Unravelling the Brain at Resting State: What Differentiates Physical Activity Levels in People's Default Mode Network?

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Contents

„Mens sana in corpore sano"

1 Introduction

The present doctoral thesis sheds light on the neuronal differences between people with different activity levels and provides the basis to improve behavior change efficiency in less active people. To understand better, what differentiates less from more active people, a theory base has to be established, a paradigm to test with has to be chosen and means of measurement are needed. This thesis provides all three and improves upon existing means, theories, and results. First, a new theory is established, then, a new means of measurement is provided, and finally, the theory is tested. Additionally, I provide the necessary means to implement a neurofeedback framework into self-developed software. In order to understand Physical Activity (PA) and ways to change its prevalence, an in-depth understanding of its associations to health is needed. All three methods together contribute the basis to brain stimulation and neurofeedback techniques, by providing the means and building upon brain computer interface platforms that support integration of these techniques inherently.

1.1 The Burden of Physical Inactivity

Physical inactivity has become a global concern in recent years. According to Xu et al., (2022), the global issue of low physical activity (LPA) has become a significant concern, with 15.74 million disability-adjusted life years (DALYs) and 0.83 million deaths attributable to LPA in 2019, revealing a critical need for interventions to promote physical activity and reduce the associated burden of disease. In response to this continuing trend, the World Health Organization (WHO) has updated its PA recommendations. The WHO now advises that adults aged 18–64 should do at least 150 minutes of moderate-intensity aerobic PA throughout the week or do at least 75 minutes of vigorous-intensity aerobic PA throughout the week, or an equivalent combination of moderate- and vigorous-intensity activity (Bull et al., 2020). However, despite these recommendations, PA has continued to decrease and conversely, obesity rates have continued to rise globally (Stankovic et al., 2021). Obasuyi (2022) found that the prevalence of obesity has increased in most countries, and at an accelerated pace in recent years. This rise in obesity is a significant concern, as it is associated with an increased risk of a range of non-communicable diseases (Nyberg et al., 2018).

Physical inactivity is a significant risk factor for various physical health conditions. Ekelund et al. (2019) found that higher levels of PA, regardless of intensity, are associated with a lower risk of cardiovascular disease. Friedenreich et al. (2016) found that physical inactivity is a risk factor for several major cancers, including breast, colon, and endometrial cancers. Fritzen et al. (2021) found that physical inactivity is a primary cause of most chronic diseases, including type 2 diabetes. Unsurprisingly then, PA has also been shown to be an effective treatment for these diseases. For example, Minto et al. (2023) found that PA can be as effective as medication in the treatment of cardiovascular diseases, while also being more sustainable. Similarly, Friedenreich et al. (2016) found that PA can reduce the risk of a wide variety of different cancers, and Xu et al. (2022) found that PA can not only prevent but also treat type 2 diabetes.

The global burden of not only physical, but also psychological disorders has increased, with physical inactivity playing a significant role (Khehra & Sankhyan, 2020; Xu et al., 2022). Stubbs et al. (2017) found that physical inactivity is associated with an increased risk of anxiety and depression. A recent study (Jung et al., 2023) found that PA has a significant impact on reducing the risk of developing major depressive disorder (MDD). The researchers found that individuals who engaged in regular PA had a 15% lower risk of developing MDD compared to those who did not engage in regular PA. Schuch et al. (2019) found that individuals who were physically inactive had a 1.44 times higher risk of developing depression compared to those who were physically active. The study also found that the risk of depression increased with the duration of physical inactivity, suggesting a dose-response relationship between physical inactivity and depression. Werneck et al. (2023) found that a lack of PA is significantly associated with an increased risk of anxiety. The authors found that individuals who were physically inactive had a 1.74 times higher risk of developing anxiety compared to those who were physically active. They also found that the risk of anxiety increased with the duration of physical inactivity, suggesting a similar dose-response relationship between physical inactivity and anxiety to the one between PA and depression.

Wiggs et al. (2023) found that children and adolescents who were physically inactive had a higher risk of Attention-Deficit / Hyperactivity (ADHD) symptoms compared to those who were physically active. The study also found that the risk of ADHD symptoms increased with the duration of physical inactivity, further suggesting a dose-response relationship with ADHD as well. Physical inactivity has also been linked to other psychological disorders. Sharma et al. (2023) found that physical inactivity was not only associated with an increased risk of anxiety, depression, and ADHD, the study also found that physical inactivity was associated with a decrease in general health and an increase in stress. In terms of the detailed connection between physical inactivity and these psychological disorders, the authors stress, that the exact mechanisms are still being explored. PA has also been shown to be effective in not only preventing, but also treating psychological disorders. Ma et al. (2023) found that PA can reduce symptoms of anxiety, and Werneck et al. (2023) found that PA can reduce various different symptoms of depression. Furthermore, Mehren et al. (2020) found that PA can reduce a wide variety of symptoms of ADHD.

Physical inactivity is a risk factor for health – looking from the other side, research has clearly shown that PA is good for health. PA is not only effective in treating disorders and preventing health disadvantages due to lack of PA, but it also leads to significant health benefits and prevents diseases in the first place. The major results of the bulk of research will be briefly described in the following.

In addition to mental health benefits, PA also has significant effects on physical health. Zhang et al. (2023) and Mu et al., (2022) found that regular PA is associated with lower risk of cardiovascular diseases (CVD). The researchers found that individuals who engaged in regular PA had a 20% lower risk of developing CVD compared to those who did not engage in regular PA. This suggests that PA could be an effective preventative measure against CVD, highlighting the importance of promoting PA as a part of cardiovascular health interventions. Moreover, PA has been found to have a preventative function against cancer. McTiernan et al. (2019) found that regular PA can reduce the risk of various types of cancer. The researchers found that individuals who engaged in regular PA had a lower risk of developing breast, colon, endometrial, kidney, bladder, esophagus, and stomach cancer compared to those who did not engage in regular PA. This suggests that PA could be an effective preventative measure against cancer, highlighting the importance of promoting PA as a part of cancer prevention interventions (McTiernan et al., 2019). PA also has a significant impact on preventing diabetes. Magkos et al. (2020) found that regular PA can reduce the risk of type 2 diabetes. The researchers found that individuals who engaged in regular PA had a 26% lower risk of developing type 2 diabetes compared to those who did not engage in regular PA. This suggests that PA could be an effective preventative measure against type 2 diabetes (Magkos et al., 2020). In addition, PA also has a significant impact on the immune system. Chastin et al. (2021) found that regular PA can enhance the immune system, particularly the innate immune system. During PA, cytotoxic immune cells are mobilized into the circulation, which can help to protect the body against various diseases. The researchers found that individuals who engaged in regular PA had a stronger immune response compared to those who did not engage in regular PA.

Beside the physiological results, PA has been found to have a significant impact on cognitive function. Carbonell-Hernandez et al. (2022) found that regular PA can improve cognitive function, particularly in areas related to memory and attention. The researchers found that individuals who engaged in regular PA had better cognitive performance compared to those who did not engage in regular PA. This suggests that PA could be an effective preventative measure against cognitive decline, highlighting the importance of promoting PA as a part of cognitive health interventions (Carbonell-Hernandez et al., 2022).

In conclusion, PA not only helps in treating disorders and preventing health disadvantages due to lack of PA, but it also leads to significant health benefits and prevents diseases in the first place. Despite the clear benefits of PA, a significant proportion of the global population does not meet the guidelines of the WHO PA guidelines. Weatherson et al. (2021) found that only 53% of Canadian post-secondary students met the PA guidelines, and 49% met the sedentary guidelines. Therefore, promoting PA should be a priority in health interventions. This highlights the need for effective strategies to promote PA and reduce sedentary behavior.

1.2 Theories of Behavior Change

So far, I have established that there is a clear need for making the people more active. Many theories try to explain how to change behavior to the better. The most dominant theories are the Transtheoretical Model (Stages of Change Model) (Prochaska & Velicer, 1997), Health Belief Model (Rosenstock, 1974), Theory of Planned Behavior (Ajzen, 1985) and the Social Cognitive Theory (Bandura, A., 1982).

Transtheoretical Model (TTM). The TTM (Prochaska & Velicer, 1997) explains the process of behavioral change in six stages. In the Precontemplation stage, individuals may be unaware of a problem with their behavior and resist feedback. Contemplation is marked by recognition of the issue but ambivalence about change, often weighing pros and cons. During Preparation, individuals intend to change soon, setting goals and planning strategies. The Action stage sees active modification of behavior, with support and rewards.

Maintenance involves sustaining the new behavior, developing skills to prevent relapse. Termination is the final stage where the new behavior is fully integrated without temptation to revert. The TTM has been applied to various health-related behaviors, including smoking cessation dietary changes, and exercise adoption (Zabaleta-del-Olmo et al., 2021; Park et al., 2003).

Health Belief Model (HBM). The HBM (Rosenstock, 1974) is a psychological model that attempts to explain and predict health behaviors. It focuses on the attitudes and beliefs of individuals. The model posits that a person will take a health-related action if they feel that a negative health condition can be avoided, they expect that taking a particular action would prevent or minimize the condition, and they believe they can successfully take the recommended health action. The HBM has been applied to many different health interventions, e.g. to increase PA in shift workers (Crowther et al., 2022), and to investigate the factors influencing physical activity participation among cancer patients (Elshahat et al., 2021).

Theory of Planned Behavior (TPB). The TPB (Ajzen, 1985) extends the Theory of Reasoned Action, adding the component of perceived behavioral control. It suggests that behavior is determined by intentions, attitudes, and norms, but also acknowledges that individuals may not always have complete control over their behavior. Intentions are influenced by attitudes towards the behavior, subjective norms, and perceived behavioral control. Attitudes towards the behavior are the positive or negative feelings of the individual about performing the behavior. Subjective norms refer to the perceived social pressure to perform or not perform the behavior. Perceived behavioral control refers to the perception by the individual of the ease or difficulty of performing the behavior. The TPB has been applied in predicting and understanding various behaviors, such as the determinants of physical activity behavior during the COVID-19 pandemic (Khani Jeihooni et al., 2022), key determinants of physical activity in older adults (Stehr et al., 2021), and factors affecting physical activity among prediabetic women (MohammadniaMotlagh et al., 2021).

Social Cognitive Theory (SCT). The SCT (Bandura, A., 1982) emphasizes the way in which individuals learn from observing others within the context of social interactions, experiences, and outside media influences. It introduces the concept of self-efficacy, which is the belief in the ability to achieve goals. The theory also considers the influence of reinforcements and punishments, as well as the role of cognitive processes in learning. Observational learning, or modeling, is a critical aspect of SCT, where individuals learn by observing the behaviors of others and the outcomes of those behaviors. Bandura emphasized the role of self-efficacy as a critical factor in determining whether individuals will attempt new behaviors and how they will persevere in the face of challenges. SCT has been applied in various fields, including education, communication, and public health. In the context of physical activity, SCT has been utilized to investigate factors affecting behavioral intention among gym-goers during the COVID-19 pandemic (Ong et al., 2022), analyze influencing factors of adolescents' PA (Liu et al., 2022), and examine social-cognitive theory constructs as mediators of behavior change in a smartphone-based PA program (Romeo et al., 2021).

Rhodes et al. (2019) demonstrated that health behavior theories, including the TTM, HBM, TPB, and SCT, were only moderately successful in predicting behavior change. This suggests either a potential limitation in the comprehensive power, or suboptimal application of these theories. Sussman et al. (2022) further supported this argument, showing that while Transtheoretical Model-based interventions did sometimes promote health behavior change, the effect sizes often were small, indicating a limited impact. In a systematic review, Bluethmann et al. (2017) found that theory was not often extensively used in the development of interventions, and the relationships between the type of theory used and the extent of theory use with effectiveness were generally weak. This raises questions about the practical utility of these theories in intervention development. Lastly, Williams et al. (2005) highlighted that positive outcome expectancy, a key construct in these theories, appears to be more predictive of PA in older adults than in young to middle-aged adults. This suggests that these theories may not be universally applicable across different age groups. Collectively, these findings suggest that while these health behavior theories provide a useful starting point, they may not be sufficient in themselves to effectively predict and promote health behavior change.

If interventions based on the most influential behavior change theories are moderately successful, better understanding of the underlying properties of the behavior is necessary in order to facilitate the desired change. Furthermore, the addition of brain stimulation techniques and neurofeedback interventions show great promise and might greatly complement and enhance the effectiveness of interventions.

1.3 Methods to Analyze Physical Activity

There are several methods available for measuring PA, each with its own advantages and limitations. I will briefly discuss the two most important and focus afterwards on the possibility of smartphone usage as a tool to measure PA.

Self-report methods (SRM). SRM such as questionnaires and activity diaries, are commonly used due to their low cost and ease of administration (Burchartz et al., 2020). However, they are subject to recall bias and may not accurately capture the intensity or duration of PA (Ndahimana & Kim, 2017). Direct observation is another method that involves trained observers recording individuals' PA. While this method can provide detailed information about the type and context of PA, it is time-consuming, expensive, and may not be feasible for large-scale studies or long-term monitoring, even less so in a natural environment (Ndahimana & Kim, 2017). Pedometers and heart rate monitors provide more objective measures of PA. Pedometers count the number of steps taken, but they do not provide information about the intensity or type of activity. Heart rate monitors can provide an estimate of energy expenditure, but they are influenced by factors other than PA, such as stress or temperature (Ndahimana & Kim, 2017).

Accelerometry. Accelerometers offer a more comprehensive and objective measure of PA. They measure the acceleration of body movements, which can be used to estimate the intensity, frequency, and duration of PA. Accelerometers can be attached at the hip, wrist, or thigh, and the data can be processed and calibrated to determine activity intensity, body position, and/or activity type (Arvidsson et al., 2019). Accelerometers have emerged as a dominant tool, with brands such as MoviSens (Giurgiu et al., 2021; Härtel et al., 2011; Hysenllari et al., 2022) and ActiGraph (John & Freedson, 2012; Sasaki et al., 2011) leading the charge. However, these devices are not without their limitations. MoviSens, while offering a high degree of sensitivity, has been found to have limited accuracy in certain contexts, particularly in the measurement of low-intensity activities (Kang et al., 2016). Similarly, ActiGraph, despite its widespread use, has been criticized for its limited ability to capture upper-body movements and activities involving static postures (Kang et al., 2016). The advent of wearable technology such as smartwatches and smart bracelets, has introduced a new dimension to PA measurement. These devices, often containing accelerometers, have shown promising accuracy in activity measurement. A systematic review (Evenson et al., 2015) found that wearable devices generally demonstrate moderate to high validity in measuring PA. Despite their advantages, accelerometers also have limitations. The accuracy of accelerometers can be affected by the placement of the sensor, the type of activity being performed, and the data processing and calibration techniques used (Arvidsson et al., 2019). However, with the advent of machine learning based algorithms, these limitations can be mitigated (Wieland, 2022). Another significant drawback of accelerometry is their proprietary nature. Most wearable technologies are not open source, meaning their software is not publicly accessible. This lack of transparency hinders repeatable science, as researchers cannot fully understand how movement is classified by these devices (Van Hees et al., 2013). For instance, ActiLife (ActiGraph, Pensacola, FL, USA) and GENEActiv PC software (ActivInsights Ltd, Kimbolton, UK) are both closed-source commercial software designed for the accelerometer hardware developed by the same companies (Migueles et al., 2019). This lack of open-source software limits the ability of researchers to fully understand and replicate the data processing and analysis methods used by these devices. Furthermore, these devices can be cost-prohibitive, limiting their accessibility for research purposes, especially in economically disadvantaged institutions, just like research-focused devices such as MoviSens and Actigraph at a similar price point as some wearables.

The ubiquity of **smartphones**, however, changes access to accelerometer devices, since as of 2020, it is estimated that 72.6% of the global population owns a smartphone (Takahashi, 2020). This widespread accessibility, coupled with the fact that smartphones are equipped with built-in accelerometers, makes them a cost-effective and readily available tool for PA measurement (Wieland, 2022). Moreover, the open-source nature of many smartphone operating systems, based on Android, allows for the development of applications that can collect and analyze accelerometry data in a transparent and reproducible manner (Bao & Intille, 2004). This is a significant advantage over proprietary wearable devices, which often do not disclose their software algorithms, thereby limiting the ability to conduct repeatable science (Silva, 2015). Even for iOS, the second most prevalent operating system in mobile devices, which is not open-source, the development of open-source applications is feasible, allowing for a degree of transparency in data collection and analysis.

1.4 The Default Mode Network

Beside physical activity, in this doctoral thesis, the brain activity in a resting state is of utmost importance. Therefore, I will focus in this chapter on the underlying neural basics which are relevant for this project: the Default Mode Network (DMN). The DMN is a network of brain regions that are active when the individual is not focused on the outside world and the brain is at wakeful rest, such as during daydreaming and mindwandering. But it is not just about daydreaming; the DMN is also active when the individual is thinking about others, thinking about themselves, remembering the past, and planning the future (Buckner et al., 2008). The concept of the DMN emerged in the early 2000s, when researchers noticed consistent brain activity in the absence of a task in functional magnetic resonance imaging (fMRI) studies (Raichle et al., 2001). The DMN includes the medial temporal lobe, the medial prefrontal cortex, and the posterior cingulate cortex/precuneus, among other areas (see figure 1). These regions are not just anatomically distinct, but also show a high level of functional connectivity, meaning they tend to activate together when the brain is at rest (Greicius et al., 2003).

The discovery of the DMN has had a significant impact on neuroscience and psychology, as it has challenged the prevailing notion that the default state of the brain is one of inactivity. Instead, the DMN suggests that the brain is continually active, processing information and maintaining internal representations even when not engaged in a task (Raichle et al., 2001). The DMN has also been implicated in a number of psychological disorders. For example, alterations in the DMN have been found in depression, with increased connectivity within the DMN, particularly between the posterior cingulate and the anterior cingulate and prefrontal cortex (Berman et al., 2011; Sheline et al., 2009). This increased connectivity has been linked to increased self-focus, a common feature of depression (Northoff et al., 2006).

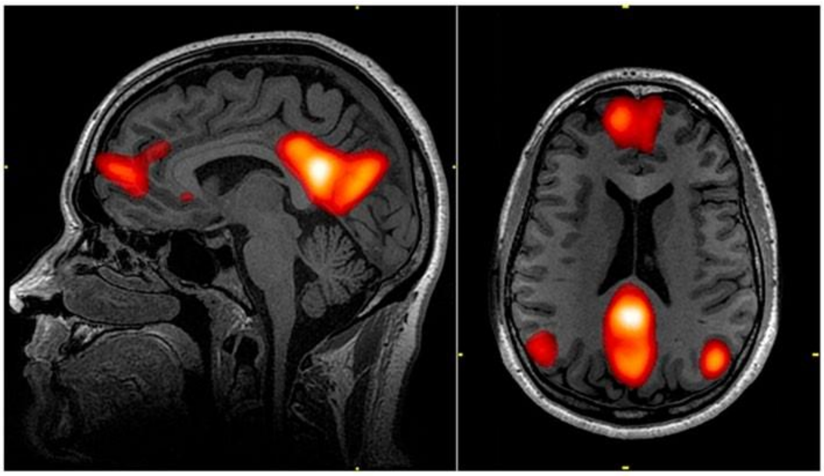

Figure 1. The Default Mode Network (figure from Graner et al. (2013)). Here as contrast highlighted areas of the medial prefrontal cortex, precuneus and bilateral parietal cortices.

In addition, research has shown that the DMN is not static, but changes over time. For example, a study by Fair et al. (2008) found that the connectivity within the DMN increases with age during childhood, suggesting that the development of the DMN may play a role in the cognitive and emotional development of children.

1.5 The Link Between the Default Mode Network and Physical Activity

Altering DMN activity shows great promise for changing behavior, since it is related to many different behavioral and cognitive paradigms, as I will discuss in-depth below. Given that DMN activity could be altered, how could this enhance theories of behavior change?

The DMN, known for its role in self-referential thinking and rumination, could potentially influence the effectiveness of health behavior theories, since its activity and / or functional connectivity can be influenced. (Sheline et al., 2009) suggested that a hyperactive DMN, which leads to excessive self-focus and rumination, could hinder the effectiveness of behavior change theories that rely on self-efficacy and motivation. This is particularly relevant for theories such as the Transtheoretical Model and the Health Belief Model, which heavily rely on an individual's self-perception and motivation to change.

For instance, in the context of the Transtheoretical Model, an individual's progression through the stages of change (from precontemplation, contemplation, preparation, action, to maintenance) could be impeded by excessive self-focus and rumination. If an individual is stuck in a pattern of negative self-referential thinking, they may find it difficult to move from the contemplation stage (where they are aware of the problem but have not yet committed to taking action) to the preparation stage (where they begin to make plans and commitments towards change), and ultimately to the action stage (where they actively modify their behavior). This could be due to a heightened focus on perceived barriers or potential failures, which could demotivate the individual and prevent them from progressing through these stages.

Similarly, the effectiveness of the Health Belief Model could also be impacted by the DMN. This model posits that an individual's decision to engage in health-promoting behavior is influenced by their perceived susceptibility to a health problem, perceived severity of the problem, perceived benefits of taking action, and perceived barriers to taking action (Limbu et al., 2022). A hyperactive DMN could potentially amplify an individual's perceived barriers or severity of the problem, thereby influencing their self-referential beliefs about health problems and their ability to address them.

(Naslund et al., 2017) proposed that the DMN's role in self-referential thinking could be a barrier to behavior change in individuals with serious mental illness. However, they also suggested that digital technology, such as mobile apps and wearable devices, could help overcome these barriers by providing real-time data and personalized interventions. These digital interventions could potentially provide external cues or reminders that help shift the individual's focus away from self-referential thinking and towards more goal-directed thoughts and behaviors. They emphasized the need for behavior change theories to guide the development and evaluation of these digital interventions, suggesting that a better understanding of the DMN and its influence on behavior could inform the design of more effective interventions.

While more research is needed to fully understand the relationship between the DMN and health behavior theories, these findings suggest that considering the role of the DMN could potentially enhance the effectiveness of these theories and the interventions based on them.

So far, I established that lack of PA is a worldwide problem causing many physiological and psychological illnesses. The leading causes of death worldwide are all associated with lack of PA, as are all of the most prevalent psychological disorders. Behavior change interventions which are theory based are not as effective as they could be. The DMN seems to be related to some aspects of all dominant theories of behavior change. Furthermore though, the DMN is related to PA itself. So far however, only few studies have tried to connect PA and the DMN. To our knowledge, this connection between PA and the DMN has not been researched directly, apart from three studies. Boraxbekk et al. (2016) showed differing DMN activity and connectivity in elderly people who are physically active compared to less physically active elderly people. Voss (2010) found that aerobic exercise training increases the connectivity in the temporal lobe within the DMN in older adults, which can lead to improvements in cognitive function, particularly in tasks that require semantic memory. This suggests that PA may have a protective effect on the brain's functional organization, potentially delaying the onset of neurodegenerative disorders. Lastly, Burdette (2010) found that acute exercise can lead to increased connectivity in the DMN. The researchers observed that a single session of moderate exercise can cause changes in the functional connectivity of the DMN, suggesting that PA can have immediate effects on brain function.

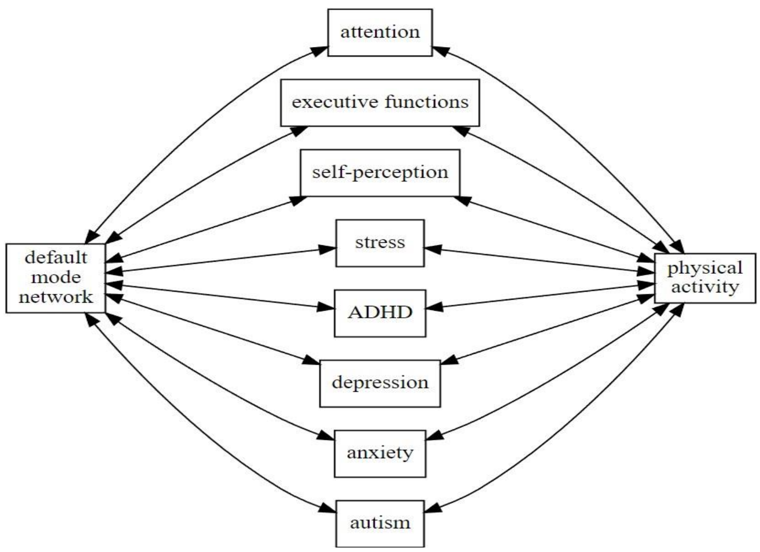

Figure 2. Diagram of argumentation. Each arrow represents an argumentative link explored using a review of available reviews and meta-analyses from the last 10 years, linking either PA or DMN to the linking paradigms bidirectionally.

However, these studies all focus on an elderly population and on acute training interventions in a specific subsample of the general population. Still, this evidences a connection, but a more comprehensive understanding is needed, given that the DMN and PA are both connected to many aspects of diseases, disease treatment and behavior change and intervention methods.

I established this connection by conducting a meta scoping review which connected the two paradigms by means of connecting each to four nonclinical and four clinical paradigms (see Figure 2 and paper 1). A very large body of research connects both the DMN and PA to attention, executive functions, self-perception, stress, Attention-Deficit and Hyperactivity Disorder (ADHD), depression, anxiety and autism spectrum disorders.

1.6 Methods to Study the Default Mode Network

The study of DMN activity can be approached through various methods, each with its own advantages and disadvantages.

Functional Magnetic Resonance Imaging (fMRI) is one such method, which allows for the visualization of brain activity by detecting changes associated with blood flow. This technique is advantageous due to its non-invasive nature and high spatial resolution, but it lacks in temporal resolution, since the measurement largely depends on the Blood Oxygen Level-Dependent (BOLD) signal, meaning the signal captured is the change in hemoglobin oxygenation levels (Rajkumar et al., 2021). Greicius et al. (2003) used fMRI to investigate the DMN. They found that the posterior cingulate cortex, inferior parietal lobule, and medial prefrontal cortex were all part of a functionally connected network, providing the first evidence of the DMN.

Positron Emission Tomography (PET) is another method used in studying the DMN. It involves the use of a radioactive tracer to visualize and measure physiological function in the body. PET provides a direct measure of metabolic activity and can be combined with MRI for simultaneous acquisition of metabolic and structural data. However, it involves exposure to radiation and has lower spatial resolution compared to fMRI (Scherr et al., 2021). Guan et al. (2021) used PET to study the DMN. They found that local neuronal activity, as measured by FDG-PET, influences functional connectivity patterns, thus contributing to the understanding of the physiological basis of the DMN.

Magnetoencephalography (MEG) is a technique that measures the magnetic fields produced by electrical activity in the brain. It offers high temporal resolution similar to EEG and better spatial resolution, but it is more expensive and less accessible than the other methods. Marzetti et al. (2014) used MEG to study the DMN. They found that the interplay between the DMN and the fronto-parietal network in the alpha band is crucial for the transition from resting state to different meditative states.

Electroencephalography (EEG) is a method that measures electrical activity in the brain using electrodes placed on the scalp. It has the advantage of high temporal resolution, allowing for the capture of fast dynamic changes in brain activity. However, it has lower spatial resolution compared to fMRI and PET, and signal quality can be affected by various factors such as muscle activity or eye movements (Al-Ezzi et al., 2021). Aforementioned factors can be isolated relatively well with modern methods and do not pose as large a threat to data quality as previously (Chen et al., 2019). Takamiya et al. (2019) used EEG to study the DMN in patients with depressive disorder. They found that electroconvulsive therapy (ECT), a treatment for severe depression, modulated resting-state EEG oscillatory patterns and phase synchronization in central nodes of the DMN. Specifically, ECT increased theta current source density in the anterior cingulate cortex, decreased beta current source density in the frontal pole, and decreased gamma current source density in the inferior parietal lobule. This study not only demonstrates that EEG is a well-suited method for studying DMN activity but also highlights an intervention method informed by EEG data results.

The use of EEG has many advantages to study DMN activity. EEG offers excellent temporal resolution, allowing researchers to measure brain activity with millisecond precision (Ibáñez-Molina et al., 2020). This is crucial when studying dynamic processes like the DMN, which involves complex interactions between brain regions over short time intervals (Mazziotta et al., 2001). While each method has its strengths and weaknesses, EEG stands out as the most suitable method for studying DMN activity due to its high temporal resolution, non-invasive nature, and relative accessibility (Berkovich-Ohana et al., 2014). Compared to other neuroimaging techniques like functional magnetic resonance imaging (fMRI), EEG is generally more cost-effective and easier to set up. EEG equipment is more accessible and affordable, making it an attractive option for many research settings. This is further in line with the strive for accessibility that is discussed above. fMRI, PET and MEG are very cost-intensive and not obtainable for economically disadvantaged institutions in low-income countries, and therefore are largely available to more highly developed country's institutions. However, their value in research is enormous and all methods with their advantages and disadvantages complement each other, and when combined, yield the best results (Yen et al., 2023). Given the emphasis on accessibility and the primary objective of easily implementing brain stimulation and /or neurofeedback frameworks, EEG emerges as the optimal approach. The portability of some EEG systems further supports this decision.

There are relatively low-cost open-source alternatives for EEG data acquisition available, which cannot be said for the other methods discussed above. In contrast to its main competitor, fMRI, EEG directly measures neural electrical activity by recording the brain's electrical activity, providing information on the synchronous firing of neurons and neural communication (Yen et al., 2023). This is particularly relevant when studying functional connectivity within the DMN (Sendi et al., 2021). While fMRI can show that two hypothetical areas A and B are simultaneously active, EEG allows for causal inference of activation, since synchronous firing of A and B shows functional connectivity, but small frequency shifts based on lag due to signal transmission time between neurons. Furthermore, EEG is a non-invasive technique, meaning it does not require surgery or the use of contrast agents. It is safe for participants, including special populations like children and clinical patients (González-López et al., 2022). Furthermore, EEG equipment is often portable, allowing researchers to conduct experiments in various settings, including natural environments or clinical settings (Simony et al., 2016). Additionally, while the spatial resolution of EEG is lower than fMRI, advanced EEG techniques, such as source localization algorithms, can help infer the neural sources of recorded brain activity. This enables a better understanding of the underlying brain regions involved in the DMN (Bonfiglio et al., 2014). Furthermore, the DMN is involved in various quickly changing cognitive processes, such as mind-wandering, self-referential thinking, and memory retrieval. EEG's high temporal resolution makes it well-suited for capturing these dynamic cognitive processes (Al-Ezzi et al., 2021). Lastly, EEG lends itself to neurofeedback better than fMRI does, due to the high temporal resolution and near real-time measurement of cognitive processes, which is not given in fMRI, due to the lag of the BOLD response (Britz et al., 2010).

1.7 Microstate Analysis and Resting State

To understand DMN functional connectivity patterns, I utilized microstate analysis, which has emerged as a powerful method for studying the DMN. This technique allows for the examination of transient, quasistable states of synchronized brain activity, providing a dynamic view of the DMN's functioning (Mazziotta et al., 2001). Microstate analysis has been particularly useful in studying pathological conditions such as Alzheimer's disease, where disruptions in the DMN are often observed. For instance, studies have shown that individuals with mild cognitive impairments, a precursor to Alzheimer's disease, exhibit altered resting DMN function, as revealed by microstate analysis (Greicius et al., 2003). Furthermore, a systematic review and meta-analysis of the DMN in healthy individuals highlighted the utility of microstate analysis in characterizing normal variance in DMN activity, which could serve as a baseline for identifying pathological changes (Mak et al., 2017).

Microstate analysis is a powerful tool for analyzing DMN activity / functional connectivity for several reasons. It helps to identify and characterize different functional brain states based on their distinct topographic configurations, representing fundamental and stable patterns of neural activity (Tarailis et al., 2023). This high temporal resolution is particularly valuable when studying transient brain events. Microstate analysis simplifies the data by reducing it to a smaller number of representative microstates, making it easier to interpret and analyze (Tarailis et al., 2023). Different microstates have been associated with specific cognitive functions and mental states, providing valuable insights into the functioning of the brain (Mak et al., 2017). Microstate analysis allows researchers to compare the occurrence and duration of microstates across different experimental conditions, tasks, or populations. This can help identify differences in brain dynamics associated with specific cognitive processes or clinical conditions (Eyler et al., 2019). Lastly, microstate analysis has shown promise in identifying biomarkers related to neurological and psychiatric disorders, indicating its potential as a diagnostic and prognostic tool (Tait et al., 2020).

While different numbers of microstates can be extracted and then retrofitted on the data to explain variance, usually 4 to 6 microstates are extracted and applied. For a recent in-depth review, see Tarailis et al. (2023). See figure 3 for examples of microstate topography maps. In the following, some associations of the microstates based on a very fast-growing body of literature will be described.

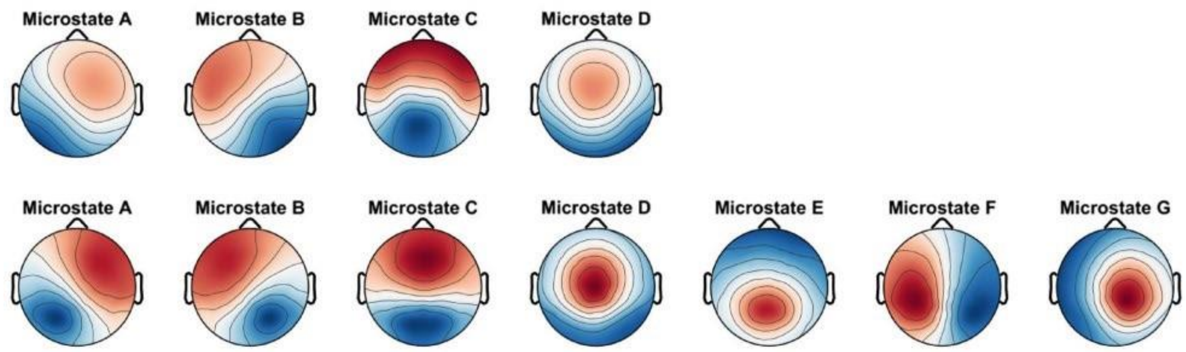

Figure 3. Topography maps of the canonical 4 microstates extracted in many studies (left) and 7 Microstate maps found by Tarailis et al. (2021) (below) (figure adapted from Tarailis et al. (2023)

Microstate A is connected with the auditory network and the temporal cortex (Ai et al., 2019; Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017). Moreover, Milz (2016) discovered that Microstate A showed a greater duration, frequency, and accounted for a larger portion of the variance during spatial and object visualisation tasks as opposed to during verbalization or periods of rest without a task. Therefore, it can be inferred that Microstate A is related to both auditory and visual processing, as well as spatial visualization.

Microstate B has been associated with several cognitive functions, including visual processing, autobiographical recall, self-visualization, and the visualization of scenes. There is also evidence of its interactions with other microstates, such as microstate C. Inverse solutions methods utilized in multiple studies (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017) have found its connectivity to visual regions. This connection to visual processing is strengthened by an augmented occurrence post visual stimulus or during an eyesopen condition (Seitzman et al., 2017). In addition, studies by Bréchet et al. (2019) and Tarailis et al. (2021) associate microstate B with autobiographical memory and the visualization of oneself and scenes. Interestingly, its prevalence decreases in euthymic bipolar patients, suggesting potential repercussions on memory and self-perception (Vellante et al., 2020).

Microstate C plays a role in several functions, including the DMN, mind-wandering, task-independent thoughts, and emotional processing, as suggested by Michel & Koenig (2018), Custo et al. (2017), and Tarailis et al. (2021). It is tied to the DMN, the 'self-experience' subnetwork, and the salience network (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017). Croce et al. (2018) further associated it with mindwandering and task-irrelevant thoughts. Microstate C has been found to be linked to relaxation (Tomescu et al., 2018) and exhibits increased prevalence during rest without any specific task (Kim, 2021; Seitzman et al., 2017; Zappasodi et al., 2017). Additionally, it is connected with cognitive decline in older adults (Jabès et al., 2021) and episodes of mind-wandering (Zappasodi et al., 2019).

Microstate D is predominantly associated with regions that intersect with the frontoparietal network, and is related to executive functions like working memory, cognitive regulation, and attention (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017). According to Croce et al. (2018), the temporal attributes of Microstate D were found to augment post-repetitive transcranial magnetic stimulation over the intra-parietal sulcus, a component of the Dorsal Attention Network. A higher occurrence of Microstate D has been observed during activities like arithmetic tasks (Bréchet et al., 2019; Kim, 2021), virtual maze navigation (Murphy et al., 2018), and tasks related to spatial relationships (Zappasodi et al., 2019).

Given that microstates B and C are most closely related to specific subdomains of the Default Mode Network (DMN), including autobiographical memory, self and scene-visualization, mind-wandering, task-negative thoughts, and emotional processing, while microstates A and D are more tied to cognitive domains outside of DMN, perception and executive functions, that variations would be primarily observed in the measurements concerning B and C, rather than A and D.

If physical activity plays a major role in this doctoral thesis, one might wonder why the **resting state** (physical inactivity) is of interest in the project. There are three major reasons for that: Firstly, the DMN is mostly active when not task oriented and in a restful state. Resting-state EEG provides a unique opportunity to study the intrinsic activity of the brain, particularly the DMN. Unlike task-related EEG, resting-state EEG captures the spontaneous, intrinsic activity of the brain, reflecting the underlying brain network dynamics without external interference (Rasero et al., 2018). This allows for a non-biased assessment of brain activity, as it does not require participants to perform any specific task, reducing potential biases introduced by task performance or differences in task difficulty. This is particularly useful for studying the DMN, which is most active during restful, mind-wandering states. Secondly, task-related EEG might not effectively capture DMN activity since its activation is attenuated during attention-demanding tasks. Especially in the microstate analysis it was shown that physical activity might interfere with the different states. Finally, resting-state EEG has shown promise in clinical applications, such as studying brain disorders and identifying biomarkers of neurological and psychiatric conditions (Newson & Thiagarajan, 2019). It provides insights into the brain's intrinsic connectivity, which can aid in understanding brain dysfunction and guiding therapeutic interventions (Püttgen & Geocadin, 2014). Since the ultimate goal is to contribute to a knowledge basis which can be useful for therapeutic and / or behavior change interventions, the data should be gathered in a paradigm which also will be used in clinical settings, to explain variance in data collected in a similar manner.

2 Scientific Work of the Present Thesis

In the following section, I provide a condensed version of each paper to contextualize the overall research work of this thesis. This has been done for better readability; however, the full text manuscripts are enclosed in the appendix. Not all detailed aspects of the methods and overlapping justifications in each introduction are deemed essential for understanding the research.

The primary purpose of a dissertation is to demonstrate the author's ability to conduct original research in their chosen field of study. It should offer new insights, knowledge, or solutions to existing problems in the field. The ultimate goal of a dissertation is to contribute to the body of knowledge in the academic discipline, enriching the understanding of the subject area and potentially paving the way for further research and / or application thereof.

I conducted original research and furthered the understanding of pre-existing paradigms and their connections. I also provided means for applying the research in therapeutic settings, such as brain stimulation and neurofeedback. Additionally, I suggested integrating the findings into existing theories of behavior change.

Three elements are essential to research a phenomenon. A theory, which puts the phenomenon into context, a means to measure and collect data to test the hypothesis and a paradigm to understand the data collected. The hypothesis posits that DMN activity varies in non-clinical populations based on PA levels. The means of how to collect data is twofold: It is necessary to measure how active people are and what is happening in their DMN. The first study laid a solid foundation for the hypothesis by establishing a theory. This was based on extensive research and utilized a novel method. The second study enhanced data collection methods related to activity and introduced a method to classify behavior. The third study establishes the hypothesized difference in a classical paradigm and provides a complete EEG pipeline, built on a platform which allows for integration of the classifier from the second study and directly integrating a neurofeedback framework. The studies are introduced in the following in an abbreviated manner, for the complete manuscripts, see appendix.

2.1 Open-Source Statement

In the subsequent chapter, it will become evident that significant effort was invested to base all research on open-source methods, ensuring maximum repeatability. It is of great importance to the author that all methods are available to everyone, and monetary restrictions should be circumvented with the goal of firstly, equal accessibility of science, and secondly, transparency of methodology. If non-open-source methods were applied, a functioning open-source alternative has been provided or is possible without much effort. All employed Matlab (The MathWorks Inc., 2023) scripts run on Octave (open-source alternative to Matlab) (GNU Octave, 2023) as well, even though free students' licenses for Matlab are available. EEGlab (Delorme & Makeig, 2004) runs natively on Octave, and a free alternative to traditional research accelerometers has been provided (Wieland, 2022) and the EEG measurement pipeline has been set up functioning on opensource OpenBCI Hardware (OpenBCI, 2021) and OpenVibe (Renard et al., 2010) software. All analysis was done using open-source programming languages such as R (R Core Team, 2021), python (Python Software Foundation., 2023) and EEGlab. All software will be provided without reservations under the GNU General Public License version 3.0 (GNU General Public License, version 3.0 (2007)). Retrieved from https://www.gnu.org/licenses/gpl-3.0.html) for reproduction, modification, but not commercial employment. For collection of control variable scores using questionnaires, I used a free account on qualtrics.com in a pseudonymised collection paradigm (Qualtrics, 2023). While this is not open-source, all the questionnaires can be administered paper-based too.

2.2 Paper 1 – Connecting the Default Mode Network and Physical Activity: A Metascoping Review.

Firstly, a sound basis for the theory to be tested had to be established. So far, research directly investigating the link between PA and the DMN has not been conducted, except for (Boraxbekk et al., 2016), who demonstrated varied DMN activity and connectivity in physically active versus less active elderly individuals, Voss (2010), who observed that engaging in aerobic exercise training among older adults resulted in heightened connectivity within the temporal lobe of the DMN and Burdette (2010), who reported that acute exercise also led to increased connectivity within the DMN. Despite this, an extensive body of *indirect* research connects PA to the DMN. The aim of the review, was to simplify and structure the existing evidence suggesting this interaction, thereby proving a very strong relation between the two paradigms. This relation highlights the need for further direct investigation to better understand the complicated interaction of the two paradigms.

Therefore, a meta-scoping review of the connection between the two paradigms had been conducted. Due to the vast volume of scientific papers pertaining both paradigms and their associations, the focus was restricted to review articles and meta-analyses that have already structured the available scientific literature. The approach included only work which was published within the last 10 years, connecting both PA and the DMN to 4 non-clinical and 4 clinical paradigms. For a diagram of argumentation, see Figure 2. A sum of 541 studies from the past decade (comprising 237 reviews, 178 meta-analyses, and 126 mixed designs) was utilized to indirectly connect DMN to PA. Out of these, 149 studies (96 reviews, 44 meta-analyses, and 9 mixed designs) provided evidence for the connection between DMN and the linking paradigms. Simultaneously, 392 studies (147 reviews, 128 meta-analyses, and 117 mixed designs) served to connect PA to these paradigms. For a more detailed breakdown, please see the Review in the appendix.

A large amount of research has linked PA to cognitive functions such as attention (Hajar et al., 2019), executive function (Hötting & Röder, 2013), self-perception (Alves et al., 2019), stress (Bischoff et al., 2019), and emotional regulation (Ubago-Jiménez et al., 2019). Furthermore, it has been correlated with the reduction of risk for numerous mental disorders including ADHD (Hoza & Smith, 2015), depression (Mammen & Faulkner, 2013), autism (Sorensen & Zarrett, 2014), and anxiety disorders (McDowell et al., 2019). Over the past two decades, a fast-growing body of research has been conducted into the DMN and found connections to the above-mentioned correlates of PA (Raichle et al., 2001; Smallwood et al., 2021). The DMN, primarily active during rest, is involved in various cognitive functions such as self-reflection, episodic memory recall, and future envisioning (Raichle, 2015). Interestingly, like PA, the DMN shows links to attention (Clayton et al., 2015), executive function (Mak et al., 2017), self-perception (Davey et al., 2016), stress (Tang et al., 2015), emotional regulation (Pan et al., 2018), and similarly to mental disorders such as ADHD (Harikumar et al., 2021), depression (Zhou et al., 2020), autism (Harikumar et al., 2021), and anxiety disorders (Coutinho et al., 2014).

The importance of DMN in research is undeniable, with 3000 publications on the topic by 2015 (Raichle, 2015). The overlap in DMN and PA research suggests potential interactions between them, an area yet to be thoroughly explored. It was hypothesized that planning future activities and motivational processes, both tied to the DMN, may influence one's likelihood to engage in physical activities. For instance, PA might affect DMN activity, which subsequently influences cognitive functions and emotions, explaining the cognitive and mental health benefits of PA. Additionally, abnormal DMN activity, often observed in several mental disorders, might impact an individual's propensity for PA by interfering with future planning processes to establish a change in behavior.

Comprehending this interplay between the DMN and PA is crucial in devising strategies that encourage PA and thus enhance physical and mental health. Concurrently, understanding the DMN's role concerning PA will enable the development of more targeted neurological therapy methods, like brain stimulation techniques such as Transcranial Magnetic Stimulation (TMS) (Wassermann & Zimmermann, 2012), transcranial Direct Current Stimulation (tDCS) (Lefaucheur et al., 2017), and neurofeedback interventions (Imperatori et al., 2019). Using this novel approach, both the DMN and PA was connected to many different paradigms, including attention, executive processes, self-awareness, stress management, ADHD, depression, anxiety, and autism spectrum disorders. Leveraging only recent, review and meta-analysis-based research, our study simplifies and sheds light on the intricate relationship between the DMN and PA.

With respect to PA, its therapeutic value is beyond dispute, as discussed above. Nevertheless, it was noted that when differences emerge in prevalence of disorders or cognitive function, these variations are frequently attributed to PA, overlooking the potential reciprocal relationship. This tendency to favor a unidirectional interpretation potentially masks the complexity of the actual situation. The presented results indicate that both the DMN and PA play vital roles in cognitive and emotional processes, and their interaction may offer valuable insights into comprehending and addressing different mental health conditions.

Given the potential connection between the DMN and PA, utilizing PA as a treatment for various conditions and related symptoms could be a promising approach. Moreover, addressing issues with DMN functionality may influence PA levels, opening up new possibilities for treating associated problems. Research has shown the efficacy of TMS in managing diverse psychological disorders (Čukić, 2020; Kan et al., 2020; Singh et al., 2020). Furthermore, targeted stimulation of the DMN through tDCS and TMS has proven effective in treating depression (Singh et al., 2020), post-traumatic stress disorder (Kan et al., 2020), and anxiety disorders (Cirillo et al., 2019). Similarly, PA has demonstrated efficacy in preventing and treating depression and anxiety (Carek et al., 2011; Martinsen, 2008).

The work presented in this thesis contributes to the current body of knowledge by presenting robust evidence that the two paradigms of DMN and PA might be more directly connected than previously thought. This posits a strong case for further investigation into the relationship between the DMN and PA and the dynamic and reciprocal interaction between these two critical factors. While still indirect in nature, the presented evidence is robust, since it is based on 541 review papers / meta-analyses over 8 connections, and this methodology allows for justification of more detailed research.

2.3 Paper 2 – A Trainable Open-Source Machine Learning Accelerometer Activity

Recognition Toolbox: Deep Learning Approach

To combat the problem regarding PA recording and analysis, I developed firstly an Android application, which allows for precise collection of accelerometry data and a machine learning algorithm, which classifies behavior of the subject using it based on the collected accelerometry, magnetometry and gyroscopy data.

An open-source, deep learning-based accelerometry behavior analysis toolbox was developed, along with a deep learning-based classifier to recognize behavior. This approach circumvents many of the limitations associated with traditional PA measurement methods, including cost, lack of transparency, and limited accessibility.

The classifier algorithm developed for this project consists of a Deep Neural Network (DNN), which has become the dominant approach for machine learning based classifying paradigms (Celard et al., 2023). Deep learning algorithms have gained significant importance in classifying human behavior based on sensor data collected from accelerometers, gyroscopes, and magnetometers (Jeyakumar et al., 2019; Lin et al., 2014; Malekzadeh et al., 2021). These algorithms, built on artificial neural networks, have become the dominant approach for activity recognition as of 2022. Particularly, DNNs, characterized by multiple layers of neurons, have been widely used (Bengio et al., 2013; Goodfellow et al., 2016). The functionality of these neurons is determined by their specific layers and interconnections.

Typically, DNN architectures consist of a Convolutional Neural Network (CNN) layer, followed by either a Feedforward Neural Network (FNN) layer or a Recurrent Neural Network (RNN) layer (Goodfellow et al., 2016). A FNN layer takes input data and applies weights and biases to compute a linear transformation followed by an activation function to generate the output for further processing. A CNN layer performs a localized and shared-weight computation, called convolution, on input data to extract relevant features and create feature maps for subsequent layers. A RNN layer processes sequential data by utilizing the output from the previous time step as an additional input, allowing it to capture temporal dependencies and create context-aware predictions. For more in-depth explanations, see (Goodfellow et al., 2016). While CNNs are proficient in handling variable input dimensions and are primarily utilized for feature extraction, FNNs work well with data of consistent dimensions, and RNNs operate with a fixed number of streams ((Malekzadeh et al., 2020).

Despite their effectiveness, DNNs with a combination of CNN, RNN, and FNN struggle with varying input dimensions. Consequently, if data collection from one sensor halts, the movement type cannot be classified by the DNN initially trained on multiple input dimensions. During extended periods of sedentary activity, certain sensors can and should be either disabled or their recording frequency lowered, in order to conserve battery life of the device. However, this changes the input dimensions for the DNN, either in terms of the number of inputs parallel in time (i.e., number of data streams from sensors) or the number of inputs serially in time (i.e., sensor measurement frequency) for the DNN. Artificially generated dummy data can compensate for missing data, although this leads to accuracy loss in classification (Ae Lee & Gill, 2018). Alternatively, a global pooling layer can be added, but this can also decrease accuracy (Ayachi et al., 2020).

Prior research on accelerometry-based movement recognition has achieved success, but not without limitations. Ordóñez & Roggen (2016) presented a deep-CNN-based framework, yielding an accuracy of up to 86.7%. The researchers found that changes in acceleration had the most significant impact on classification accuracy. Similarly, Wang et al. (2019) identified strengths and weaknesses of deep learning models for activity classification. Despite impressive performance on trained data, models often struggle with sensor noise, input variability, and lack of extensive, labelled accelerometry datasets. To at least partially counter this, the accelerometry dataset will be available.

In response to these shortcomings, Malekzadeh et al. (2021) introduced a model that incorporates a dimension-adaptive pooling (DAP) layer, enhancing DNNs' robustness to changes in sampling rates and sensor availability. Additionally, the researchers proposed a dimension-adaptive training (DAT) layer, combined with the classical CNN/FNN/RNN approach and the DAP layer. They asserted that their dimension-adaptive neural architecture (DANA) can maintain classification accuracy, even under varying sensor availability and sampling rate changes.

The efficacy of this model was tested on four publicly available datasets, including the MotionSense dataset, which consists of accelerometer data from 24 students at Queen Mary University of London (Ronao & Cho, 2016). The objective for this study was not only to improve on this architecture but also to validate its performance using this data. The robustness of the DANA model holds promising implications for accelerometry research. The modified classifier consists of an improved version of the DANA model by Makzeladeh et al. (2021) with several layers removed and modified in the architecture, and with extensive fine-tuned hyperparameter testing applied. Our simplified model removed several layers of the original model yet yielded better training times and classification accuracy. The model was trained on two datasets as comparison, including the original dataset by Makzeladeh et al. (2021), which is an open-competition dataset as a benchmark for machine learning in accelerometry (MotionSense, Github, Malekzadeh et al., 2021). In addition to the original dataset, own data was collected with our own Android application. It consisted of the movement data of 68 participants of the university of Bern who moved up and down stairs, walked, jogged, sat, and stood with the active app on a smartphone, replicating the MotionSense open competition dataset. The algorithm was then trained on the original data and our own data and efficiency was compared to the DANA model trained on the original data and on our data.

Our algorithm outperforms the original DANA model on our own data, while yielding comparable performance on the original benchmark dataset, while being significantly more efficient to train. Furthermore, our algorithm is easily retrainable to classify any new behavior, which is a further massive advantage over commercial accelerometry devices. Compared to benchmark open competition datasets, our algorithm performs well and is free to the public and the scientific community. Our classifying algorithm is fast time-series high frequency based and can be used and retrained in many different applications, with a notable mention of EEG in real-time acquisition scenarios, such as neurofeedback or brain computer interface technology. The application and algorithm have been published in JMIR AI (Wieland, 2022) and the corresponding code on GitHub.

2.4 Paper 3 – Difference in Default Mode Network Activity Between People of Differing Activity Levels: An EEG Microstate Study.

So far, I established a strong case for PA and the DMN being connected directly based on a very large body of research. Subsequently, I significantly improved the means of measuring PA, by making them more accurate, transparent, adaptable, accessible, and repeatable and significantly enhancing the available means for behavior classification and PA data collection. In my third paper, PA levels are directly connected to DMN activity, using a direct experimental approach.

In order to gather data on the activity of the default mode network, two experiments were reproduced, a study previously conducted by Li et al. (2021) and one by (Dimitriadis et al., 2016). The structure of the first experiment included a period for instruction and preparation, followed by two task blocks wherein participants counted upward-facing triangles. In between these task blocks were two rest periods, each lasting three minutes. During these rest intervals, participants were advised to stay still and relax without any specific guidelines. In the second experiment, blocks of increasingly difficult arithmetic tasks were presented, with breaks lasting two minutes with the same instructions as in the first experiment. The EEG data collected during the breaks was analyzed using an established EEG microstate analysis toolbox by (Koenig et al., 2002).

The PA of the participants was evaluated after the EEG data collection was completed. For this, MoviSens accelerometers were handed out, and the participants were guided to attach them at the hip for an uninterrupted period of one week, while being awake. After completing the designated week with the devices, participants proceeded to complete the Godin-Shepherd Leisure-Time PA questionnaire (Amireault & Godin, 2015), which was adapted to additionally solicit details about the duration of light, moderate, and intense PA in the preceding week - essentially, the week following the experiment and during which the accelerometer data was gathered. Along with the MoviSens accelerometers, 10 participants had the HumanActivityRecorder App (Wieland, 2022) installed on their Android smartphones, serving as a means to crossverify the accuracy of the data obtained from the MoviSens devices. Utilizing the data from the MoviSens accelerometers, participants were then classified into a more active or less active group, based on a median split evaluation.

EEG data was measured using active electrodes and gUSB (G-TEC GmbH, 2020) equipment. For details, see the complete manuscript in the appendix. Data was acquired using OpenVibe, an open-source braincomputer interface software. To further warrant accessibility in line with our goal of maximum transparency and repeatability, the whole setup was tested with OpenBCI hardware, albeit with passive electrodes, since no active electrode setups are available at this time. Preprocessing was done using the eeglab plugin by Delorme et al. (Delorme & Makeig, 2004). To extract and calculate microstate topographies and statistics, the microstate toolbox by Poulsen et al. was utilized (Poulsen et al., 2018). For maximum repeatability, the approach outlined by Thomas Koenig was followed (2017, https://thomaskoenig.ch/index.php/software/10-eeglab-plugin-manual).

I chose to employ the default values and only adjusted the Matlab script found in the Microstate toolbox to enable parallel computing. Our analysis proceeded with an a priori of 4, 5, and 6 microstates. Upon finding that the inclusion of 4 to 6 microstates accounted for an extra 5% of the global variance explained (4 microstates: 77.27% Global Explained Variance (GEV), 5 microstates: 79.32% GEV, 6 microstates: 83.24% GEV), it was decided to conduct the data analysis using 4 microstates. This decision aligns with insights from earlier studies (Van De Ville et al., 2010), which ascertained that employing more than 4 microstates contributes minimally to the explanatory power of resting state EEG data. The introduction of more microstates for analysis inordinately decreases power and complicates the process without proportionate gains in explanation. Moreover, activity in the default mode network is mostly linked with Microstate B, C, and F, with C and F sharing substantial similarities and overlaps both in association (Khanna et al., 2014) and topography (Tarailis et al., 2021). Consequently, the use of more than 4 microstates would only increase complexity while diminishing accuracy.

A total of 33 (20 female, 13 male) participants took part in the experiment with a mean age of 30.645 years (sd = 5.431). Standard MoviSens DataAnalyzer Cutoffs yielded a total mean of 190.074 active minutes per day (sd = 63.553min), of which 117.074min (sd = 45.018min) were light activity, 63.518min (sd = 31.407) moderate activity and 11.631min (sd = 11.191min) vigorous activity. Questionnaire values and measured values only showed a small correlation of r = 0.371.

Differences in globally explained variance, occurrence, global field power, and mean duration of each of the microstates were calculated for both groups in both experiments. The results show statistically significant differences between Microstate B and C between the groups.

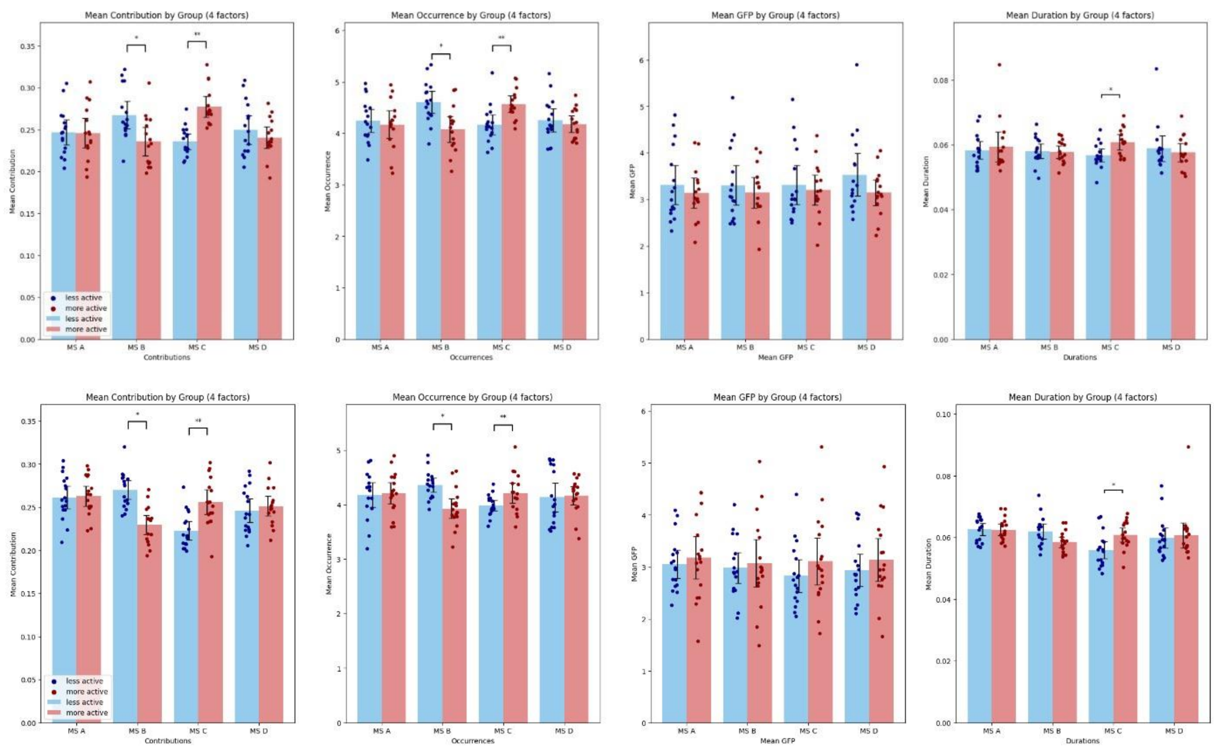

Figure 4. Mean contribution to variance, mean occurrence, mean global field power and mean duration of microstates A, B, C and D (Tarailis, 2023) in experiment 1 (top) and experiment 2 (bottom). Error bars are confidence intervals based on Tukey's HSD corrected for multiple comparison. Significant differences are marked with brackets. * for p<0.05, ** for p <0.01, *** for p<0.001. Microstate B explained significantly more of the globally explained variance than microstate C in the group that was less active. Microstate B explained significantly more of the globally explained variance and occurred more often than microstate C in the group that was less active. Microstate C explained significantly more of the globally explained variance and occurred more often than microstate B in the group that was more active. Microstate C persisted significantly longer on average in the more active group.

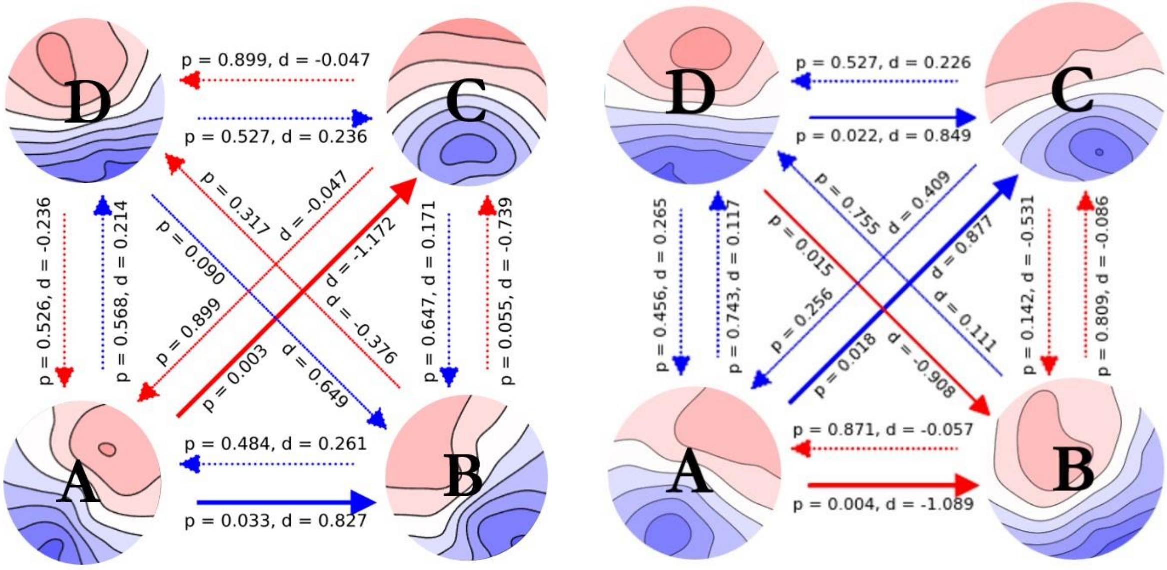

Figure 5. Transition probability difference maps from microstate to microstate with original microstate maps from experiment 1 (left) and from experiment 2 (right). The transition probability is positive, if it is more likely in the less active group and negative if it is more likely in the active group. Dotted arrows denote non-significant differences, full arrows denote significant differences. Blue arrows denote that the probability is higher in the less active group, red arrows that it is more likely in the more active group. Note, that effect sizes are included, and several transition probabilities are different between the groups. "d" denotes Cohen's d, p-values are based on Tukey's HSD, two sided and multiple corrections corrected.

This study reveals distinct differences in the incidence, duration, and contribution to variance by microstates among participants with varying levels of activity. Notably, Microstate B and C contribute differently to the global variance in EEG and manifest differently often across the groups. Additionally, Microstate C generally has a longer duration in the more active group. Overall, there is a heightened inclination in the less active group to transition from Microstate A to B, while in the more active group, a pronounced propensity for transitioning from Microstate A to C is observed, in the first experiment. However, in the second experiment, the reverse pattern and a heightened probability to transition from microstate D to C emerged.

Microstate B, which is connected to visual processing, self-visualization, autobiographical memory, and scene visualization, presented more frequently in the group with lower PA. This might suggest an intensified engagement with these cognitive processes in the less active group, possibly as an adaptive mechanism for their diminished PA. This observation aligns with the studies by (Antonova et al., 2022) and D'Croz-Baron et al. (D'Croz-Baron et al., 2021), which reported an amplified occurrence of microstate B following visual stimuli or during the eyes-open state. In addition, the decreased occurrence of microstate B in euthymic bipolar patients, as found by (Vellante et al., 2020), hints at possible implications for memory and self-focus in the less active group. This is in agreement with the observation that Microstate C was both less frequent and of shorter duration in the less active group. Microstate C, tied to the DMN, mind-wandering, tasknegative thoughts, and emotional processing, was more frequently observed in the more active group.

This implies that PA might boost these cognitive processes, an observation in line with the study by Croce et al. (2018) that connected microstate C with task-negative thoughts and mind-wandering. The elevated occurrence of microstate C during no-task rest, as noted by Kim et al. (2021) and Seitzman et al. (2017), further substantiates this inference. Considering the link of Microstate C with episodes of mind-wandering, as per (Zanesco et al., 2021), it can be suggested that more active individuals might exhibit a more relaxed state during rest, facilitating mind-wandering. Furthermore, the DMN is believed to guide internal attention (Kim, 2015), which further suggests that the more active individuals are more introspective during the resting state.

Microstate A, linked with the temporal cortex, auditory network, and visual processing, did not exhibit any significant differences between the groups with higher and lower PA. This indicates that these cognitive processes may not be significantly influenced by levels of PA, at least as per the resting state EEG activity. This finding is consistent with the observations made by Milz et al. (2016), who noted that Microstate A had a longer duration, a higher incidence rate, and accounted for more variance during tasks involving object and spatial visualization compared to verbalization tasks and the resting state with no task. Microstate D, linked to executive functions such as working memory, cognitive control, and attention, did not show any significant difference between the two groups. This indicates that the levels of PA may not have a substantial impact on these cognitive processes. This is in harmony with the findings of Croce et al. (2018), who documented that the temporal attributes of microstate D were amplified after repetitive transcranial magnetic stimulation over the intra-parietal sulcus, a component of the Dorsal Attention Network. Given that the recorded resting state time window did not necessitate outward attention, it was unlikely for a difference in this microstate to emerge between the groups. The heightened presence of microstate D during arithmetic tasks (Bréchet et al., 2019; Kim, 2021), virtual maze training (Murphy et al., 2018), video gaming (Wang et al., 2019), and tasks involving spatial relationships (Zappasodi et al., 2019) further corroborates this interpretation. It's crucial to distinguish between inward and outward attention here; inward attention is generally associated with the DMN, while outward attention is believed to be managed by the dorsal attention network (Kim, 2015). Consistent with this rationale, a difference was noted in microstate C between the groups, but not in D, as C is believed to be most strongly associated with the DMN.

The increased probability of transitioning from microstate A to B in the less active group and from A to C in the more active group may just mirror the higher occurrence rate of microstates B and C in these respective groups. Alternatively, the enhanced likelihood of shifting from microstate A to B in the less active group could be perceived as a transition from auditory and visual processing related to microstate A to visual processing, self-visualization, autobiographical memory, and scene visualization tied to microstate B. This might hint at a compensatory mechanism in the less active group, suggesting a brain resource reallocation from auditory to visual processing and memory-oriented tasks. This inference is backed by the studies of Antonova et al. (2022) and D'Croz-Baron et al. (2021), who reported an augmented presence of microstate B following visual stimuli or during the eyes-open state, which aligns well with our paradigm.

Conversely, the differing probability of transitioning from microstate A to C in the more active group and less active group respectively, could be viewed as a shift from auditory and visual processing to DMNassociated activities, mind-wandering, task-negative thoughts, and emotional processing tied to microstate C. This could indicate that PA bolsters these cognitive processes, in alignment with the study by Croce et al. (2018) that associated microstate C with task-negative thoughts and mind-wandering. However, it is crucial to acknowledge that these interpretations are conjectural, and further research is required to validate these hypotheses and fully comprehend the implications of these results for cognitive functionality and health.

The very similar results in microstate variance explanation, occurrence, duration and global field power strength in both experiments indicates, that these factors relate to default mode network activity in general, while the differing results from the transition probabilities indicate, that these relate to the experimental design.

In summary, the results of this study imply that levels of PA might impact specific facets of resting state EEG activity, especially those related to visual processing, self-representation, autobiographical memory, scene visualization, mind-wandering, task-negative thoughts, and emotional processing. Nonetheless, a more comprehensive understanding of these associations and their implications for cognitive health and functionality necessitates further investigation.

3 General Discussion

With the previously presented works, I have firstly established a very profound base supporting our theory – and proven a connection of two highly researched paradigms which have not yet been connected in this manner. Secondly, I significantly improved the means of activity tracking and behavior classification – and thereby made them both more accessible and transparent to the scientific community, while also saving on potential costs. Thirdly, I proved the proposed connection between DMN and PA, using proven and established EEG measurement and analysis methodologies and made the whole collection and measurement pipeline more accessible and transparent for the scientific community as well. This opens a new focus of research that has great potential in preventing and treating many of most prevalent and costly physical and psychological diseases and better understanding and connecting a vast body of scientific results. Lastly, in order to facilitate this, I have built a pipeline to acquire data and a classifier to classify frequency-based time series signals. The EEG pipeline is implemented in a software which allows for direct addition of neurofeedback frameworks.

3.1 Interaction of the Links Between DMN and PA

While investigating the connection between DMN and PA using 4 non-pathological paradigms and 4 pathological links, it should be noted, that those links themselves are highly interconnected. I will briefly discuss some of the most important interactions since it bears relevance to understand the complexity thereof for future research and to better put into perspective the results of the presented research. However, the complete interaction of the links is outside of the scope of the present thesis.

Non-pathological / Cognitive Links. Many of the above discussed links of DMN and PA are themselves interlinked in a very complex manner. Attention, executive function, self-concept, and stress are interconnected constructs that collectively contribute to overall psychological health and cognitive performance. Attention, a cognitive process that allows for the selection and processing of specific stimuli, is integral to the functioning of executive processes, as highlighted in a study by (Kofler et al., 2018), which posits that executive function skills like working memory and inhibitory control require a robust attentional foundation to effectively facilitate goal-directed behaviors. Similarly, self-concept, or an individual's perception of their abilities and potential, is influenced by their capacity for attention and executive function. (Bailey et al., 2018) found that a positive academic self-concept correlated with better performance on tasks requiring executive function, which underscores the role these cognitive processes play in shaping self-perception. Stress, meanwhile, can impact these cognitive processes significantly. Research from (Shields et al., 2016) shows that acute and chronic stress can negatively affect cognitive functions, including attention and executive function, which subsequently impacts the self-concept of an individual. However, a positive self-concept can act as a buffer against stress, enhancing resilience and promoting better stress-coping mechanisms. This idea is supported by a study from (Diehl & Hay, 2010), which found that positive self-concept can act as a protective factor against the negative impacts of stress, particularly in youth populations.

Pathological Links. ADHD, depression, anxiety, and ASD, although distinct in terms of their clinical definitions, exhibit a complex interplay of both genetic and neurological characteristics that may offer some explanation for their common features and frequent co-occurrence. Research indicates shared genetic pathways and a connection to functional abnormalities in key brain networks, particularly the DMN. Studies like those of (Antshel et al., 2013) and (Demontis et al., 2019) have identified shared genetic variants among these disorders, suggesting potential genetic correlations. In addition, abnormal functional connectivity within the DMN has been associated with these disorders. Evidence shows that ADHD, as illustrated in the work by (Sidlauskaite et al., 2016), depression, and anxiety disorders, as shown in the research of (Kaiser et al., 2015), as well as ASD, as demonstrated by (Mulders et al., 2015), all exhibit disruptions in the DMN's functional connectivity. This suggests that the commonality in neurological changes could be a potential driving force for the co-occurrence of these disorders.

In the third study, further evidence to the interaction of these aforementioned pathological links was found. Different questionnaires have been assessed and to control for the potential influence of known covariates, i.e. the pathological links. Firstly, the Godin-Shepard leisure time activity questionnaire (Amireault & Godin, 2015) was implemented, modified, so it also asked for minutes of low, moderate and vigorous activity in the week before (i.e. the week after the experiment and the week in which accelerometry was measured). To assess ADHD levels, the Adult ADHD Self-Report Scale (ASRS)(Kessler et al., 2005) was implemented, which is an 18-item self-report questionnaire designed to assess Attention Deficit Hyperactivity Disorder

(ADHD) in adults. To assess depression, anxiety and stress levels, the Depression, Anxiety and Stress level Questionnaire Short (DASS-21) was implemented (Henry & Crawford, 2005).

A strong correlation between stress and depression scores have been observed, moderate correlation between anxiety and stress, and small to moderate correlations between depression and anxiety, depression and autism spectrum symptoms, anxiety and ADHD, and stress and ADHD. Further small correlations emerged between stress and autism spectrum symptoms, see Figure 6.

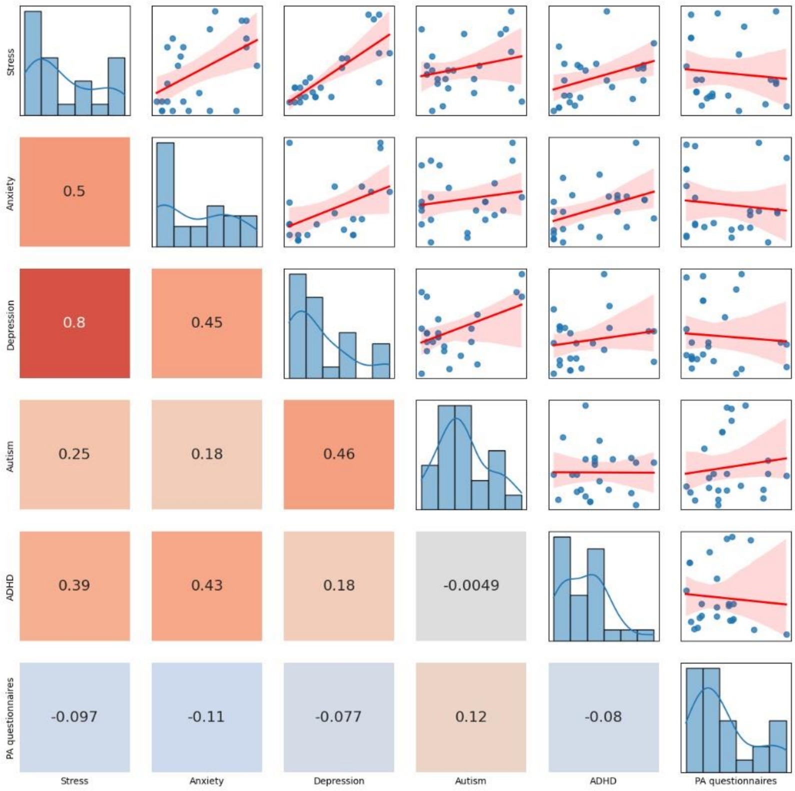

Figure 6. Cross correlogram of the questionnaire scores in the third study. Note the moderate to strong correlations between ADHD, autism spectrum symptoms, depression, and anxiety scores.

3.2 Reflection on Theories of Behavior Change

In the introduction section, it was shown, that given, that DMN activity and / or functional connectivity could be altered, this could enhance theory-based behavior modification interventions. It was established, that PA and DMN are indirectly connected via a large body of research. Further, it was shown in an EEGexperiment, that the DMN and PA are directly connected. Additionally, the basis for modification of DMN activity / functional connectivity was implemented. So, how could this enhance theory-driven intervention approaches based on the most popular theories of behavior change?

(Naslund et al., 2017) put forth the idea that the role of the DMN in introspective thinking could pose a hurdle to behavior change in individuals with severe mental illness. However, they also proposed that digital technology, such as mobile applications and wearable devices, could help surmount these hurdles by providing real-time data and personalized interventions. I have provided an application that is open-source and therefore modifiable to meet these needs. These digital interventions could potentially offer external prompts or reminders that help divert the focus of the individual from introspective thinking towards more goal-oriented thoughts and actions. They underscored the necessity for behavior change theories to guide the creation and assessment of these digital interventions, suggesting that a deeper comprehension of the DMN and its influence on behavior could inform the design of more effective interventions. I have contributed to this by providing a direct link between behavior and specific DMN activity / functional connectivity patterns.

Furthermore, Sheline et al. (2009) proposed that an overactive DMN, resulting in excessive introspection and contemplation, could undermine the effectiveness of behavior change theories that depend on selfbelief and motivation. This is especially pertinent to theories such as the Transtheoretical Model and the Health Belief Model, which are largely dependent on the self-perception and motivation of an individual to change.

Within the framework of the Transtheoretical Model, the journey of an individual through the stages of change (ranging from precontemplation, contemplation, preparation, action, to maintenance) might be hindered by excessive introspection and contemplation. If an individual is caught in a cycle of negative selfreferential thought, they may struggle to transition from the contemplation stage (where they recognize the issue but have not yet decided to act) to the preparation and then to the action stage (where they actively alter their behavior). Contemplation is marked by recognition of the issue but ambivalence about change, often weighing pros and cons. During preparation, individuals intend to change soon, setting goals and planning strategies. If dysfunctional DMN activity leads to excessive rumination in this phase, this could be disrupted by neurofeedback. Rumination in this context could be an intensified focus on perceived obstacles or potential failures, which could demotivate the individual and deter them from initiating action. Targeting the excessive introspection and contemplation with neurofeedback can be implemented by training the deep learning classifier in OpenVibe to recognize overly microstate C – laden thought patterns and recondition by negative reinforcement.

In a similar fashion, the effectiveness of the Health Belief Model could be influenced by the DMN. This model suggests that an individual's choice to participate in health-promoting behavior is shaped by their perceived vulnerability to a health issue, the perceived severity of the issue, the perceived benefits of taking action, and the perceived obstacles to taking action. An overactive DMN could potentially intensify the perceived obstacles or the severity of the problem by an individual, thereby impacting their self-referential beliefs about health issues and their capability to tackle them. This would be somewhat in line with the Transtheoretical Model in that an overactive DMN may hinder progression. (Desai et al., 2023), showed the potential of repetitive Transcranial Magnetic Stimulation (rTMS) as a treatment for depression by showing effects on the DMN. The study found that repetitive rTMS significantly altered DMN connectivity in male patients with depression, indicating that rTMS could be a promising therapeutic approach for this population.

3.3 Reflection on Physical Activity Measures

To control for possible influences of the pathological links on the effect of PA on the DMN and to look more precisely at the found effects, I further employed mixed effects linear modelling, including all measured control variables, anxiety score, depression score, autism score, ADHD score and stress score. This revealed a significant effect of PA measured by accelerometry (PAA) on the respective DMN microstate differences, indicating, that these indeed are connected. In both experiments, PAA significantly contributed to the higher variance explanation of microstate B in the less active group to the higher variance explanation of microstate C in the more active group, to the higher occurrence of B in the less active group, higher occurrence of C in the more active group and longer duration of C in the more active group. Furthermore, none of the control variables anxiety score, depression score, autism score, ADHD score and stress score significantly contributed to the effect of PAA on the specific dependent variables of global variance explanation, occurrence, or duration of microstates. However, it should be noted, that while PAA explains a significant part of the variance of the effects mentioned in a mixed effect linear modelling, that linear modelling based on accelerometry of one week should not be over-interpreted. While PAA seems clearly related to the differences, more research is needed to better understand the connection between PA and DMN EEG microstate activity, especially based on long-term accelerometry data. Furthermore, the PA measured by questionnaire did not contribute significantly to any of the effects, which, given the low to moderate correlation of $r = 0.37$ between measured and self-report PA, is not surprising.

Finally, the Hawthorne effect concerns research participation, the consequent awareness of being studied, and possible impact on behavior (McCambridge et al., 2014). The effect can manifest in various ways, such as participants changing their behavior due to the attention they receive or the desire to please the researcher. While previous research (Vanhelst et al., 2017) did not find that the awareness of wearing an accelerometer does affect PA in youth, there is a lack of research into this topic and our population did not include youths. It is possible, that simply wearing an accelerometer has a different effect on behavior in physically more active subjects than it has in physically less active subjects.

3.4 Reflection on Attention Networks

While I have shown a clear connection between DMN and attention, attention modulation is much more complex. A link from PA to the DMN using attention has been established, however, this link remained unspecific, due to scope restraint. To facilitate deeper understanding, I will briefly discuss this link in more depth. Attention is thought to be governed not only by the DMN, yet the DMN is crucially involved. As discussed above, attention can be classified into outward and inward attention from the point of view of subjects. Inward attention is believed to be largely governed by the DMN (Kim, 2015), while outward attention is governed by different networks. The human brain is a dense network of interconnected components, which collectively perform a wide range of cognitive operations (Poldrack, 2015). Attention is thought to be modulated by the dorsal attention network (DAN), ventral attention network (VAN), central executive network (CEN), salience network (SN), and default mode network (DMN) and are notable functional networks implicated in attention, executive regulation, and other cognitive processes (Menon, 2011). These networks overlap anatomically and functionally, as seen in figure 7 (Ross & Van Bockstaele, 2021).

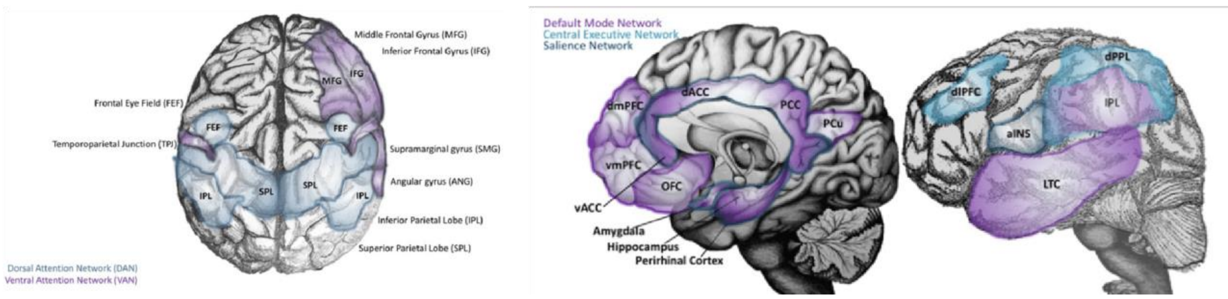

Figure 7. Core regions of the dorsal attention network, ventral attention network, central executive network, salience network and default mode network. Figure from Ross & Van Bockstaele, (2021)

Dorsal Attention Network (DAN). Primarily associated with top-down attentional regulation, the DAN is tasked with focusing attention on particular objects or locations within the visual field, contributing to tasks requiring concentrated attention like reading or searching for an item (Corbetta & Shulman, 2002).

Ventral Attention Network (VAN). Contrarily, the VAN is engaged in bottom-up attentional processes, orienting attention towards unexpected or prominent stimuli within the environment (Corbetta et al., 2008).

Central Executive Network (CEN). The CEN, managing executive functions such as working memory and decision-making, is essential in goal-oriented behavior and the integration of information from diverse brain regions (Menon, 2011).

Salience Network (SN). The SN plays a crucial part in recognizing and evaluating the salience of both external stimuli and internal states (Menon & Uddin, 2010).

The interaction between these networks is convoluted and fluid, as they often cooperate to support an array of cognitive functions (Sporns, 2011). To show the complexity and facilitate further understanding thereof, I will briefly look at two examples of what their interaction might look like.

Task Engagement and Disengagement: At the onset of a goal-oriented task that necessitates concentrated attention (like solving a math problem), the DAN and CEN become active, working in concert to maintain task engagement and appropriately direct attention (Dosenbach et al., 2008). Concurrently, the DMN minimizes distractions by reducing its activity (Raichle et al., 2001). This would correspond to microstate D, largely associated with executive processes and attentional control. resulting in lower occurrence of the microstate C pattern, since it is connected to DMN activity (Custo et al., 2017; Michel & Koenig, 2018; Tarailis et al., 2021). However, during breaks or moments of daydreaming, the DMN elevates its activity while the DAN and CEN may disengage (Mason et al., 2019), resulting in the inverse pattern, while the brain is regulating inward versus outward attention, a higher occurrence of microstate D for outward attention and C for inward attention was expected.

Salience Detection and Attention Shift: Upon encountering an unexpected or salient stimulus (e.g., a sudden movement or loud sound), the SN activates, signaling its significance. Subsequently, the VAN redirects attention towards the salient stimulus (Corbetta et al., 2008). Here, I would expect less activity in the microstate C pattern and higher occurrence of the microstate D pattern.

Cognitive Control and Task Switching: During complex tasks necessitating rule-switching (e.g., engaging in a strategy game), the CEN plays a pivotal role in maintaining current task rules and transitioning between them (Dosenbach et al., 2008). Additionally, the DAN and VAN might direct attention to relevant stimuli or locations during the task (Corbetta & Shulman, 2002). Since attention is involved and working memory, both of which have been shown to be related to the microstate D pattern (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017), I would expect higher occurrence of this state.

While the interaction is much more complex, it is important to note firstly, that specific link between DMN and PA via attention is more complicated than it might seem from the research work presented here and secondly, that the authors are aware of the complexity. The full spectrum of interaction of how PA relates to the DMN and interacts with it, is outside of the scope of this thesis, however the EEG data gathered allows for research into this interaction and will be published to encourage further investigation. Not only are the DMN and executive function interconnected (as seen above, see CEN), but also other links, an issue which will be addressed next.

3.5 Application of the Work

Brain Stimulation Techniques. At the very beginning of his doctorate, the author co-published a study on the interaction of the VAN and DAN (Paladini et al., 2020) and the reaction of the two networks to Transcranial Direct Current Stimulation (tDCS) on the temporoparietal junction (TPJ) (where the DAN and VAN intersect). However, it should be noted that the corresponding experiment was conducted prior to the doctorate in collaboration with the ARTORG centre for biomedical engineering research in Bern as part of the master's degree of the author and is not part of this thesis. Nevertheless, it bears relevance as an example of altering the functional connectivity of brain networks by using externally applied stimulation of the human brain. It was shown that stimulation of the TPJ can simulate the symptoms of hemineglect in healthy subjects, an attention-based disorder (for more information about the condition, see (Sarwar & Emmady, 2023)).

Similarly, research has shown that changes in executive function, self-perception, and stress can be induced in healthy subjects through the application of brain stimulation techniques such as tDCS and TMS. In a study by (Abedanzadeh et al., 2021), tDCS was utilized to modulate the dorsolateral prefrontal cortex (DLPFC), a brain region associated with executive functions. The researchers found that anodal stimulation of the DLPFC resulted in enhanced cognitive control in healthy participants. Additionally, a study by (Shelby, 2022) applied TMS to the left dorsomedial prefrontal cortex (dmPFC), a region linked to selfperception. The results indicated that inhibitory TMS led to alterations in self-referential processing, affecting self-perception in healthy individuals. Moreover, a study by (Carnevali et al., 2020) employed tDCS over the left DLPFC and modified healthy participants' stress response. These findings provide valuable insights into the neural underpinnings of executive function, self-perception, and stress, furthering our understanding of these cognitive and emotional processes.

Neurofeedback. Neurofeedback is a form of biofeedback that utilizes real-time monitoring of brain activity to enable individuals to regulate and modulate their brain functions consciously. This technique operates on the principle of operant conditioning, where individuals receive feedback about their brain activity through visual or auditory cues in response to specific mental tasks or desired brain states. The process involves the use of electroencephalography (EEG) or functional magnetic resonance imaging (fMRI) to measure brain activity, and the feedback is presented in a way that allows participants to gain awareness and control over their neural patterns. By providing information on their brain's current state, individuals can learn to self-regulate, promoting positive changes in cognition, emotions, and behavior. Neurofeedback has shown promise as a non-invasive and effective tool for various neurological and psychological conditions, including anxiety (Micoulaud-Franchi et al., 2021), ADHD (Lofthouse et al., 2012), and even enhancing cognitive performance (Sitaram et al., 2017).

Neurofeedback has shown promise in modulating DMN activity using electroencephalography (EEG) as the monitoring tool (Russell-Chapin et al., 2013). EEG-based neurofeedback involves real-time measurement and feedback of brainwave patterns, enabling individuals to actively regulate their brain activity (Sitaram et al., 2017). By providing participants with visual or auditory cues corresponding to their DMNrelated brainwave activity, they gain awareness of their current neural state and can learn to self-regulate, potentially influencing the functioning of the DMN. Research studies, such as those conducted by (Imperatori et al., 2017) and (Nicholson et al., 2020), have explored the effectiveness of EEG-based neurofeedback in targeting DMN connectivity and activity. These studies demonstrate how individuals can be trained to enhance DMN coherence and reduce DMN hyperactivity, offering a non-invasive and promising approach to improving cognitive and emotional well-being in individuals with DMN-related disorders.

The data measurement, collection and analysis pipeline developed in the experiments has been developed on top of the OpenVibe brain computer interface software (Renard et al., 2010). The software has been developed as an open-source platform to facilitate real-time behavior and cognition recognition based on machine learning, as a software platform to design, test, and use brain-computer interfaces in real and virtual environments. OpenVibe interacts with many programming languages and scripting languages such as C++, C#, Python, R, Matlab, lua and more. This makes it an attractive choice for the research community since many scientists are familiar with at least one of the aforementioned languages. While there are many natively implemented feature extraction and neural pattern recognition functions that are already machine learning based, OpenVibe allows for relatively easy implementation of proprietary classifier trained on own datasets. Since OpenVibe can natively interact with python scripts, the frequency time-series based classifier can be implemented after being trained on an individual's EEG measurements. Just like the classifier can sort 9dimensional data input from magnetometer, gyroscope and accelerometer axes into (in our case) 6 different behavior classes, it can easily be adapted to classify n-dimensional EEG sensor data input into x pattern classes (e.g. microstate dominance, frequency) where n denotes number of electrodes and x denotes number of pattern classes.

Neurofeedback techniques have already been implemented using OpenVibe: (Nawaz et al., 2023) utilized OpenVibe, to implement neurofeedback with the aim of enhancing cognitive abilities, specifically working memory performance, in healthy individuals. The authors focused on the Alpha EEG rhythm (8-13 Hz), which was captured from frontal sensors, based on which signals they managed to provide individuals with the ability to modulate their brain activity. The study found that EEG-based alpha neurofeedback training significantly improved working memory capacity in healthy participants. The neurofeedback training (NFT) group showed a significant increase in their working memory capacity compared to the control group, as measured by the N-back task. The NFT group also showed a significant increase in alpha power during the neurofeedback training sessions. These findings suggest that EEG-based alpha neurofeedback training may be a promising neuromodulation technique for improving cognitive function in healthy individuals.

3.6 Conclusion

Within this thesis an efficient retrainable algorithm was provided (Wieland, 2022)which classifies behavior based on multisensory frequency based sensory input. This allows for easy implementation of positive and negative feedback loops based on top of a classifier and real-time filtering framework in brain-computer interfaces. OpenVibe further allows for integrating and real-time combination of different sensor modalities, such as e.g., accelerometry, magnetometry, gyroscopy, EEG, electrooculography (EOG), electromyography (EMG), electrocardiography (ECG) and technically, every other sensor array which can provide data to a smartphone or computer. In the case of the OpenBCI hardware, the EEG experiment was implemented with, all the aforementioned sensors are natively included in the OpenBCI Cyton base model already.

Within this thesis a solid base for implementing neurofeedback therapy approaches to modify the underlying DMN activity which is related to PA has been provided: First, a solid argumentation that the DMN and PA are connected bidirectionally was described in terms of scoping review. Second, an efficient, frequency based, multisensory based application and a multimodal input dimension adaptive classifier, which can be retrained on new data to recognize behavior or frequency patterns was developed. Third it was shown that isolated functional connectivity differences between active and less active subjects. Furthermore, a large dataset of experimental and resting state EEG data and corresponding data on the screening scores of the most associated pathologies of the participants for further research into isolating differences in brainwave patterns was provided. Last and not least, I have provided an EEG recording pipeline, implemented in an open-source brain-computer interface software which has been proven in neurofeedback studies.

While there is a vast number of interactions between different variables linking PA to the DMN, only a few of which were discussed above, I do not see this as detrimental to the argumentative connection between the DMN and PA, but as a strengthening argument to link PA to the DMN. The complexity only adds to more interconnections to be explored to fully understand how both interact, in order to develop strategies to make people more active. However, all hinges in the end, on the application of the gathered additional knowledge, which will be discussed next.

The aforementioned approaches remain to be tested, neurofeedback approaches, tDCS, TMS approaches, and theory based combined approaches. The implementation and testing elude the scope of this thesis but have been made possible by the presented research. Real-time EEG microstate recognition and classification can be implemented using the tools and data provided with this research. Better understanding of the intricate interaction patterns between the different factors connecting and interacting with PA and DMN is necessary and new field of research has been opened. Further research will strengthen the direct connection of DMN and PA and the understanding of the complex interactions of their correlates.

While the groups in the experiments in our third study have not significantly differed in any of the measured control variables, which also are the linking paradigms in our meta-scoping review, the connection of PA and DMN in pathological subpopulations might be of particular interest. This would offer great insight into the interaction of the links between PA and DMN and serve as additional indicator of differing dysfunctional activity in the DMN and the shared consequences for different pathologies.

Finally, the direct influence of PA as manipulated variable on DMN activity is of particular interest. This might best be tested by actively manipulating the PA levels of different groups and comparing the resulting, optimally repetitive measurements. This would further serve as justification and guidance for future PA and combined DMN and PA interventions as discussed above.

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5 Artificial Intelligence Statement

In the course of the present work, several artificial intelligence (AI) tools have been utilized. Elicit (Ought, 2023) has been used to find scientific literature (Ought, 2023). Elicit is an AI based research tool that simplifies search for academic literature as well as assisting in generating an overview over selected scientific articles. ChatPDF (Lichtenberger & Lage, 2023) has been utilized to get overview about contents of scientific work. ChatPDF allows for summarizing and interacting with PDF files. ChatGPT (OpenAI, 2023) Model GPT-3.5 and GPT-4 have been utilized to refine the grammar and enhance the stylistic presentation of the text content of this thesis and to assist in Python, R and Matlab programming. ChatGPT is a large language model, trained on a very large knowledge base, using natural language processing techniques.

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6 Appendix

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Wieland, F., Wang, X., Nigg, C., & Erlacher, D. Difference in Microstate Activity Pattern Between Active and Inactive Healthy Adult's Default Mode Network

Connecting the Default Mode Network and Physical Activity: A Meta-scoping Review

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Abstract

In the evolving landscape of neuroscience and physical health, the interplay between the default mode network and physical activity remains a focal point of research. This review undertook a rigorous examination of 4505 studies, identifying 541 as pertinent to our inquiry. Our search spanned five prominent databases: SCOPUS, PubMed, SportDiscus, Cochrane, and APA PsychInfo. Our methodology involved a two-pronged approach: initially, we connected DMN and PA to a total of eight paradigms, both non-pathological and pathological. Subsequently, we collected all meta-analyses and review papers from the last 10 years which explored these

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connections. Our findings indirectly connect the default mode network and physical activity, underscoring a tangible link.This association not only paves the way for future research trajectories but also hints at broader implications in the realms of health and cognition.

Keywords: default mode network, physical activity, exercise health, therapy

Introduction

Physical activity (PA) is well-established as crucial for maintaining health. It has been linked to benefits such as improved heart health, weight management, mood enhancement, and increased lifespan [1]. Conversely, a lack of PA is associated with several diseases and mental health issues [2]. However, a significant portion of the global population does not meet the recommended physical activity guidelines set by the World Health Organization [3–5]. Identifying the factors that hinder physical activity are therefore of utmost priority for developing effective strategies to promote healthier lifestyles.

In light of these implications, it is crucial to consider the broader impacts of PA beyond just physical health benefits. PA is related to cognitive functions through those, to mental wellbeing. PA has been extensively shown to be linked to cognitive functions such as attention (Hajar et al., 2019), executive function [6], self-perception [7], coping with stress [8] , and emotional regulation [9]. It is also associated with reducing the risk of various mental disorders including ADHD [10], depression [11], autism spectrum disorder symptoms [12], and anxiety disorders [13].

Cognitive functions and their neuronal associations have been thoroughly researched in the past [14–16]. During the last two decades, a group of brain structures have increasingly been researched and found to be connected to many of the aforementioned PA correlates, termed the Default Mode Network (DMN) [17,18].

The Default Mode Network

The DMN is a large-scale brain network consisting of interconnected brain regions such as the medial prefrontal cortex, posterior cingulate cortex, and bilateral angular gyri [17]. It is predominantly active during rest and is associated with self-referential thinking, theory of mind, episodic memory retrieval, and envisioning the future [19]. The DMN plays a vital role in selfreferential processing, where individuals engage in introspective activities such as evaluating their traits and experiences [20], which is of utmost importance in many pathologies. In addition, the DMN is implicated in theory of mind, which refers to the ability to attribute mental states to oneself and others [21].

The DMN is also critically involved in planning and decision-making processes. During planning, individuals must anticipate the future, evaluate possible outcomes, and develop strategies, functions closely related to the DMN [22]. Specifically, the DMN is instrumental in autobiographical planning, allowing individuals to construct and evaluate potential future scenarios based on personal past experiences [22,23]. This ability to simulate future events helps individuals to anticipate outcomes and make informed decisions [24]. Additionally, a meta-analysis by [25] emphasizes the involvement of the DMN in value-based decision making, meaning assessing the personal significance of perceived consequences of decision outcomes, thereby facilitating motivation based on anticipated reward or negative valence avoidance.

Besides its role in normal cognitive functions, the DMN has also been linked to various psychiatric and neurological disorders. Abnormalities in DMN activity and connectivity have been implicated in conditions such as Alzheimer's disease, depression, and autism [26]. The network is also associated with various other pathologies, suggesting its broader relevance in mental health [19].

Similar to PA, the DMN has been linked to attention [27], executive function [28], selfperception [29], stress [30], emotional regulation [31], and the same mental disorders such as ADHD [32], depression [33], autism [32], and anxiety disorders [34].

The body of research related to the DMN and therefore scientific impact cannot be understated, at 3000 publications on the topic as of 2015 [19].

Physical Activity and the Default Mode Network

The shared links in PA and DMN research suggests that there might be an interaction between PA and the DMN which has so far not been sufficiently explored scientifically. As example, it might be reasonable to believe that planning of future events, as well as motivational processes influence, whether or not we will be physically active in the near future. To evidence this line of argument, one might note that the DMN has been shown to be linked to future planning, i.e. to simulate future events [20,35,36], as well as motivational processes [19,37,38].

For example, PA could be influencing the activity of the DMN, which in turn has effects on cognitive functions and emotions. This could explain why PA has mental health benefits and enhances cognitive performance. Additionally, abnormal DMN activity, which is observed in several mental disorders, might affect an individual's engagement in PA.

To our knowledge, this connection between PA and the DMN has not been researched directly. However, some studies show connections of PA to parts of the DMN: [39], showed that PA over a decade modifies age-related decline in perfusion, gray matter volume, and functional connectivity of the posterior default-mode network. The researchers measured physical activity using a combined measure of both aerobic and non-aerobic fitness, which they referred to as a "physical activity score". They then used multiple measures of brain health, including functional connectivity, gray matter volume, white matter integrity, and cerebral perfusion, to examine the relationship between physical activity and brain health in aging. They concluded, hat PA is positively associated with functional connectivity within the most age-sensitive resting state brain networks, as well as gray matter volume, white matter integrity, and cerebral perfusion and found that PA is positively associated with functional connectivity between the posterior cingulate cortex (PCC) and the middle frontal gyrus (MFG) in elderly people. Voss [40] observed that engaging in aerobic exercise training among older adults increased the taskindependent differentiation between the executive network and the DMN and Burdette [41] reported that acute exercise also led to increased connectivity within the DMN, in an experiment, the exercise group showed greater connectivity within the hippocampus and ACC based on network analysis. These findings connect PA at least partly to the DMN, by showing connections between PA and part of the DMN.

However, there is a very large body of research connecting PA indirectly to the DMN. In this review, we argue that this interaction indeed exists and simplify and structure the available ample evidence. We conducted a systematic scoping meta-review of the recent literature available. Due to the very large body of scientific papers, we focussed only on review papers and meta-analyses already structuring the available scientific literature.

Present Study

We carried out a review of reviews and meta-analyses from the last 10 years, connecting both the DMN and PA to attention, executive function, self-perception, stress, ADHD, depression, autism and anxiety (see figure 3). Many more links exist, however these are the most extensively researched and best understood ones and serve to illustrate the complex connection.

Understanding this interaction between DMN and PA is vital for creating strategies that promote PA and, consequently, physical and mental health. In turn, understanding the activity in the DMN relating to physical activity will enable to find more precisely targeting neurological therapy approaches, such as brain stimulation like transcranial magnetic stimulation [42], transcranial direct current stimulation [43] or EEG based neurofeedback [44].

Methods

In compliance with the PRISMA 2020 guidelines [45], adherence to aforementioned guidelines was maintained to the extent allowed by the innovative methodology employed. A systematic meta-review was conducted, wherein the associations between PA, DMN, and their shared relationships were analyzed (see figure 2). For the context of this study, systematic meta-review is defined as an exhaustive analysis solely based on review papers and meta-analysis papers. Due to the vast extent of literature of research relevant to each association, the scope of the systematic review was restricted to the following parameters. Papers included in the study had to be no older than ten years and belong to the categories of review paper, meta-analysis paper, or a combination thereof. The restriction of literature to the last 10 years as of writing was chosen to maximize relevance of the information to future research. The rapid pace of technological and methodological innovation means that older research may not reflect the current state of knowledge or practice. By focusing on more recent studies, this review ensures that the findings are aligned with the latest methodologies, tools, and understanding in the subject area. The goal of this study was not to exhaustively capture all relevant information ever published, but to prove a link between two paradigms, using a strong line of reasoning based on existing and relevant literature. Furthermore, for associations that are non-pathological in nature, such as attention, executive function, self-perception, stress or emotional regulation, the papers had to be based on non-clinical populations. Conversely, in pathological associations such as ADHD, depression, anxiety, or autism spectrum disorders, clinical populations as well as nonclinical comparisons had to be present in the base data for the review and or metaanalysis. Furthermore, we restricted our search to the following databases: PsychInfo, SCOPUS, PubMed, Cochrane and SportDiscus.

Software

To maximize repeatability of the conducted research, jupyter notebooks running on Python 3.11 were utilized. Data was extracted from PubMed and APA PsychInfo using their application programming interface (API). Their respective APIs allow for easy specification of the search parameters. The query string in both databases was identical. Either "default mode network OR task-negative network OR resting-state network" or "physical activity" together with XXXX for the respective links and synonyms of the links' names. For attention, "attention OR attentive" was used, for executive functions, "executive function OR executive control", for self perception “self perception OR self-perception OR self concept OR self-concept OR concept of the self”, for stress “stress”, for emotional regulation “emotional regulation OR emotional control OR emotional self regulation OR emotional self-regulation OR affective regulation”, for ADHD “attention deficit hyperactivity disorder OR attention-deficit hyperactivity disorder OR attention deficit / hyperactivity disorder OR ADHD OR ADD OR attention deficit disorder OR attention-deficit disorder”, for depression “depression OR MDD OR depressive disorder OR major depression disorder OR major depressive disorder”, for anxiety “anxiety”, and for autism spectrum disorder “autism OR ASD OR autism-spectrum disorder OR autism spectrum disorder” was utilized. The Cochrane and SportDiscus databases’ APIs could not be accessed, and searches were performed manually, and results saved in CSV files. Search parameters for SCOPUS were defined using the advanced search method. Combination of search terms followed the aforementioned pattern, to illustrate, the following pattern was used for ADHD and PA related reviews and meta-analyses: TITLE-ABS-KEY ("physical activity") AND ((TITLE-ABS-KEY ("ADHD") OR TITLE-ABS-KEY ("ADD") OR TITLE-ABS-KEY ("attention deficit") OR TITLE-ABS-KEY ("attention-deficit")) AND PUBYEAR > 2012 AND (DOCTYPE ("re") OR DOCTYPE (“meta”)) OR (KEY(“review”) OR KEY(“meta”)) AND (LIMIT-TO (SUBJAREA , "NEUR") OR LIMIT-TO (SUBJAREA , "PSYC") OR LIMIT-TO (SUBJAREA , "SOCI") OR LIMITTO (SUBJAREA , "BIOC") OR LIMIT-TO (SUBJAREA , "MEDI")). SCOPUS uses an untransparent proprietary matching and synonym algorithm which yields many results not containing either of the keywords in either of the subcategories “title” “abstract” or “key” (denoting keywords matching). The API does not allow for obtaining the abstract, which compelled us to manually search, save CSV files and then clean them.

Further data cleaning

After obtaining CSV files, they were loaded into a jupyter notebook, running on Python 3.11

[46] and standard toolboxes. Those comprised pandas [47] for data frame handling, numpy [48] for high efficiency data parallelizing and fuzzywuzzy [49] for parallel computing fuzzy logic similarity based cross matching. Subsequently to cleaning the data, CSV files, only containing title, abstract and dois, were loaded into ASReview [50] for screening of articles. The data was restricted to those three columns, such that factors potentially influencing the sorting algorithm were minimized. The data from APA PsychInfo, PubMed and SCOPUS databases were screened separately with ASReview to also minimize database-specific formatting influencing the data sorting algorithms and to allow for separate testing for within- and between-rater reliability.

ASReview

ASReview is a Python based, graphical user interface based, semi supervised machine learning based tool that enables the user to efficiently screen large amounts of scientific papers [51] After manual sorting of few studies into relevant and irrelevant, either a support vector machine, naïve bayes classifier, random forest algorithm or neural network is trained on the data and presents studies according to relevance first. With each manual classification, the algorithm is updated, and the relevance converges further, allowing for great efficiency of sorting [52]. The default naïve bayes classifier was employed to minimize algorithm training time. A cut-off criterion of stopping the screening process after 200 studies labelled as irrelevant in immediate succession was applied [53]. However, only 3 times out of 42 (3 databases time 16 links) this stopping criterion was met.

Each of the files' columns were renamed and standardized to load into ASReview later.

Cochrane and SportDiscus yields were limited and thus screened manually. APA PsychInfo, PubMed and SCOPUS yields were combined in the following manner: First, APA PsychInfo data was loaded, columns renamed, and data restructured, such that it was compatible with ASReview input requirements. Subsequently, the data was screened using ASReview for each link separately and the resulting CSVs exported. Next, the respective PubMed files were loaded and all APA PsychInfo overlaps removed. This was done using fuzzy logic partial content matching of abstract and title with an 85% matching exclusion criterion and parallel processing, to ensure that duplicates were removed. Subsequently, the files were exported and screened, using ASReview. In the next step, the SCOPUS files were imported into the jupyter notebook and counter matched at the same 85% fuzzy logic counter matching exclusion criterion. Since SCOPUS employs similarity based algorithmic sorting, titles and abstracts were checked again, so only the ones containing the search terms remained. All duplicates were excluded and a randomly selected 20% of the PubMed files were exported again for within and inter-rater reliability testing. The resulting CSVs were exported to, and screened using, ASReview. After screening, the resulting CSVs were reimported to the jupyter notebook and within-rater reliability was calculated and the data of all respective files combined, and duplicates removed. 20% of the data of each file of each link were combined and exported for inter-rater reliability testing. An independent rater with a PhD in neuropsychology (Rebecca Coray) counter screened 20% of the data using ASReview with the same parameters. In case of an accuracy of less than 80%, the complete sorting was planned to be repeated, however, this did not apply for either within- (95.19% accuracy) or inter-rater (89.14%) reliability.

Exclusion criteria for screening

Utilizing ASReview, the following exclusion criteria were employed for the screening process: For the non-clinical links, only reviews and meta-analyses based on non-clinical subpopulations were included. For the clinical links, only reviews and meta-analyses including at least one nonclinical control group or study were selected. The study in question had to link the search terms and be published after 2012. All studies deemed relevant were screened again to ensure the application of the criteria.

Results

A total of 4505 records matched with the queries in the 5 databases. Before screening, a total of 914 duplicates were removed from the screening files. Through manual screening, an additional 2986 records were removed in total. 605 files were sought for retrieval, however, only 570 could be successfully retrieved. Another 5 records, upon second screening, had to be excluded because they did not methodology criteria; they were non-clinical links, but not only being based only on healthy subgroups or they were clinical links, but did not include nonclinical control groups. Furthermore, 25 studies, upon more thorough screening, were excluded due to paradigm issues. Those issues consisted of missing control group / being based on case studies only (n = 13), containing no measures of comparison and / or statistics (n = 8) and being strongly biased towards hypothesis confirmation, i.e. only comprising studies confirming the hypothesis (n = 4).

541 studies from the last 10 years (comprising 237 reviews, 178 meta-analyses, and 126 mixed designs) were used to connect DMN to PA in an indirect manner. A total of 149 (comprising 237 reviews, 178 meta-analyses, and 126 mixed designs) were included for evidence of the connection of DMN and the linking paradigms, whereas 392 studies (147 reviews, 128 metaanalyses, and 117 mixed designs) were included to connect PA to them. For detailed information, see figure 3, depicting exact numbers of studies connecting the two paradigms.

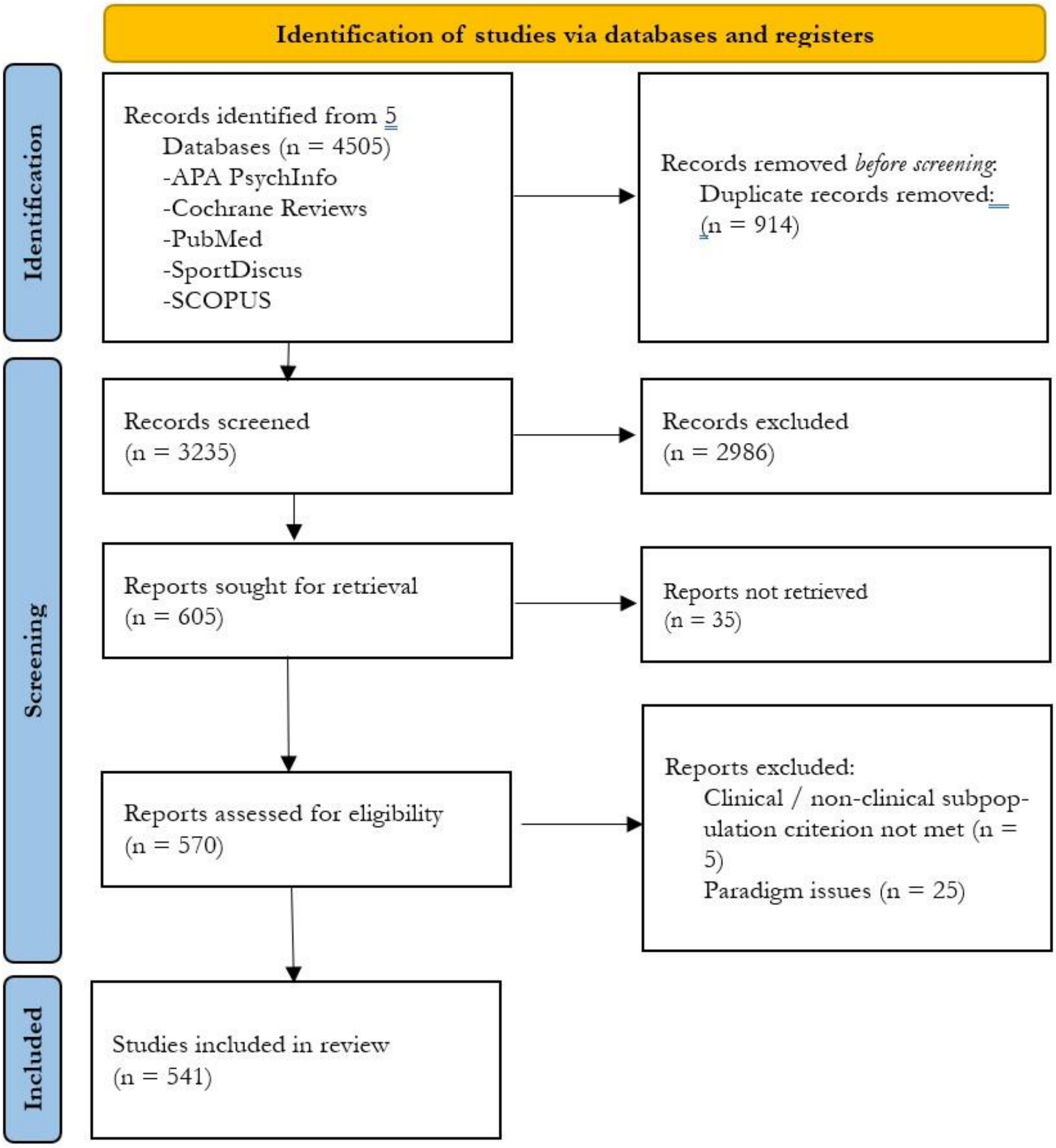

Fig 2 PRISMA flowchart of study identification, screening, and inclusion

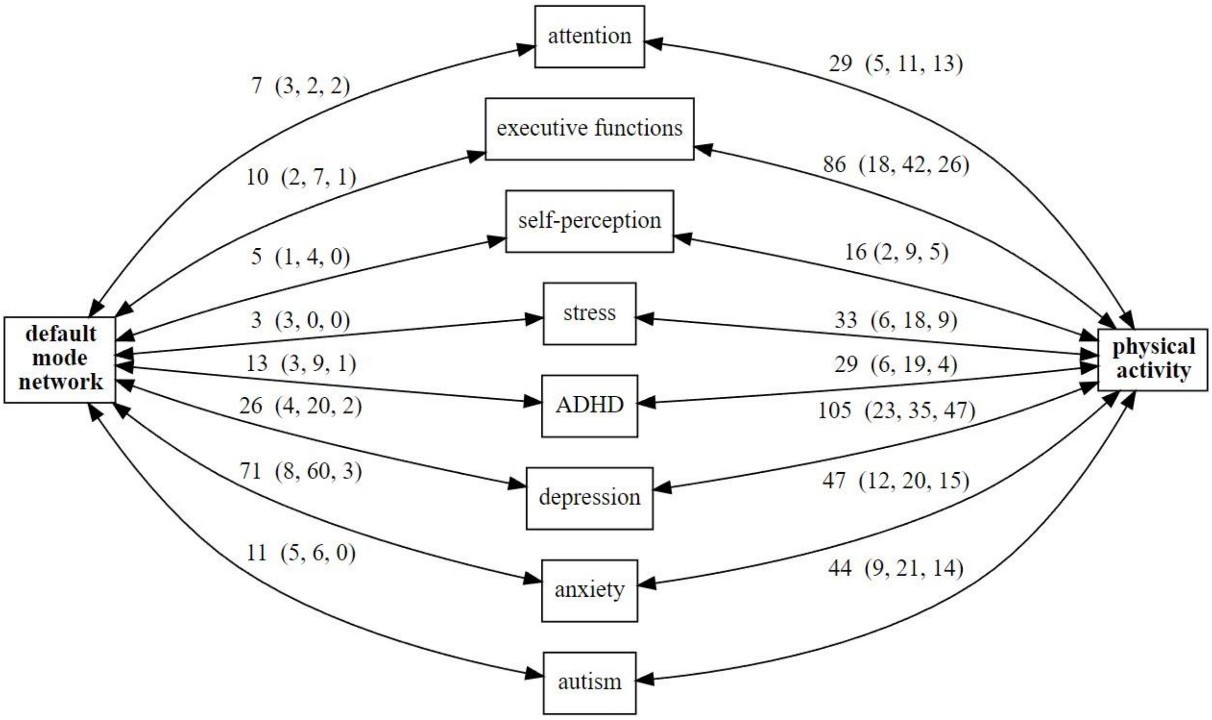

Fig 3. Diagram of argumentation with reviews and meta-analyses. Each arrow represents an argumentative link explored using a review of available reviews and meta-analyses from the last 10 years, linking either PA or DMN to the linking paradigms bidirectionally. Results are displayed as numbers: total papers (reviews, meta-analyses, combined approaches).

Intra- and Inter-rater-reliability

20% of files form each data base were randomly inserted into the screening of the data from another database to test for within rater reliability and given to a second independent rater to test for inter-rater reliability. Of the 645 double screened files within rater, 614 were classified identically (95.19% accuracy) and between rater 575 (89.14%). For detailed information, see Appendix 1.

Discussion

Our novel approach connected both DMN and PA to many research areas like attention, executive functions, self perception, stress, ADHD, depression, anxiety and autism. By showing this bidirectional connection using only recent and only review-/ and meta-analyses-based research, we established a strong connection between the DMN and PA. We found that a lot of reviews are at least partially based on correlative measures, yet the conclusions drawn are unidirectionally or the evidence is presented as being unidirectional. While the therapeutic value of PA is unquestionable, differences in prevalence of diseases or in cognitive functions are often interpreted to be influenced by PA but not vice versa [54–57]. However, the evidence we present, strongly connects the two paradigms of DMN and PA and justifies further research into the connection between them.

Due to the sheer amount of research reviewed here, we only briefly review each of the links here, using selected reviews and meta analyses gathered in the reviewing process: PA has been found to have a positive impact on cognitive functions, including attention, suggesting that engaging in physical activity could potentially enhance attentional control, which is crucial for various cognitive processes [58]. Conversely, attention abilities predict physical activity performance [59,60]. The DMN is also highly implicated in being associated with attention, interacting with the dorsal attention network for external attention, while it itself is more associated with internal attention [61].

PA interventions have also been shown to significantly improve executive functions in children and adolescents, indicating the potential of physical activity in enhancing cognitive processes that are crucial for goal-directed behavior [62]. Conversely, Executive functions predict physical activity behavior [59] and the DMN and the frontoparietal control network interact dynamically to support executive functions [63].

Moreover, PA is positively associated with body image and self-esteem in children and adolescents, suggesting that PA could potentially enhance self-perception, contributing to better mental health and well-being [64]. Conversely, self perception predicts PA levels in adolescents, even when controlled for BMI and weight status [65], while the DMN is also involved in self-referential mental activity, which is crucial for self-perception [66].

The DMN is involved in the cognitive and emotional aspects of stress processing (Soares et al., 2013), while PA serves as a buffer against stress, with individuals who are physically active being less likely to experience the adverse effects of stress [67]. At the same time, stress leads to being less physically active in adults [68]. This study highlights, that evidence which is correlative often is interpreted in a unidirectional fashion, whereas the connection is unclear.

Furthermore, PA interventions improve cognitive functions and reduce all symptoms in adults with ADHD, such as inattention, hyperactivity/impulsivity, emotional problems, and behavioral problems [69], while the DMN is disrupted in individuals with ADHD, which could potentially contribute to attention deficits and hyperactivity [32].

There is also a significant inverse relationship between PA and depression, with PA serving as an effective strategy for the prevention and treatment of depression [70] and depression severity predicting physical activity levels [71], while the DMN is hyperconnected in individuals with depression, and this hyperconnectivity is associated with the severity of depressive symptoms [72].

PA interventions can also improve motor skills, social skills, and behavioral issues in individuals with autism [73], while children and adolescents with autism spectrum disorders show lower levels of activity than their [74], while the DMN is disrupted in individuals with autism, and this disruption is associated with deficits in social cognition [75].

Lastly, there is a significant inverse relationship between PA and anxiety, with PA serving as an effective strategy for the prevention and treatment of anxiety [76], while anxiety and depression can lead to lower physical activity levels [77]. Anxiety is also strongly connected to the DMN, which has significant structural and functional connectivity differences in people with anxiety, compared to healthy adults [78].

In conclusion, the current review provides compelling evidence for the indirect connection between the DMN and PA through various linking paradigms. These findings suggest that both the DMN and PA play crucial roles in cognitive and emotional processes, and their interaction could potentially provide new insights into the understanding and treatment of various mental health conditions.

Future directions

Further investigation into the specific connection between PA and the DMN is necessary to better understand the nature of the direct link. Experimental paradigms directly manipulating or measuring PA or the DMN activity can shed light on the specific connection.

Transcranial magnetic stimulation (TMS) has been shown to be effective in treating various psychological disorders [79–81]. Specific stimulation of the DMN using tDCS and TMS have been shown to be effective in treating depression [81], post traumatic stress disorder [80] and anxiety disorders [82]. Similarly, PA has been shown to be effective in preventing and treating depression and anxiety [83,84].

Following the reasoning that DMN and PA are connected, not only could PA be used as treatment for many pathologies and associated symptoms, but treating DMN functionality issues could impact PA levels, opening a new field of possibilities in treating many associated problems. It is therefore of utmost importance to further research and understand the link between DMN and PA.

Limitations

Current paradigm only connects the two main paradigms in an indirect manner, albeit based on ample literature. Whereas the connective links between PA and the linking paradigms have been shown bidirectionally, meaning that e.g. PA has an effect on attention, and, attention ability has an effect on PA - many of the DMN links are based on neuropsychological research. Many studies are by nature of the research method correlative, meaning that e.g. it is hard to determine whether subjects' attention ability impacts functional connectivity in the DMN or altered functional connectivity affects attention ability, even though it is likely to be the case to be bidirectional. This bidirectionality is by e.g. individuals with depression showing altered activity in the dorsolateral prefrontal cortex, but this altered activity is possible to be corrected for in part by transcranial magnetic stimulation of the same areas [72]. On the other hand, we have shown, that in healthy subjects, symptoms can be induced by altering brain activity [85]. To account for this untransparent bidirectionality, however, we applied our meta meta review approach, which alleviates this, providing ample evidence for each link. Since we link the DMN to PA using many different links based on large scientific bodies, the clearer becomes the indication that the two paradigms are in fact bidirectionally interconnected, even if it should not be the case for one of the links. However, causality is hard to prove, even if changing brain activity is proven to induce symptoms, we do not know whether symptoms cause altered brain activity. However, given that e.g. grieving over losing a loved one (an external factor) causes similar DMN activity as individuals with major depression episodes show [86], or externally induced fear and anxiety disorders sharing DMN abnormalities [87], there is actually evidence for bidirectionality.

Furthermore, it should be noted, that attention, while positing a strong link between the DMN and PA, is governed only partly by the DMN, more recent approaches explain attention ability with the triple network model approach [88]. The triple network model consists of three core neurocognitive networks: the DMN, central executive network (CEN), and salience network (SN) as the three most important intrinsic networks for human brain activation regarding attention. To explore the interaction of these is outside the scope of this paper, however it should be noted, that the CEN and SN have been implicated to play roles in many of the links as well (e.g. , [89,90]. While the DMN by nature mostly is associated with resting state activity, it should be noted that its activity is strongly implicated in antagonistic dynamics in regard to task-positive networks [91].

Furthermore, while our approach samples ample literature, by nature of this approach, overlap could not be accounted for in all review papers and meta-analyses papers. While overlap is expected to be significant, the argumentation is not weakened by this, since different approaches, even if on the same basis, only strengthen the argumentative links and similar approaches replicate, and therefore also strengthen, argumentative linking.

It should be noted that many of the links used to connect the two main paradigms are heavily interconnected themselves, although this escapes the scope of this paper.

Future research

While in this paper strong evidence has been provided, the evidence remains indirect. To our knowledge, few studies attempted to connect the DMN and PA so far directly, showing greater anteroposterior DMN functional connectivity in long-term elderly yoga practitioners [92] and that aerobic exercise may be associated with changes in brain activity within the DMN [93], although evidence remains moderate. To examine the direct relation, randomized controlled trials with repeated measures would be needed, or direct measurement of physical activity levels and neural activity in healthy and or pathological subgroups are needed.

Another approach would be therapeutical, showing altering PA levels over a longer period of time changes DMN activity as opposed to a control group with the same PA level. Neurofeedback approaches based on the DMN have shown great promise [94,95], as have TMS approaches [96,97] and tDCS approaches [98,99], in modifying pathologies connecting the DMN to PA. Thus, future research should focus on the effect of applying these techniques on PA levels.

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Appendix

File	Total	Included	meta analysis	review	combined design	extracted control	within rater	true positive	true negative	false positive	false negative	between rater	true positive	true negative	false positive	false negative
DMN-attention	69	7	6	3	2	14	13	0	13	0	1	12	11	1	1	1
PA-attention	239	29	10	28	9	48	46	3	43	0	2	43	26	17	4	1
DMN-executive functions	151	10	3	8	1	31	29	12	17	0	2	28	27	1	1	2
PA-executive functions	362	86	33	77	24	73	69	30	39	0	4	65	45	20	3	5
DMN-self perception	209	5	1	4	0	42	40	34	6	1	1	37	21	16	3	2
PA-self perception	45	16	5	16	5	9	9	6	3	0	0	8	6	2	0	1
DMN-stress	41	3	0	3	0	9	9	7	2	0	0	8	4	4	0	1
PA-stress	304	33	11	31	9	61	58	1	57	2	1	54	43	11	2	5
DMN-ADHD	282	13	4	10	1	57	54	32	22	1	2	51	39	12	5	1
PA-ADHD	75	29	8	25	4	15	14	2	12	0	1	13	12	1	0	2
DMN-depression	109	26	10	18	2	22	21	2	19	0	1	20	2	18	1	1
PA-depression	648	105	54	89	38	130	124	12	112	3	3	116	50	66	6	8
DMN-anxiety	240	71	9	65	3	48	46	17	29	1	1	43	13	30	3	2
PA-anxiety	310	47	24	38	15	62	59	49	10	1	2	55	24	31	3	4
DMN-autism	18	11	4	7	0	4	4	0	4	0	0	4	0	4	0	0
PA-autism	97	44	16	40	12	20	19	2	17	0	1	18	0	18	1	1

Appendix 1: Inter-rater and within-rater reliability confusion matrix.

Original Paper

A Trainable Open-Source Machine Learning Accelerometer Activity Recognition Toolbox: Deep Learning Approach

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Abstract

Background: The accuracy of movement determination software in current activity trackers is insufficient for scientific applications, which are also not open-source.

Objective: To address this issue, we developed an accurate, trainable, and open-source smartphone-based activity-tracking toolbox that consists of an Android app (*HumanActivityRecorder*) and 2 different deep learning algorithms that can be adapted to new behaviors.

Methods: We employed a semisupervised deep learning approach to identify the different classes of activity based on accelerometry and gyroscope data, using both our own data and open competition data.

Results: Our approach is robust against variation in sampling rate and sensor dimensional input and achieved an accuracy of around 87% in classifying 6 different behaviors on both our own recorded data and the MotionSense data. However, if the dimension-adaptive neural architecture model is tested on our own data, the accuracy drops to 26%, which demonstrates the superiority of our algorithm, which performs at 63% on the MotionSense data used to train the dimension-adaptive neural architecture model.

Conclusions: *HumanActivityRecorder* is a versatile, retrainable, open-source, and accurate toolbox that is continually tested on new data. This enables researchers to adapt to the behavior being measured and achieve repeatability in scientific studies.

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KEYWORDS
activity classification; deep learning; accelerometry; open source; activity recognition; machine learning; activity recorder; digital health application; smartphone app; deep learning algorithm; sensor device

Introduction

Background

The last decade has seen a significant increase in worldwide smartphone ownership [1], with approximately half of the world's population now owning a smartphone and a device penetration rate of 80% in Germany and the United Kingdom [2]. Even low-end smartphones are equipped with various sensors, including accelerometers, gyroscopes, proximity sensors, magnetometers, and GPS receivers, along with energy-efficient processors and stable internet connections.

With the advent of smartphones and wearables, physical activity analysis has greatly gained in popularity.

Accelerometry-based behavior analysis has a variety of applications, such as fall detection in older patients [3], health monitoring [4], work-related stress analysis [5], and sleep analysis [6]. The widespread use of accelerometry in everyday smartphone apps has reduced the cost of gyroscope and accelerometer sensors, which has in turn accelerated their development. While wearables have gained popularity as accelerometer devices, smartphones still make up the majority of them.

Many studies have shown the accuracy and reliability of smartphone sensors in accelerometry [7-9]. Although wearables tend to provide more accurate behavior classifications, the potential of using smartphones far outweighs the additional accuracy gained from wearables. Although they are more precise thus far [10], the cost of wearables for larger study populations is very high, compared with the widespread popularity and affordability of smartphones, making them a more accessible option for research. Additionally, smartphone apps are easier to distribute, update, configure, and adapt to specific research questions than wearables. Wearables also have the disadvantage of limited software support and closed-source software, making research based on previous software nonreproducible after algorithm updates. This means that wearables bought for research purposes must be replaced on a regular basis.

Most importantly, however, the default software of wearable manufacturers is in almost all cases not open-source, meaning that after each change of the algorithm (ie, app update) that classifies behavior, research based on previous software is not reproducible anymore. Furthermore, in most cases, charges apply for the use of the said software. On the other hand, some smartphone manufacturers offer free, open-source toolboxes for movement activity recognition, such as Samsung and Huawei. However, these toolboxes only recognize a limited number of activity types and are at the time of writing not trainable to new activities. The purpose of both, however, is for them to be integrated into applications, so they can be used to determine whether a smartphone user is moving and is active or not, in order to interact with application functionality, such as energy saving while not moving, clocking active hours, or encouraging movement when a user is inactive. While data can be collected and stored, the behavior classes are fixed and neither trainable nor retrainable. To address these limitations, the scientific community needs access to an open-source, adaptable behavior analysis toolbox that also facilitates reproducible research and is adaptable to specific research questions. To fulfil this need, we present our open-source, deep learning–based behavior analysis toolbox. Our Human Activity Analysis toolbox includes a proprietary Android app, 2 deep learning algorithms, scripts to process data, and a continually expanding sample data set. The toolbox has been validated with a sample of 68 University of Bern students and employees.

Activity Recognition and Deep Learning Background

Deep learning algorithms have gained importance in classifying human behavior based on sensor data collected from accelerometers, gyroscopes, and magnetometers [11-18] (for a deeper understanding and comprehensive overview, see [19]). These algorithms are based on artificial neural networks, and specifically, deep neural networks (DNNs) have become the dominant approach for activity recognition as of 2022. DNNs consist of multiple layers of neurons of similar or different types, and the functionality of these neurons is determined by the nature of the layers and the way they are interconnected [20,21]. It is important to note that a standard neural network consists of many simple, connected processors called neurons, each producing a sequence of real-valued activations. Depending on the problem and how the neurons are connected, such behavior may require long causal chains of computational stages. Thus, if multiple layers of neurons are used sequentially, we speak of DNNs [20].

Most DNN architectures consist of a convolutional neural network (CNN) layer, followed by either a feedforward neural network (FNN) layer or a recurrent neural network (RNN) layer. Unlike the output from an RNN neuron, which is fed back into the same layer, the output from an FNN neuron is only connected to the next layer. CNNs handle variable input dimensions quite well and are mainly used for feature extraction for the RNN or FNN layer, which, combined with a prior CNN, output a better generalization than if fed with raw sensor data [22]. However, FNNs only work well with data of the same input dimensions, and RNNs only work with a fixed number of streams. As a result, the widely used CNN-RNN-FNN combinations do not work with varying input dimensions. This means that if data collection from one sensor stops, the movement type cannot be classified by the DNN that was trained on multiple input dimensions. In order to save battery life in smartphones during long-term recordings, it is often desirable to temporarily disable certain sensors or to vary the sampling rate of sensors, which results in changing the input dimensions for the DNN.

When a participant is sitting for an extended period, disabling the gyroscope sensor can conserve battery life. This is because the rotational position is unlikely to change significantly without significant acceleration changes unless the person is in an aircraft and the gravitational acceleration is being compensated for in the data. In order to determine when the activity type changes, it is sufficient to use a low recording frequency. This means that it is possible to deactivate the gyroscope and magnetometer and lower the accelerometer recording frequency. To determine when the activity type changes, a very low recording frequency suffices, so it is desirable to deactivate the gyroscope and magnetometer and lower the accelerometer recording frequency significantly. Dummy data can be generated to compensate for missing data in order to maintain the accuracy of the trained CNN-FNN-RNN model [23]. However, this approach can result in a loss of accuracy in classification. Another solution is to insert a global pooling layer, but this also leads to a reduction in accuracy. This, however, leads to accuracy loss in classification. Another solution is to insert a global pooling layer [24], but this also leads to a reduction in accuracy.

Previous publications on accelerometry-based movement recognition have shown great success but significant limitations. Ordóñez and Roggen [15] presented a deep-CNN–based framework, which they tested against models such as decision tree, random forest, and support vector machines. Trained and then tested on a data set, the accuracy reached up to 86.7%. The authors then analyzed which component of the data had the biggest impact on classification accuracy and determined this to be changes in acceleration, which is in line with our own results.

Wang et al [11] offer a comprehensive survey of recent advancements in activity recognition and associated methodologies. Their work sheds light on the various strengths and weaknesses of deep learning models when it comes to activity classification. Although most models perform accurately on their trained data [25], significant limitations remain. First, the lack of extensive, labeled accelerometry data sets limits their efficacy. Second, the generalization capabilities of models need improvement. Third, models struggle with sensor noise and input variability, highlighting a need for greater robustness. Our algorithms aim to address these issues, working to mitigate the associated limitations and enhance overall model performance. To achieve this, we build upon previous research by incorporating and improving upon their methodologies while also introducing our own additional data set for algorithm training.

Malekzadeh et al [26] proposed a new model, which tries to counteract the aforementioned shortcomings by introducing a *dimension-adaptive pooling* (DAP) layer, which makes DNNs robust to changes in not only sampling rates but also dimensional changes of the data due to varying sensor availability.

The authors also introduced a *dimension-adaptive training* layer, and combined it with the classical CNN-FNN-RNN approach and the DAP layer. They claim that dimension-adaptive neural architecture (DANA) can prevent losses in classification accuracy, even under varying sensor availability and temporal sampling rate changes. This model was tested on 4 publicly available data sets, including the MotionSense [27] data set, which consists of accelerometer data from 24 students at Queen Mary University of London.

Our goal was to not only implement this model into our own DNN, but also to improve upon it and validate it using our own data. The robustness of the DANA model is very promising, making it a valuable addition to our research.

Methods

Ethical Considerations

According to the guidelines stated on the Ethics Commission page of the University of Bern's Faculty of Human Sciences, no ethics committee approval was required for this research. This conclusion is based on the fact that all data was collected with participants' informed consent, the data collection was conducted anonymously, and the research activities only involved non-hazardous tasks such as standing, sitting, walking, and ascending or descending stairs. No personal data was collected.

Training Data

The data used for the initial training of the neural network was gathered from the MotionSense Github repository. These data consist of accelerometer and gyroscope readings from an iPhone 6s (Apple Inc), collected at a frequency of 50 Hz by 24 participants who followed a set of actions on the campus of Queen Mary University of London. These actions included ascending or descending stairs, sitting, walking, standing, and jogging (Figure 1). The data recorded gravity, acceleration, rotation, and attitude on 3 axes.

After conducting a principal component analysis, we found that the X, Y, and Z acceleration and rotational changes were the most predictive factors in classifying the participant’s behavior (Figure 2). Therefore, only these 6 values were used in the training of the algorithm. As a result, our app only records these 6 values, which are then used for further analysis.

To gather more data and validate our model, we set up our own course of action on the campus of the Centre for Sports Science at the University of Bern, modeled after the course used at Queen Mary University. A total of 68 participants (aged 21-59, median 26, SD 3.2 years), who were students and employees of the University of Bern, completed the course while our *HumanActivityRecorder* Android app (Multimedia Appendix 1) was running and collecting data. All participants were fully informed about the task and gave their consent for the data collection.

The course consisted of approximately 300 seconds of walking, jogging, sitting, and walking up and down stairs and standing still (Figure 3). All participants completed all segments of the course, and the corresponding data segments were manually labeled for use in training the models.

Figure 1. Course for accelerometer data collection on the campus of the Queen Mary University of London for the MotionSense data set; graph from Malekzadeh et al [26].

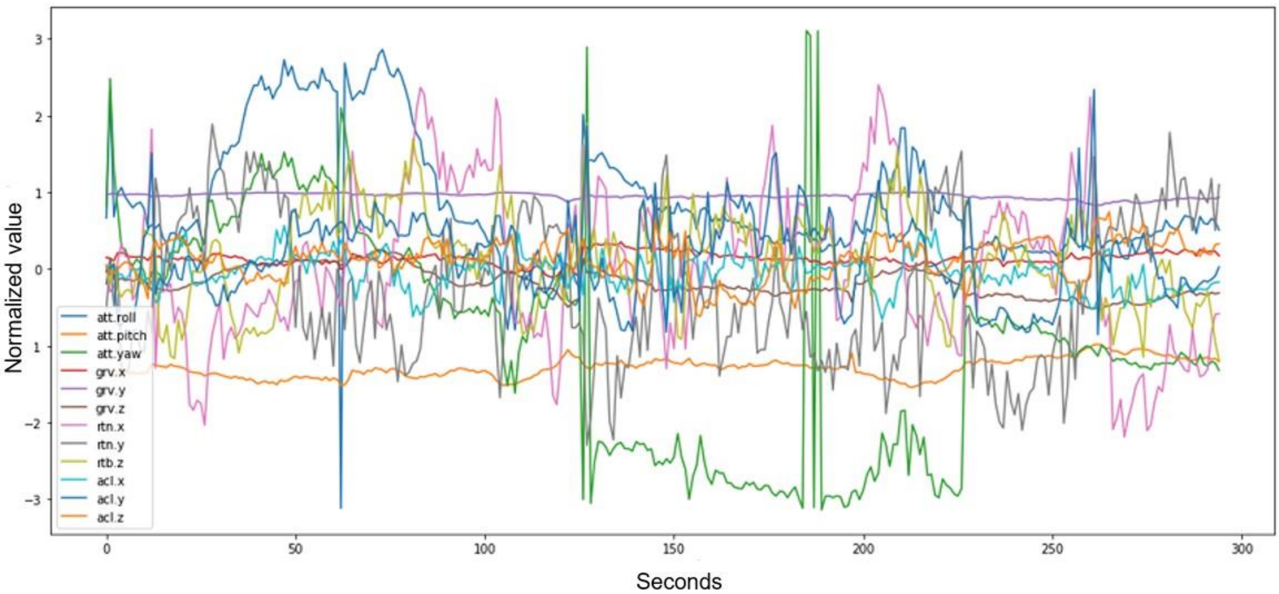


Figure 2. Data example of the MotionSense data set. Note that some values do not change significantly when normalized over the course of recording and are therefore of lesser interest for the prediction of behavior.

Figure 3. Course on the premises of the University of Bern. Participants followed the indicated path, starting walking, followed by jogging, sitting, ascending stairs, standing, and descending stairs. Completion took an average of approximately 300 seconds.


walking
jogging
sitting
stairs up
standing
stairs down

The participants completed the course in 2 groups with different instructions. Group 1 (n=29, median age 26, SD 5.2 years) was instructed to wear the smartphone in their preferred manner. Group 2 (n=39, median age 27, SD 4.7 years) wore the smartphone in the right front trousers'pocket, with the display facing toward the body and the top of the phone pointing down while standing. This placement is consistent with the data collection method used for the *MotionSense* data set, as discussed above. It was found that the orientation of the smartphone has a significant impact on the performance of the model. To ensure consistency and comparability between the data sets, our algorithm was trained on the data of group 2, as wearing the smartphone in an individually preferred manner (group 1) resulted in significantly worse performance in classification accuracy. For a detailed comparison of classification accuracy between groups 1 and 2, please refer to Multimedia Appendix 2.

App

The accelerometer and gyroscope data were collected using our custom-made *HumanActivityRecorder* Android app, which was developed using Android Studio 4.1 with Java 1.8.0_271 (Figure 4). The app records accelerometer and gyroscope data at a sampling rate of 50 Hz and is publicly available on the Google Play Store as version 13 of the *HumanActivityRecorder* app. The accelerometer data are recorded in the x-, y-, and z-axes, while the gyroscope data consist of rotation around these axes (roll, pitch, and yaw) at the same frequency. The data are then automatically sent to a server and can be downloaded as a CSV or JSON file. The source code is available on Github [28]. The app is compatible with Android 5.0 and later versions. We used an Honor View 20 smartphone for data collection to ensure consistency in recording. Only 1 device was used.

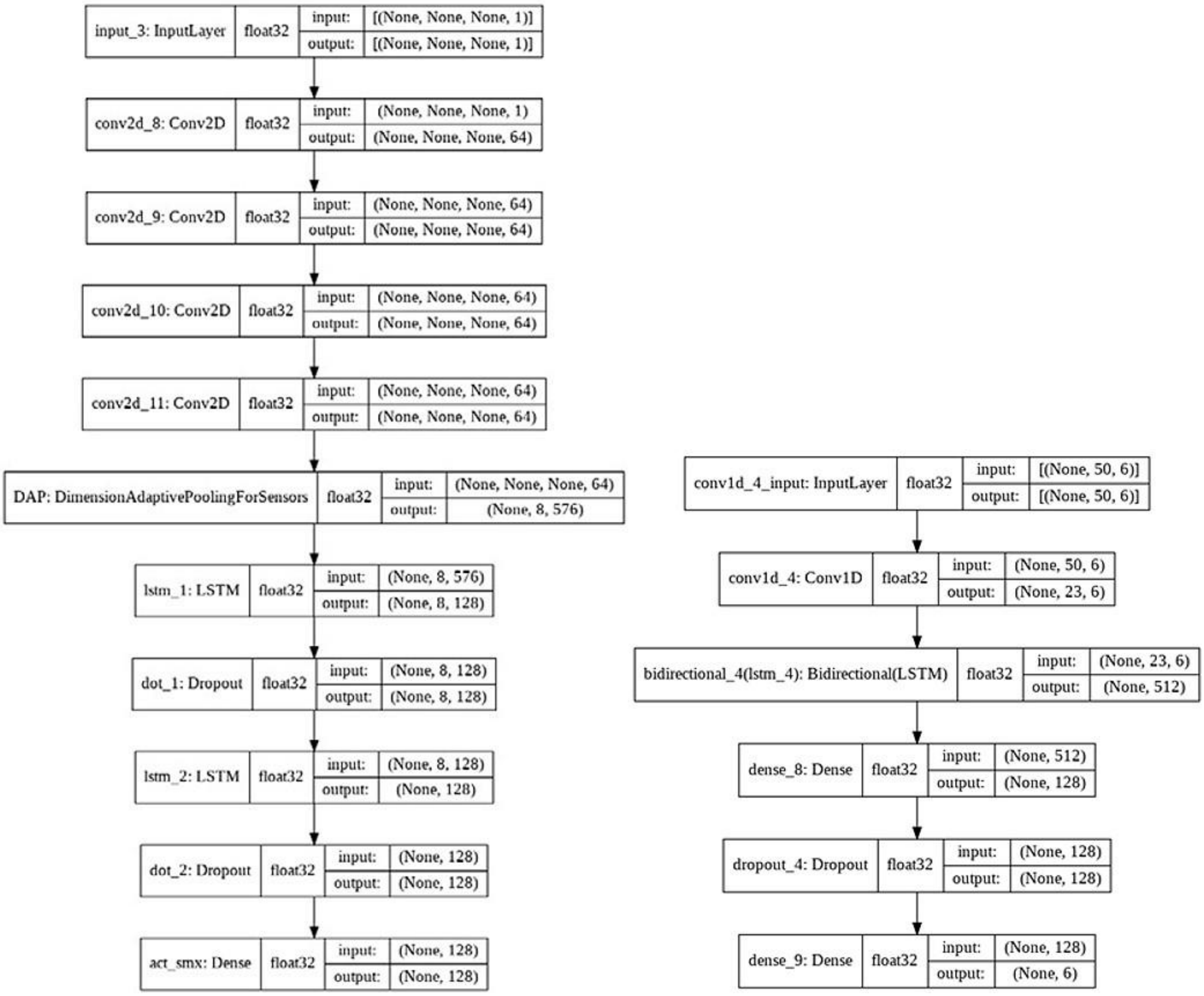


Figure 4. Comparison of the models used in our study. The dimension-adaptive neural architecture (DANA) model, consists of several additional layers, which we found did not improve the classification of our data. Note that in our simplified model, the dimension-adaptive pooling (DAP) layer has been omitted as well, since our data are dimensionally consistent. LSTM: Long short-term memory.

Recording

Before beginning the data collection process, the participants were asked for their name, age, and consent. The data collection paradigm was explained to them and demonstrated through a walk-through by the data collector. The participants then completed the course, which included walking, jogging, sitting, ascending and descending stairs, and standing still, while the app recorded their accelerometer and gyroscope data. After completing the course, the participants were given a chocolate bar as an incentive. The accelerometer data were processed and categorized using a Jupyter notebook script, which automates the workflow to ensure consistency in categorization. This script is part of our toolbox.

Deep Learning Model

We implemented a modified version of the DANA model proposed by Malekzadeh et al [19], which involved removing and modifying several layers. This modification was made after testing the model (trained and tested on *MotionSense* data) and finding that the omission of these layers did not noticeably decrease the model's performance.

It is important to note that in our simplified model, we removed the DAP layer as our input data are dimensionally consistent at the time of testing. To validate the models, we trained them both on the *MotionSense* data set and our own data set, as well as testing both combinations.

Results

Through a systematic variation of the number of nodes and layers, we determined that the best balance between accuracy and complexity is achieved with the described architecture. This architecture was determined based on the accuracy of the models in classifying movement types of the *MotionSense* data set when trained on the same data set. Interestingly, when we trained on the *MotionSense* data set and tested on our own data, our model performed better than DANA, yet still with room for improvement, at 63% vs 26%.

When trained on the same data set as the one they are tested on, both models performed well in classifying behavior. The DANA model achieved approximately 87% accuracy when trained and tested on the MotionSense data set and approximately 90% accuracy when trained and tested on our own data, depending on the sampling rate (Figure 5). However, when trained on the MotionSense data set and tested on our own data, the accuracy of DANA drops to around 26%, also depending on the dimensionality of the input, while our model performs at around 63%, but much less robust against the dimensionality input (Figure 6). This still leaves room for improvement but shows the comparatively high generalization ability of our model. It is important to note that neither the MotionSense data nor our own data include magnetometer data, which is why the DANA model performs poorly (at or near zero accuracy) when reduced to only magnetometer input. The graph includes this information for consistency.

Figure 5. Accuracy in classifying using the dimension-adaptive neural architecture (DANA) model (A) trained and tested on MotionSense data; (B) our model trained and tested on our data; (C) DANA trained on MotionSense and tested on our data; and (D) our model trained on our own data and tested on MotionSense data. Note that the dimensionality is varied here to showcase the robustness, and our model is impacted more strongly by a varied dimensionality input. Acc: accelerometer; Gyr: gyroscope; Mag: magnetometer.

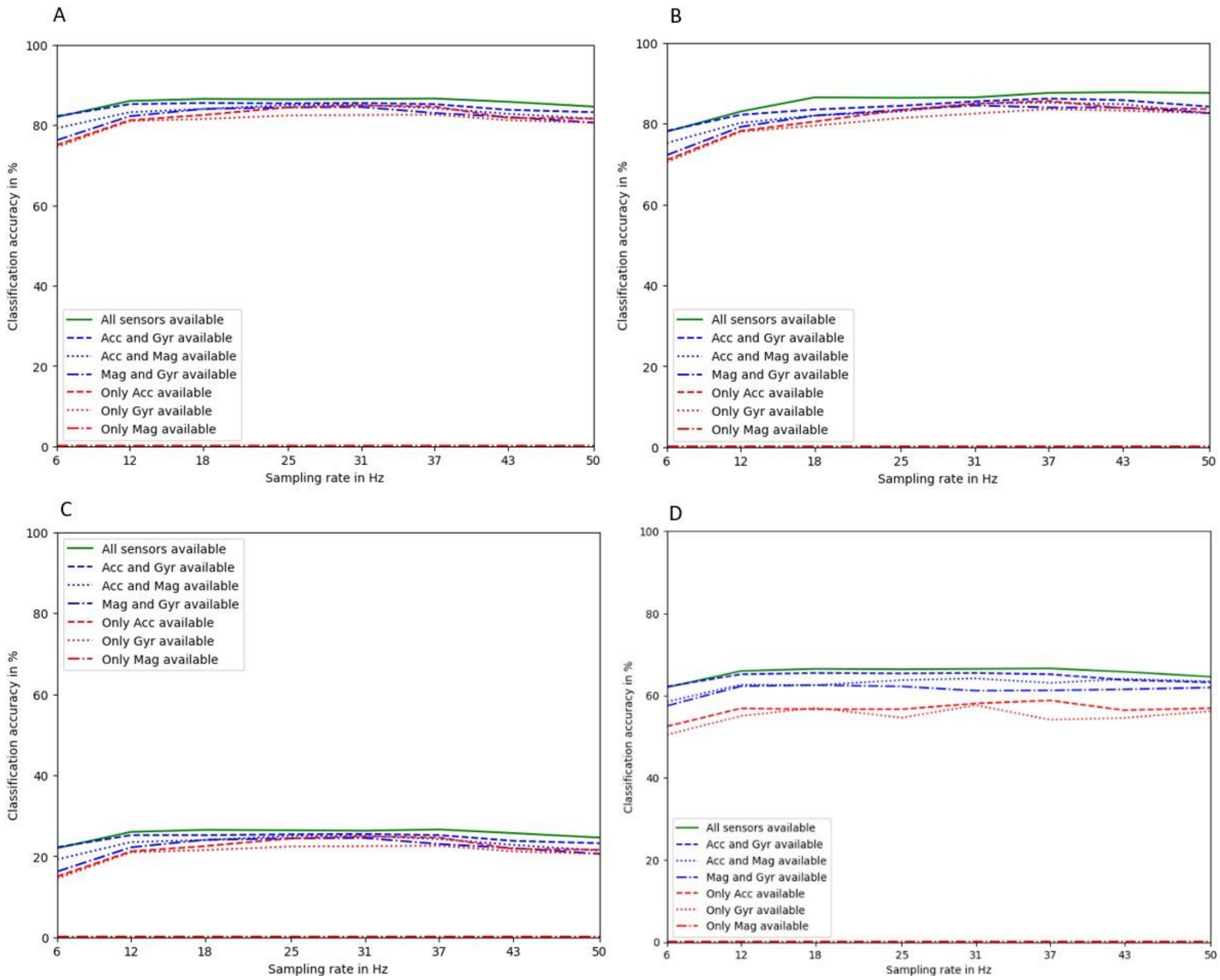
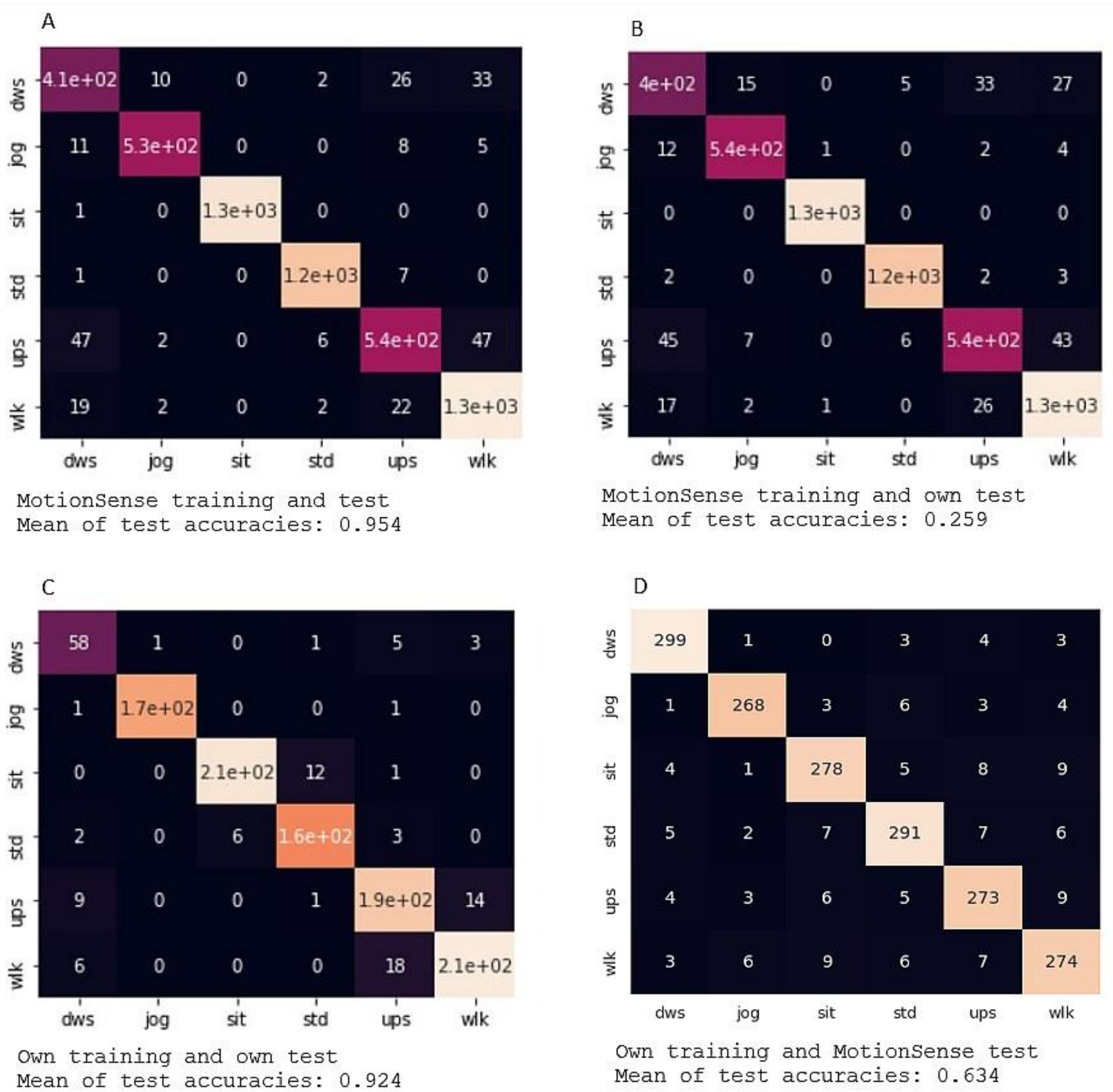


Figure 6. Confusion matrices of accuracy in classifying (A) using our own simplified model trained on MotionSense data tested on MotionSense data; (B) trained on MotionSense data and tested on own data; (C) trained and tested on our own data; and (D) trained on our own data and tested on MotionSense data. Note that dimensionality is not varied here as all sensors are available. dws: downstairs; jog: jogging; sit: sitting: std: standing; ups: upstairs; wlk: walking.



Our simplified model does not include the DAP layer and is less robust against input dimensional variance, as our input data dimensions did not vary. However, it is easily adaptable if desired. Despite this, our model outperforms the DANA model in terms of accuracy. When trained on the MotionSense data set and tested on it, our model achieved 95.4% accuracy. It was equally accurate when trained on our own data and tested on it, with 92.4% accuracy. However, when trained on the MotionSense data and tested on our own data, accuracy drops to 25.8%, but when trained on our data and tested on MotionSense, accuracy reached 63.4%.

Discussion

Conclusions

Both models included in our toolbox perform well when trained and tested on the same data set. However, they do not perform well when trained on one data set and tested on the other, as was the case in our study. This highlights the problem of the unavoidable part of overfitting the collected data to improve algorithm performance, although this is controlled for as far as possible. Despite this, both models (DANA and our own) performed similarly when trained on one data set and tested on the other. Our model is slightly more accurate, but the DANA model is more robust with regards to dimensional variance in the input. However, there is a significant difference in computing time when training the models. The DANA model, when trained using Google Colab with CPU and GPU resources, took around 11 hours to train each time. On the other hand, our model can be trained in about 5 minutes with 100 epochs of training using only CPUs in Google Colab. Note that this estimation does not include hyperparameter testing.

Given the amount of data used to train the models, the results are surprisingly accurate. Commercial wearables, such as sports-oriented smartwatches, often have a function to display the user's current activity. However, these displayed activities are often incorrect, even for activities that seem obvious to the user. Considering these devices are widely available and sold to millions of people, we expected movement detection to be much more challenging, and our accuracy to be in the low 60% range.

While the accuracy of movement classification is very good, there is still room for improvement, which we plan to achieve by training the algorithm on additional data from diverse populations or environments. We recommend using the DANA model to classify behavior in data that have been gathered at different dimensions or with variable input dimensions. However, if the input type is consistent, we recommend our model as it is slightly more accurate and much easier to train. Both algorithms are available at our Github repository, along with the *HumanActivityRecorder* app and the scripts to process the data. In a future step, we plan to integrate both algorithms into the app and evaluate their performance in a subsequent study.

Limitations

The orientation of the smartphone during recording has an impact on classification accuracy if the sample size is not large enough, as shown in our comparison of classification accuracy of groups 1 and 2 (Multimedia Appendix 2). However, if trained on large data sets with varying orientation, this effect disappears. For comparability, we based our model on the group with the same orientation as in the *MotionSense* data set. Accounting for orientation was outside the scope of our study. To address the impact of smartphone orientation on classification accuracy in medium-sized samples, an easy solution would be to incorporate an orientation recognition stage that detects the orientation of the smartphone and branches the data to models that have been individually trained on each orientation. This would ensure more accurate classification regardless of the smartphone orientation.

Authenticity

The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of this study do not constitute endorsement by this Journal. This manuscript has not been published elsewhere, and it has not been submitted simultaneously for publication elsewhere.

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Data Availability

All data used are available [28].

Authors' Contributions

FW was the principal investigator, drafted the manuscript, and trained the algorithm; CN provided guidance for publishing.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Screenshots of the Android app. From left to right: start screen, sociodemographics, and recording screen.
[PNG File , 151 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Accuracy of the classification of our model (A) trained and tested on group 1 data; (B) trained on group 1 data and tested on MotionSense data; (C) trained and tested on group 2 data; and (D) trained on group 2 data and tested on MotionSense data. Group

1 was instructed to wear the smartphone wherever they preferred individually. Group 2 was instructed to wear it screen inside, top facing downward in the right trouser pocket, in line with data collection for the MotionSense data set, to ensure maximum comparability.
[PNG File , 139 KB-Multimedia Appendix 2]

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Abbreviations

CNN: convolutional neural network
DANA: dimension-adaptive neural architecture
DAP: dimension-adaptive pooling **DNN:**
deep neural network
FNN: feedforward neural network
RNN: recurrent neural network

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Difference in Default Mode Network Activity Between People of Differing Activity Levels: An EEG Microstate Study

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Abstract

Objective: This research sought to elucidate the disparities in EEG microstate patterns between individuals with varying levels of physical activity, specifically distinguishing between more active and less active cohorts.

Methods: A total of 33 participants were enrolled in the study, undergoing two separate experiments. Resting-state EEG data were collected during breaks, and microstate analysis was employed to discern the temporal characteristics of the EEG.

Results: Our findings revealed that the more active group exhibited a higher occurrence and prolonged duration of Microstate C. Furthermore, Microstate C accounted for a greater proportion of the EEG variance in the more active group compared to the less active group. Conversely, the less active group demonstrated a higher frequency of Microstate B occurrences, which also explained a larger portion of the EEG variance in this group.

Conclusion: These results suggest distinct neural patterns of resting-state EEG activity between more active and less active individuals, with specific microstates being predominant in each group. The implications of these findings provide valuable insights into the neural correlates of physical activity levels and their potential impact on brain dynamics.

Keywords: EEG microstates, physical activity, resting-state EEG, default mode network

1 Introduction

Engaging in physical activity (PA) is fundamental for sustaining health. PA is documented to contribute to many benefits including cardiovascular health, weight management, mood enhancement, and increased lifespan (Warburton & Bredin, 2017). However, insufficient PA is associated with numerous health risk factors and mental health problems (Daniele et al., 2022).

Alarmingly, a significant fraction of the global population fails to meet the PA guidelines determined by the World Health Organization (Luzak et al., 2017; WHO, 2022, 2023). Hence, it is imperative to identify barriers to PA and develop effective strategies for helping everyone achieving healthier lifestyles.

Evidence posits that PA is closely associated with cognitive functions such as attention, executive function, self-perception, stress management, and emotional regulation (Alves et al., 2019; Bischoff et al., 2019; Hajar et al., 2019; Hötting & Röder, 2013; Ubago-Jiménez et al., 2019). Moreover, PA is instrumental in mitigating the risk of mental disorders including ADHD, depression, autism symptoms, and anxiety disorders (Hoza et al., 2016; Mammen & Faulkner, 2013; McDowell et al., 2019; Sorensen & Zarrett, 2014).

Recently in neuroscience, there has been a surge in research on the Default Mode Network (DMN) over the past two decades (Raichle, 2015; Raichle et al., 2001b; Smallwood et al., 2021). The DMN is a large-scale brain network that is predominantly active during periods of rest and has been implicated in self-referential thinking(Andrews-Hanna et al., 2014; Buckner et al., 2008), memory retrieval (Cabeza & Jacques, 2007; Svoboda et al., 2006) and envisioning the future (Schacter et al., 2017; Spreng et al., 2009). It consists of brain regions such as the medial prefrontal cortex, posterior cingulate cortex, and bilateral angular gyri (Raichle, 2015). The DMN plays a pivotal role in self-referential processing where individuals engage in introspective activities evaluating their traits and experiences (Andrews-Hanna et al., 2014). Additionally, the DMN is associated with Theory of Mind, autobiographical planning, and decision-making processes (Dixon et al., 2020; K. C. R. Fox et al., 2015; Schacter et al., 2017; Spreng et al., 2009).

There are striking parallels between the effects of PA and the functionalities of the DMN, as both are associated with attention, executive function, self-perception, stress regulation, emotional regulation, and various mental disorders (Clayton et al., 2015; J. Coutinho et al., 2014; Davey & Harrison, 2018; Harikumar et al., 2021; Mak et al., 2017; Pan et al., 2018; Y. Tang et al., 2021; J. Zhou & Seeley, 2014).

These common associations of PA and the DMN merit exploration. For instance, it is plausible that the DMN, by facilitating future planning and motivational processes, influences the engagement in PA (Andrews-Hanna et al., 2014; Bado et al., 2014; Di Domenico & Ryan, 2017; Golland et al., 2007; Konishi et al., 2015; Raichle, 2015). Conversely, PA might modulate DMN activity which subsequently impacts cognitive functions and emotions. Additionally, aberrant DMN activity, which is observed in several mental disorders, might influence an individual's level of PA, since e.g. depression, anxiety and ADHD are all linked to both the DMN and PA (Wieland et al, 2023) and people with depressive and / or anxiety symptoms show lower physical activity levels (Difrancesco et al., 2019; Pearce et al., 2022). Specific stimulation of the DMN using tDCS and TMS have been shown to be effective in treating depression (Singh et al., 2020) and anxiety disorders (Cirillo et al., 2019), which could in turn lead to higher PA levels in individuals. Understanding the relationship between DMN and PA better could improve existing therapeutic models and give rise to new therapeutic methods.

In recent years, the approach of microstate analysis of electroencephalography (EEG) data has strongly gained in popularity in neuroscience (A. Mishra et al., 2020) and has being used to study DMN activity (Gulyaev et al., 2023). This microstate approach characterizes the recorded electrical signals by isolating non-overlapping, distinct topographies (Abreu et al., 2021; Koenig et al., 2002). Microstates are short-time stable functional connectivity states of different brain areas, characterized through short-term stable topographically distinctive distributions. These topographies are identified through a competitive fitting process, based on spatial correlation, which are then mapped back to the original signals. Notably, the identified topographies remain consistent across studies and are not affected by factors such as the number of electrodes, state of the eyes (open or closed), frequency range chosen for analysis, or the clustering algorithms employed (Abreu et al., 2021; Férat et al., 2022; Khanna et al., 2014; Von Wegner et al., 2016; Zanesco et al., 2021; K. Zhang et al., 2021).

These distinct patterns arise from specific areas in the brain where neurons are located and show nearly synchronized activity, indicating simultaneous firing (Michel & Koenig, 2018; Seeber & Michel, 2021). This concurrence of activity implies potential associations with diverse functional and physiological processes. In contrast to the event-related potential (ERP) methodology which gauges the brain's continuous responses to stimuli, the resting-state approach focuses on the brain's intrinsic neural activity. This spontaneous activity offers a wealth of information regarding the state of the brain, as well as insights into the communication dynamics among various brain regions over different time scales (M. D. Fox et al., 2005; Koenig et al., 2005; Snyder & Raichle, 2012). Furthermore, the resting-state EEG assessment has been traditionally employed in clinical studies and holds the advantage of recording near-natural neuronal activity, not influenced by experimental manipulation by tasks. It is imperative to recognize that resting-state microstates are potentially instrumental to understand the functionality of the brain during periods of non-task engagement and therefore more natural neuronal activity.

A range of toolkits and plugins compatible with MATLAB (Hatz et al., 2015; Poulsen et al., 2018; Tait & Zhang, 2022; Tarailis et al., 2021), Python (Férat et al., 2022; Milz, 2016; Von Wegner et al., 2016), BrainVision Analyzer (Michel & Koenig, 2018) have been developed, facilitating the incorporation of the microstate methodology in electrical neuroimaging. The temporal attributes, topographic strength, similarities and differences, and sequence characteristics of the derived microstates are frequently compared across diverse groups and conditions.
While more prevalent in EEG based studies, microstates have been found in data from other brain imaging modalities, such as functional Magnetic Resonance Imaging (fMRI) (Abreu et al., 2021; Britz et al., 2010; Schwab et al., 2015; Van De Ville et al., 2010), functional Near-Infrared Spectroscopy (fNIRS) (Tait & Zhang, 2022), Positron Emission Tomography (PET) (Rajkumar et al., 2021), Transcranial Magnetic Stimulation (TMS) (Croce et al., 2018; Qiu et al., 2020; Sverak et al., 2018), and Magnetoencephalography (MEG) (Coquelet et al., 2022).

Microstate analysis is utilized to study brain activity in different wakefulness and sleep stages (Bréchet et al., 2020; Brodbeck et al., 2012; Diezig et al., 2022; Q. Wang et al., 2021), in different age and gender groups (Koenig et al., 2002; Tomescu et al., 2014; Zanesco et al., 2021), or under the effect of pharmacological substances (Artoni et al., 2022; B. Schiller et al., 2021; M. J. Schiller, 2019; Yoshimura et al., 2007). Microstate analysis has also been used in neurofeedback studies (Asai et al., 2022; Diaz Hernandez et al., 2018) and tested in rodent models (Mégevand et al., 2008; R. Mishra & Bhavsar, 2021).

Microstate analysis has also been employed in studying executive functions, self-perception, attention, stress, and emotional regulation. For example, in examining executive functions, it was found that microstate dynamics were related to performance in cognitive tasks requiring executive control (Seitzman et al., 2017). In terms of attention, microstate analysis has been used to investigate attentional networks and their efficiency (Milz, 2016). Furthermore, microstates have been linked to stress, with specific microstate configurations associated with stress levels and the body's response (Hu et al., 2021). Additionally, emotional regulation has been explored through microstate analysis, with findings suggesting that different microstate classes may reflect varying emotional processing mechanisms (Zerna et al., 2021).

Microstate analysis has been extensively utilized in pathology research. For example, ADHD specific microstate classes were found to be altered indicating abnormal processing of attention and impulsivity (Férat et al., 2022). In depression and anxiety research, microstate analysis revealed abnormal temporal patterns, suggesting disruptions in resting-state networks (He et al., 2021). In the context of autism, alterations in microstate parameters were associated with atypical brain connectivity and social impairments (Das et al., 2022).

For an in-depth review of the associations of the most often extracted microstates, see According to this review, mostly, 4 microstates are extracted, since this enables a good balance between globally explained variance of the EEG signal, parsimony, complexity and statistical power.

Microstate A is associated with the temporal cortex and auditory network, as indicated by ample research (Bréchet et al., 2019; Britz et al., 2010; T. Chen et al., 2020; Custo et al., 2017). Additionally, (Milz, 2016) observed that during object and spatial visualization tasks, microstate A exhibited a longer duration, increased occurrence rate, and explained more variance compared to during verbalization and the no-task resting state. In summary, microstate A has been linked to both auditory and visual processing and spatial visualisation.

Microstate B is associated with visual processing, self-visualization, autobiographical memory, and scene visualization. Its roles in self and scene visualization also involve interactions with other microstates, notably microstate C. Microstate B is linked to visual areas according to various studies using inverse solutions methods (Bréchet et al., 2019; Britz et al., 2010; Chen et al., 2020; Custo et al., 2017).. Its association with visual processing is reinforced by an increased presence after visual stimuli or in the eyes-open state(Antonova et al., 2022; D'Croz-Baron et al., 2021; Jabès et al., 2021; Seitzman et al., 2017). Furthermore, microstate B is associated with autobiographical memory and self and scene visualization (Bréchet et al., 2019; Tarailis et al., 2021). Its presence is reduced in euthymic bipolar patients, with potential implications for memory and self-focus (Vellante et al., 2020).

Microstate C is involved with the DMN, mind-wandering, task-negative thoughts, and emotional processing (Custo et al., 2017; Michel & Koenig, 2018; Tarailis et al., 2021). It is associated with the Default Mode Network (DMN), 'self-experience' subnetwork, and salience network (Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017). Croce et al. (2018) linked it to task-negative thoughts and mind-wandering. Microstate C has been associated with relaxation (Tomescu et al., 2022), and increased presence during no-task rest (Kim, 2015; Seitzman et al., 2017; Zappasodi et al., 2017). It is also linked to cognitive decline in older individuals (Jabès et al., 2021)and mindwandering episodes (Zanesco et al., 2020).

Microstate D is primarily linked to areas overlapping with the frontoparietal network, and is associated with executive processes such as working memory, cognitive control, and attention

(Bréchet et al., 2019; Britz et al., 2010; Custo et al., 2017).(Custo et al., 2017) reported that its temporal properties increased after repetitive transcranial magnetic stimulation over the intraparietal sulcus, part of the Dorsal Attention Network. Several studies have noted an increased presence of Microstate D during arithmetic tasks (Bréchet et al., 2019; Kim, 2021), virtual maze training (Murphy et al., 2018), video gaming (Wang et al., 2021), and spatial relationship tasks (Zappasodi et al., 2019).

The purpose of this study is to directly link PA and the DMN by showing different neuronal patterns in Microstate Duration, Occurrence, Variance explanation or Global field power between groups of differing PA levels. Since microstates B and C relate the most to DMN specific subdomains (autobiographical memory, self and scene visualization, mind-wandering, task-negative thoughts, and emotional processing), whereas microstates A and D relate more to non-DMN specific cognitive domains, differences in measures regarding B and C, but not A and D were expected.

PA and DMN share many associations to paradigms in neuroscience, in both healthy and pathological subpopulations (Wieland & Nigg, 2023). Many of those associations have been explored using the EEG microstate methodology (Khanna et al., 2015). Therefore, this paper aims to further investigate the link between PA and DMN, using this well-established methodology. The conducted experiment seeks to directly link PA and DMN by focussing on the neurological differences between individuals of differing PA levels. The goal is establishing a link between the two paradigms that is implicated by ample literature, but not directly achieved so far. It is of great importance to better understand the interaction between DMN and PA, in order to devise strategies to promote PA, and consequently physical and mental health. Furthermore, understanding DMN activity concerning PA could lead to the development of targeted neurological therapies.

2 Methods

2.1 OpenSource Paradigm Statement

All our methods are chosen so the experiment is repeatable with open source hardware and software. While we used gUSB research equipment for data acquisition, it is possible to run the same software using open source EEG equipment, such as OpenBCI (OpenBCI, 2021) hardware. The whole acquisition pipeline was tested on OpenBCI hardware, using the Cyton module with piggyback daisy module. The only difference is the port to the OpenVibe Software, which was implemented using a lab streaming server (LSL) from the native OpenBCI software, also we used passive electrodes for a lack of active electrode equipent compatible with OpenBCI hardware. for data analysis, we used the eeglab plugin running on Matlab (The MathWorks Inc., 2023), however, EEGlab (Delorme & Makeig, 2004) also runs on Octave (GNU Octave, 2023), which is open source. All scripts and data are available on GitHub, albeit anonymized.

2.2 Participants

A total of 33 (20 female, 13 male) participants took part in the experiment with a mean age of 30.645 years (sd = 5.431). 2 of the participants were left-handed, but no difference in microstates maps was observed compared to right-handed participants. No significant difference between less active and more active group was observed in anxiety score ($p = 0.371$, $d = 0.231$), depression score ($p = 0.883$, $d = 0.057$), stress level score ($p = 0.294$, $d = 0.408$), autism score $p = 0.905$, $d = 0.021$) or ADHD score ($p = 0.318$, $d = 0.750$) was observed. Furthermore, the microstate analysis was done with median split groups of all scores, but no significant results emerged.

Ethical approval was acquired from the ethics committee of the University of Bern (No. 202306-02). All Participants took part in the experiment out of their own free will and signed a form stating so. They were informed, that at all times, they are allowed to stop the experiment without experiencing any disadvantage or having to name any reason for doing so. Data was acquired pseudonymized only and all data was handled on secured and encrypted platform only.

2.3 Experimental Design

In order to gather data on the activity of the default mode network, we reproduced to experiments, a study previously conducted by Li et al. (2021) and one by Dimitriadis et al. (2016). The structure of the first experiment included a period for instruction and preparation, followed by two task blocks wherein participants counted upward-facing triangles (see Figure 1). In between these task blocks were two rest periods, each lasting three minutes. During these rest intervals, participants were advised to stay still and relax without any specific guidelines. In the second experiment, blocks of by block increasingly difficult arithmetic tasks were presented, with breaks lasting two minutes with the same instructions as in the first experiment. The EEG data collected during the breaks was analyzed using an established EEG microstate analysis toolbox by Koenig et al. (Koenig et al., 2002).

--- Figure 1 about here ---

2.4 Measurement

EEG data was acquired using two piggyback g-tec gUSBamp 16 channel signal amplifiers from gtec (https://www.gtec.at/product/gusbamp-research/) with a total of 32 electrodes. Both amplifiers were connected to have a common ground and reference and signals were synchronized using a synchrolink cable. Each gUSBamp amplifier was connected to a g-tec GAMMAbox active electrode driver box module using 4 channels, which in turn split up into 16 active electrodes.

2.4.1 Accelerometery

Activity levels were measured using movisens Move 4 accelerometer (Bouten et al., 1993) with hip belts and firmware version 1.16.5. Data acquisition period was 7 days and 2 hours. We analyzed data starting 1h after the accelerometer was given to participants until 1h before measurements stopped. Acquired data was analyzed using the DataAnalyzer provided by movisens GmbH (https://www.movisens.com/de/). Participants were instructed to wear the Accelerometer at all times, were allowed to take it off for sleeping and were instructed to mark all times in which they forgot to wear it. A total of 3 participants forgot to wear it for 1 day of measurement. Missing data was extrapolated from the other days of recording. In conjunction with the movisens accelerometers, 10 participants had the HumanActivityRecorder App (Wieland, 2022) installed on their Android smartphones, collecting data for verification of the movisens data acquisition accuracy. Based on accelerometry data from movisens, participants were distributed into a more active and a less active group with a median split.

2.4.2 Questionnaires

To asses participant's activity levels, get their weight, height, handedness, assess their ADHD, depression, anxiety and autism tendency and overall stress levels, we administered an online questionnaire using Qualtrics (homepage of Qualtrics). The questionnaire consisted of a general information part (weight, height, age, handedness and gender) and three questionnaires. Firstly, we implemented the Godin-Shepard leisure time activity questionnaire (Amireault & Godin, 2015), modified, so it also asked for minutes low, moderate and vigorous activity in the week before (i.e. the week after the experiment and the week in which accelerometery was measured). To assess ADHD levels, we implemented the Adult ADHD Self-Report Scale (ASRS)(Kessler et al., 2005) which is an 18-item self-report questionnaire designed to assess Attention Deficit Hyperactivity Disorder (ADHD) in adults. To assess depression, anxiety and stress levels, the Depression, Anxiety and Stress level Questionnaire Short (DASS-21) was implemented (Henry & Crawford, 2005).

2.4.3 EEG

EEG data was acquired, marked and written using OpenVibe V 3.4.0. Both gUSBamp-research amplifiers were connected to a Acer aspire 5 laptop (17” display, Ryzen 7 8 -core 16 threads processor, 32GB RAM, Nvidia RTX 2080Ti, PCiSSD) separately via USB 3.0. Each data stream was connected using a separate port and a separate acquisition server to OpenVibe, using the gUSBamp legacy driver of OpenVibe. Signals from both streams were merged and combined with keyboard and stimulation input, using TCP tagging with drift correction disabled. TCP tagging enables correction for device drift, i.e. the time difference between the internal clock of the amplifiers and the internal clock of the connected computer. Stimulus presentation and keypresses are then marked according to the time difference between the clocks at time of occurrence, thereby minimizing time difference errors. Stimuli were presented using OpenVibe display image boxes running on custom lua scripts. Stimulus material was generated using python 3.11 and matplotlib V3.7.1, using portable network graphics format. After mutiplexing keybord input, stimulus markers and EEG data stream, the resulting datastream was written into csv files on the internal PCiSSD.

2.5 Data analysis

2.5.1 EEG Preprocessing

Data analysis was done using the eeglab V2023.0 plugin, running on Matlab V2023a. Special attention was given to maximum repeatability, achieved through minimizing manual data manipulation and using batch processing and established automation functions of all preprocessing and processing steps if possible. First, the data was band pass filtered from 0.3 to 40 Hz. This bypasses the electrical grid interference at 50Hz and is in accordance with most studies using the microstates paradigm, according to (Tarailis et al., 2021). Subsequently the data was re-referenced using a global average of all electrodes.

However, EEG raw data was manually cleaned in two steps: Bad epochs and blinks were removed by hand, after it was determined, that the built-in burst correction (clean_rawdata()) did remove epochs of interference neither reliably or nor consistently over different subjects.

Additionally, the interpolation of data by artifact subspace reconstruction (ASR) introduced artefactual interference into the data, which in later steps loads on factors in the independent component analysis and biases the variance explained by different independent components, as well as introducing additional dimensionality into the data, by the nature of adding a factor to the data. Since the later analysis approach relies on microstate analysis, the authors opted to not use the ASR function to not affect accuracy in later analysis steps, which rely on cross frequency coupling.

During manual cleaning, special attention was paid to repeatability. All data sets were cleaned, then the first 10 deleted again and cleaned again to minimize learning effect impact on cleaning efficiency by the person cleaning the data. Subsequently, independent component analysis (ICA) was applied to the data to purge artifactual components. Bad channels were removed and spherically interpolated only if deemed absolutely necessary. In 4 out of 33 cleaned sets, 1 channel was removed, in 1 dataset, 3 channels were removed. Before the ICA, a principal component analysis (PCA) was applied to determine the dimensionality of the data. The output of the PCA was fed into the ICA as number of individual components to extract. The results of the ICA was inspected using the TESA (TMS-EEG signal analyser) V1.1.1 toolbox for eeglab (Mutanen et al., 2020; Rogasch et al., 2017). This toolbox allows for automatic classification of independent components and visual inspection of each classification, in conjunction with the power frequency spectrum and scalp topography of the component, along with a classification which is adequately accurate, and subsequently removes unwanted components. Again, all datasets were cleaned using this method of visual checks of the automatic classification and correction, then the first 10 were deleted and classified again to account for learning effects of the person conducting the analysis.

All previous steps were automated, scripted and the Matlab script is available online (flu_wieland on GitHub). Where possible, we used the parallel computing toolbox in Matlab to allow for much faster processing of the data.

2.5.2 Microstate analysis

For maximum repeatability, we closely followed the approach outlined by Thomas Koenig (2017, https://thomaskoenig.ch/index.php/software/10-eeglab-plugin-manual). We opted to use all default values and only customized the Matlab script provided in his Microstate toolbox to allow for parallel computing. We run the analysis with a priori 4, 5 and 6 Microstates. After determining, that from 4 to 6 microstates an additional 5% of variance more was explained globally (4 Microstates: 77.27% globally explained variance (GEV), 5 microstates: 79.32% GEV, 6 microstates: 83.24% GEV), we opted for analysis of the data using 4 microstates. This is in line with experience from previous studies (Van De Ville et al., 2010), which determined, that using more than 4 microstates adds little to explaining power of resting state EEG Data. Adding more microstates for analysis disproportionally reduces power and adds complexity in respect to additionally gained explanation. Furthermore, default mode network activity is most associated with Microstate B, C and F, with C and F having strong similarities and overlapping both in association (Khanna et al., 2014) and topography (Tarailis et al., 2023). Therefore, using more than 4 Microstates would only add complexity while reducing accuracy.

Data was filtered from 2 to 20 Hz with 2000 filtering coefficients. Fitting parameters were set to 4 classes, a lambda (non smoothness penalty) of 1 and b (label smoothing window in ms) of 20, polarity was ignored, PeakFit was enabled (fitting of the microstates on global field power peaks), rectifying and normalizing disabled. We used atomize-agglomerate hierarchical clustering (AAHC) instead of k-means clustering for determining microstate maps, since the latter is nondeterministic, but the former is (Šubelj et al., 2016).

Since we deployed a between-subjects design rather than a within-subjects design, we calculated the mean microstate maps on individual level and retrofitted them on the data, not using global field power peaks. Individual templates were autosorted according to similarity to the integrated norm template (Koenig et al., 2002) GrandGrandMean microstate maps were calculated and corresponded well with the norms as described in (Tarailis et al., 2023). Globally explained variance by, and occurrence, duration and global field power of, the microstates were quantified and extracted.

2.6 Statistical Analysis

Extracted data was analyzed and plotted using Jupyter Notebook (Jupyter Development Team., 2023) running on Python 3.11 (Python Software Foundation., 2023), utilizing the matplotlib, seaborn, statsmodels, numpy, scipy and pandas toolboxes. To detect group differences, n by 2 way ANOVAs where n = number of factors were employed as omnibus tests and if significant, posthoc Tukey's HSD tests for multiple comparisons were used to determine differences.

To control for interference by any of the control variables, the microstate quantification paradigm was calculated with groups of each variable, left-handed vs. right-handed, groups based on median split in depression scores, anxiety scores, ADHD scores and Stress level scores.

3 Results

3.1 Group Differences in PA

Standard MoviSens DataAnalyzer Cutoffs yielded a total mean of 190.174 active minutes per day (sd = 63.553min), of which 117.074min (sd = 45.018min) were light activity, 63.518min (sd = 31.407) moderate activity and 11.631min (sd = 11.191min) vigorous activity. Based on accelerometry data from movisens, participants were distributed into a more active and a less active group with a median split. The characteristics of the two groups are described in Table 1. The questionnaire yielded a total mean of 125.817 active minutes per day (sd = 85.174min), of which 67.224min (sd = 70.851min) were light activity, 35.541min (sd = 23.207) moderate activity and 31.987min (sd = 21.201min) vigorous activity. However, these values only showed a small correlation with measured values of $r = 0.371$.

3.2 Experiment 1

Microstate maps corresponded to normative maps (see Figure 2) and maps found in most microstate studies (Tarailis et al., 2023). Deviations are based on differences in statistical power and inter-study differences.

--- Figure 2 about here ---

3.2.1 Globally Explained Variance

Globally, 77.25% of variance was explained by retrofitting individual microstate templates. Microstate B explained significantly more variance (*p-adj* = 0.0079, d = 1.02) in the less active group than the more active group. Microstate C explained significantly more variance (*p-adj* = 0.002, d = 2.07) in the more active group than in the less active group. Microstate A (*p-adj* = 0.922, d = 0.035) and D (*p-adj* = 0.374, d = 0.325) did not differ between the groups in regard to explained variance (see Figure 3).

--- Figure 3 about here ---

3.2.2 Occurrence

Parallel to explained variance, microstate B did occur significantly more often in the less active group (p = 0.002, d = 1.216) than in the active group. Microstate C did occur significantly more often in the more active group (p = 0.002, d = 1.261). Microstates A (p = 0.650, d = 1.642) and D (p = 0.573, d = 0.205) did not occur differently often. Global field power

None of the microstates A (p = 0.487, d = 0.254), B, (p = 0.530, d = 0.229), C (p = 0.675, d = 0.152) or D (p = 0.139, d = 0.550) occurred with different global field power between the groups.

3.2.3 Duration

Microstates A (p = 0.676, d = 0.150), B, (p = 0.862, d = 0.063) and D (p = 0.591, d = 0.196) did not occur differently long in the groups. However, microstate C did occur for longer in the more active group (p = 0.008, d = 1.020).

3.2.4 Transition Probability

Transition from microstate A to B appeared more often in the less active group (p = 0.033, d = 0.827), from A to C more often in the more active group (p = 0.003 d = 1.172). All other transitions did not significantly differ between the groups (see Figure 4, left).

--- Figure 4 about here ---

3.3 Experiment 2

3.3.1 Globally Explained Variance

Globally, 78.37% of variance was explained by retrofitting individual microstate templates. Microstate B explained significantly more variance (*p-adj* < 0.001, d = 1.591) in the less active group than the more active group. Microstate C explained significantly more variance (*p-adj* < 0.001, d = 1.912) in the more active group than in the less active group. Microstate A (*p-adj* = 0.994, d = 0.002) and D (*p-adj* = 0.601, d = 0.108) did not differ between the groups in regard to explained variance.

3.3.2 Occurrence

Parallel to explained variance, microstate B did occur significantly more often in the less active group (*p-adj* < 0.001, d = 1.356) than in the active group. Microstate C did occur significantly more often in the more active group (*p-adj* < 0.001, d = 1.298). Microstates A (p = 0.898, d = 0.043) and D (p = 0.643, d = 0.0.160) did not occur differently often. Global field power

None of the microstates A (p = 0. 0.705, d = 0. 0.130), B, (p = 0.972, d = 0.011), C (p = 0.408, d = 0.287) or D (p = 0.778, d = 0.0971) occurred with different global field power between the groups.

3.3.3 Duration

Microstates A (p = 0.846, d = 0.066), B, (p = 0.067, d = 0.6496) and D (p = 0.972, d = 0.011) did not occur differently long in the groups. However, microstate C did occur for longer in the more active group (p = 0.004, d = 1.054).

3.3.4 Transition Probability

Transition from microstate A to B appeared more often in the less active group ($p = 0.033$, $d = 0.827$), from A to C more often in the more active group ($p = 0.003$ $d = 1.172$) and from D to C more often in the less active group ($p = 0.022$, $d = 0.849$). All other transitions did not significantly differ between the groups (see Figure 4, right).

4 Discussion

Present paper shows clear differences in microstate occurrence, duration, and variance explanation between subjects of different activity levels. Microstate B and C show difference in contribution to global variance in EEG and occur differently often between the groups, microstate B contributing more to explained variance in the less active group and occurring more often, microstate C contributing less in the less active group and occurring less often. Furthermore, microstate C occurs generally longer in the more active group. Overall, in the less active group, a heightened tendency to switch from microstate A to microstate B occurs in the less active group, while a heightened tendency of switching from microstate A to C in the more active group.

Microstate A, associated with the temporal cortex, auditory network, and visual processing, did not differ between the physically more active and less active groups. This suggests that physical activity levels may not significantly impact these cognitive processes, at least in terms of resting state EEG activity. This aligns with the findings of (Milz, 2016), who observed that microstate A exhibited a longer duration, increased occurrence rate, and explained more variance during object and spatial visualization tasks compared to during verbalization and the no-task resting state.

Microstate B, associated with visual processing, self-visualization, autobiographical memory, and scene visualization, occurred more often in the less active group. This could indicate a heightened focus on these cognitive processes in the less active group, potentially as a compensatory mechanism for reduced physical activity. This is in line with the findings of Antonova et al.

(2022) and (D'Croz-Baron et al., 2021), who found an increased presence of microstate B after visual stimuli or in the eyes-open state. Furthermore, the reduced presence of microstate B in euthymic bipolar patients, as reported by (Vellante et al., 2020), suggests potential implications for memory and self-focus in the less active group. This is in line with the finding, that Microstate C occurred less often and for shorter times in the less active group as well.

Microstate C, associated with the DMN, mind-wandering, task-negative thoughts, and emotional processing, occurred more often in the more active group. This is in line with findings, that PA is an effective way to deal with stress symptoms (Hamer et al., 2018). This suggests that physical activity may enhance these cognitive processes, consistent with the findings of Croce et al. (2018a), who linked microstate C to task-negative thoughts and mind-wandering. The increased presence of microstate C during no-task rest, as reported by (Kim, 2021) and (Seitzman et al., 2017b), further supports this interpretation. The association of microstate C with mindwandering episodes (Zanesco et al., 2020) suggests that more active people might be more relaxed during resting state, make it easier to let the mind wander. Furthermore, the DMN is thought to govern inward attention (Kim, 2015), which further supports that more active people are more introspective at resting state.

Microstate D, associated with executive processes such as working memory, cognitive control, and attention, did not differ between the two groups. This suggests that physical activity levels may not significantly impact these cognitive processes. This aligns with the findings of (Croce et al., 2018), who reported that the temporal properties of microstate D increased after repetitive transcranial magnetic stimulation over the intra-parietal sulcus, part of the Dorsal Attention Network. Since in the measured resting state time window, outward attention was not necessary, a difference in this microstate between groups was unlikely to occur. The increased presence of microstate D during arithmetic tasks (Bréchet et al., 2019; Kim, 2021), virtual maze training (Murphy et al., 2018), video gaming (Li et al., 2021), and spatial relationship tasks (Zappasodi et al., 2019) further supports this interpretation. It is important to distinguish here between inward and outward attention, where inward attention is generally associated with the DMN and outward attention is thought to be governed by the dorsal attention network (Kim, 2015). I line with this reasoning, a difference was observed in the Microstate C between the groups but not D, since C is thought to be associated most strongly with the DMN.

The heightened likelihood of change from microstate A to B in the less active group in experiment 1 and lessened likelihood in the more active group in experiment 2 could be interpreted as differences in shift from auditory and visual processing associated with microstate A to visual processing, self-visualization, autobiographical memory, and scene visualization associated with microstate B. This interpretation is supported by the findings of (Antonova et al., 2022; D'Croz-Baron et al., 2021), who found an increased presence of microstate B after visual stimuli or in the eyes-open state, which is likely, given our paradigm.

On the other hand, the heightened likelihood of change from microstate A to microstate C in the more active group could be interpreted as a shift from auditory and visual processing to DMN activity, mind-wandering, task-negative thoughts, and emotional processing associated with microstate C. The heightened likelihood in the less active group to switch from D to C could relate to a switch from arithmetic processing to default mode network activity. Several studies have noted an increased presence of Microstate D during arithmetic tasks (Bréchet et al., 2019; Kim, 2021), and microstate C is related the most to the DMN. This could mean that subject from the less active group were more often thinking about the arithmetic tasks in the breaks between the task blocks. It is however important to note that these interpretations are speculative and further research is needed to confirm these hypotheses and fully understand the implications of these findings for cognitive function and health. More research is needed to better understand change likelihood in microstate paradigms.

In conclusion, your findings suggest that physical activity levels may influence certain aspects of resting state EEG activity, particularly in relation to visual processing, self-visualization, autobiographical memory, scene visualization, mind-wandering, task-negative thoughts, and emotional processing. However, more research is needed to fully understand these relationships and their implications for cognitive function and health.

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6 Tables

6.1 Table 1

	more active	less active
n (m/f)	17 (6/11)	16 (6/10)
age	28.70 (5.01)	31.77 (6.23)

PAA	m = 242.769min (sd = 48.623)	m = 144.538min (sd = 31.338min)

Table Caption

Group characteristics of the more active and less active group after median split according to accelerometery data.

7 Figures

7.1 Figure 1

Experiment 1 Experiment 2

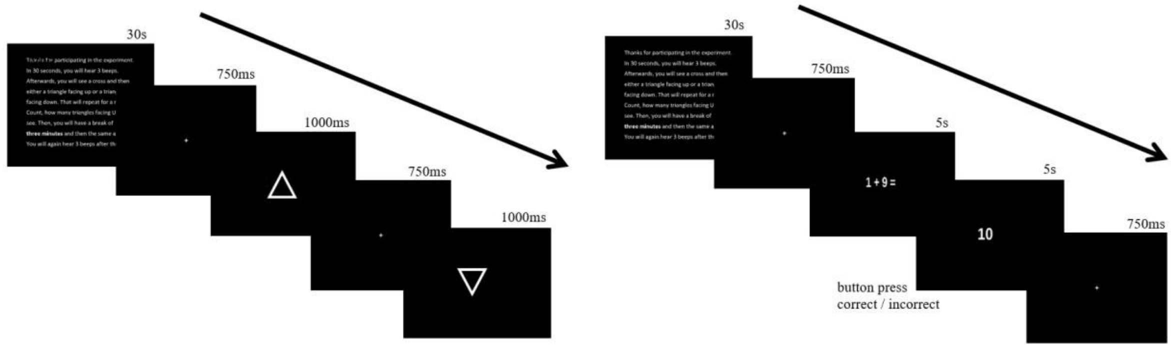


Figure Caption

Experiment timelines of instruction and task blocks. In experiment 1 (left), participants counted triangles facing up and in the breaks were instructed to relax and not to move. In experiment 2 (right), participants reacted with button press to either correct or incorrect results shown after arithmetic tasks.

7.2 Figure 2

Microstate maps

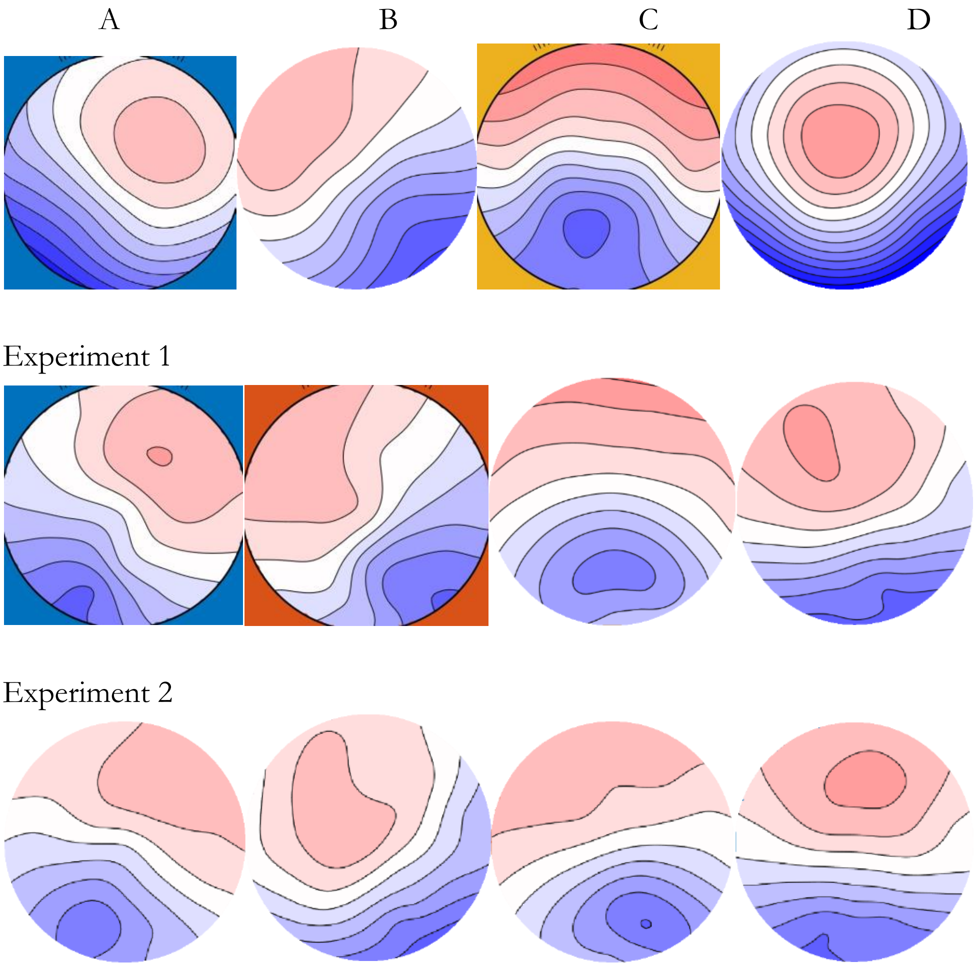


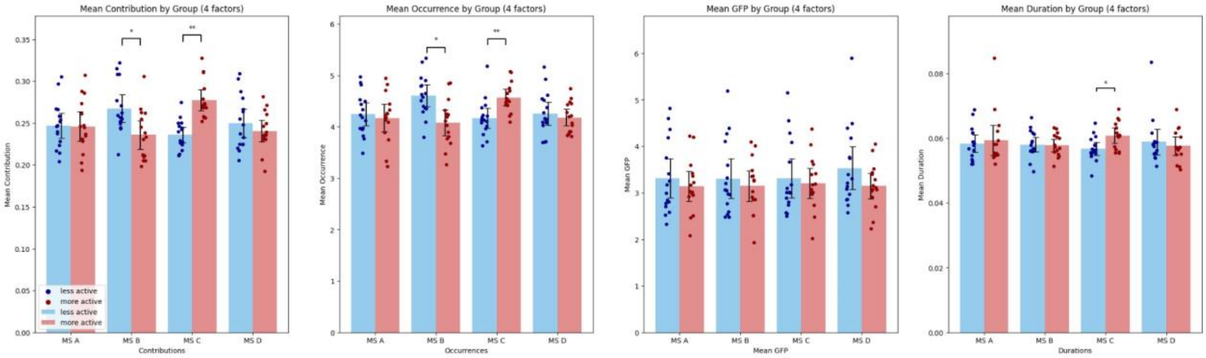
Figure Caption

Normative (upper row) versus acquired (middle and lower row) microstate maps. Microstate A, B,
C and D maps correspond to the normative maps and maps found in most microstate studies (Tarailis et al., 2023). Deviations are based on difference in statistical power and inter-study differences.

7.3 Figure 3

Experiment 1

Experiment 1



Experiment 2

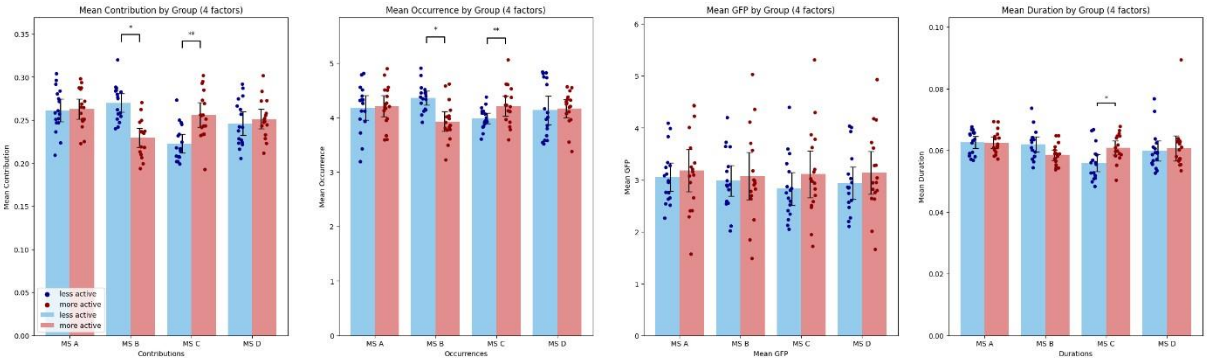


Figure Caption

Mean contribution to variance, mean occurrence, mean global field power and mean duration of microstates A, B, C and D (Tarailis, 2023). Error bars are confidence intervals based on Tukey's HSD corrected for multiple comparison. Significant differences are marked with brackets. * for p<0.05, ** for p <0.01, *** for p<0.001. Microstate B explained significantly more of the globally explained variance than microstate C in the group that was less active. Microstate B explained significantly more of the globally explained variance and occurred more often than microstate C in the group that was less active. Microstate C explained significantly more of the globally

7.4 Figure 4

explained variance and occurred more often than microstate B in the group that was more active. Microstate C persisted significantly longer on average in the more active group.

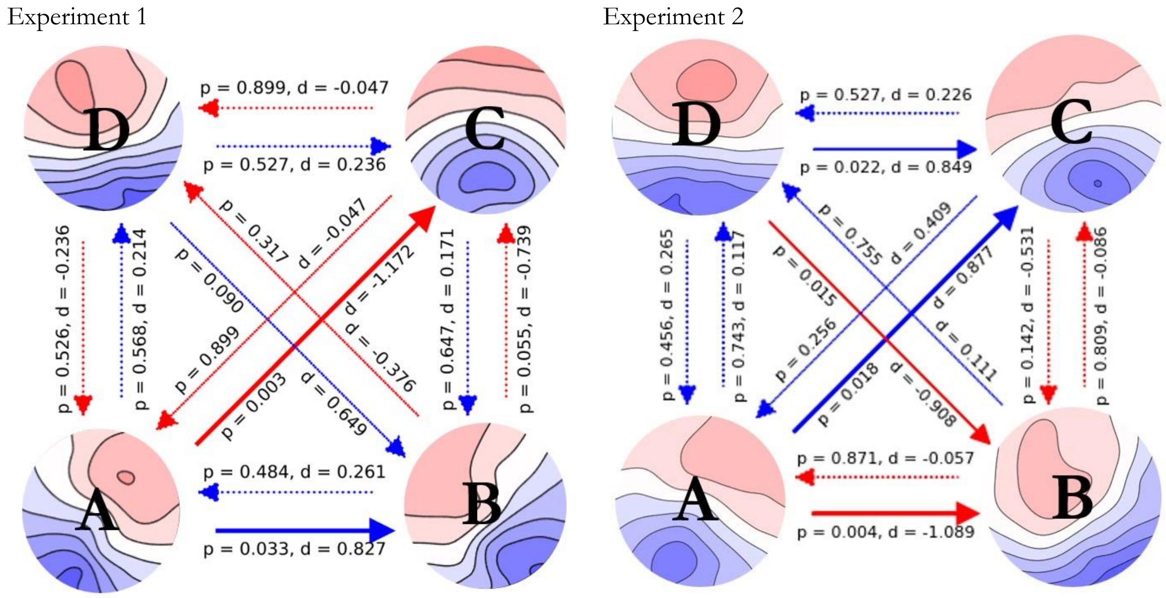
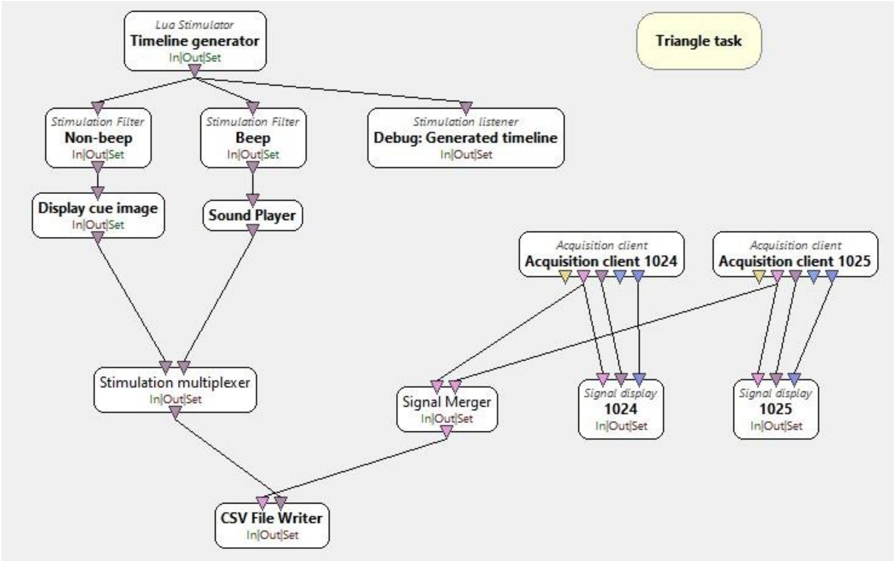


Figure Caption

Transition probability difference maps from microstate to microstate with original microstate maps. The transition probability is positive, if it is more likely in the less active group and negative if it is more likely in the active group. Dotted arrows denote non-significant differences, full arrows denote significant differences. Blue arrows denote that the probability is higher in the less active group, red arrows that it is more likely in the more active group. Note, that effect sizes are included, and several transition probabilities are different between the groups. “d” denotes Cohen’s d, p-values are based on Tukey’s HSD, two sided and multiple corrections corrected.

8 Appendix

Experiment 1



Experiment 2

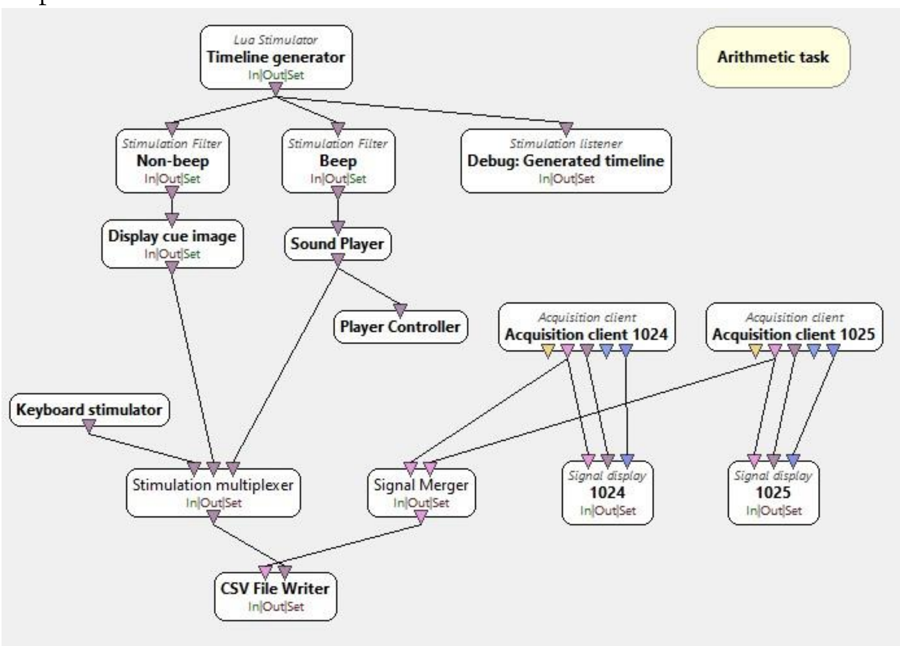


Figure Caption

Schemata of the OpenVibe EEG recording, interaction and writing pipeline of datastream combination.