, from approximately day 23 (which is also the starting point of the intervention) to approximately day 90 (after the 5^{th} session), the autoregression decreased from a weak positive to a weak negative autoregression (.3 at its lowest point). After day 90, the autoregression again started to rise towards the pre-intervention values. Still, the confidence interval included zero over the whole time period, visually indicating a non-significant effect. Only around day 30 and 90, the confidence interval is close to excluding zero. The cross-lagged effect of physical activity on TST was linearly decreasing from positive (.5 at its highest point), to zero. At the beginning, more physical activity led to more sleep the following night, and less physical activity led to less sleep the following night, but the effect seemed to disappear over the time-period. This statistically significant effect had a confidence interval that excluded zero until day 80.

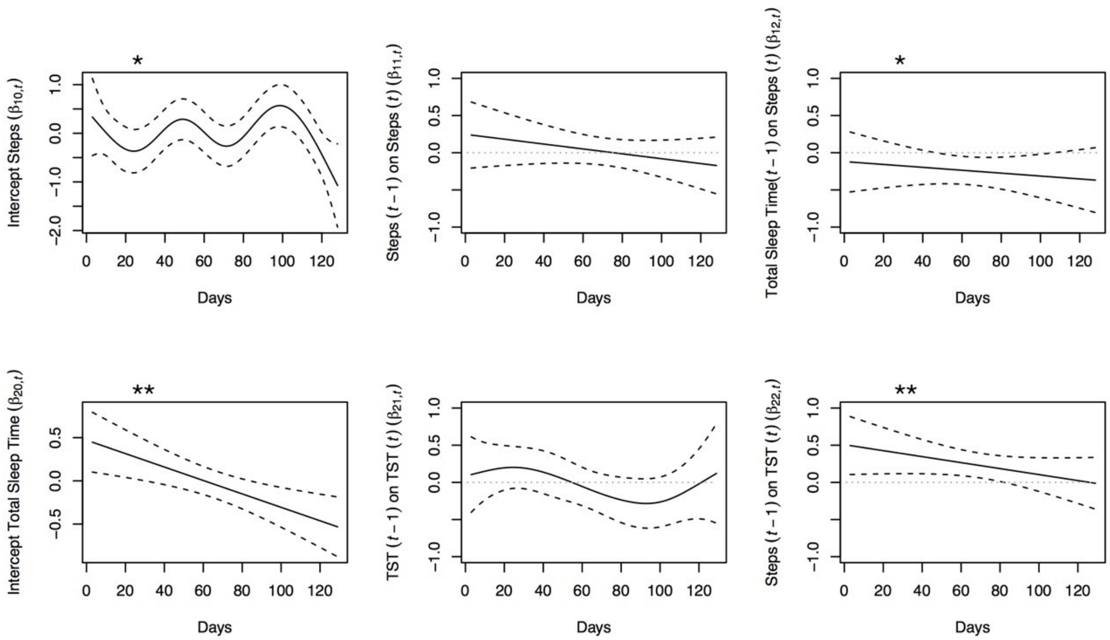


Figure 4. Graphs depicting the parameters of sleep and steps when parameters where allowed to vary over time (model 1). The CBT-I intervention started at day 22 and lasted until day 114.
* = *p* > .05
** = *p* > .01

4 Discussion

In the present study, the person-specific changes in the relationship between sleep (TST) and physical activity (steps per hour) occurring during a CBT-I treatment were investigated. This was accomplished through analyzing temporal aspects of EMA-data (i.e., intensive longitudinal data) gathered from one single participant, and by creating a bivariate cross-lagged time series model allowing time variation. The aim was to explore how the model could describe the temporal evolution occurring in the system of physical activity and sleep during a psychological treatment. I investigated whether sleep on time point t is a function of its intercept, of itself at t - 1 (i.e., autoregressive effects) and of physical activity at $t – 1$ (i.e., cross-lagged effects), and whether physical activity at time point t is a function of its intercept, of itself at $t – 1$ and of sleep at $t – 1$. I hypothesized that the bidirectional dynamics between sleep and physical activity would change over time due to treatment effects. Results are not intended to be generalized to other individuals, and since the present study adopted an explorative design, the results should be interpreted with caution.

4.1 Time Series Analysis of Physical Activity and Sleep as a Bivariate System

It was hypothesized that no overall trends would be identified for the intercept and autoregression of physical activity, since the intervention techniques used did not specifically target a change in the participant’s activity levels. The results for both the intercept and the autoregression were in accordance with the hypotheses. The intercept did vary over time, but it varied in a cyclic manner that did not indicate any overall general increase or decrease from the equilibrium. The results for the cross-lagged effect of sleep on physical activity contradicted the hypothesis. I predicted that, at the beginning of treatment, less sleep would lead to less physical activity the following day (a positive association), and I expected this association to lessen over the course of the treatment. The results instead indicate a negative association throughout the treatment. In the light of the qualitative information gained about the participant, this result could in part be explained by the fact that the participant did not subjectively report any tendencies of cancelling activities due to less sleep, as she had a fairly active lifestyle. This participant might not have tried to compensate sleep loss by excessive resting (Haario et al., 2013), possibly indicating that her everyday physical activities were not affected by lack of sleep. These results could beneficially be reflected back to the patient to encourage her to maintain this behavior, since this type of behavior has been shown to have favorable effects on sleep overall (Kredlow et al., 2015). These results suggests that, for this participant, insomnia does not dictate the life activities of the following day.

The decrease seen in the intercept of TST was unexpected. Several important points are worth mentioning in relation to this finding. First, the intervention techniques used could during the intervention period lead to a temporary decrease in TST, since the participant is actively encouraged to get up at the same time every morning, regardless of the time for falling asleep. Secondly, at the end of the intervention, the participant also reported an insight about possibly needing less sleep than she had previously believed, and that her desired TST might neither be as necessary nor as beneficial for her as she first thought, another aspect possibly explaining the decrease seen. Therefore, when considering the qualitative information in addition to the quantitative data gathered, a decrease in the intercept of TST over the course of the intervention is understandable and should not simply be interpreted as her sleep problems worsening. Both her self-reported SOL and sleep effectivity were lower towards the end of the intervention, compared to the beginning, and all confidence intervals for sleep parameters in the sleep diary were narrower, indicating that her sleep had somewhat more stability post-treatment. Regarding sleep quality, the confidence interval is restricted to higher ratings towards the end of treatment (2- 4), compared to the beginning of treatment (0-4), even though the average is slightly lower. These factors also indicate positive treatment outcomes. As stated in the introduction, it is worth pointing out the diagnosis of insomnia does not take in consideration the actual time slept, but rather the subjective view on the sleep quality and its consequences (American Psychiatric Assosication, 2013). Thirdly, at the time of the treatment the participant also reported sleep problems of less severe nature, compared to previous time periods. As the participant’s TST was fairly high already at the beginning of treatment, a major increase in sleep time was not feasible. A high TST at the beginning of treatment allows little room for a further increase, due to ceiling effects of sleep (Chennaoui, Arnal, Sauvet, & Léger, 2015). However, when considering the pattern identified in both of the explorative polynomial functions, it seems as if the general decrease in TST might have been stabilized somewhat during the intervention period, even though it dropped again after the end of treatment. As the participant reported her problems to be fluctuating in severity, these results could also potentially be viewed as the treatment slowing down or delaying an upcoming period of worsening of the symptoms, but that this stabilizing treatment effect was not maintained after the end of the intervention. Additionally, TST has been among the sleep variables showing the smallest amount of change during treatment at a group-level (van Straten et al., 2017). It is possible that other variables might have been better able to depict the actual changes occurring in the sleep patterns. For instance, since the participant's main complaint was a high SOL, and since data gathered from the sleep diary showed that SOL had decreased post-intervention, it could have been of interest to follow these changes as well. Since the activity tracker provided objective minute-by-minute data for TST, while information about SOL was mainly gathered subjectively through the sleep diary, I regardless chose to focus on TST.

Regarding the autoregression of TST, it seems as if the intervention had the hypothesized direction of the effect, even though statistically insignificant. The autoregression decreased from slightly positive to negative over the course of the treatment, even though it returned to its previous state again after the treatment. Interestingly, even though the confidence interval included zero indicating that the results might have appeared by chance, the visually apparent changes in direction of the effect appear close to the beginning and slightly before the end of treatment. It could be argued that for a person with well-functioning sleep, the autoregression of TST would be close to zero, indicating random variation, and that the sleep would tend to quickly be drawn back towards its equilibrium, even when occasional perturbations occur (Armstrong et al., 2019). A single night of less sleep does not tend to alarm a person with well-functioning sleep, and thus, do not lead to cognitive hyperarousal and worry about sleep loss. The autoregression of healthy sleepers could also be expected to be negative, so that one night of sleep disruption leads to more sleep the following night, due to an increase in sleep pressure (Borbely, 1982). Since the participant had an autoregression close to zero to begin with, indicating random variation, and decreased towards a slightly negative value during treatment, one could argue that her sleep system was already fairly flexible to begin with, which is in accordance to her qualitative report of having a period of less severe problems. The decrease in the autoregression could potentially have been more pronounced and reached significance if the participant had had sleep problems of a more severe nature. Since the participant reported her sleep problems to be fluctuating, it would have been of interest to study the changes occurring over a longer time span.

The results of the cross-lagged effect of physical activity on TST disconfirmed the hypothesis. It was expected that physical activity would have little effect on sleep in the beginning of treatment, due to masked sleepiness, but that a positive effect would appear over the course of the treatment, due to a decrease in cognitive hyperarousal (i.e., less masked sleepiness, allowing the effects of physical activity on sleep to appear). Instead, the results indicated an opposite pattern, where the cross-lagged effect decreased from positive to zero, meaning that in the beginning of treatment, more physical activity had an association with more sleep the following night, but that this effect disappeared over the course of the treatment. These results could possibly indicate that the intervention was either not successful in decreasing cognitive hyperarousal, or, that the participant became less dependent on needing physical exhaustion to be able to fall asleep at night. The results could indicate that other factors than physical activity became more relevant in predicting sleep.

In sum, it can be concluded that the analyzes did, in fact, identify changes that in a standard time-invariant VAR model would have been overseen. Also, we gained more information on the behaviors of sleep and physical activity of this specific participant. For instance, knowing that the participant was being physically active despite less sleep is valuable information when providing psychological intervention. Still, the driving-forces of any change detected cannot be surely determined. Since idiographic approaches evidently do not include control-groups, it cannot with certainty be told whether any changes seen are caused by, for example, seasonal changes (Finland has a dark winter and summers with lots of light, seasonal changes possibly affecting sleep patterns), by placebo effects, by the actual CBT-I treatment or by other unidentified factors.

4.3 Strengths, Limitations and Implications for Future Research

The main strength of the present study is that it illustrates how a novel TV-VAR model can be used for identifying and visualizing the dynamic changes occurring in a psychological system over time. If temporal variation had been collapsed, as in traditional VAR analyses, changes occurring during the treatment period would have been overseen (Bringmann et al., 2018). Also, an individualized model has the potential to become far more applicable in clinical practice, since the model is based on data from the single individual. The objective data gathered from an activity tracker can efficiently be combined and interpreted together with qualitative reports, to gain a fuller understanding of the patient's behaviors, and equally as important, information that is more clinically reliable. Here, it could for instance be noticed that the participant did not report any tendencies of excessive daytime resting due to less sleep, and the numerical results agreed with the qualitative information gathered. In some circumstances, it could be beneficial to reflect the results back to the patient for psycho-educative purposes. For instance, being able to numerically show the patient how the use of certain therapeutic tools causes significant changes in their system of sleep could work as an important motivating factor and increase treatment adherence. Visualizing patterns of change during treatment to the patient could help reinforce any changes made. Other strengths of this study are that no additional burden to the participant was caused by gathering intensive longitudinal data, and that the study was performed in an ecologically valid, free-living setting.

The study has several limitations worth mentioning. A central limitation of the study is its idiographic approach. Since the results cannot be generalized to other individuals, new data have to be gathered and analyzed for each individual. Nevertheless, this limitation can also be considered its major strength (van der Krieke et al., 2015) since the methodology in question naturally tackles the problem of heterogeneity between individuals and group-to-individual generalizability and consequently bridges the research gap of personalized modelling (Haslbeck et al., 2017). A development of multilevel versions of the TV-VAR analysis tools would enable investigation of both intra- and interindividual effects in parallel (Bringmann et al., 2018).

More time points and data collection over a longer period of time could possibly have been necessary. For detecting smaller changes, a large number of time points are needed (Bringmann et al., 2018). More than 200 time points have been suggested as needed for detecting small changes, even though larger changes can be detected already at around 60 time points. Still, to model non-stationary data where no sudden changes or shifts in the data are known, and for the smoothers penalizing the allowed curvature of the functions to work properly, over 100 time points has been considered acceptable (Bringmann et al., 2017), which was the case in the present study. Also, the TV-VAR model is unable to model abrupt changes, since it assumes change to be gradual. Bringmann et al. (2018) suggest that TV-VAR models could beneficially be combined with regime switching models, which allow modelling of both sudden and gradual changes. It is worth mentioning that results might not be generalizable to other time windows of that very individual. The study did not use a research graded activity tracker.

It would have been of interest to include more variables (e.g. SOL, TIB and other measures of physical activity or sedentary behavior) and different types of time lags (e.g. t – 2) into the model, to build a fuller understanding of the changes occurring and the length of temporal delay of the system, but multivariate time-varying models demand a very large amount of data points, and quickly grow complex causing problems with interpretation and identification of spurious connections (Costantini et al., 2015; Tibshirani, 1996). Thus, the variables in non-stationary models are needed to be kept at a minimum. These types of analyses are currently in constant development, and future research should focus on improving the regularization techniques used (see e.g., Haslbeck & Waldorp, 2020) and develop ways of automating the TV-VAR analyzes, to be able to provide clinicians with readily available tools that are time-efficient and easy to use, providing opportunities of personalized medicine processes in health care, such as improved diagnostics or tailor made treatment interventions (van der Krieke et al., 2015).

4.4 Conclusions

The present study is a proof-of-principle study of using novel time-varying time series methodology to exploratively investigate changes in the bivariate system of sleep and physical activity occurring during CBT-I treatment. For this very participant, I could not identify any significant autoregressive effects of either TST or physical activity, and there were no apparent changes occurring in these parameters over the course of the intervention. Yet, by visual inspection I was able to identify an indication of a decrease in the autoregression of TST occurring approximately in parallel to the intervention. Still, these results were not robust enough to reach significance in this data set. A significant decrease in TST could be identified over time, and it seems as if the positive association between daytime physical activity and sleep the following night disappeared over the course of the treatment. TST also had a significant effect in predicting physical activity the following day, but in a pattern opposite of the expected, so that less sleep predicted more physical activity the following day, and vice versa.

Some of the results were unexpected. As the hypotheses were formulated based on theoretically relevant concepts and group-level data, the results in some instances illustrate how using EMA-data to identify unique, patient-specific processes can elucidate the studied phenomena in ways that would not be possible in cross-sectional designs. Future research would do well to focus on developing the regularization techniques further, to create models that are able to account for both abrupt and gradual changes, and to find ways of automating the TV-VAR analyses, to enable their use in clinical contexts.

5 En fallstudie som genom tidsserieanalys undersöker sambandet mellan sömn och fysisk aktivitet under en kognitiv beteendeterapeutisk behandling för insomni

5.1 Introduktion

Problem med sömn har stora följder för både psykosocial och somatisk hälsa (Roth, 2007) och orsakar på ett samhälleligt plan omfattande ekonomisk påfrestning (Daley m.fl. 2009). Sömn har en väldokumenterad association till fysisk aktivitet, som på gruppnivå konstaterats gå i båda riktningar (Kline, 2014). Ändå verkar sambandet dessa emellan variera i både styrka och riktning individer emellan (Armstrong m.fl., 2019). Den omfattande interindividuella variationen har på senaste år väckt frågor om huruvida resultat från studier på gruppnivå kan generaliseras till den enskilda individen (Fisher, 2015; Fisher & Boswell, 2016; Fisher m.fl. 2018; Molenaar, 2004). Utöver problemet med variation på individnivå, förbises ofta intraindividuella temporala effekter (Hamaker & Wichers, 2017). Dessa problem kan beaktas genom att man, utöver att endast undersöka sambandet mellan sömn och fysisk aktivitet på gruppnivå, även undersöker på vilket sätt styrkan och riktningen på sambandet dynamiskt förändras för en specifik individ till följd av exempelvis psykologisk behandling. Tidsseriedesign erbjuder nya explorativa N = 1-tekniker för att undersöka unika dynamiska system (Bringmann, Ferrer, Hamaker, Borsboom, & Tuerlinckx, 2018; Haslbeck, Bringmann, & Waldorp, 2020). Syftet med ifrågavarande studie var att undersöka samspelet mellan total sömnmängd och fysisk aktivitet för en enskild klient i en behandlingskontext, där kliniska longitudinella data analyseras genom en tidsvarierande tidsseriedesign.

Insomni och sambandet mellan sömn och fysisk aktivitet

Insomni karaktäriseras enligt The International Classification of Diseases (ICD-11, World Health Organization, 2018) av ihållande svårigheter med insomning, nattsömnens längd, upprätthållande eller kvalitet, problem vilka kvarstår trots att möjligheterna för sömn är goda. Insomnin ger även följder dagtid såsom exempelvis trötthet eller irritabilitet. Liknande kriterier återfinns i The Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Assosication, 2013). I diagnostiseringen av insomni beaktas den kvalitativa och subjektiva upplevelsen av sömn, snarare än den faktiska sömnmängden eller insomningstiden och personer som lider av insomni tenderar ofta att underskatta bådadera (Perlis, 2001). Insomni drabbar omkring 10 % av vuxna finländare (Ohayon & Partinen, 2002), en siffra som är relativt enhetlig med globala estimat (Ohayon, 2002). Dessutom upplever ungefär hälften av den finska befolkningen tillfälliga självrapporterade sömnproblem (Kronholm m.fl. 2016). Kognitiv beteendeterapi betraktas som en effektiv förstahandsbehandling för insomni (van Straten m.fl. 2017).

Tidigare forskning har undersökt sambandet mellan fysisk aktivitet och sömn. Fysisk aktivitet har visat sig ha fördelaktig effekt på sömn (Kredlow m.fl. 2015; Kubitz m.fl. 1996; Youngstedt m.fl. 1997). Det finns ändå studier som pekar mot en ännu starkare omvänd association (Baron m.fl. 2013; Haario m.fl. 2013; Schmid m.fl. 2009). I en tidsseriebaserad studie av associationen mellan sömn och fysisk passivitet hos småbarn (Armstrong, Covington, Unick & Black, 2019) kunde man på gruppnivå konstatera att sömn predicerade fysisk passivitet bättre än det omvända. När man undersökte parametrarna på individnivå kunde man dessutom konstatera att både styrkan och riktningen på sambandet varierade stort mellan individer, något som belyser behovet av ideografisk design för att få information om samspelet mellan sömn och fysisk aktivitet för den enskilda individen.

Tidsseriedesign i psykologisk forskning

Tidsseriedesign härstammar från ekonometri (Dahlhaus, 1997), men har nyligen börjat användas inom psykologisk forskning (Bringmann m.fl. 2013) för att analysera temporala förhållanden mellan en rad olika psykologiska variabler både på gruppnivå (t.ex. Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015; Groen m.fl. 2019; Kramer m.fl. 2014; Lutz m.fl. 2018; Snippe m.fl. 2017) och på individnivå, där personspecifika modeller skapas (t.ex. Bak, Drukker, Hasmi, & Van Jim, 2016; Fisher, 2015; Kroeze m.fl. 2017; van der Krieke m.fl. 2015; Wichers & Groot, 2016). Vissa studier har även kombinerat analyser av data på både gruppnivå och på individnivå (t.ex. De Vos m.fl. 2017; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017; Hartmann m.fl. 2015). Fördelen med de personspecifika modellerna är att de är mer kliniskt tillämpbara och exakta, eftersom de härstammar från ifrågavarande individ snarare än data på gruppnivå. Modellerna kan exempelvis användas som stöd för att planera och skräddarsy interventioner (Bak m.fl. 2016) eller för att förutspå avhopp från behandlingar (Lutz m.fl. 2018), men är inte avsedda för generalisering till en större grupp individer (Schuurman m.fl. 2016). I tidsserieanalyser används kliniskt longitudinellt data, som samlats in med ekologisk momentan skattning (Shiffman, Stone & Hufford, 2008) med hög exakthet och god ekologisk validitet (Fisher, 2015; Shiffman m.fl. 2008). Genom att analysera temporala associationer i data, kan prediktiva förhållanden variabler emellan identifieras (Bringmann m.fl. 2013) och kausala samband härledas (Granger, 1969). I bivariata tidsvarierande tidsseriemodeller kan intercept, autoregressiva effekter och tidsfördröjda temporala regressioner mellan variablerna undersökas. Därtill tillåts parametrarna variera över tid (Bringmann m.fl. 2018), vilket är ändamålsenligt när dynamiska förändringar till följd av psykologisk behandling undersöks.

Syfte och hypoteser

Syftet med ifrågavarande studie var att explorativt undersöka den unika dynamiska samverkan mellan total sömnmängd och fysisk aktivitet hos en enskild deltagare med insomnibenägenhet under en kognitiv beteendeterapeutisk behandling. Detta förverkligades genom explorativ analys av tidsseriedata som insamlats under interventionen. Jag och min forskningsgrupp var speciellt intresserade av att upptäcka potentiella förändringar i hur sömn och fysisk aktivitet predicerade sig själva över tid, samt hur en variabels tidsfördröjda version av sig själv kunde predicera den andra variabeln vid följande tidpunkt (*eng.* cross-lagged effects).

Vi förväntade oss att den autoregressiva effekten av totalt sömnmängd skulle vara positiv i början av behandlingen, något som indikerar starka överföringseffekter till följande tidpunkt (Armstrong m.fl. 2019). Vi förväntade oss att denna över tid skulle gå från positiv till noll eller negativ, till följd av en ökad flexibilitet i sömnsystemet och ett ökat inflytande av naturliga sömnprocesser såsom sömntryck och dygnsrytm (Borbely, 1982). Vi förväntade oss ingen förändring i interceptet eller autoregressionen för fysisk aktivitet, eftersom ingen behandlingskomponent riktades mot att förändra nivån av fysisk aktivitet. Vi förväntade oss att den fördröjda regressionen av fysisk aktivitet under dagen och total sömnmängd följande natt skulle vara tidsvarierande, så att ett positiv samband skulle uppstå eller öka under behandlingens gång. Slutligen, ifall att en positiv tidsfördröjd association mellan total sömnmängd och fysisk aktivitet följande dag kunde identifieras, förväntade vi oss att denna effekt skulle avta under behandlingen.

5.2 Metod

Deltagare, procedur och intervention

Datainsamlingen för ifrågavarande studie erhöll en positiv bedömning av den forskningsetiska nämnden vid Åbo Akademi den 8 januari, 2019. Deltagaren var en finsk 23-årig kvinnlig studerande som anmält intresse för deltagande i en kostnadsfri psykologisk intervention för sömnproblem. Deltagaren blev screenad av en legitimerad psykolog. Informerat samtycke till deltagande i studien samlades in. Interventionen erbjöds av en psykologistuderande (ifrågavarande författare), som en del av en kurs i internetbaserad behandling av sömnproblem, vid den psykologiska institutionen vid Åbo Akademi. Deltagaren rapporterade subjektiva svårigheter med insomning, orsakade av sömnstörande tankar samt ljus- och ljudkänslighet vid insomningsögonblicket. Deltagaren hade en aktiv livsstil och upplevde inte att sömnproblemen hindrade henne i vardagen men att de gav negativa subjektiva upplevelser dagtid. Insomnia Severity Index-scores (Bastien m.fl. 2001) indikerade kliniskt signifikant insomni av medelsvårighet (17 poäng).

Datainsamlingsperioden bestod av en interventionsfas samt en för- och efterfas. Deltagaren bar under hela perioden en aktivitetsklocka och fyllde under interventionsfasen i en sömndagbok (Jernelöv, 2008). Hela datainsamlingsperioden pågick under ungefär 127 dagar och 128 nätter. Interventionens innehåll baserade sig på en manualiserad kognitiv beteendeterapeutisk intervention utformad av Manber och Carney (2016), och behandlingens innehåll modifierades enligt deltagarens egna förutsättningar och önskemål. Behandlingen bestod av sex internetbaserade videosessioner som pågick 30–60 minuter per gång, under en period på 13 veckor.

Mått och statistiska analyser

En konsumentklassad aktivitetsklocka (Fitbit Charge 3, Fitbit, 2018) användes för att erhålla dagliga medeltal för sömn och aktivitetsnivå. Total sömnmängd och steg användes som mått för tidsserieanalyserna. En sömndagbok användes för att samla in kompletterande subjektiva mått för sömn, humör och aktivitetsnivå. Sömndagboken användes i huvudsak för vägledning under behandlingen och för att undersöka överrensstämmelsen mellan subjektiva och objektiva mått på sömn. The Insomnia Severity Index (ISI), utvecklat av Morin (1993), är ett instrument för subjektiv självskattning av symtom på insomni, som användes för att mäta svårighetsgraden av sömnproblemen före och efter interventionen. The Dysfunctional Beliefs and Attitudes about Sleep Scale, DBAS-16 (Morin, Vallières, & Ivers, 2007) användes för att utvärdera vilka maladaptiva föreställningar deltagaren hade om sömn, och styrkan på dessa.

Medeltal och standardavvikelser för före- och eftermätningarna kalkylerades. Före- och eftermätningar samlades in under 21 respektive 16 dagar. Korrelationer mellan mått från aktivitetsklockan och mått från sömndagboken beräknades. Från aktivitetsklockan samlades totalt 128 mätningar, och från sömndagboken 80 och 81 punkter, för natt- respektive dagvariabler. Aktivitetsklockan hade inget bortfall, och sömndagboken hade ett bortfall på 12 – 13 %. Variablerna standardiserades för att möjliggöra jämförelse av parametrar.

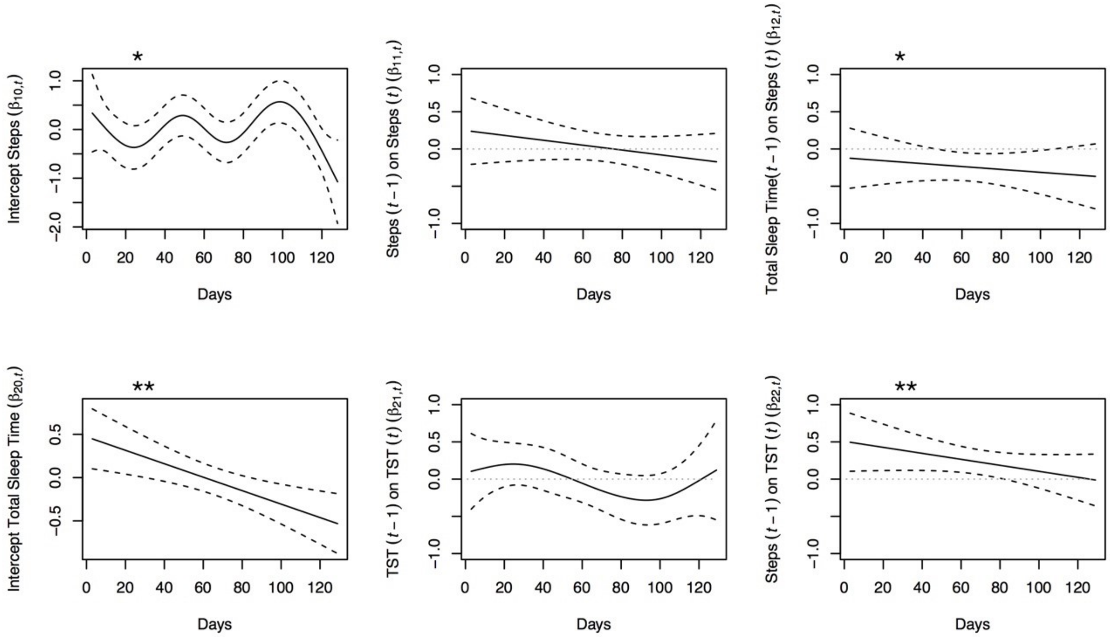
För att utföra tidsserieanalyserna användes dataprogrammet R 3.5.3. Den semi-parametriska tidsvarierande vektorautoregressiva modellen (TV-VAR), presenterad i Bringmann m.fl. (2018), användes för att skapa en bivariat lag-1 modell. TV-VAR är en utveckling av den temporalt stationära vektor-autoregressiva modellen, VAR (Brandt & Williams, 2007), men använder sig istället av tidsvarierande parametrar för att möjliggöra modellering av de dynamiska aspekterna av temporala förhållanden variabler emellan. Ett tidsvarierande angreppssätt bör användas ifall kliniska longitudinella data som sannolikt involverar tidsvarierande aspekter används och ifall data har mer än 100 tidpunkter, vilket var fallet i denna studie (Bringmann m.fl. 2018). TV-VAR modellen använder generaliserad additiv modellering för att estimera förhållandet variabler emellan och funktionernas tillåtna volatilitet reglerades och begränsades med generaliserad korsvalidering (eng. generalized cross-validation, GCV; Golub, Heath, & Wahba, 1979), en teknik som utfördes i *mgcv* paketet i R (Wood, 2006). När modellen tillåter tidsvariation inspekteras parametrarna i modellen visuellt eftersom information om eventuell variation över tid går förlorad ifall modellen endast inspekteras numeriskt. Regressionerna utfördes så att en regression mellan den ena variabeln vid tidpunkt t jämfördes mot sig självt och den andra variabeln vid tidpunkt $t - 1$, en mätning tidigare, vilket ger information om hur väl en variabels värde tenderar predicerar sig självt och den andra variabeln vid följande tidpunkt. Vi estimerade totalt 8 olika modeller per variabel och modellselektion utfördes därefter genom jämförelse av index för passform, inspektion av signifikansparametrar och visuell inspektion.

5.3 Resultat

Deltagarens före- och eftermätningar för ISI var 17 respektive 14 poäng (på en skala 0 – 28). Före- och eftermätningen för D-BAS hade medelvärden på 5 respektive 3. Ett medelvärde på över 3,8 indikerar generellt att personen kan ha orealistiska förväntningar på sömn (Carney m.fl. 2010). Modellselektion genom inspektion av index för passform samt inspektion av signifikansparametrar kunde inte entydigt påvisa vilken modell som passade data bäst. Därför valdes en modell där alla parametrar tilläts variera över tid, och denna inspekterades visuellt.

I visuell inspektion av rådata påvisades inga tydliga trender för fysisk aktivitet, men en svag nedåtgående trend för TST kunde identifieras. Inga plötsliga förändringar eller abrupta skiften upptäcktes i data. En lineär regressionslinje samt två explorativa supplementära regressionspolynom applicerades på rådata för sömn: ett lägre tredje gradens polynom och ett högre tjugonde gradens polynom. Dessa explorativa regressionslinjer användes som stöd för visuell inspektion och för att upptäcka potentiella icke-linjära trender eller förändringar. Index för passform indikerade att den linjära regressionslinjen hade bäst passform. Alla tre linjer bekräftar en nedåtgående trend i data, och när regressionspolynomen inspekteras tyder dessa på att sömnmängden är något mer stabil under interventionen, men sjunker markant efter slutet av interventionen. Dessa fynd är dock endast av explorativ art.

Tidsvarierande parametrar presenteras i figur 1. Från vänster till höger, på både den övre raden (steg) och den nedre raden (sömnmängd) indikerar panelerna (1) interceptens funktion, (2) de autoregressiva funktionerna och (3) de tidsfördröjda regressionerna mellan variablerna. Interceptet för fysisk aktivitet var tidsvarierande och cykliskt, men hade ingen tydlig uppåt- eller nedåtgående trend. Autoregressionen visade en icke-signifikant, svagt nedåtgående trend. Den tidsfördröjda regressionen av sömnmängd på fysisk aktivitet visade en lineär negativ regression; när deltagaren sov mindre, tenderade hon vara mer aktiv följande dag, och när hon sov mer, var hon mindre aktiv följande dag. Effekten var över hela tidsperioden liten (från -0,01 till -0,03). Interceptet för sömnmängd var lineärt och tidsvarierande, samt minskade signifikant över tidsperioden. Autoregressionen för sömnmängd var icke-signifikant men linjen visade intressant nog att autoregressionen minskande under största delen av interventionen, även om linjen hade en svagt uppåtgående riktning både före och efter interventionsfasen. Det fördröjda sambandet mellan fysisk aktivitet och sömnmängd följande natt var signifikant och avtog lineärt från positiv (0,05 vid sin högsta punkt) till noll. I början predicerade mer fysisk aktivitet mer sömn följande natt och mindre fysisk aktivitet predicerade mindre sömn följande natt, men denna effekt avtog över tid.



Figur 1. Graferna visar parametrarna för sömn och steg, när dessa tilläts variera över tid. Den kognitiva beteendeterapeutiska interventionen började dag 23 och fortsatte fram till dag 114.
* = $p > 0.05$
** = $p > 0.01$

5.4 Diskussion

Inga förändringar förväntades i interceptet eller autogregressionen för fysisk aktivitet eftersom ingen interventionsteknik avsåg att påverka mängden fysisk aktivitet. Resultatet var i enlighet med detta. Resultaten för den fördröjda associationen mellan sömnmängd och fysisk aktivitet följande dag förkastade vår hypotes om att mindre sömn skulle leda till mindre aktivitet följande dag eftersom att sömnbrist hos insomnipatienter ofta leder till överdriven kompensatorisk vila dagtid (Haario m.fl. 2013). Istället uppvisade denna deltagare en negativ association över hela tidsperioden. I ljuset av den kvalitativa informationen om klienten kan detta resultat förklaras med att deltagaren inte subjektivt rapporterade några tendenser till att avboka aktiviteter på grund av sömnbrist och att hon hade en relativt aktiv livsstil överlag. Dessa resultat skulle med fördel ha kunnat återges till klienten för att uppmuntra och motivera henne till att upprätthålla detta beteende, eftersom det har visat sig ha fördelaktiga effekter på sömn (Kredlow m.fl. 2015).

Minskningen i interceptet av sömnmängd var oväntad. Resultatet kan tänkas förklaras med att minskningen är en temporär följd av interventionens tekniker, en följd av nya insikter om sömnbehov hos klienten, eller att deltagaren redan från början hade en relativt stor sömnmängd per natt. För autoregressionen av sömnmängd verkar interventionen haft den förväntade effekten på parameterns riktning. Den visade under behandlingen en nedåtgående trend i enlighet med hypotesen, men resultatet var inte robust nog att nå signifikans. Minskningen kunde möjligen varit mer uttalad ifall deltagaren hade haft sömnproblem av svårare grad. Resultaten för den fördröjda associationen mellan fysisk aktivitet på sömnmängd följande natt förkastade vår hypotes. Resultaten indikerade en motsatt trend, där sambandet avtog från positivt till noll; effekten försvann över tid. Resultatet kan tänkas förklaras av att behandlingen inte effektivt hade lyckats minska kognitiv hyperaktivering vid insomning eller att deltagaren blivit mindre beroende av att vara fysiskt uttröttad för att kunna sova. Andra faktorer framom fysisk aktivitet kan ha fått ökad betydelse för att påverka sömnmängd. Resultaten gav oss mer information om sömnbeteenden hos denna deltagare, vilka skulle ha förbisetts i en standard stationär vektor-autoregressiv modell. Drivkrafterna bakom de identifierade förändringarna kan dock inte med säkerhet fastställas. Resultaten är inte avsedda att generaliseras till andra individer. Eftersom ifrågavarande studie var av explorativ art, ska resultaten tolkas med försiktighet.

Styrkor, svagheter och sammanfattning

Studiens huvudsakliga styrkor är att den beaktar temporala faktorer och adresserar problemet med heterogenitet individer emellan. Metoden har högre klinisk applicerbarhet än modeller på gruppnivå, eftersom den utgår ifrån personspecifika data. Ingen ytterligare börda för deltagaren orsakades av datainsamlingen, och studien gjordes i en ekologiskt valid miljö. Svagheter är att resultaten inte kan generaliseras till andra personer och kan heller inte med säkerhet antas vara generaliserbara till andra tidsfönster för samma individ. Fler datapunkter och en längre period för datainsamling skulle ha gett mer robusta resultat. TV-VAR analyser kan inte modellera abrupta förändringar, eftersom analysen antar att all förändring sker gradvis (Dahlhaus, 1997). Studien använde inte en forskningsklassad aktivitetsklocka. Att inkludera fler variabler, såsom insomningstid, tid i sängen och andra mått på fysisk aktivitet och stillasittande, samt olika längder på tidsfördröjningen (t.ex. t – 2) skulle även ha varit av intresse. Multivariata tidsvarierande modeller kräver dock en väldigt stor mängd datapunkter, vilket skapar problem med tolkning samt falska kopplingar (Costantini m.fl. 2015; Tibshirani, 1996). Därmed måste variablerna i icke-stationära modeller hållas till ett absolut minimum.

Sammanfattningsvis visar ifrågavarande studie hur en tidsvarierande tidsseriemetod kan användas för att explorativt undersöka de förändringar som sker i det bivariata systemet för sömn och fysisk aktivitet under en kognitiv-beteendeterapeutisk behandling. En del av resultaten var överraskande i förhållande till våra hypoteser baserade på teoretiska koncept och data på gruppnivå, något som illustrerar fördelen med att undersöka patientspecifika processer. Implikationer för framtida forskning är att utveckla regulariseringsteknikerna, så att analyserna utöver att modellera gradvisa förändringar, även kan identifiera abrupta förändringar i tillstånd. Utveckling av flernivåversioner av TV-VAR analysen kunde möjliggöra analys av data på både intra- och interindividnivå parallellt. TV-VAR analyserna behöver automatiseras för att kunna få användning i klinisk kontext.

6 References

American Psychiatric Assosication. (2013). *Sleep-Wake Disorders. In Diagnostic and statistical manual of mental disorders* (5th ed.). Washington, DC. https://doi.org/https://doi.org/10.1176/appi.books.9780890425596.dsm12

Armstrong, B., Covington, L. B., Unick, G. J., & Black, M. M. (2019). Featured article: Bidirectional effects of sleep and sedentary behavior among toddlers: A dynamic multilevel modeling approach. *Journal of Pediatric Psychology*, *44*(3), 275–285. https://doi.org/10.1093/jpepsy/jsy089

Baglioni, C., Battagliese, G., Feige, B., Spiegelhalder, K., Nissen, C., Voderholzer, U., … Riemann, D. (2011). Insomnia as a predictor of depression: A meta-analytic evaluation of longitudinal epidemiological studies. *Journal of Affective Disorders*, *135*(1–3), 10–19. https://doi.org/10.1016/j.jad.2011.01.011

Bak, M., Drukker, M., Hasmi, L., & Van Jim, O. S. (2016). An n=1 Clinical network analysis of symptoms and treatment in psychosis. *PLoS ONE*, *11*(9). https://doi.org/10.1371/journal.pone.0162811

Banno, M., Harada, Y., Taniguchi, M., Tobita, R., Tsujimoto, H., Tsujimoto, Y., … Noda, A. (2018). Exercise can improve sleep quality: A systematic review and meta-analysis. *PeerJ*, *6:e5172*. https://doi.org/10.7717/peerj.5172

Barlow, D. H., & Nock, M. K. (2009). Why Can’t We Be More Idiographic in Our Research? *Perspectives on Psychological Science*, *4*(1), 19–21. https://doi.org/10.1111/j.1745-6924.2009.01088.x

Baron, K. G., Reid, K. J., & Zee, P. C. (2013). Exercise to improve sleep in insomnia: Exploration of the bidirectional effects. *Journal of Clinical Sleep Medicine*, *9*(8), 819–824. https://doi.org/10.5664/jcsm.2930

Bastien, C. H., Vallières, A., & Morin, C. M. (2001). Validation of the insomnia severity index as an outcome measure for insomnia research. *Sleep Medicine*, *2*, 297–307. https://doi.org/10.1016/S1389-9457(00)00065-4

Blom, K., Tarkian Tillgren, H., Wiklund, T., Danlycke, E., Forssén, M., Söderström, A.,

… Kaldo, V. (2015). Internet-vs. group-delivered cognitive behavior therapy for insomnia: A randomized controlled non-inferiority trial. *Behaviour Research and Therapy*. https://doi.org/10.1016/j.brat.2015.05.002

Borbely, A. A. (1982). Two-Process Model of Sleep Regulation. *Encyclopedia of Neuroscience*, *1*, 195–2041. https://doi.org/10.1007/978-3-540-29678-2_6166

Borkovec, T., Wilkinson, L., Folensbee, R., & Lerman, C. (1983). Stimulus control treatment applications. *Behaviour Research and Therapy*, *21*(3), 247–251.

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

Bringmann, L. F., Lemmens, L. H. J. M., Huibers, M. J. H., Borsboom, D., & Tuerlinckx, F. (2015). Revealing the dynamic network structure of the Beck Depression Inventory-II. *Psychological Medicine*, *45*(4), 747–757. https://doi.org/10.1017/S0033291714001809

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., … Tuerlinckx, F. (2013). A Network Approach to Psychopathology: New Insights into Clinical Longitudinal Data. *PLoS ONE*, *8*(4). https://doi.org/10.1371/journal.pone.0060188

Buysse, D. J., Ancoli-Israel, S., Edinger, J. D., Lichstein, K. L., & Morin, C. M. (2006). Recommendations for a Standard Research Assessment of Insomnia. *SLEEP*, *29*(9), 1155–1173. https://doi.org/https://doi.org/10.1093/sleep/29.9.1155

Carney, C. E., Buysse, D. J., Ancoli-Israel, S., Edinger, J. D., Krystal, A. D., Lichstein, K. L., & Morin, C. M. (2012). The Consensus Sleep Diary: Standardizing Prospective Sleep Self-Monitoring. *Sleep*, *35*(2), 287–302.

https://doi.org/10.5665/sleep.1642

Carney, C. E., Edinger, J. D., Morin, C. M., Manber, R., Rybarczyk, B., Stepanski, E. J., & Wright, H. (2010). Examining maladaptive beliefs about sleep across insomnia patient groups. *Journal of Psychosomatic Research*, *68*(1), 57–65. https://doi.org/10.1016/j.jpsychores.2009.08.007.Examining

Chennaoui, M., Arnal, P. J., Sauvet, F., & Léger, D. (2015). Sleep and exercise: A reciprocal issue? *Sleep Medicine Reviews*, *20*, 59–72. https://doi.org/10.1016/j.smrv.2014.06.008

Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L. J., & Cramer, A. O. J. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality*, *54*, 13–29. https://doi.org/10.1016/j.jrp.2014.07.003

Dahlhaus, R. (1997). Fitting time series models to nonstationary processes. *Annals of Statistics*, *25*(1), 1–37. https://doi.org/10.1214/aos/1034276620

Daley, M., Morin, C. M., LeBlanc, M., Grégoire, J.-P., & Savard, J. (2009). The Economic Burden of Insomnia: Direct and Indirect Costs for Individuals with Insomnia Syndrome, Insomnia Symptoms, and Good Sleepers. *Sleep*, *32*(1), 55–64. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2625324/

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), 217–241. https://doi.org/10.1007/s11336-014-9417-x

De Vos, S., Wardenaar, K. J., Bos, E. H., Wit, E. C., Bouwmans, M. E. J., & De Jonge, P. (2017). An investigation of emotion dynamics in major depressive disorder patients and healthy persons using sparse longitudinal networks. *PLoS ONE*, *12*(6), 1–18. https://doi.org/10.1371/journal.pone.0178586

Evenson, K. R., Goto, M. M., & Furberg, R. D. (2015, December 18). Systematic review of the validity and reliability of consumer-wearable activity trackers. *International Journal of Behavioral Nutrition and Physical Activity*. BioMed Central Ltd.

https://doi.org/10.1186/s12966-015-0314-1

Feehan, L. M., Geldman, J., Sayre, E. C., Park, C., Ezzat, A. M., Yoo, J. Y., … Li, L. C. (2018). Accuracy of Fitbit Devices: Systematic Review and Narrative Syntheses of Quantitative Data. *JMIR MHealth and UHealth*, *6*(8), e10527. https://doi.org/10.2196/10527

Fisher, A. J. (2015). Toward a dynamic model of psychological assessment: Implications for personalized care. *Journal of Consulting and Clinical Psychology*, *83*(4), 825–836. https://doi.org/10.1037/ccp0000026

Fisher, A. J., & Boswell, J. F. (2016). Enhancing the Personalization of Psychotherapy With Dynamic Assessment and Modeling. *Assessment*, *23*(4), 496–506. https://doi.org/10.1177/1073191116638735

Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences*, *115*(27), 6106–6115. https://doi.org/10.1073/pnas.1711978115

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, *126*(8), 1044–1056. https://doi.org/10.1037/abn0000311

Fitbit, I. (n.d.). Fitbit Help. Retrieved June 4, 2019, from https://help.fitbit.com/

Fitbit, I. (2018). Fitbit Charge 3, Fitbit Inc. Retrieved June 3, 2019, from https://www.fitbit.com/charge3

Golub, G. ., Heath, M., & Wahba, G. (1979). Generalized cross-validation as a method for choosing a good ridge parameter. *Technometrics*, *21*(2), 215–223. https://doi.org/10.1080/00401706.1979.10489751

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*, 424–438.

Groen, R. N., Snippe, E., Bringmann, L. F., Simons, C. J. P., Hartmann, J. A., Bos, E. H., & Wichers, M. (2019). Capturing the risk of persisting depressive symptoms: A dynamic network investigation of patients' daily symptom experiences. *Psychiatry Research*, *271*, 640–648. https://doi.org/10.1016/j.psychres.2018.12.054

Haario, P., Rahkonen, O., Laaksonen, M., Lahelma, E., & Lallukka, T. (2013). Bidirectional associations between insomnia symptoms and unhealthy behaviours. *Journal of Sleep Research*, *22*(1), 89–95. https://doi.org/10.1111/j.1365-2869.2012.01043.x

Hamaker, E. L., & Wichers, M. (2017). No Time Like the Present: Discovering the Hidden Dynamics in Intensive Longitudinal Data. *Current Directions in Psychological Science*, *26*(1), 10–15. https://doi.org/10.1177/0963721416666518

Hamilton, J. D. (1994). *Time series analysis.* NJ: Princeton University Press.

Hartmann, J. A., Wichers, M., Menne-Lothmann, C., Kramer, I., Viechtbauer, W., Peeters, F., … Simons, C. J. P. (2015). Experience sampling-based personalized feedback and Positive affect: A randomized controlled trial in depressed patients. *PLoS ONE*, *10*(6), 1–16. https://doi.org/10.1371/journal.pone.0128095

Haslbeck, J. M. B., Bringmann, L. F., & Waldorp, L. J. (2020). A Tutorial on Estimating Time-Varying Vector Autoregressive Models. *Multivariate Behavioral Research*, 1–39. https://doi.org/10.1080/00273171.2020.1743630

Haslbeck, J. M. B., & Waldorp, L. J. (2020). MGM: Estimating time-varying mixed graphical models in high-dimensional data. *Journal of Statistical Software*, *93*(8). https://doi.org/10.18637/jss.v093.i08

Jernelöv, S. (2008). *Sov gott! råd och tekniker från kbt*. Månpocket.

Keele, L. (2008). *Semiparametric regression for the social sciences*. Chichester, England: John Wiley and Sons. https://doi.org/10.1002/9780470998137

Kline. (2014). The Bidirectional Relationship Between Exercise and Sleep: Implications for Exercise Adherence and Sleep Improvement. *American Journal of Lifestyle Medicine*, *8*(6), 375–379.

Kramer, I., Simons, C. J. P., Hartmann, J. A., Menne-Lothmann, C., Viechtbauer, W., Peeters, F., … 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.

Kredlow, M. A., Capozzoli, M. C., Hearon, B. A., Calkins, A. W., & Ott, M. W. (2015). The effects of physical activity on sleep: a meta-analytic review. *Journal of Behavioral Medicine*, *38*(3), 427–449. https://doi.org/10.1007/s10865-015-9617-6

Kroeze, R., van der Veen, D. C., Servaas, M. N., Bastiaansen, J. A., Voshaar, R. C. O. V., Borsboom, D., … Riese, H. (2017). Personalized feedback on symptom dynamics of psychopathology: A proof-of-principle study. *Journal for Person-Oriented Research*, *3*(1), 1–10. https://doi.org/10.17505/jpor.2017.01

Kronholm, E., Partonen, T., Härmä, M., Hublin, C., Lallukka, T., Peltonen, M., & Laatikainen, T. (2016). Prevalence of insomnia-related symptoms continues to increase in the Finnish working-age population. *Journal of Sleep Research*, *25*(4), 454–457. https://doi.org/10.1111/jsr.12398

Kubitz, K. A., Landers, D. M., Petruzzello, S. J., & Han, M. (1996). The Effects of Acute and Chronic Exercise on Sleep A Meta-Analytic Review. *Sports Medicine*, *21*(4), 277–291. https://doi.org/10.2165/00007256-199621040-00004

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

Manber, R., & Carney, C. E. (2016). *KBT vid sömnproblem: terapeutmanual vid individanpassad behandling* (1st ed.). Stockholm: Natur&Kultur.

Miller, W. R., & Rollnick, S. (2012). *Motivational Interviewing. Helping People Change* (3rd ed.).

Molenaar, P. C. M. (2004). A Manifesto on Psychology as Idiographic Science: Bringing the Person Back Into Scientific Psychology, This Time Forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Morin, C. M., Vallières, A., Guay, B., Ivers, H., Savard, J., Mérette, C., … Baillargeon, L. (2009). Cognitive behavioral therapy, singly and combined with medication, for persistent insomnia: A randomized controlled trial. *JAMA - Journal of the American Medical Association*, *301*(19), 2005–2015. https://doi.org/10.1001/jama.2009.682

Morin, C. M., Vallières, A., & Ivers, H. (2007). Dysfunctional Beliefs and Attitudes about Sleep (DBAS): Validation of a Brief Version (DBAS-16). *SLEEP*, *30*(11), 1547–1554. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2082102/pdf/aasm.30.11.1547.pdf

Morin, M. C., Belleville, G., Bélanger, L., & Ivers, H. (2011). The Insomnia Severity Index: Psychometric Indicators to Detect Insomnia Cases and Evaluate Treatment Response. *SLEEP*, *34*(5), 601–608. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3079939/

Ohayon, M. M. (2002). Epidemiology of insomnia: What we know and what we still need to learn. *Sleep Medicine Reviews*, *6*(2), 97–111. https://doi.org/10.1053/smrv.2002.0186

Ohayon, M. M., & Partinen, M. (2002). Insomnia and global sleep dissatisfaction in Finland. *Journal of Sleep Research*, *11*, 339–346. https://doi.org/10.1046/j.1365-2869.2002.00317.x

Ohayon, M. M., & Roth, T. (2003). Place of chronic insomnia in the course of depressive and anxiety disorders. *Journal of Psychiatric Research*, *37*(1), 9–15. https://doi.org/10.1016/S0022-3956(02)00052-3

Perlis, M. L. (2001). Beta / Gamma EEG Activity in Patients with Primary and. *Sleep*, *24*(1), 110–117.

Riemann, D., Spiegelhalder, K., Feige, B., Voderholzer, U., Berger, M., Perlis, M., & Nissen, C. (2010). The hyperarousal model of insomnia: A review of the concept and its evidence. *Sleep Medicine Reviews*, *14*(1), 19–31. https://doi.org/10.1016/j.smrv.2009.04.002

Roth, T. (2007). Insomnia: Definition, prevalence, etiology, and consequences. *Journal of Clinical Sleep Medicine*, *3*(5), 3–6.

Schmid, S., Hallschmid, M., Jauch-Chara, K., Wilms, B., Benedict, C., Lehnert, H., …

Schultes, B. (2009). Short-term sleep loss decreases physical activity under free-living free-living conditions but does not increase food intake under time-deprived laboratory conditions in healthy men. *The American Journal of Clinical Nutrition*, *90*(11), 1476–1482. https://doi.org/10.3945/ajcn.2009.27984.1

Schuurman, N. K., Ferrer, E., de Boer-Sonnenschein, M., & Hamaker, E. L. (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods*, *21*(2), 206–221. https://doi.org/10.1037/met0000062

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *The Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Sivertsen, B., Krokstad, S., Øverland, S., & Mykletun, A. (2009). The epidemiology of insomnia: Associations with physical and mental health. The HUNT-2 study. *Journal of Psychosomatic Research*, *67*(2), 109–116. https://doi.org/10.1016/j.jpsychores.2009.05.001

Snippe, E., Viechtbauer, W., Geschwind, N., Klippel, A., De Jonge, P., & Wichers, M. (2017). The impact of treatments for depression on the dynamic network structure of mental states: Two randomized controlled trials. *Scientific Reports*, *7*, 1–10. https://doi.org/10.1038/srep46523

Thorndike, F. P., Ritterband, L. M., Saylor, D. K., Magee, J. C., Gonder-Frederick, L. A., & Morin, C. M. (2011). Validation of the Insomnia Severity Index as a Web-Based Measure. *Behavioral Sleep Medicine*, *9*, 216–223. https://doi.org/10.1080/15402002.2011.606766

Tibshirani, R. (1996). Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

van der Krieke, L., Emerencia, A. C., Bos, E. H., Rosmalen, J. G., Riese, H., Aiello, M., & … de Jonge, P. (2015). Ecological Momentary Assessments and Automated Time Series Analysis to Promote Tailored Health Care: A Proof-of-Principle Study. *JMIR Research Protocols*, *4*(3), e100. https://doi.org/10.2196/resprot.4000 van Straten, A., van der Zweerde, T., Kleiboer, A., Cuijpers, P., Morin, C. M., & Lancee, J. (2017). Cognitive and behavioral therapies in the treatment of insomnia: A meta-analysis. *Sleep Medicine Reviews*, *38*, 3–16. https://doi.org/10.1016/j.smrv.2017.02.001

Wichers, M., & Groot, P. C. (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. *Psychotherapy and Psychosomatics*, *85*(2), 114–116. https://doi.org/10.1159/000441458

Wickham H (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. ISBN 978-3-319-24277-4, https://ggplot2.tidyverse.org.

Wohlgemuth, W. K., Edinger, J. D., Fins, A. I., & Sullivan, R. J. (1999). How many nights are enough? The short-term stability of sleep parameters in elderly insomniacs and normal sleepers. *Psychophysiology*, *36*, 233–244. https://doi.org/10.1017/S0048577299971214

Wong, M. M., Robertson, G. C., & Dyson, R. B. (2015). Prospective Relationship Between Poor Sleep and Substance-Related Problems in a National Sample of Adolescents. *Alcoholism: Clinical and Experimental Research*, *39*(2), 355–362. https://doi.org/10.1111/acer.12618

Wood, S. N. (2006). *Generalized additive models: An introduction with R.* FL: Chapmanand Hall/CRC.

Yang, Y., Shin, J. C., Li, D., & An, R. (2017). Sedentary Behavior and Sleep Problems: a Systematic Review and Meta-Analysis. *International Journal of Behavioral Medicine*, *24*(4), 481–492. https://doi.org/10.1007/s12529-016-9609-0

Youngstedt, S. D., O'Connor, P. J., & Dishman, R. K. (1997). The effects of acute exercise on sleep: A quantitative synthesis. *Sleep*, *20*(3), 203–214. https://doi.org/10.1093/sleep/20.3.203

MATILDA THORS

PRESSMEDDELANDE

En fallstudie som genom tidsserieanalys undersöker sambandet mellan sömn och fysisk aktivitet under en kognitiv-beteendeterapeutisk behandling för insomni

Pro gradu-avhandling i psykologi

Fakulteten för humaniora, psykologi och teologi, Åbo Akademi

Associationen mellan sömn och fysisk aktivitet är väldokumenterat och har på gruppnivå konstaterats gå i båda riktningarna. Sambandet mellan dessa verkar ändå variera i styrka individer emellan, och dylika interindividuella skillnader har länge förbisetts i forskning. Likaså har den temporala dynamiken mellan olika faktorer inom individen försummats. Den omfattande inter- och intraindividuella variationen har inom forskningsfältet väckt frågor om huruvida resultat på gruppnivå kan generaliseras till den enskilda individen.

I en pro gradu-avhandling i psykologi vid Åbo Akademi tillämpade Matilda Thors en ny tidvarierande tidsseriedesign för att undersöka dynamiska och personspecifika aspekter i kopplingen mellan fysisk aktivitet och sömn hos en insomnibenägen klient under behandling för insomni. Resultaten visar att för denna person fanns ett positivt samband mellan fysisk aktivitet dagtid och sömn följande natt, men denna koppling försvann över tid. Därtill kunde sömn signifikant predicera fysisk aktivitet, men för denna klient i motsatt riktning till vad som förväntats: mindre sömn predicerade mer fysisk aktivitet och mer sömn predicerade mindre fysisk aktivitet följande dag. Den totala sömntiden minskade även signifikant över tid. Variablernas förmåga att predicera sig själva över tid var icke-signifikanta, men visade för sömn ändå en nedåtgående riktning under behandlingstiden.

Studien illustrerar hur en ny tidsvarierande tidsseriemetod kan användas för att explorativt utforska personspecifika processer och förändringar över tid i olika psykologiska system. Vissa av resultaten för denna klient var oväntade i förhållande till uppställda hypoteser som gjorts på basis av studier på gruppnivå, något som belyser vikten av personspecifikt data. Resultaten är inte avsedda att generaliseras till en större grupp av individer, utan syftet är att utveckla metoden för att kunna ge kliniker ett välbehövt data-drivet verktyg som kan öka förståelsen för den unika klienten och som kan användas för vägledning i kliniskt beslutsfattande. Metoden kan på sikt öka möjligheterna till skräddarsydda behandlingar.

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